



Faculty of Computer Science and Information Technology

Iban Plaited Mat Motif Classification using Adaptive Smoothing

Silvia Joseph

**Doctor of Philosophy
2024**

Iban Plaited Mat Motif Classification Using Adaptive Smoothing

Silvia Joseph

A thesis submitted

In fulfillment of the requirements for the degree of Doctor of Philosophy

(Computer Science)

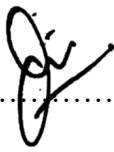
Faculty of Computer Science and Information Technology

UNIVERSITI MALAYSIA SARAWAK

2024

DECLARATION

I declare that the work in this thesis was carried out in accordance with the regulations of Universiti Malaysia Sarawak. Except where due acknowledgements have been made, the work is that of the author alone. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.



.....
Signature

Name: Silvia Joseph

Matric No.: 17010135

Faculty of Computer Science and Information Technology

Universiti Malaysia Sarawak

Date: 5th September 2024

ACKNOWLEDGEMENT

First and foremost, I would like to express my sincere gratitude to my supervisor Dr. Irwandi Hipni Bin Mohamad Hipiny. I feel very fortunate to have been a PhD student under his supervision by having a critical thinking skill. His advice and guidance have played a pivotal role in shaping the direction of my research. I am thankful for his guidance, support, advice, and valuable time he spent with me all the way through my PhD.

I am thankful to, AP Ts. Dr Hamimah binti Ujir who offered me valuable suggestions and advices. Thank you to my second supervisor, AP Dr. Jacey Lynn Minoi and Ts. Dr Sarah Flora Anak Samson Juan for your support.

Thanks to the Faculty of Computer Science and Information Technology (FCSIT), Universiti Malaysia Sarawak and the Centre for Graduate Studies for the advice and support given to all the postgraduate students.

Special thanks to Amanda Raeny the degree student of Fine Arts, Faculty of Applied and Creative Arts that helps me alot with my data analysis and who turn out to be a great friend. To all the craftswomen from *Rumah Temeling Ibai Bintong, Lubuk Antu and Kampung Sg Engkabang, Serian*, thank you for the knowledge sharing and assistance help me a lot. I acknowledge the support from the Public Service Department Malaysia *for* the study leaves with full paid salary. Thank you for the trust which is given to me to complete my PhD.

Finally, I would like to thank my family especially my children (Wawan, Tino & Tito) for their prayers, love, support and understanding. Their encouragement helpful in enduring the ups and downs of my graduate studies and have been a strong driving force throughout my work. Thank you all.

ABSTRACT

Iban plaited mats hold a significant cultural importance amongst Borneo's indigenous communities. These mats are intricately crafted with culturally significant patterns, incorporating a mix of diagonal, symmetrical, geometric, and non-geometric designs. Classifying these motifs poses a challenge due to their complex stylization and incorporation of multiple smaller patterns surrounding the main motif. This work introduces a new image dataset comprising of cleaned, cropped, and perspective corrected Iban plaited mat motif images. First, the accuracy of the Scale Invariant Feature Transform (SIFT) combined with the Random Sample Consensus (RANSAC) algorithm was assessed on the dataset. The optimal peak threshold value for SIFT is reported to be $2.0e-2$, and it achieved 100.0% matching accuracy for scale and rotation set. Next, additional local feature descriptors, combined with RANSAC, were evaluated on an expanded dataset. BRISK+RANSAC emerged as the top performer, achieving an average matching accuracy of 85.4%. BRISK+RANSAC encountered challenges in handling unresolved classes in sets with blur, illumination, and viewpoint changes. This is attributed to the spurious classification of smaller motifs affecting the label assignment. To address this issue, an improved classification method with adaptive smoothing is proposed. This method utilizes dynamic thresholds for edge detection and uses morphological operations to enhance the smoothed edges. The proposed method attained 100.0% accuracy for several sets and obtained an average increase of 10.2% accuracy over the baseline method.

Keywords: Pattern matching, Image classification, Local feature descriptors, Iban plaited mat motifs.

Klasifikasi Motif Tikar Anyaman Iban Menggunakan Adaptive Smoothing

ABSTRAK

Tikar anyaman Iban merupakan seni anyaman tradisional yang menjadi identiti masyarakat Iban di Borneo. Ianya mengandungi pelbagai motif cantik dan rumit, dengan corak yang menggabungkan rekabentuk berjenis pepenjuru, simetri, geometri dan bukan geometri. Pengklasifikasian motif bagi tikar anyaman Iban adalah sukar disebabkan corak motif yang kompleks serta kewujudan motif bersaiz kecil sebagai hiasan tambahan. Kajian ini memperkenalkan satu dataset baharu yang hanya mengandungi imej motif utama. Dataset ini telah diuji menggunakan kaedah Scale Invariant Feature Transform (SIFT) yang digabung bersama kaedah Random Sample Consensus (RANSAC). Dikenalpasti nilai SIFT yang optimum adalah $2.0e-2$, yang mencapai ketepatan padanan 100.0% bagi set skala dan set putaran. Seterusnya, beberapa deskriptor imej yang lain, turut dinilai menggunakan dataset yang bersaiz lebih besar. BRISK+RANSAC muncul sebagai kombinasi terbaik, dengan purata ketepatan padanan sebanyak 85.4%. Namun, kombinasi ini menghasilkan kes pelbagai padanan bagi set imej kabur, pencahayaan serta sudut imej yang berbeza, berpunca daripada motif kecil yang mempengaruhi ketepatan padanan. Kaedah berasaskan “adaptive smoothing” adalah dicadangkan, di mana nilai “dynamic thresholds” digunapakai semasa pengesanan garis tepi dan operasi morfologi diaplikasikan bagi menambah baik kualiti garisan. Kaedah ini memperolehi ketepatan padanan motif 100.0% untuk majoriti set dan dengan purata peningkatan sebanyak 10.2%.

Kata kunci: *Padanan corak, klasifikasi imej, penerangan ciri tempatan, dan motif tikar anyaman Iban.*

TABLE OF CONTENTS

	Page
DECLARATION	i
ACKNOWLEDGEMENT	ii
ABSTRACT	iii
ABSTRAK	iv
TABLE OF CONTENTS	v
LIST OF TABLES	xii
LIST OF FIGURES	xv
LIST OF ABBREVIATIONS	xxii
CHAPTER 1 INTRODUCTION	1
1.1 Introduction	1
1.2 Problem Statement	6
1.2.1 Challenges in Extracting Feature Information from Cultural Patterns	7
1.2.2 Ensuring Robustness	8
1.3 Research Questions	8
1.4 Research Objectives	9
1.5 Hypothesis	9
1.6 Research Contributions	10

1.7	Scope of Study	12
1.8	Research Gap	15
1.8.1	The absence of a comprehensive and systematically curated Iban plaited mat image dataset.	15
1.8.2	The presence of multiple prominent motifs inside a single plaited mat	17
1.9	Thesis Outline	19
	CHAPTER 2 LITERATURE REVIEW	21
2.1	Overview	21
2.2	Visual Characteristics of Iban Plaited Mat Motifs	21
2.3	Pattern Recognition	24
2.3.1	Local Feature Descriptors	26
2.3.2	Machine Learning Classifiers	27
2.3.3	Edge Detectors	28
2.3.4	Morphological Operations	33
2.3.5	Outlier Removal	34
2.4	Pattern Recognition Usage in the Domain of Art and Culture	35
2.4.1	Local Feature Descriptors	35
2.4.2	Machine Learning Classifiers.	38
2.4.3	Edge detectors in Cultural Pattern Extraction	42
2.5	Summary	46

CHAPTER 3 EVALUATION OF LOCAL FEATURE DESCRIPTORS AND ADAPTIVE SMOOTHING	48
3.1 Overview	48
3.2 The General Research Workflow	48
3.3 Research Pipeline	50
3.4 Experimental Setup and Dataset	53
3.4.1 Image Acquisition	54
3.4.2 Image Pre-processing	55
3.4.3 Dataset and entropy value	58
3.4.4 Image Preprocessing	63
3.4.4.1 Image preparation for the First and Second Experiment	63
3.5 Feature Descriptor and Proposed Approach	69
3.5.1 Feature Descriptor using Scale-Invariant Feature Transform (SIFT) algorithm Peak Thr parameter value of 0.02, 0.04, 0.06 and 0.08.	70
3.5.1.1 Scale-Invariant Feature Transform (SIFT) keypoint and descriptors.	70
3.5.2 Feature Descriptor SIFT with Peak Thresholding parameter value of 0.02, SURF, BRISK, MSER AND FAST.	72
3.5.2.1 Scale-Invariant Feature Transform (SIFT) with Peak Thr parameter value of 0.02	72
3.5.2.2 Speeded-Up Robust Features (SURF)	76
3.5.2.3 Binary Robust Invariant Scalable Keypoints (BRISK)	78

3.5.2.4 Maximally Stable Extremal Regions (MSER)	80
3.5.2.5 Features from accelerated segment test (FAST)	82
3.5.3 Proposed Method Adaptive Smoothing	84
3.5.3.1 Edge Extraction	86
3.5.3.2 Gaussian Smoothing	86
3.5.3.3 Image Gradient Calculation	87
3.5.3.4 Non-maximum Suppression	87
3.5.3.5 Checking for the Connected Edges	88
3.5.3.6 Probabilistic Hough Transform	89
3.5.3.7 Detail Process	90
3.5.3.8 Edge Appearance Improvement	93
3.5.3.9 Producing Edge Images at Different PoRE Values	94
3.5.3.10 Preparation of Query Images (Test Sequences)	95
3.6 Outlier Removal	97
3.7 Evaluation Approach	97
3.8 Discussion and Conclusion	100
CHAPTER 4 TESTING AND IMPLEMENTATION	102
4.1 Overview	102
4.2 Experiment 1 (SIFT with peak threshold value of 0.02, 0.04, 0.06 and 0.08)	102
4.2.1 Results and Analysis Experiment 1	103

4.2.2 Comparing the Matching Quality of Each Mat Motif Class When Using Peak Threshold Value SIFT with RANSAC performance against common image deformations.	113
4.2.3 Finding the Optimal Peak Threshold for SIFT	129
4.2.4 Summary	141
4.3 Experiment II (Matching evaluation SIFT, SURF, BRISK, MSER and FAST)	142
4.3.1 SIFT PeakThr parameter value of 0.02 and SURF descriptor matching	143
4.3.2 BRISK and FAST descriptor matching	143
4.3.3 MSER descriptor matching	144
4.3.4 Matching Verification	144
4.4 Performance Results and Discussion	145
4.4.1 Blur Sequence	145
4.4.2 JPEG Compression	148
4.4.3 Illumination change	151
4.4.4 Scale change	154
4.4.5 Viewpoint change	157
4.4.6 Scale + Rotation change	160
4.4.7 Confusion matrix results	163
4.4.8 Failure point for each image descriptor	180
4.4.9 Performance Measures	182

4.4.10 Summary	189
4.5 Motif Classification using Adaptive Smoothing (Proposed Method)	190
4.5.1 Detected Keypoints	191
4.5.2 Matching Results	195
4.5.3 Confusion Matrix Results, Using Scheme 4	198
4.5.4 Comparative Failure Points for each Scheme	202
4.5.5 Optimal Scheme and Optimal PoRE Value	206
4.5.6 Summary	210
4.6 Conclusion	211
CHAPTER 5 CONCLUSIONs AND RECOMMENDATIONS	213
5.1 Conclusion	213
5.2 Summary of Contributions	214
5.3 Limitation and Challenges	216
5.3.1 Dataset Size	216
5.3.2 Limited Knowledge on Iban Plaited Mat Motifs.	216
5.3.3 Enhance Matching Accuracy in Homogenous Motif Image.	217
5.3.4 Challenges of False Correspondences in Highly Complex Motifs: Implications for Recognition and Classification.	217
5.4 Future Work	218
5.4.1 Enhancing Deep Learning Model Training: Expanding the Iban Plaited Mat Motif Dataset	218

5.4.2	Assessing Computational Efficiency: Evaluating Matching Speed in Motif Classification Algorithms	218
5.4.3	Expanding the Multi-Material Dataset	219
	REFERENCES	220
	APPENDICES	244

LIST OF TABLES

	Page
Table 3.1: Synthetic images and entropy value of simple motif.	60
Table 3.2: Incremental values for each image deformation type. (Joseph et al., 2021)	65
Table 3.3: Synthetic query images of <i>Buah Bandau</i> (a) the blur sequence, (b) Illumination change sequence, (c) JPEG compression change sequence, (d) Scale change sequence (e) Viewpoint change sequence and (f) Scale+Rotation change sequence.	66
Table 3.4: Baseline and the 4 schemes.	85
Table 3.5: Parameters used for Canny edge detection.	92
Table 3.6: Parameter values used for edge counting with ProHT.	92
Table 3.7: Possible Outcomes for a Binary Classification	98
Table 4.1: Number of found keypoints in query and reference image, correspondences, inliers and rejected outliers. Using SIFT + RANSAC at optimal peak threshold value of 0.02 on the Blur sequence (Level 1).	105
Table 4.2: Number of found keypoints in query and template image, correspondences, inliers and rejected outliers. Using SIFT + RANSAC at optimal peak threshold value of 0.02 on the Blur sequence (Level 5).	107
Table 4.3: Visualized keypoints detected (green color) in the reference images (no deformation) at the optimal PeakThr parameter value of 0.02.	109
Table 4.4: Visualized distribution of SIFT build feature descriptor detected in the clean synthetic template images at the PeakThr parameter value of 0.02.	111
Table 4.5: Classification statistics of PeakThr parameter values of 0.02, 0.04, 0.06, and 0.08 for every image deformation sequences, belonging to <i>Buah Bulan Sebayon</i> .	114
Table 4.6: Comparison in the number of SIFT matches between deformation first level to fifth level at Optimal PeakThr parameter value of 0.02.	117
Table 4.7: SIFT matching result between target vs. query image pairs belonging to the Blur sequences, without (a) and with (b) RANSAC. The results were generated using the optimal peak threshold value of 0.02.	119

Table 4.8: Example of SIFT matching result of the template image vs. query image without RANSAC (a) and with RANSAC (b) at the PeakThr parameter value of 0.04. (Illumination change).	120
Table 4.9: SIFT matching result between target vs. query image pairs belonging to the Scale change sequences, without (a) and with (b) RANSAC. The results were generated using a non-optimal peak threshold value of 0.06.	121
Table 4.10: SIFT matching result between target vs. query image pairs belonging to the Viewpoint change sequences, without (a) and with (b) RANSAC. The results were generated using a non-optimal peak threshold value of 0.08.	122
Table 4.11: The failure point of SIFT+RANSAC, at optimal PeakThr parameter value of 0.02, for each image deformation category.	139
Table 4.12: Failure point of SIFT+RANSAC, at PeakThr parameter value of 0.04, for each image deformation category.	140
Table 4.13: Failure point of SIFT+RANSAC, at PeakThr parameter value of 0.06, for each image deformation category.	140
Table 4.14: The failure point of SIFT+RANSAC, at PeakThr parameter value of 0.08, for each image deformation category.	140
Table 4.15: Classification statistics of Blur sequences belonging to <i>Buah Lang Antu</i> and <i>Buah Nabau Besundang</i> .	146
Table 4.16: Classification statistics of JPEG Compression sequences belonging to <i>Buah Lintah Tanah</i> and <i>Buah Mata Punai</i> .	148
Table 4.17: Classification statistics of Illumination sequences belonging to <i>Buah Sebayen</i> and <i>Buah Andu</i> .	151
Table 4.18: Classification statistics of Scale change sequences belonging to <i>Buah Bandau</i> and <i>Buah Mayau</i> .	154
Table 4.19: Classification statistics of Viewpoint change sequences belonging to <i>Buah Kandung Nibung Berayah</i> and <i>Buah Nabau Ngelantar</i> .	157
Table 4.20: Classification statistics of Scale+Rotation change sequences belonging to <i>Buah Tungku</i> and <i>Buah Suri Ai</i> .	160
Table 4.21: The failure point of SIFT + RANSAC (with Peak Thr value of 0.02), for each image deformation category.	180
Table 4.22: The failure point of SURF + RANSAC for each image deformation category.	181

Table 4.23: The failure point of BRISK + RANSAC for each image deformation category.	181
Table 4.24: The failure point of MSER + RANSAC for each image deformation category.	181
Table 4.25: The failure point of FAST + RANSAC for each image deformation category.	181
Table 4.26: Comparison between deformations Level 1 vs. Level 5 regarding the number of detected BRISK keypoints in <i>Buah Lang Antu</i> . The query images were generated using the PoRE value of 75.0%, for every image deformation category, with and no morphological dilation.	195
Table 4.27: Failure points, obtained using Scheme 4.	202
Table 4.28: Failure points, obtained using Scheme 3.	203
Table 4.29: Failure points, obtained using Scheme 1.	203
Table 4.30: Failure points, obtained using Scheme 2.	204
Table 4.31: The mean accuracy achieved by each scheme against different image deformation category. The PoRE value for Scheme 3 and 4 is 75.0%.	207

LIST OF FIGURES

	Page
Figure 1.1: An example of a decorative Iban plaited mat containing <i>Buah Lang Antu</i> as the main motif, made using (a) natural fiber vs. (b) colored fibers.	3
Figure 1.2: Non-geometric motifs, from left to right, <i>Buah Nabau Ngelantar</i> , and <i>Buah Tungku</i> .	5
Figure 1.3: Geometric motifs, from left to right, <i>Buah Panchar Matahari</i> , and <i>Buah Tabak Kumang</i> .	5
Figure 1.4: Example of decorative plaited mat made using natural fibers.	12
Figure 1.5: Raw photos of Iban plaited mats. Each mat contains one central motif, i.e., (a) <i>Buah Bulan Sebayon</i> , (b) <i>Buah Burung Kenyalang</i> , (c) <i>Buah Lang Antu</i> , (d) <i>Buah Engkatak Tingkap Pama Merap</i> , (e) <i>Buah Nabau Besundang</i> and (f) <i>Buah Nabau Ngelantar</i> .	14
Figure 1.6: Example of mat with free composition of Nabau (serpent-dragons) and human figures, $2.94 \times 1.39\text{m}$ (9'7" $\times$ 4'6") (Sellato, 2012).	17
Figure 1.7: Two examples of an Iban plaited mat motif with small motif(s) as fillers, (a) an animal-based motif, i.e., <i>Buah Burung Garuda</i> , and (b) a fairy based motif, i.e., <i>Buah Sabayan</i> . The filler motifs are circled and numbered (1– 4).	18
Figure 2.1: An example of a (1.96m $\times$ 0.94m) ceremonial mat, decorated with the motif of <i>Buah Talam Kumang</i> . The mat is plaited with two “pulau”. The (2) decorative edge is positioned between two strengthening rows of transposed twill, i.e., “sapa” (1 and 3).	22
Figure 2.2: An example of a 2.16 meters long ritual mat decorated with the motif of <i>Buah Nabau Ngelantar</i> (serpent-dragons). The mat is plaited with a single large “pulau”. The (2) decorative edge is positioned between two strengthening rows of transposed twill, i.e., “sapa” (1 and 3).	22
Figure 2.3: A mat motif, i.e., <i>Buah Tungku</i> , acts as the central motif. Another motif, i.e., <i>Buah Mata Punai</i> , acts as the filler, (1) and (2). The above image was sourced from (Joseph et al., 2023).	23
Figure 2.4: Two motifs, (a) <i>Buah Lang Antu</i> and (b) <i>Buah Burung Garuda</i> , act as the central motif whilst another motif (circled) acts as a filler.	23
Figure 3.1: Research workflow.	49

Figure 3.2: Graphical summary phases of the research pipeline I. The above image is adapted from (Joseph et al., 2021).	51
Figure 3.3: Graphical summary phases of the research pipeline II.	52
Figure 3.4: Graphical summary phases of proposed methodology. (Joseph et al., 2023).	53
Figure 3.5: Sample photos of plaited mats captured at Rumah Temeling Ibai Bintong, Lubuk Antu, Sarawak.	55
Figure 3.6: Our camera setup.	55
Figure 3.7: From left to right, (a) <i>Buah Nabau Ngelantar</i> (BNN), (b) <i>Buah Bong Midang</i> (BBM), and (c) <i>Buah Panchar Matahari</i> (BPM).	57
Figure 3.8: SIFT feature extraction; (a) Scale-space generation; (b) DoG image generation; (c) detection of local maximum and minimum; (d) gradient calculation and (e) histogram calculation and generation of 128-dimensional vectors. Image 3.7 (c) and (d) are sourced from (Lowe, 1999).	71
Figure 3.9: The visualized SIFT PeakThr values 0.02 keypoints detected (green color) in the synthetic images of our dataset a) simple motifs and (b) complex motifs. The corresponding <i>Ntmp</i> are indicated below the images.	74
Figure 3.10: Visualized feature descriptors on selected synthetic images of our dataset (a) simple motifs and (b) complex motifs.	75
Figure 3.11: Visualized SURF keypoints detected (green color) in the synthetic images belonging to our dataset. (a) Simple motifs and (b) complex motifs. The corresponding <i>Ntmp</i> are indicated below the images.	77
Figure 3.12: The visualized BRISK keypoints detected (green color) in the selected synthetic images. (a) Simple motifs and (b) complex motifs. The corresponding <i>Ntmp</i> are indicated below the images.	79
Figure 3.13: Visualized MSER ellipse keypoints detected (green color) in selected synthetic images. (a) Simple motifs and (b) complex motifs. The corresponding <i>Ntmp</i> are indicated below the images.	81
Figure 3.14: The appearance and distribution of the FAST keypoint detected (green color) in the clean synthetic template images.	83
Figure 3.15: A flowchart describing our general research workflow.	86
Figure 3.16: Two threshold values, minVal and maxVal. Image sourced from (Bradski, 2000).	89

Figure 3.17: Flowchart of the adaptive smoothing process.	91
Figure 3.18: Reference images produced using standard Canny edge algorithm, without (top) and with dilation (bottom). The mat motifs are (a) <i>Buah Lang Antu</i> , (b) <i>Buah Bandau</i> and (c) <i>Buah Andu</i> .	93
Figure 3.19: Images for the following motif classes (top to bottom row), from left to right, were created using PoRE values of 100.0%, 75.0%, and 20.0%: <i>Buah Andu</i> , <i>Buah Burung Garuda</i> , <i>Buah Bandau</i> , <i>Buah Tungku Lebur</i> , and <i>Buah Nabau Besundang</i> . The versions (a) without dilation and (b) with dilation are both displayed.	94
Figure 3.20: Sample query images produced with Canny edge detection with varying degrees of deformation from top to bottom. Query images for the <i>Buah Lang Antu</i> sequence for blur, the <i>Buah Burung Garuda</i> sequence for JPEG compression, the <i>Buah Lintan Tanah</i> sequence for illumination change, the <i>Buah Tungku Lebur</i> sequence for viewpoint change, the <i>Buah Nabau Besundang</i> sequence for scale change, and the <i>Buah Tangkai Gajai Besembah</i> sequence for scale+rotation change is displayed in the column to the left.	96
Figure 4.1: Average Matching Accuracy for each mat motifs at PeakThr parameter value of 0.02, 0.04, 0.06, and 0.08 (Blur change).	123
Figure 4.2: Average Matching Accuracy for each mat motifs at PeakThr parameter value of 0.02, 0.04, 0.06, and 0.08 (JPEG Compression).	124
Figure 4.3: Average Matching Accuracy for each mat motifs at PeakThr parameter value of 0.02, 0.04, 0.06, and 0.08 (Illumination change).	124
Figure 4.4: Average Matching Accuracy for each mat motifs at PeakThr parameter value of 0.02, 0.04, 0.06, and 0.08 (Scale change).	125
Figure 4.5: Average Matching Accuracy for each mat motifs at PeakThr parameter value of 0.02, 0.04, 0.06, and 0.08 (Scale+Rotation change).	125
Figure 4.6: Average Matching Accuracy for each mat motifs at PeakThr parameter value of 0.02, 0.04, 0.06, and 0.08 (Viewpoint change).	127
Figure 4.7: Visualized of geometric and highly repetitive motifs that had a low average matching accuracy.	127
Figure 4.8: Visualized of simple motif <i>Buah Mata Punai</i> (BMP) that have less intricate details and variations.	128
Figure 4.9: Confusion Matrix for SIFT+RANSAC, at PeakThr parameter value of (a) 0.02, (b) 0.04, (c) 0.06, (d) 0.08. (Blur change).	130

Figure 4.10: Confusion Matrix for SIFT+RANSAC, at PeakThr parameter value of (a) 0.02, (b) 0.04, (c) 0.06, (d)0.08 (Illumination change).	131
Figure 4.11: Confusion Matrix for SIFT+RANSAC, at PeakThr parameter value of (a) 0.02, (b) 0.04, (c) 0.06, (d) 0.08 (JPEG compression).	132
Figure 4.12: Confusion Matrix for SIFT+RANSAC, at PeakThr parameter value of (a) 0.02, (b) 0.04, (c) 0.06, (d)0.08 (Scale change).	133
Figure 4.13: Confusion Matrix for SIFT+RANSAC, at PeakThr parameter value of (a) 0.02, (b) 0.04, (c) 0.06, (d)0.08 (Viewpoint change).	134
Figure 4.14: Confusion Matrix for SIFT, at PeakThr parameter value of (a) 0.02, (b) 0.04, (c) 0.06, (d) 0.08 (Scale + Rotation).	135
Figure 4.15: Average matching accuracy of SIFT+RANSAC, at PeakThr parameter value of 0.02, 0.04, 0.06, and 0.08; following six image deformations.	136
Figure 4.16: Precision of SIFT+RANSAC, at PeakThr parameter value of 0.02, 0.04, 0.06, and 0.08; following six image deformations.	137
Figure 4.17: True Positive Rate or sensitivity of SIFT+RANSAC, at PeakThr parameter value of 0.02, 0.04, 0.06, and 0.08; following six image deformations.	137
Figure 4.18: F1 Score of SIFT+RANSAC, PeakThr parameter value of 0.02, 0.04, 0.06, and 0.08; following six image deformations.	138
Figure 4.19: Misclassification rate of SIFT+RANSAC, PeakThr parameter value of 0.02, 0.04, 0.06, and 0.08; following six image deformations.	138
Figure 4.20: Visualized SURF keypoints in reference image of (a) <i>Buah Lang Antu</i> , and query image with blur (b) level 1, (c) level 2, (d) level 3, (e) level 4 and (f) level 5.	147
Figure 4.21: Matching results of (a) <i>Buah Lang Antu</i> and (b) <i>Buah Nabau Besundang</i> using SURF+RANSAC at deformation of blur change first level vs. third level (left to right column)	147
Figure 4.22: Visualized BRISK keypoints in reference image of (a) <i>Buah Mata Punai</i> , and query image belonging to JPEG Compression sequence: (b) level 1, (c) level 2, (d) level 3, (e) level 4 and (f) level 5.	150
Figure 4.23: Matching results of (a) <i>Buah Lintan Tanah</i> and (b) <i>Buah Mata Punai</i> using BRISK + RANSAC for JPEG Compression comparing first level (left column) and fifth (right column).	150

Figure 4.24: Visualized MSER keypoints in reference image of (a) <i>Buah Andu</i> , and query images belonging to Illumination sequences, (b) level 1, (c) level 2, (d) level 3, (e) level 4 and (f) level 5.	153
Figure 4.25: Matching results of (a) <i>Buah Sebayon</i> and (b) <i>Buah Mata Punai</i> utilising test sequences from Illumination change levels 1 and 5 (left to right column) with MSER + RANSAC	153
Figure 4.26: Visualized BRISK keypoints in the reference image of (a) <i>Buah Bandau</i> and query images belonging to the Scale change sequences, (b) level 1, (c) level 2, (d) level 3, (e) level 4 and (f) level 5.	156
Figure 4.27: Matching results of (a) <i>Buah Bandau</i> and (b) <i>Buah Mayau</i> utilising Scale change level 1 (left column) vs. level 5 (right column) test sequences with BRISK + RANSAC.	156
Figure 4.28: Visualized FAST keypoints in the reference image of (a) <i>Buah Kandung Nibung Berayah</i> , and query images belonging to the Viewpoint change sequences (b) level 1, (c) level 2, (d) level 3, (e) level 4 and (f) level 5.	159
Figure 4.29: Matching results of (a) <i>Buah Kandung Nibung Berayah</i> and (b) <i>Buah Nabau Ngelantar</i> level 1 vs. level 4 (left to right column) utilising FAST + RANSAC at Viewpoint.	159
Figure 4.30: Visualized SIFT+RANSAC keypoint in reference image of (a) <i>Buah Tungku</i> , and query images belonging to the Scale+Rotation sequences (b) level 1, (c) level 2, (d) level 3, (e) level 4 and (f) level 5.	162
Figure 4.31: Matching results of (a) <i>Buah Tungku</i> and (b) <i>Buah Suri Ai</i> utilising test sequences from Scale+Rotation Change first level and fifth level (left to right column) using SIFT + RANSAC.	162
Figure 4.32: Confusion matrixes from SIFT+RANSAC classification results (with PeakThr value of 0.02), under the following image deformation type, i.e., (a) Blur (b) JPEG Compression (c) Illumination change (d) Viewpoint change (e) Scale change, and (f) Scale+Rotation.	166
Figure 4.33: Confusion matrixes from the SURF+RANSAC classification outcomes, i.e., (a) Blur (b) JPEG Compression (c) Illumination change (d) Viewpoint change (e) Scale change, and (f) Scale+Rotation.	169
Figure 4.34: Confusion matrixes from the classification results using BRISK+RANSAC, under the following image deformation type, i.e., (a) Blur (b) JPEG Compression (c) Illumination change (d) Viewpoint change (e) Scale change, and (f) Scale+Rotation.	173

Figure 4.35: Confusion matrixes from the classification results using MSER+RANSAC, under the following image deformation type, i.e., (a) Blur (b) JPEG Compression (c) Illumination change (d) Viewpoint change (e) Scale change, and (f) Scale+Rotation.	176
Figure 4.36: Confusion matrixes from the classification results using FAST+RANSAC, under the following image deformation type, i.e., (a) Blur (b) JPEG Compression (c) Illumination change (d) Viewpoint change (e) Scale change, and (f) Scale+Rotation.	179
Figure 4.37: Precision for each feature descriptor against 6 typical image deformations.	183
Figure 4.38: True positive rate for each feature descriptor against 6 typical image deformations.	185
Figure 4.39: F1 Score for each feature descriptor against 6 typical image deformations.	186
Figure 4.40: Misclassification rate for each feature detector and descriptor against 6 typical image deformations.	188
Figure 4.41: Matching accuracy for each feature detector and descriptor against 6 typical image deformations.	189
Figure 4.42: Visualized BRISK descriptors (green color) on reference images produced using standard Canny edge detection.	192
Figure 4.43: Visualized BRISK descriptors (green color) in reference images of <i>Buah Mata Punai</i> produced using ProHT PoRE-Canny algorithm with PoRE values of (a) 100.0%, (b) 75.0%, (c) 70.0%, (g) 50.0%, and (h) 20.0%. No dilation.	193
Figure 4.44: Visualized BRISK descriptors (green color) in reference images of <i>Buah Mata Punai</i> produced using ProHT PoRE-Canny algorithm with PoRE values of (a) 100.0%, (b) 90.0%, (c) 80.0%, (d) 85.0%, (e) 75.0%, (f) 70.0%, (g) 50.0% and (h) 20.0%. With dilation.	194
Figure 4.45: Matching results using BRISK+RANSAC	197
Figure 4.46: Confusion matrixes produced using Scheme 4. (a) blur change, (b) Illumination change, (c) JPEG Compression, (d) Scale change, (e) Viewpoint change and (f) scale+rotation.	201
Figure 4.47: Three motifs with a high rate of misclassification.	205
Figure 4.48: Three motifs that with failure cases under blur, scale and scale+rotation.	206

Figure 4.49: Baseline vs. Scheme 4 (PoRE value of 75.0%). Average accuracy obtained for each image deformation category.	208
Figure 4.50: Average matching accuracy obtained by each scheme under each deformation category.	209
Figure 4.51: Average matching accuracy while using Scheme 4 at various PoRE values.	210

LIST OF ABBREVIATIONS

BBS	<i>Buah Bulan Sebayan</i>
BBK	<i>Buah Burung Kenyalang</i>
BBM	<i>Buah Bong Midang</i>
BMP	<i>Buah Mata Punai</i>
BNB	<i>Buah Nabau Besundang</i>
BNN	<i>Buah Nabau Ngelantar</i>
BETPM	<i>Buah Engkatak Tingkap Pama Merap</i>
BPM	<i>Buah Panchar Matahari</i>
BTM	<i>Buah Talam Kumang</i>
BT	<i>Buah Tungku</i>
BLA	Buah Lang Antu
BB	<i>Buah Bandau</i>
BA	<i>Buah Andu</i>
BBBekarung	<i>Buah Bulan Bekarung</i>
BBBepayung	<i>Buah Bulan Bepayung</i>
BBG	<i>Buah Burung Garuda</i>
BKNB	<i>Buah Kandung Nibung Berayah</i>
BP	<i>Buah Pama</i>

BK	<i>Buah Kesulai</i>
BLM	<i>Buah Lang Menyarung</i>
BLT	<i>Buah Lintan Tanah</i>
BM	<i>Buah Mayau</i>
BS	<i>Buah Sebayan</i>
BSA	<i>Buah Suri Ai</i>
BTGB	<i>Buah Tangkai Gajai Besembah</i>
BTL	<i>Buah Tungku lebur</i>
TP	True Positive
FP	False Positive
FN	False Negative
N_{tmp}	number of detected reference image's keypoints
N_{qry}	Number of detected query image's keypoints
N_{crp}	The number of matches found
N_{mch}	The number of correct matches after RANSAC
Img	Image
TP	True Positive
FP	False Positive
FN	False Negative

CHAPTER 1

INTRODUCTION

1.1 Introduction

Pattern recognition, a ubiquitous technology, has proven invaluable across diverse domains, notably in advancing the ongoing digitalization endeavors within arts and culture. Concurrently, governmental and private entities, exemplified by the United Nations Educational, Scientific and Cultural Organization (UNESCO), are spearheading initiatives to safeguard both tangible and intangible cultural heritages from the brink of extinction, harnessing novel technologies to bolster their preservation and promotion (Blake, 2014). UNESCO elucidates intangible cultural heritage as encompassing the practices, representations, knowledge, and skills integral to cultural legacy, transmitted across generations within specific community groups, thus retaining profound significance according to (Blake, 2014).

Another perspective on intangible cultural heritage, articulated by (Mohd Noor & Abd Aziz, 2018), defines it as an observable, tangible, and perceptible phenomenon inherent in a product or artistic creation, yet dissipating upon its loss or extinction. Efforts to safeguard such heritage entail digitizing these intangible cultural elements, with resultant digital outputs potentially serving as tourism attractions (Copeland, 2004). Establishing a structured database becomes imperative for efficient indexing and retrieval of these digitized records. Here, pattern recognition assumes a pivotal role by autonomously assigning unique identifiers to these records based on their visual characteristics. Integrating this functionality into a smartphone application could empower

tourists or visitors to capture images of cultural artifacts, explore matches within the database, and access relevant information about the products.

One intangible cultural heritage in need of preservation is the Iban plaited mat motif. The intricate designs adorning these decorative mats within the Iban community in Borneo hold profound cultural significance, reflecting both the environment and traditional beliefs of this indigenous group. Each motif carries its own unique meaning and taboos, contributing to the rich tapestry of Iban heritage. However, despite their importance, the comprehensive documentation of these motifs has been lacking, posing a risk to their preservation (Sellato, 2012). In light of this, leveraging pattern recognition technology presents a promising solution to this challenge. Drawing inspiration from successful image recognition applications like Pinterest and Google Lens, which have proven popular among smartphone users as reported by (Buyer, 2017), pattern recognition can play a pivotal role in automatically identifying and categorizing these intricate motifs based on their visual characteristics. By integrating this functionality into a smartphone application, tourists and visitors can effortlessly capture images of plaited mats, explore matches within a comprehensive database, and access relevant information about the cultural significance of each motif. This initiative aligns with global efforts, including those of UNESCO and the Sarawak Government, to embrace digitization and Industry 4.0 technologies in preserving and promoting cultural heritage, particularly emphasizing the significance of the Iban plaited mat motif as a symbol of Sarawak's cultural identity. Therefore, it is imperative for the government to allocate resources and establish initiatives aimed at documenting and safeguarding this heritage to ensure that future generations inherit not only tangible artifacts but also a deep appreciation for the cultural legacy they represent.

The Iban plaited mat motif is a traditional weaving pattern commonly used by the Iban people of Sarawak, Malaysia. The features a combination of geometric and non-geometric shapes that pose challenges for manual classification and identification by non-experts. These motifs are integral to various Iban cultural heritage products, particularly decorative plaited mats characterized by patterned abstract designs with distinct ethnic and regional traits. Central to these mats is the plaiting technique, traditionally executed by hand without the use of a loom and primarily crafted from natural fibers sourced from the abundant rainforests, such as *bemban* (*donax grandis*) and rattan (*calameae*). However, due to the scarcity of these natural resources, Iban craftswomen have shifted to using artificial colored strings. Figure 1.1 depicts an image of a plaited mat motif, specifically the *Buah Lang Antu* pattern, woven from both natural and colored fibers.



(a)



(b)

Figure 1.1: An example of a decorative Iban plaited mat containing *Buah Lang Antu* as the main motif, made using (a) natural fiber vs. (b) colored fibers.

Typically, the names of symbols and the meanings or praises associated with them are orally transmitted and not directly recorded on the mat. In many cases, multiple motifs are incorporated into a single mat, with the central motif serving as the main character and smaller motifs acting as fillers to complement or enrich the narrative. The design of the mat is considered the intellectual property of the individual plaiter, and often, only they possess the comprehensive understanding necessary to explain the entire story behind the motifs.

Iban plaited mat motifs are named after natural phenomena, mostly stylized beyond recognition (Sellato, 2012). The names fall into loose categories (i.e., classes), such as plants, animals, firmaments, faeries and common items (Durin, 2014). A mat motif is named as a "*buah*" (literally a fruit). Besides the classics, new patterns may also be revealed to the craftswoman via her dream, and in such cases, only the craftswoman may name and plait the pattern (Sellato & Fogel, 2013). The motifs are created via a human cognitive process representing an artistic interpretation of nature in geometric and non-geometric shapes. Motifs can be classed as either as simple or complex based on the entropy level (i.e., complex motifs contain richer information).

As mentioned earlier, the plaited mats contain geometric and non-geometric motif(s) arranged in a repetitive and symmetrical manner. Figure 1.2 shows two side-by-side mats, the first containing *Buah Nabau Ngelantar*, and the second containing *Buah Tunku*. Both are a non-geometric motif arranged in a symmetrical and repetitive manner. Figure 1.3 shows two side-by-side mats, the first containing *Buah Panchar Matahari*, and the second containing *Buah Tabak Kumang*. Both are a geometric motif, also arranged in a symmetrical and repetitive manner.



Figure 1.2: Non-geometric motifs, from left to right, *Buah Nabau Ngelantar*, and *Buah Tungku*.



Figure 1.3: Geometric motifs, from left to right, *Buah Panchar Matahari*, and *Buah Tabak Kumang*.

Drawing from our observations, it becomes evident that each motif possesses unique visual traits that can be leveraged for label classification purposes. Consequently, this chapter asserts the necessity of scrutinizing existing pattern recognition methodologies. Tackling the challenge of extracting feature information from cultural patterns demands a fusion of sophisticated image processing techniques, machine learning algorithms, and domain expertise. By crafting methodologies adept at selectively removing insignificant elements while preserving crucial ones, researchers can guarantee a more precise motif representation and analysis. It is imperative that the descriptor solely extracts

relevant and discriminative features to establish a robust image representation capable of accommodating diverse image deformations and transformations.

1.2 Problem Statement

Data pre-processing serves as the foundational step in any multiway analysis, as emphasized by (Rizzi and Vichi, 1995). It plays a crucial role in ensuring the accuracy and validity of subsequent analyses. Despite the existence of numerous feature extraction and classification systems, challenges persist in data pre-processing, particularly concerning the evaluation of local feature descriptors within cultural motif datasets. This evaluation is essential for determining the efficacy of these descriptors in capturing the unique characteristics of cultural motifs amidst common visual distortions, such as geometric and photometric variations. Furthermore, it involves assessing the descriptors' performance in extracting key features from cultural motifs while minimizing interference from factors like small, repetitive image elements (e.g., ornaments) and noisy backgrounds. Therefore, effective data pre-processing is indispensable for laying the groundwork for accurate and insightful analyses of cultural motifs.

The core issue pertains to the difficulty of delineating and aligning distinctive attributes within cultural motifs. According to (Yarlott & Finlayson, 2016), motifs, which serve as recurring elements in folklore, are essential for organizing narratives spanning various cultures and tracking the evolution of stories over time. Historically, extracting motifs from narratives has been a manual process, devoid of a structured conceptual basis. Thus, this study aims to extract motif features from Iban mat motifs utilizing a local feature descriptor, especially within the context of scant prior research on this specific dataset. With the introduction of the Iban mat motif dataset, there is a notable gap in the literature

and in the existing body of knowledge concerning the application of local feature descriptors to this cultural motif. Local feature descriptors are critical for identifying and describing distinctive characteristics within images, enabling tasks like recognition, matching, and classification.

However, applying these descriptors to the Iban mat motifs presents unique challenges due to the intricacies of the motifs themselves and the lack of prior work to draw upon. The problem statement highlights the need to develop methodologies tailored to the characteristics of Iban mat motifs, ensuring accurate and effective feature description and matching. This involves addressing factors such as geometric and photometric variations, perspective distortions, and the presence of small, repetitive elements. Ultimately, the goal is to pioneer research in this area by establishing a robust framework for describing and matching discriminative features on Iban mat motifs, thereby contributing to the broader field of cultural motif analysis and recognition.

1.2.1 Challenges in Extracting Feature Information from Cultural Patterns

The challenge of extracting feature information from the main motif of cultural patterns, especially those with small motifs and background noise, is complex. Cultural patterns often exhibit intricate and diverse designs, featuring a wide array of motifs and embellishments posing difficulty in isolating the main motif. Additionally, noise in the background exacerbates this challenge by obscuring the main motif and introducing unwanted artifacts as mention in Batik recognition (Shidi & Suyoto, 2011) the primary issue lies in discerning significant elements, like the main motif, from insignificant ones such as small details or noise.

1.2.2 Ensuring Robustness

Another challenges in image recognition, influenced by factors such as camera pose, viewing angle, distance, and environmental conditions, contribute significantly to changes in image appearance and underscore the necessity of ensuring the robustness of proposed feature extraction methods for motif classification against common image deformations. As emphasized by researchers (Liang, 2022) and (Bu & Jiang, 2022), the considerable diversity in the shapes, positions, scales, and rotations of ornaments within cultural patterns poses a substantial obstacle in cultural pattern recognition. Image deformations, including blur, changes in illumination, scale alterations, rotations, and JPEG compression artifacts, further exacerbate these challenges by introducing variability in image characteristics, thereby impeding accurate object or pattern identification. This complexity is heightened in cultural pattern recognition due to the intricate designs and diverse ornamentation present within cultural motifs, necessitating advanced approaches to overcome this problem.

1.3 Research Questions

The research questions are:

- i. How to describe and match discriminative features on Iban mat motifs using a local feature descriptor?
- ii. How to determine whether an image element is to be retained or discarded from the learned model?
- iii. How to ensure that the proposed feature extraction method for motif classification remains robust against common image deformations?

1.4 Research Objectives

This research aims to:

- i. To evaluate existing local feature descriptors against Iban plaited mat motif dataset.
- ii. To develop a new features extraction method utilizing adaptive smoothing that eliminates small and repetitive image elements (i.e., ornaments) while preserving the necessary ones.
- iii. To evaluate the effectiveness of the proposed method in enhancing edge detection accuracy and to evaluate its robustness against six common image deformations, namely Blur, JPEG compression, Illumination change, Viewpoint change, Scale change, and Scale combined with Rotation (Scale+Rotation).

1.5 Hypothesis

The following hypotheses will be examined.

H0: Local feature descriptor cannot describe and match image features on Iban plaited mats.

H1: Local feature descriptor is able to describe and match image features on Iban plaited mats.

H0: The removal of minor motif does not improve the classification accuracy.

H1: The removal of minor motif improves the classification accuracy.

H0: The proposed classification method with adaptive smoothing is not invariant/robust to common image deformations.

H1: The proposed classification method with adaptive smoothing is invariant/robust to common image deformations.

1.6 Research Contributions

This study introduces a new image dataset, namely the Iban plaited mat motif dataset, serves as a valuable resource for future research endeavors in this field. This dataset is meticulously curated and includes a variety of motifs, ranging from simple to complex designs. These motifs are arranged in a repetitive and symmetrical manner, characteristic of traditional Iban weaving techniques. The dataset encompasses a diverse range of patterns, comprising both geometric and non-geometric combinations. Researchers can leverage this dataset to explore various aspects of pattern recognition, image processing and cultural studies related to the Iban plaited mat motif.

Apart from that, this study includes a thorough performance analysis of selected feature descriptors using the dataset. The analysis reveals the capability of local feature descriptors to effectively describe and match Iban mat motifs within images subjected to common geometric and photometric visual deformations. This intensive analysis highlights the robustness and versatility of these feature descriptors in capturing the intricate details and variations present in the Iban plaited mat motifs, even under challenging conditions such as geometric and photometric transformations. Such findings contribute significantly to the understanding of how these descriptors perform in real-world applications, particularly in the context of cultural pattern recognition and image processing tasks.

Introducing a new classification method that incorporates adaptive sampling to enhance the recognition of Iban plaited mat motifs, a traditional craft featuring large central motifs surrounded by smaller decorative elements. The proposed approach utilizes adaptive smoothing to selectively eliminate minor image features while preserving larger, discriminative structures of the main motif. This involves applying a smoothing function with an adaptive threshold, effectively filtering out insignificant details while retaining essential motif characteristics. Additionally, the pipeline includes morphological dilation to further enhance the appearance of retained structures, ensuring clearer and more accurate classification results. This comprehensive strategy offers a tailored solution for effectively recognizing and classifying Iban plaited mat motifs, considering their unique complexities and characteristics.

Furthermore, this research contributes significantly in two vital areas: enhancing edge detection accuracy and evaluating method robustness against common image deformations. Firstly, it investigates how the proposed method enhances edge detection accuracy, a pivotal aspect of image processing crucial for tasks such as object detection and segmentation. Secondly, the study evaluates the method's robustness against six common image deformations: Blur, JPEG compression, Illumination change, Viewpoint change, Scale change, and Scale combined with Rotation. By subjecting the method to these deformations, the research aims to gauge its effectiveness and reliability across diverse real-world scenarios, providing valuable insights into its practical applicability and potential limitations. Overall, this research advances the understanding of edge detection techniques and their performance under various image deformations, facilitating the development of more robust and adaptable image processing algorithms.

1.7 Scope of Study

The dataset was specifically limited to decorative Iban plaited mats crafted using artificial strings. This decision was made primarily because capturing images of plaited mats made from natural fibers, (i.e., the *bemban* material without the dye colorings) presents significant challenges. Plaited mats woven from natural fibers tend to exhibit light reflections and other optical phenomena that can distort or obscure the captured images. These reflections make it difficult to accurately capture the intricate details and patterns present in the mats, thereby limiting the effectiveness of image processing and pattern recognition algorithms applied to the dataset. By focusing solely on decorative mats made from artificial strings, the dataset ensures that the captured images are of sufficient quality and clarity to facilitate meaningful analysis and research in the field of cultural pattern recognition and image processing see Figure 1.4.



Figure 1.4: Example of decorative plaited mat made using natural fibers.

Initially, a collection of plaited mat images comprising 50 different motifs was assembled. However, during the data curation process, discrepancies and incomplete information concerning motif naming were uncovered. Consequently, only 20 unique mat motif classes could be confidently identified and utilized for further analysis. This decision was made to uphold the dataset's integrity and accuracy, as clear and consistent labeling of motifs is paramount for pattern recognition and classification endeavors. By concentrating on the 20 unique mat motif classes with reliable naming information, the dataset maintains a standard of quality and usability conducive to subsequent research and analysis in the realm of cultural pattern recognition.

Plaited mats showcasing select motif classes are visually illustrated in Figure 1.5, offering a tangible representation of the diversity and intricacy inherent in the motifs featured within the dataset. To assess the resilience of the feature descriptors and classification methods, a standardized array of image deformations was applied. This selection of deformations, consistent with those utilized in prior research such as (Mikolajczyk, 2005), ensures uniformity and facilitates comparison in the evaluation process. The deformations encompassed in this study include Blur, JPEG compression, Illumination, Viewpoint change, Scaling, and Scaling combined with Rotation. Employing a methodology akin to (Mikolajczyk, 2005), image sequences were generated for each deformation class. These sequences comprise a succession of images, with each image undergoing incremental degrees of transformation corresponding to the specific deformation under assessment. Through this systematic approach to image deformations, the study endeavors to evaluate the efficacy and resilience of the feature descriptors and classification methods across a spectrum of challenging scenarios commonly encountered in real-world applications of cultural pattern recognition and image processing.



(a) *Buah Bulan Sebayan*



(b) *Buah Burung Kenyalang*



(c) *Buah Lang Antu*



(d) *Buah Engkatak Tingkap Pama Merap*



(e) *Buah Nabau Besundang*



(f) *Buah Nabau Ngelantar*

Figure 1.5: Raw photos of Iban plaited mats. Each mat contains one central motif, i.e., (a) *Buah Bulan Sebayan*, (b) *Buah Burung Kenyalang*, (c) *Buah Lang Antu*, (d) *Buah Engkatak Tingkap Pama Merap*, (e) *Buah Nabau Besundang* and (f) *Buah Nabau Ngelantar*.

The complete dataset is available in the following link:

https://drive.google.com/drive/folders/1_ZxZJKQnmU0C39w0lZxD3SQpah6m71xd?usp=drive_link

1.8 Research Gap

The research gap in Iban plaited mat motif classification lies in the lack of comprehensive studies addressing the variability and complexity of these motifs. Existing classification approaches often focus on limited aspects of the motifs, such as simple geometric features, and may not adequately capture the intricate details and cultural significance embedded within the motifs. Additionally, the availability of labeled datasets specifically tailored for Iban plaited mat motifs is limited, making it challenging to develop and evaluate classification algorithms effectively. Furthermore, there is a need for research that explores advanced computer vision techniques tailored to handle the unique characteristics and challenges posed by Iban plaited mat motifs, including variability in lighting conditions, texture, and perspective distortion. Addressing these gaps would contribute to the development of more accurate and culturally sensitive classification methods for Iban plaited mat motifs.

1.8.1 The absence of a comprehensive and systematically curated Iban plaited mat image dataset.

The availability and quality of datasets play a pivotal role in advancing scientific inquiry and innovation across various disciplines. However, despite the burgeoning interest and advancements in preservation efforts of Sarawak's indigenous cultural heritage, a critical research gap persists due to the absence of a comprehensive image dataset for Iban plaited mats.

The primary cause for this is the lack of publicly shared images of Iban plaited mats. Iban plaited mats are typically purchased for private collections and are considered as family heirlooms. They are expensive due to the difficulty in sourcing the original materials (i.e., split and sliced rattan strands) and the scarcity of skilled plaiters. It is a

complex process that typically requires over two weeks of plaiting (Sellato, 2012). Iban mat plaiting is a dying practice and was included in (Chin, 1983) list of endangered Sarawak's traditional art and craft heritage that requires Sarawak state's protection. The modern (and cheaper) versions are mass-produced and use modern materials such as nylon. The incorporated motifs are often very coarse and simplified to further reduce cost. Furthermore, rare motifs such *Nabau* (serpent-dragons) and human figures as show in Figure 1.6 are rarely incorporated in these mass-produced plaited mats, and the only way to acquire them is to seek the service of an expert plaiter.

In addition, Iban plaited mat imagery are typically acquired for aesthetic reasons, hence unsuitable for an image classification exercise. Seminal datasets used for evaluating image descriptors, such as Mikolajczyk and Schmid (2005) are captured in multiple pre-planned environment conditions to emulate common image deformations such as scale change, rotation change, illumination change, viewpoint change, and image artefacts produced by the capturing device. The deformations can also be digitally added to produce synthetic images, as practiced in (DeTone et al. 2018) and (Anantrasirichai et al., 2019).

The scarcity and inconsistency of available images hinder robust statistical analyses, predictive modelling, and algorithmic development. Without access to a reliable and standardized dataset, researchers encounter difficulties in validating findings, replicating experiments, and ensuring the reproducibility of results, thereby undermining the credibility and rigor of scientific endeavors.



Figure 1.6: Example of mat with free composition of Nabau (serpent-dragons) and human figures, $2.94 \times 1.39\text{m}$ (9'7" $\times$ 4'6") (Sellato, 2012).

1.8.2 The presence of multiple prominent motifs inside a single plaited mat

Unlike other similar cultural objects such as Batik, Iban plaited mats typically incorporate two or more prominent motifs. Batik does have filling patterns (i.e., *isen-isen*), but the design is separate from the prominent motifs and does not overlap; with its main purpose being a way to add textures, shadows, and light to the overall design (Priyanto & Heriwati, 2022).

The presence of plural motifs is due to the imagery inside the plaited mat, like other Iban ritual objects, being used to tell a story based on the interaction between motifs. According to (Gavin, 2003), prominent motifs in Iban ritual textiles are worked into the background and are called *sigi buah*, i.e., ‘single’ or ‘separate’ pattern. Smaller prominent motifs are called *pengalit*, i.e., ‘space-filler,’ since they are literally used to fill the empty spaces of the *buah*, or main pattern. The smaller motif functions as a companion or a food item for the main motif. For example, motifs like *Buah Baya* (*baya* is crocodile in Iban) are

given pictorial food to eat so they don't become hungry and break out of their barriers and feast upon their makers (Heppel, 2006). Higher-ranked motifs are accompanied by these lesser-ranked motifs to indicate its status since only powerful motifs require what in effect is a kind of offering (Gavin, 2003). Besides that, some weavers tend to use small motifs as fillers for decorative purposes; see Figure 1.7 (a) for an example of an animal-based motif, i.e., *Buah Burung Garuda*, that has fillers to act as “foods” to feed the main figure depicted in the main motif (Selleto, 2012) and (Durin, 2014). Sometimes, the small motifs are also added to indicate scale. Figure 1.7 (b) shows an example of a fairy-based motif, i.e., *Buah Sabayan* that has a “heart” and small ornament act as decorative fillers.

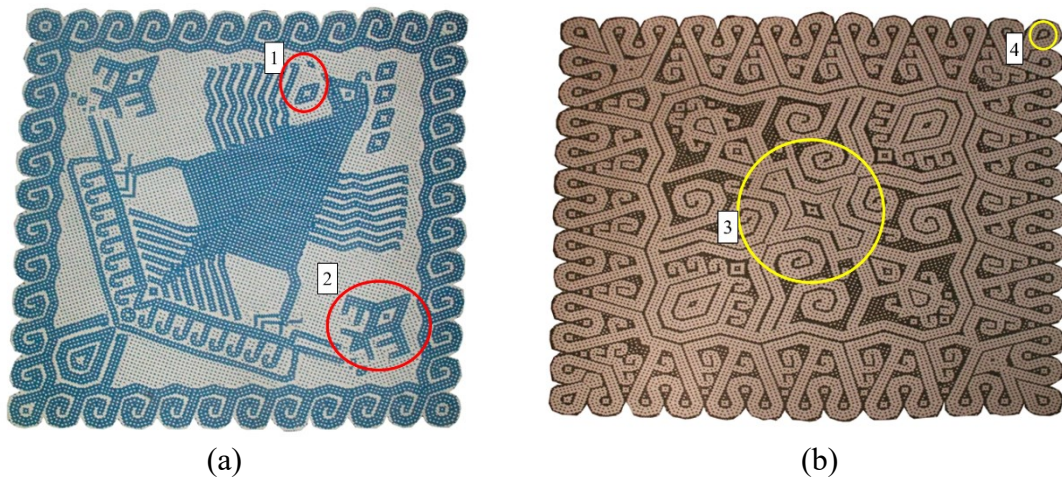


Figure 1.7: Two examples of an Iban plaited mat motif with small motif(s) as fillers, (a) an animal-based motif, i.e., *Buah Burung Garuda*, and (b) a fairy based motif, i.e., *Buah Sabayan*. The filler motifs are circled and numbered (1– 4).

The presence of plural motifs presents a challenge to image-based descriptors used in existing work in the domain of cultural object classification. The ambiguity can be resolved by suppressing minor motifs (background) while retaining the major motif (foreground) prior to classification. A vast number of existing studies have explored the

foreground-background segmentation problem in Computer vision, (Mittal et al., 2022), (Ulku and Akagündüz, 2022), (Yu et al., 2023) and (Yang & Yang, 2024). Nevertheless, the effectiveness of these methods on our custom dataset is yet to be tested hence is a valid research gap.

1.9 Thesis Outline

The organization of the remaining chapters of this thesis is as follows:

In Chapter 2 overview of the relevant literature to the research is provided. It begins with reporting research articles describing the visual characteristics of Iban decorative plaited mat motifs. Following that, existing work on the application of pattern recognition in the field of art and culture is described. Additionally, a review of the various computer vision/image processing algorithms used in the study is conducted.

In Chapter 3 presents a comprehensive methodology encompassing three main contributions. Firstly, introduces a new dataset featuring Iban plaited mat motifs. Secondly, evaluated several local feature and region descriptors, including Scale Invariant Feature Transform (SIFT) algorithm by Lowe (1999) using various peak threshold values, namely 0.02, 0.04, 0.06, and 0.08. Speeded Up Robust Features (SURF) by (Bay et al., 2008), Binary Robust Invariant Scalable Keypoints (BRISK) by (Stefan Leutenegger, 2011), Maximally Stable Extremal Regions (MSER) by (Matas et al., 2002) and Features from Accelerated Segment Test (FAST) by (Rosten & Drummond, 2006), to gauge their robustness against various image deformations. Thirdly, proposes a modified Canny algorithm (ProHT PoRE Canny) with an adaptive lower threshold, aiming to enhance edge detection accuracy. This methodology establishes a comprehensive framework for assessing and improving image descriptor performance in the context of diverse image

deformations including Blur, JPEG Compression, Illumination change, Viewpoint change, Scaling, and Scaling+Rotation, with increasing levels of complexity against our dataset.

In Chapter 4 focuses on the potential implementation and testing of feature descriptor matching performance on the Iban plaited mat motif, along with the investigation of the accuracy of feature extraction using adaptive smoothing and its influence on the classification performance, supported by the obtained results.

In Chapter 5 conclude the thesis with a summary of the main results obtained, followed by a discussion of the significant contributions made, as well as the limitations and challenges encountered during the study. Additionally, suggestions for potential future research directions in the exploration of the Iban Plaited mat motif dataset are provided.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

This chapter delves into the related work concerning pattern recognition, robust image retrieval, and classification. The review commences with an examination of research articles investigating the visual features of Iban plaited mat motifs. Subsequently, it covers pattern recognition algorithms both in a broader context and specifically within the realm of cultural and art digitalization. Additionally, feature descriptors, machine learning algorithms, and edge detectors utilized in the present study are also reviewed.

2.2 Visual Characteristics of Iban Plaited Mat Motifs

A typical Iban plaited mat motif consists of a main central motif and smaller motifs that act as fillers. The primary motif takes on a significant role in defining the precise significance, with the smaller motifs functioning as either decorative additions or providing support to the main motif, e.g., as foods, companions et cetera. These motifs are usually arranged in a repetitive manner to complete the mat design (Sellato & Fogel, 2013).

The standard rectangular plaited mat, see Figure 2.1 and Figure 2.2, consists of an outer border and two or more inner frames of transposed twill. In the center of the mat, called the "pulau", a single main motif may be seen as a single piece or in a repeating pattern. The "pulau" may also contain a mixture of central and filler motifs.



Figure 2.1: An example of a (1.96m × 0.94m) ceremonial mat, decorated with the motif of *Buah Talam Kumang*. The mat is plaited with two “pulau”. The (2) decorative edge is positioned between two strengthening rows of transposed twill, i.e., “sapa” (1 and 3).



Figure 2.2: An example of a 2.16 meters long ritual mat decorated with the motif of *Buah Nabau Ngelantar* (serpent-dragons). The mat is plaited with a single large “pulau”. The (2) decorative edge is positioned between two strengthening rows of transposed twill, i.e., “sapa” (1 and 3).

The larger motifs act as fillers to fill in the empty space around the main theme, while the smaller motifs play a dominating role in identifying the unique meaning. (Durin, 2014), refer to Figure 2.3 and Figure 2.4.

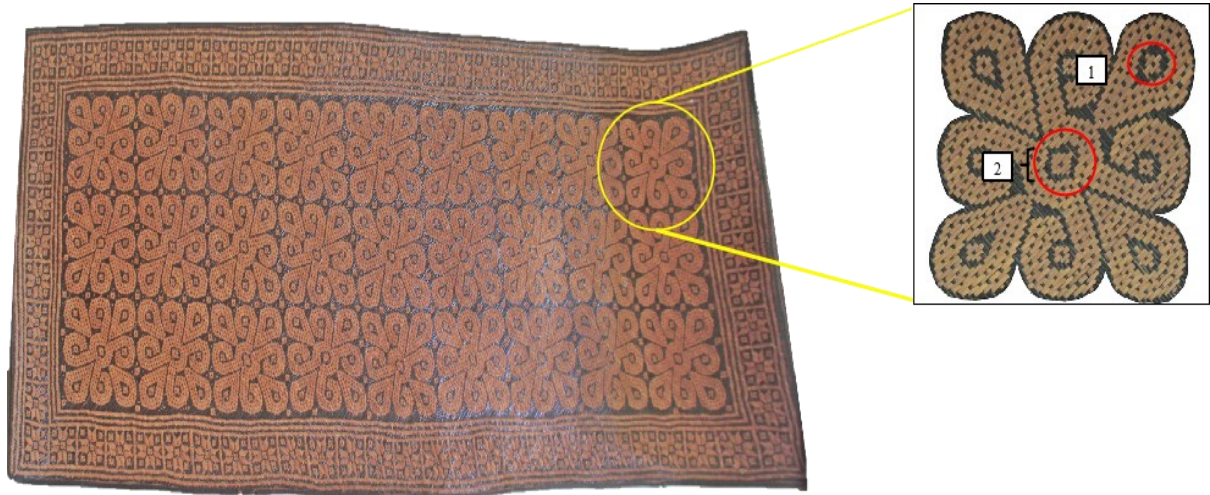


Figure 2.3: A mat motif, i.e., *Buah Tungku*, acts as the central motif. Another motif, i.e., *Buah Mata Punai*, acts as the filler, (1) and (2). The above image was sourced from (Joseph et al., 2023).

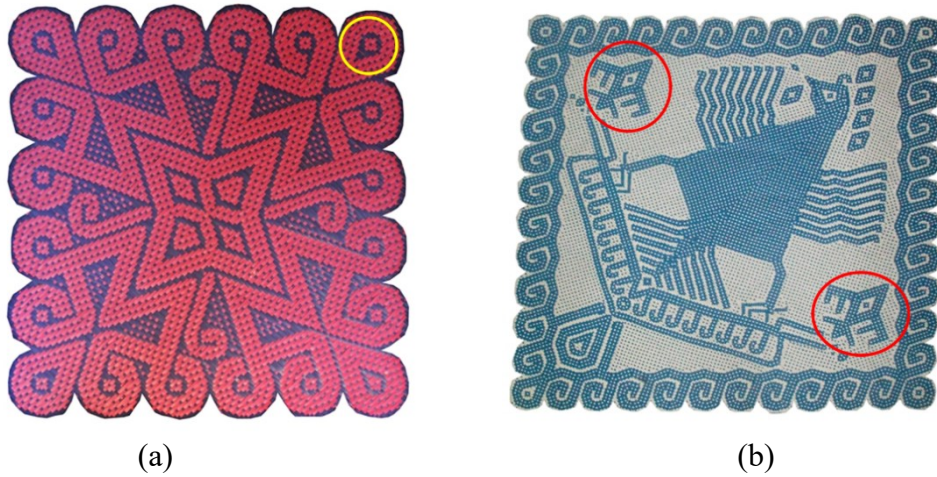


Figure 2.4: Two motifs, (a) *Buah Lang Antu* and (b) *Buah Burung Garuda*, act as the central motif whilst another motif (circled) acts as a filler.

Each motif possesses unique characteristics, necessitating the extraction of discriminative and robust visual features while excluding irrelevant ones. Moreover, the pattern matching task must account for the diverse appearances, positions, scales, and rotations of both primary and secondary motifs. Additionally, typical image deformations present in the input images further complicate the task.

2.3 Pattern Recognition

Pattern recognition is a method for classifying data based solely on information found on the pattern itself. The primary process of pattern recognition involves segmenting the pattern of interest from the image, extracting its specific features, selecting the most defining features, and determining the class membership based on the extracted features. Pattern recognition is utilized in a variety of applications including imaging in the fields of biology and medicine (Meyer-Baese & Schmid, 2014), machine learning (Bishop, 2006) and artificial intelligence (Chen, 2013). A good pattern recognition method can accurately recognize the same patterns on unfamiliar objects from a different angle or viewpoint, and even when the objects are partly hidden (Rosenfeld, 1976).

Cultural patterns are essential to cultural identity, as they reflect a distinct history and culture of a particular group. These patterns are typically composed of intricate, complex designs that vary significantly from one pattern to another. These patterns are unique in their regionality, contrast, regularity, texture, and geometric features (Liang, 2022). The robust matching of cultural patterns had received a lot of attention up to this point. Examples of such studies by (Albert et al., 2014), they introduce a new approach to analyzing mosaics using Symmetry Groups, a mathematical concept focuses on extracting objects, their arrangement, and the Wallpaper Group tests were conducted on Islamic

Geometric Patterns, resulting in successful retrieval of the Wallpaper Group in 85% of cases. And (Ghosh et al., 2021) they proposed method utilizes a convolutional neural network (CNN) framework to extract and classify features from the artwork's images. The framework includes convolution, pooling, and dense layers that apply specific filters to generate attributes from the dataset images. The study focuses on a Roman mosaic, which was digitally reconstructed using close-range photogrammetry. The proposed method demonstrated robustness in analyzing geometric forms in the mosaic, achieving an accuracy of over 97%. This method holds potential for application in various pattern identification problems related to artworks. (Cosovic et al., 2019) discussed the categorization of classification methods based on different types of cultural heritage. They focused on tangible and intangible heritage. Each method was characterized by its feature representation, classification algorithm, and results. For tangible movable heritage, rule-based algorithms, genetic algorithms, Naive-Bayes, support vector machines, and KNN were used. Tangible immovable heritage primarily utilized CNN and decision trees. Intangible heritage employed CNN, decision trees, KNN, CFR-GMM, and support vector machines. Research done by (Jamil et al., 2006), measured the efficiency of *songket* motifs image retrieval using geometric shape descriptors, investigates the efficiency of retrieving *songket* motif images using various combinations of five geometric shape descriptors, leveraging their faster computational capabilities. Future research should focus on enhancing the accuracy of the retrieval rate. The paper by (Jamil et al., 2012), presents guidelines and recommendations for contrast enhancement, noise reduction, binarization, and morphological operations. The paper emphasizes that there is no one-size-fits-all approach for digitizing motif images. It recommends experimenting with various techniques to achieve the most accurate representation of the original motif. The guidelines

and suggestions provided in the paper can be employed to digitize motif images using image processing techniques, taking into account the findings from the conducted experiments. Study by (Mahawan & Harjoko, 2017), the aim of their research was to identify the optimal feature extraction method for recognizing and classifying Bali carving pattern images, focusing on the accuracy of the HOG (Histogram of Oriented Gradients) feature extraction method coupled with PCA (Principal Component Analysis) trained using LVQ (Learning Vector Quantization). The results of the test data reveal that the highest accuracy achieved by HOG is 90%. Based on these findings, it was recommended for future research to explore methods that effectively separate objects from backgrounds to optimize edge detection outcomes. Beside applying the patterns on material surfaces, existing work (Han & Jain, 2013), (Xing & Patel, 2016) and (Kim et al., 2016) had also explored feature recognition and matching using local invariant features on biometric art patterns, such as tattoo images.

2.3.1 Local Feature Descriptors

Local features in pattern recognition are visual properties of an object. Ideally, these features are robust against two-dimensional or three-dimensional image translation, rotation, and scaling (i.e., affine and non-affine transformations). Also, the features should not be sensitive to noise. Discriminative features are unique to a particular object class, and consistent with similar values within the same object class. Local features are detected and extracted from inside an image using a feature detector. A feature descriptor then produces a robust representation of the features set thus enabling similarity measurement between one or more images.

One commonly-used method for local feature descriptor is Scale-Invariant Feature Transform (SIFT) (Lowe, 1999). SIFT identifies local extrema in Different-of-Gaussian

images, then build a 128-bit histogram from the surrounding image region. A variant of SIFT, i.e., Speeded-Up Robust Features (SURF) by (Bay et al., 2006) was then introduced to reduce the computational time. SURF uses a similar approach to SIFT but is faster and more robust to changes in illumination and contrast. Another variant of SIFT, i.e., Binary Robust Invariant Scalable Keypoints (BRISK) by (Leutenegger et al., 2011), is a local feature descriptor designed to be more computationally efficient and faster. BRISK works by detecting interest points inside an image, such as corners or edges, and then extracting features around those points, later represented as binary strings. (Rosten et al., 2006) developed Features from Accelerated Segment Test (FAST) that works by detecting corners inside an image. The FAST algorithm is very computationally efficient, which makes it apt for real-time applications. Instead of describing a fixed-size small image region surrounding a keypoint, Maximally Stable Extremal Regions (MSER) by (Matas et al., 2002) describes a dynamically-sized image region. MSER is a blob detector that finds stable regions inside an image across different scales and orientations. It works by thresholding an image at different levels and then detecting connected pixel components that remain stable.

2.3.2 Machine Learning Classifiers

Machine learning (ML) plays a crucial role in image classification. Choosing the correct ML infrastructure allows an efficient image representation that can be measured for similarity with others. There are two broad types of ML methods, i.e., supervised vs. unsupervised. Supervised ML algorithms, such as Support Vector Machines (SVM) and k-nearest neighbors (KNN), are trained on a set of labelled images. The algorithms seek to optimize boundaries between classes based on the supplied labels inside the training data. Unsupervised ML algorithms, such as clustering and dimensionality reduction methods,

learn these boundaries without the need for labelled data. Clustering methods, such as k-means or hierarchical clustering, group similar images together based on their common visual features. Dimensionality reduction methods, such as Principal Component Analysis (PCA) or t-distributed Stochastic Neighbors Embedding (t-SNE), reduce the high-dimensional image data into a lower-dimensional space, making it easier to explore patterns and relationships within the data (Fiorenza et al., 2018).

2.3.3 Edge Detectors

Edge detection and contour line extraction are crucial in image processing as they capture a significant portion of the image's information by identifying boundaries of homogeneous regions based on attributes like intensity and texture (Volkov et al., 2010), (Bhardwaj & Mittal, 2012). Edge detection methods is essential for image segmentation and transforms the original image into an edge image using techniques such as Robert operator (Roberts, 1965), Prewitt operator (Prewitt, 1970), Sobel edge detection technique by (Sobel, 1970), Laplacian of Gaussian by (Marr, 1982) and Canny (Canny, 1986) are available for detecting edges, each with its own approach to identifying discontinuities in intensity values. Research by (Shrivakshan & Chandrasekar, 2012) their study on Shark Fish Classification through Image Processing, examining gradient-based edge detection filters including Roberts, Sobel, and Prewitt, Laplacian-based edge detector, and Canny edge detector, comprehensively assessing their advantages and disadvantages, with evaluation indicating that under noisy conditions, Canny, LoG, Sobel, Prewitt, and Roberts demonstrated better performance, respectively.

Many research studies have been conducted using edge detection algorithms. Well, used in applications such as object recognition (Ramadevi, 2010), (Yasir et al., 2011), segmentation, feature extraction, and 3D reconstruction (Wang et al., 2020) extracted edge

points as image features and used a similarity measure to perform matching. In (Joseph et al., 2017), they proposed a method that combines microscope automation, digital image acquisition, edge detection, and color analysis to classify thin section images. By analyzing edge and color profiles of pixels within each cell, and using a majority voting scheme for individual cell classifications, as reported, this combination increases the average classification accuracy. A comparison of edge detection techniques for feature extraction were performed by (Dubey et al., 2020), they suggested that by using hybrid approach which can group together the advantages of Sobel with Canny edge detectors and uses a median filter in order to remove any noise for a better output. Another comparison study by (Ahmed, 2018), reported Canny edge detection outperforming other edge detectors Sobel and Prewitt and it achieves the highest accuracy. (Joshi & Vyas, 2018) reported that the Canny method was capable of detecting both strong and weak edges besides produce high quality edge maps. The performance of the Canny algorithm relies heavily on two adjustable parameters: Sigma, which represents the standard deviation for the Gaussian filter, and the threshold values (T1 and T2) according to (Ding & Goshtasby, 2001).

Research done by (Das, 2016), (Nadernejad et al., 2008) and (Shrivakshan & Chandrasekar, 2012) revealed that Canny's edge detection algorithm exhibits higher computational costs in comparison to Sobel, Prewitt, and Roberts' operators. However, it surpasses them in terms of performance. Assessment of images in noisy environments indicated that Canny, Laplacian of Gaussian, Sobel, Prewitt, and Roberts algorithms performed well, ranked in that order. Edge detection techniques may employ either gradient or Laplacian transformation methods, with the latter being more efficient for certain features but susceptible to overlooking mapping lines in specific scenarios. Study by (Ansari et al., 2017) experimentally showcased that the Canny edge detector surpasses

other techniques such as Roberts, Prewitt, Sobel, and LoG by proficiently delineating both inner and outer edges of objects while exhibiting superior noise resistance. Although Sobel edge detection demonstrated better capability in identifying continuous outer boundaries of objects, it proved to be less effective overall when compared to Canny, which excelled in delivering more precise and cleaner edges.

While the Canny edge detector is widely utilized and recognized as an effective edge detection technique, it does come with limitations and potential drawbacks in pattern recognition applications. The sensitivity of the Canny edge detector to image noise can cause false edge detections or missed edges. Additionally, its parameters necessitate sensitive tuning to attain desirable results, as incorrect parameter settings may result in missed or false detections. Combining the Canny edge detector with other algorithms enhances edge detection robustness, especially in complex or noisy image scenarios.

Some studies have achieved success by combining the Canny edge detector parameters with other algorithms. (Cao et al., 2018), (Bachofer, 2017), (Liu et al., 2017) and (Li & Liu, 2022) this fusion offers comprehensive edge detection by leveraging the strengths of each method, ensuring a more adaptable system across varied image conditions. Improved accuracy in identifying important edges is achieved through the synergy of multiple algorithms, while parameter tuning sensitivity is reduced, streamlining the process. Ultimately, this approach provides a more reliable extraction of significant image features, such as motifs, where precision is crucial.

Another method for detecting individual edges inside a region of interest is Hough Transform by (Duda & Hart, 1972). The Hough Transform is a computer vision technique used for detecting shapes such as lines, circles, and ellipses in images. It works by transforming the image from the spatial domain into a parameter space, where shapes are

represented by their parameters (e.g., a line's distance and angle from the origin). The technique involves iterating over each point in the image and calculating possible parameters for shapes passing through that point, accumulating the results in an accumulator. Peaks in the accumulator indicate the presence of shapes in the image, making the Hough Transform a powerful method that can handle occlusions and varying line angles, as a popular choice for line detection tasks. However, according to (Walsh & Raftery, 2002), Hough Transform requires iterating through every point in the image and accumulating votes for all possible parameters, resulting in high computational complexity, especially for large images or complex shapes. This approach also demands a dense representation of the parameter space, which consumes significant memory. As image and parameter space size increase, the method becomes impractical due to rising computational and memory demands. Study by (Lapušinskij, et al., 2021) demonstrated the effectiveness of Hough Transform and Canny edge detector methods in detecting cumuliiform clouds. It introduced detection methods utilizing these techniques, along with threshold parameters for automatic determination of cloud presence. Testing against a dataset showed promising results, with an average detection accuracy of 87%, despite dataset imbalance. Further improvements in dataset balance and method parameters could enhance accuracy. The Hough Transform is sensitive to noise, potentially leading to false positives, and produces an accumulator with continuous values, making peak detection challenging. Additionally, processing every point in the image can result in redundant computations, especially if multiple points contribute to the same line or shape. (Mukhopadhyay & Chaudhuri, 2015) in their study, the Hough Transform was highlighted as an efficient method for identifying lines in images. Despite being over fifty years old, Hough Transform remains a crucial tool, with over 2500 research papers exploring its variants, generalizations, properties, and

applications across diverse fields. The current paper serves as a comprehensive survey of Hough Transform and its variants, addressing their limitations, overcoming modifications, implementation challenges in software and hardware, and applications in various domains. With over 200 references included, this survey aims to provide researchers and students with a thorough understanding of Hough Transform, aiding them in its proper application to their specific problems of interest.

Probabilistic Hough Transform (ProbHT) by (Kiryati et al., 1991), were introduced to address the limitations of the standard Hough Transform, such as high computational complexity, large memory requirements, lack of scalability, sensitivity to noise, difficulty in peak detection, and redundant computations (Kälviäinen, 1994). ProbHT use a random sampling approach to select a subset of edge points, reducing the computational burden and speeding up the process. By focusing on a smaller, more representative sample of points, ProbHT achieve similar results to the standard Hough Transform while being more efficient and less sensitive to noise (Kälviäinen, 1995). (Andrei, 2022) in their study presents a method for enhancing Lane detection and tracking by employing a Probabilistic Hough transform instead of a regular one, along with a parallelogram region of interest (ROI) in place of a trapezoidal one, resulting in a notable improvement with an approximate 30% decrease in overall runtime and up to a 3% increase in accuracy compared to the original method.

ProbHT are used in many Computer vision applications, (Bharodiya, 2022) presented a work on using ProbHT with medical images, such as X-rays and MRI scans. ProbHT detects edges that can be used for further analysis and diagnosis. (Riaz et al., 2021) presented an image feature extraction using ProbHT to perform a robust and straightforward skew detection for scanned documents. The probabilistic Hough transform

provides multiple advantages over the standard Hough transform in computer vision applications. Its selective sampling approach significantly enhances efficiency by focusing on relevant edge points rather than considering all possible lines or shapes in the parameter space, making it particularly effective for large images or complex shapes. This approach also contributes to faster processing speeds, reducing computational burden and enabling quicker detection of lines or shapes. Additionally, the probabilistic Hough transform requires less memory as it processes only a subset of edge points, rendering it suitable for memory-constrained environments like embedded systems or real-time processing scenarios. Moreover, its robustness to noise ensures accurate detection results even in noisy environments, while its adaptability allows for parameterization of the sampling process, enhancing versatility. Furthermore, the method's capability to handle partial occlusion and its suitability for real-time processing applications. Each of the visual tasks in research review requires extracting object boundaries or perceiving obvious edges from the original image, Therefore, the stability detection of image edge details in order to efficiently perform the actual task.

2.3.4 Morphological Operations

Morphology encompasses a wide array of image processing techniques that focus on shapes within images. These operations involve applying a structuring element to an input image, resulting in an output image of identical dimensions (Maragos, 1996). Each pixel's value in the output image is determined by comparing it with neighboring pixels in the input image. Among the fundamental morphological operations are dilation and erosion, where dilation expands object boundaries by adding pixels, and erosion contracts them by removing pixels. The extent of modification depends on the structuring element's

size and shape. In both dilation and erosion, the state of a pixel in the output image is determined by a rule applied to the pixel and its neighbors in the input image, with specific rules defining each operation.

In both edge detection and adaptive smoothing, morphological dilation plays a crucial role by expanding object boundaries within images, thereby accentuating edges and improving visual quality (Said, 2016). By adding pixels to object edges, dilation increases contrast between neighboring regions, enhancing edge detection. This process, when combined with adaptive smoothing techniques like Gaussian blurring or bilateral filtering, refines edges and reduces noise, leading to improved image analysis. Furthermore, when applied to pattern or motif datasets, morphological dilation emphasizes and refines the structural characteristics of patterns, aiding in pattern recognition and analysis. Particularly useful for intricate or subtle patterns, dilation highlights defining features and improves their representation, complementing other image processing techniques for comprehensive pattern categorization.

2.3.5 Outlier Removal

Random Sample Consensus (RANSAC) by (Fischler & Bolles, 1981) is a powerful algorithm commonly employed in pattern classification tasks due to its robustness against outliers and its ability to estimate model parameters from noisy data. In pattern classification, RANSAC can be utilized to fit models to observed data while handling noisy or imperfectly matched samples. In the context of image processing and computer vision, RANSAC can be applied to tasks such as object recognition, shape detection, and feature matching. By iteratively selecting random subsets of data points and fitting models to them, RANSAC identifies the best model that describes the underlying pattern within the dataset, effectively filtering out outliers and irrelevant data points. This makes

RANSAC particularly useful for tasks where the data is corrupted by noise or contains outliers, allowing for more accurate and reliable pattern classification results.

RANSAC was widely used in past studies to effectively remove outlier matching, including in robotics (Martínez-Otzeta, 2015), and image matching (Li, et al., 2018) and (Widiaty et al., 2018). Overall, the robustness, flexibility, parameterization capabilities, efficiency, and widespread adoption of RANSAC have contributed to its popularity and effectiveness in effectively removing outlier matching in previous studies.

2.4 Pattern Recognition Usage in the Domain of Art and Culture

Existing pattern recognition related work in the domain of art and culture are aplenty. This work can be broadly categorized into texture-based, shape-based and color-based approaches. In addition to these broad categories, some studies employ hybrid approaches that combine several types of feature descriptor and/or machine learning algorithms. The following sub-sections addresses the use of local feature descriptors, machine learning methods, and edge detectors specifically for cultural or art objects.

2.4.1 Local Feature Descriptors

In cultural and art image analysis, the selection of appropriate features holds paramount importance owing to the intricate and diverse visual components inherent in such imagery. The features chosen significantly influence the effectiveness and interpretability of classification tasks concerning cultural and art images. According to (Qiaoling et al., 2023), the presence of visual elements in cultural and art images necessitates the careful selection of appropriate features. Local feature descriptors play a pivotal role in various computer vision-based methods for cultural and art classification. These descriptors encode crucial visual attributes within an image, including color, texture,

and shape, facilitating the identification of patterns and similarities across inter and intra-classes. Demonstrated to be effective in capturing the distinctive visual traits of specific classes, they enable the identification and classification of diverse pattern and motif within cultural and art imagery. Examples are *batik* motif classification by (Nurhaida et al., 2015) they applying the Scale Invariant Feature Transform (SIFT) for feature extraction and integrates the Hough transform as a reliable approach for object detection, particularly to address mismatched keypoints stemming from the symmetrical and repetitive nature of batik patterns. The proposed method, tested on 20 fundamental batik patterns, exhibits enhanced performance compared to the conventional SIFT matching technique, yielding an equal error rate of 8.47%. However, notable challenges arise due to the intricate symmetrical and repetitive characteristics inherent in batik designs. Research by (Yunari et al., 2015) employing texture feature extraction via the Gray Level Cooccurrence Matrix (GLCM) method, alongside classification utilizing Artificial Neural Network Learning Vector Quantization (LVQ). In their study, (Nugrowati et al., 2014) introduced an image classification approach for a batik image retrieval system, which integrates color and shape features. To extract the color feature, they employed 3D-Vector Quantization, a method adept at representing color distribution diversely while simplifying image color complexity. Complementing the color feature, they utilized the Hu moment method for extracting batik shape features. This method yielded orthogonal invariant moments capable of accommodating variations in scale, position, and rotation. (Minarno et al., (2014) proposed method, known as co-occurrence matrices of sub-band images, addresses the challenges of classifying six types of batik motif sourced randomly from the internet. This approach integrates the strengths of gray-level co-occurrence matrices (GLCM) with discrete wavelet transform (DWT). Initially, DWT is used to decompose the original image

into sub-band images. Subsequently, GLCM was applied to these sub-band images to extract texture features, which serve as inputs for a probabilistic neural network (PNN). The method had proven robust for classifying batik images, achieving a maximum accuracy of 72%. However, challenges arise due to various types of noise in the batik images, such as uneven brightness, fabric folds, differing motif sizes, low contrast, and watermarks.

In study conducted by (Murinto & Aribowo, 2016), ten Batik motifs from various regions including Batik of Jambi, Batik of Pekalongan, and Batik of Yogyakarta were analyzed utilizing multiscale segmentation methods. The process involved segmenting grayscale batik images using the Hidden Markov Tree (HMTSeg) algorithm to identify the motifs' patterns. In the pattern recognition phase, the Euclidean distance method was employed for distance measurement. Notably, the structure of the yarn and texture noise significantly affected the color appearance of the textile images, posing challenges in color image segmentation. Despite these difficulties, the matching accuracy reached 80%. (Fahmi et al., 2016) examines the impact of feature selection and reduction on the batik retrieval process using four feature extraction methods (Gabor filter, log-Gabor filter, GLCM, and LBP). This work reported the same limitations and weaknesses, i.e., sensitivity to changes in scale and 2D/3D orientation. Whilst local feature descriptors can provide some degree of invariance to translation, rotation, and scaling, they might not be entirely invariant to changes in lighting, colour, or texture. Research by (Kasim, 2016), they discussed on various methods of feature extraction for batik pattern recognition. These methods are categorized into groups based on visual features, including color extraction, texture analysis, and shape detection of batik ornaments. (Kasim et al., 2017) proposed an image classification method that compares the classification accuracy of

neural networks across seven different classes of batik based on their texture features, shape characteristics, and a combination of both texture and shape features of the ornament shapes found in batik images, aiming to classify images using artificial neural networks. Texture features are extracted from batik images using gray level co-occurrence matrices (GLCM), encompassing Angular Second Moment (ASM), contrast, correlation, and inverse different moment (IDM). Shape features are derived through binary morphological operations. Integration of texture and shape features results in significantly improved accuracy, achieving a 90.48% accuracy rate. However, challenges persist due to the diverse sizes and shapes of ornament forms within batik images, presenting complexities in classification.

2.4.2 Machine Learning Classifiers.

Machine learning based classifiers have been widely used for label classification in this domain. K-Nearest Neighbors (KNN) have been used with varying levels of success. (Rangkuti et al., 2021) proposed a feature extraction algorithm named Multiscale and Multilevel Extended Center Symmetric Local Binary Pattern (M2ECS-LBP) to address the challenges of classifying *batik* images that encounter changes in scale and rotation. The results show that K-NN's classification accuracy was between 78.4% and 81.7% for images experiencing change in scale and rotation. K-NN performed much better with images with only scale changes, achieving accuracy between 98.0% and 99.0%. they mentioned that the main challenge of using K-NN is the high dimensionality of the feature space. (Kasim et al., 2017), combined texture and shape features in *batik* images to classify them using Artificial Neural Networks (ANNs). Texture-based features are extracted using grey-level co-occurrence matrices, while shape-based features are extracted using binary morphological operations. As reported, the use of ANNs with combination of texture and

shape features effectively improves the accuracy of the *batik* image classification. In (Azhar et al., 2015), their research utilizes feature extraction methods Bag-of-Features (BoF) and SIFT, coupled with classification using SVM, achieving proficient identification of batik image types. Analytical findings emphasize the importance of determining the optimal number of clusters or vocabulary size for accuracy, as it significantly influences image description. Overall, the system effectively labels batik image types, demonstrating its robustness. Future experiments may involve continued refinement of cluster selection to enhance performance. Research by (Sulistianingsih, Soesanti, & Hartant, 2018) applied Gray Level Co-occurrence Matrix (GLCM) technique to extract features from images of batik patterns such as Kawung, Lereng, Nitik, and Tambal. By applying GLCM, a total of twenty features were extracted from the batik images. The method was able to reduce the irrelevant features by 70%. The findings indicate that classifying batik images using Backpropagation achieved an accuracy of 83%, while using the K-Nearest Neighbor method achieved an accuracy of 67%. Proper feature selection, which involves removing redundant features, can lead to higher accuracy. A system for classifying Indonesian *batik* motifs using Multi Texton Histogram (MTH) for feature extraction, and k-Nearest Neighbor (K-NN) and Support Vector Machine (SVM) for classification was developed by (Minarno et al., 2018). Their results indicate that K-NN had a higher average accuracy compared to SVM.

Convolutional Neural Networks (CNNs) have also shown promising results in this domain. In (Janković, 2020), classification of cultural heritage images was performed using 5 classification algorithms, i.e., MLP, averaged one dependence estimators, forest by penalizing attributes, k-Nearest Neighbor rough sets, and analogy-based reasoning. As reported, MLP obtained the best classification accuracy. However, a major limitation of

MLP is that the accuracy drops when the feature space is highly dimensional, or when the training dataset is imbalanced. (Rangkuti, Harjoko, & Putra, 2019) research introduces the multiscale and multilevel extended center symmetric local binary pattern (M2ECS-LBP) algorithm to address the challenges in classifying batik images that undergo changes in scale and rotation. The study uses k-Nearest Neighbors (kNN) and Artificial Neural Network (ANN) for automatic batik pattern recognition. The M2ECS-LBP algorithm is found to be highly reliable for image feature extraction, supporting classification tasks effectively. The classification accuracy can exceed 99% for images with changes in scale but consistent rotation, demonstrating the effectiveness of the approach. (Girsang & Muhathir, 2021), Histogram of Oriented Gradients was used as a feature extraction method together with Multilayer Perceptron (MLP) applied for image classification on batik. Another reported work by (Meranggi et al., 2022) trained a Convolutional Neural Network (CNN) model to classify *batik* motifs. They used data augmentation to expand the training set, however as reported, it did not significantly increase the classification accuracy. Nevertheless, the quality of the dataset did significantly impact the classification accuracy.

Combinations between Batik patterns are becoming increasingly challenging to identify there for (Mirarno et al., 2020) proposed a feature extraction method using the Multi Texton Co-Occurrence Descriptor (MTCD) and validated it with an SVM classifier, which was further assessed using Logistic Regression (LR). Testing on the Batik datasets demonstrated that the combination of MTCD with SVM and LR yielded high accuracy, showcasing their effective and reliable capability in classifying batik images. (Septiarini et al., 2022) evaluated six classes of *Samarinda Sarong* using color moments, Gray Level Co-occurrence Matrix (GLCM), and Local Binary Pattern (LBP) to generate features. The study employs Correlation Based Feature Selection (CFS) to choose the most

discriminatory features, which was then input into an Artificial Neural Network (ANN). However, the study's main drawback was the lack of cross-validation to verify the evaluation results of the method. They achieved the highest performance with an accuracy value of 100%. Despite that they concluded that proper preprocessing and feature extraction techniques significantly impact classification results.

While in research conducted by (Rangkuti, Harjoko, & Putra, 2021) when evaluating the same Batik dataset in their previous mention study (Rangkuti, 2019) they concluded that using kNN method was better than using artificial neural networks especially when the data is well-preprocessed and the features are appropriately selected. However, kNN can be computationally expensive for large datasets and may struggle with high-dimensional data. The study by (Han, Shi, & Shi, 2022) proposed a convolutional neural network (CNN) model for image recognition in cultural and creative product design. The adaptability of the visual analytics system is crucial for integrating deep learning technology. However, the study found that validating and analyzing user and cultural product design with real-time impact cases can be challenging due to the complex background and interference issues. A flexible solution is needed to manage these challenges, as human creative work is dynamic and affects the classification of transmitters. For future research, the study recommends implementing a hybrid algorithm to analyze product design performance using image recognition. (Minarno, Soesanti, & Nugroho, 2024) used a dataset consisting of 60 Batik Nitik categories and employed several classifiers, including K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Decision Tree (DT), Naïve Bayes (NB), and Linear Discriminant Analysis (LDA). Their experimental results showed that combining the fusion of Microstructure Co-occurrence Histogram (MCH) and gray-level co-occurrence matrices (GLCM) features with the

(LDA) classifier produced the best performance compared to other classifiers and scenarios. Evaluation results showed that due to distinctiveness and uniformity of the Batik Nitik motif, which are notable characteristics, often create significant challenges in differentiating one design from another.

There are some areas for improvement and limitations associated with Machine Learning based classifiers. According to (Goodfellow et al., 2016), ML models are sensitive to the quality and size of the training data. The model's performance will improve if the training data is less noisy, complete, and accurate. In our case, it is difficult to obtain a quality dataset of the required size. One of the reasons is opinions on culture and art are often subjective. This subjectivity makes it difficult to create a standardized dataset that a ML model can learn from. Crucially, for these kind of imagery data, the amount of data tends to be limited, especially for lesser-known artists or styles. This is particularly true for Iban plaited mats as digital copies are rarely available.

2.4.3 Edge detectors in Cultural Pattern Extraction

Edge detectors play a crucial role in extracting features from cultural patterns or motifs, such as those found in traditional textiles, artwork, or architectural designs, by identifying contours and boundaries, highlighting shapes and lines, and aiding in isolating motifs from their backgrounds. They enable pattern segmentation by allowing the extraction of specific areas of interest and facilitate the detection of unique shapes, curves, and lines for classification or analysis. Edge detection simplifies image complexity by focusing on significant intensity changes and aids in analyzing shapes and symmetry within motifs, providing insights into design principles. Advanced algorithms like Canny

offer noise resistance for cleaner feature extraction, and the extracted features can be used as inputs for pattern recognition algorithms to classify and analyze cultural patterns.

Some researchers have used edge detection techniques for feature extraction in various studies, such as batik classification. (Jamil & Sembok, 2003) discussed the effectiveness of several popular gradient-based edge detection techniques, i.e. Roberts, Sobel, Prewitt, Laplacian of Gaussian and Canny, when applied to a small dataset containing 25 Malaysian traditional Songket motifs. As reported, the results indicate that the Roberts operator is the most suitable for detecting edges in binary images. While the results of the Laplacian of Gaussian operator can be improved by experimenting with different filter width (σ), the advantage of the Roberts operator lies in its simplicity and computability. However, they found out that Robert's operator and Canny edge detector is highly subjected to detection of false edges due to the noise signals. (Nurhaida et al., 2012) compared the performance of Gray Level Co-occurrence Matrices (GLCM), Canny edge detector, and Gabor filters in terms of their accuracy under multiple testing scenarios. They reported that using GLCM features achieved the highest classification accuracy. Research by (Fanani et al., 2014) they comprise two phases for geometric features extraction: for *Klowongan* by deleting collinear points to obtain dominant points used as control points, and extracting features for *Isen-Isen* by saving coordinates of connected components, collectively representing the geometric features of the batik image for reconstruction. Experimental results demonstrate visually similar reconstructed images compared to the original batik image. In (Rangku et al., 2015), aims to enhance similarity percentage and retrieval speed for characteristic batik images, focusing on texture and shape attributes. Employing a decision tree with treeval and treefit functions, image feature extraction utilizes approximation coefficients derived from wavelet transform method at Daubechies

level 2 and invariant movement. Seven pattern types were evaluated and the study achieves over 80-85% similarity percentage of batik patterns. Again, the classification accuracy was low for complex motifs. They suggested for further research to explore additional methods and functions for identifying images with complex characteristics or shapes. Research by (Yuhandri et al., 2017) proposed developing chain code algorithms to extract motifs from Songket fabric. They used image color segmentation to categorize image areas based on color similarity and converts them to binary format. Mathematical morphology is applied for object detection using dilation and hole filling. Moore's algorithm tracks Songket motif contours to accurately represent and analyze complex patterns in the fabric.

Research by (Ahmad et al., 2021) introduces a novel, robust and straightforward skew detection method for scanned documents, which uses Probabilistic Hough Transformation (PHT) for line detection in a first step and clusters the lines in a second step based on parallelism. The cluster with maximum parallel lines represents the expected skewed lines. The proposed method was tested on real scanned images taken from the Document Image Skew Estimation Contest (DISEC'13), Pashto, and Tobacco800 datasets. The proposed method performs well both in terms of accuracy and efficiency. It was efficient and robust to noise. Furthermore, it also works on Arabic and Latin scripts.

Another research by (Boudraa et al., 2020) they proposed a novel technique for skew angle detection and correction in scanned historical documents. Their method uses morphological skeletonization to reduce the amount of data, and Progressive Probabilistic Hough Transform (PPHT) to search for edges. (Zang et al., 2020) proposed an efficient probabilistic point cloud registration method that integrates a novel shape descriptor based on principal local directions with curve constraints. The method was tested on datasets containing images historical monuments and artefacts. The proposed method outperformed

commonly used approaches on the following metrics, i.e., rotation and translation errors, robustness as well as runtime. However, the method faced challenges with ambiguous objects featuring repetitive structures, leading to incorrect correspondences and transformations. Study by (Rangkuti et al., 2012 and (Hidayattullah et al., 2020) employed Canny edge detector to extract features from *batik* motifs. Research by (Shidi & Suyoto, 2011), Canny and Peewit operator is used for *batik* classification, however they failed to resolve several issues, such as noise and complex motifs, that affect the matching accuracy. Study conducted by (Sanabila & Manurung , 2009) utilized a template matching-based approach for detecting batik motifs. This method involves detecting the motif using a template image and applying the Generalized Hough Transform. While the experiment demonstrated that the Hough transform yields good performance, it was noted to consume significant computational resources. Research by (Yunari et al., 2018) performed feature texture extraction with Gray Level Co-occurrence Matrix (GLCM) as a method for extracting textural features and Artificial Neural Network Learning Vector Quantization (LVQ) as a method to classify. the average value is 98.98%. While study by (Kusanti, 2019) employed a combination of the Otsu method and Canny methods to create an application system for enhancing the identification of seven Surakarta batik classes, including their characteristic features and shapes. Segmentation was achieved by dividing the image into object areas using Otsu and defining object boundaries with Canny to capture image characteristics. The processed segmentation involved selecting and extracting quantitative information from existing features using the GLCM method. The approach yielded an accuracy rate of 93%.

Consequently, the classification and retrieval of images based on texture features have emerged as focal points in several studies. As for Probabilistic Hough Transform

(PHT), a combination with Canny edge detector was proposed in (Song et al., 2017). The Canny edge detector extracts edge information, and the resulting edge pixels are passed to the Probabilistic Hough Transform module. This module identifies the parameters of the line that best fit the edge pixels. These combinations lead to a more accurate and reliable line detection, especially in the presence of noise, or missing edge pixels.

Despite the relatively limited number of studies on cultural motif edge detection using probabilistic Hough transform, this approach presents several notable advantages. Primarily, its inherent robustness to noise ensures accurate edge detection in intricate motifs often affected by image noise. Additionally, the method's efficiency in complex visual environments and adaptability to varied motif shapes make it suitable for diverse cultural contexts. Its potential for real-time processing further enhances its applicability, particularly in cultural heritage preservation or digital artwork analysis. Moreover, the versatility and customization options of the probabilistic Hough transform allow for tailored parameterization to optimize detection accuracy for different motif types and contexts. Overall, while less explored, this approach holds promise for facilitating feature extraction in cultural motif analysis and interpretation, warranting further research and exploration in cultural heritage and artistic domains.

2.5 Summary

This chapter provides an overview of existing research on local feature descriptors, ML-based classifiers, and edge detectors, highlighting the need to effectively separate main features from noisy backgrounds to optimize feature detection. Noisy backgrounds present significant challenges in pattern recognition, hindering accurate identification of relevant objects and patterns. Potential solutions include advanced image segmentation

techniques, adaptive thresholding methods, and machine learning-based approaches. Future research should prioritize robust methods adaptable to various noise and background complexities to advance pattern recognition. The chapter focuses on exploring local feature descriptors and ML-based classifiers, suitable for domain-specific datasets due to their accuracy and computational efficiency. However, challenges arise from image deformations and noisy backgrounds, indicating a need for improved algorithms to accurately extract motif features while excluding background noise interference.

As a result, the research's first significant contribution is the investigation of existing local feature descriptors against the Iban Plaited Mat motif dataset under common geometric and photometric visual deformations and it is vital to design a robust feature descriptor that exploits the characteristics of our dataset to reduce false matching as much as possible.

The second and third contribution of this thesis will thus use the edge filter to alleviate this problem by removing most of the background noise whilst retaining the discriminative image structures. This methodology holds promise for application to Iban plaited mat motif images, as texture features are significant due to the intricate patterns and often noisy backgrounds; in contrast, color features may be less distinguishing since the same plaited mat motif can be woven in different colors, and shape features are less prominent because the shape of plaited mat motifs tends to remain consistent, while texture variations contribute more significantly to their visual diversity and to a deeper understanding of these culturally significant motifs. This chapter also listed out the other existing models and techniques that are used in this study.

CHAPTER 3

EVALUATION OF LOCAL FEATURE DESCRIPTORS AND ADAPTIVE SMOOTHING

3.1 Overview

This chapter outlines the research methodology, encompassing the general research workflow in Section 3.2 and the presentation of the research pipeline in Section 3.3. In Section 3.4, the experimental setup, comprising the system specifications and dataset used, is described. Additionally, the dataset preparation process is explained, aiming to establish credibility, transparency, replicability, and reliability in our work. In Section 3.5, research provides a detailed account of feature extraction utilizing local feature descriptors and adaptive smoothing techniques, employing the newly introduced Iban plaited mat motif dataset. These contributions encompass three key aspects of the study. In section 3.6, brief explanation on outlier removal use to iterative method recognized for its efficient removal of outliers during model estimation. The evaluation outlined in Section 3.7, along with the subsequent discussion and conclusions provided in Section 3.8, bring this chapter to a close.

3.2 The General Research Workflow

The general research workflow of our work is established in this section, see Figure 3.1. In total, three separate research frameworks had been established, each designed to address a research question outlined in Chapter 1. The top row illustrates the successive stages through which each input image must pass to complete the pipeline. The pipeline

begins with the 'Image acquisition' stage, where digital cameras were used to capture the decorative plaited mats as raw images.

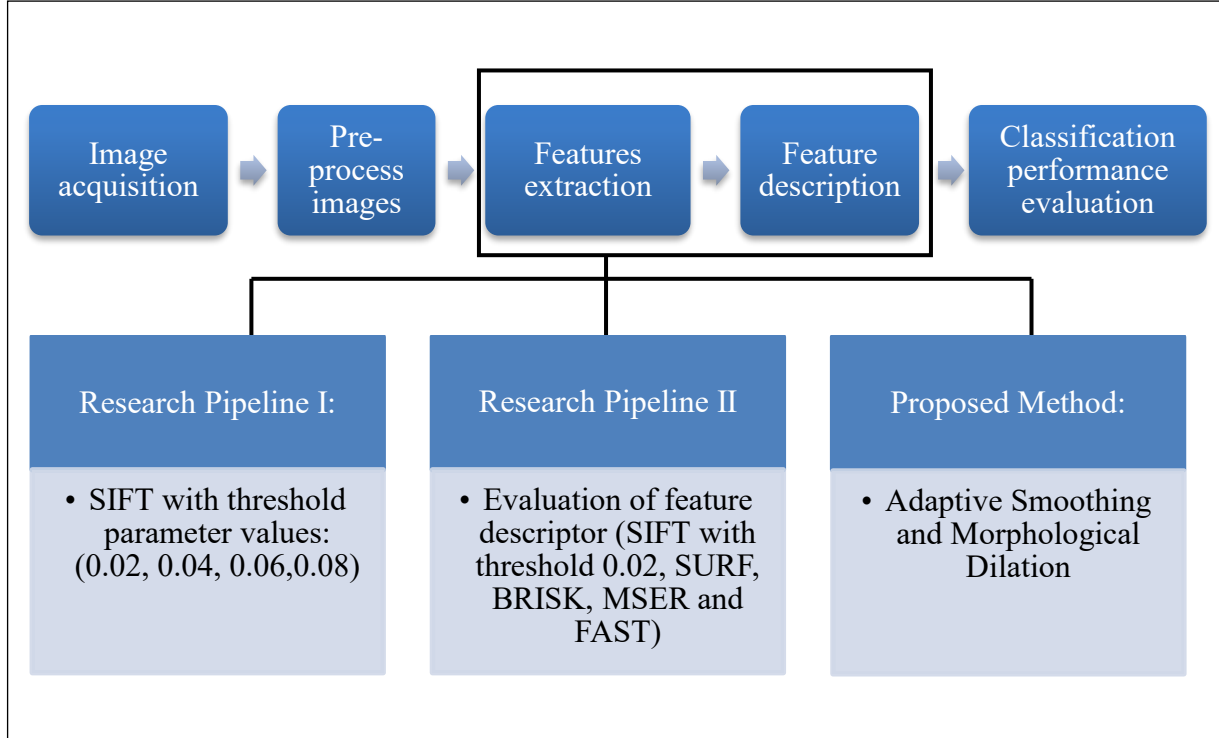


Figure 3.1: Research workflow.

The next stage is the 'Pre-processing' of the captured raw images. The images are down sampled to a smaller resolution of 800 x 533 pixels for performance reason. Next, synthetic images were generated, consisting of cropped and perspective-corrected versions of the raw images. This process prevents ambient noise from affecting the generated picture descriptors. The aim is to assess the performance of the descriptors in matching same-label images based purely on the motifs' visual properties rather than any noise interference. Increasing degrees of common image deformations are then applied to the synthetic images to produce the test sequences. As previously noted, the process follows the list of common image deformations as described in Mikolajczyk (2005). The

subsequent stages include 'Feature extraction' and 'Feature analysis'. Local feature descriptors are employed to identify interesting image features from the motif images and construct their descriptors. In the final stage, 'Pattern matching and classification,' the descriptors are matched using a similarity measure. The class label of the top-matching descriptor from the learned set is then assigned to the query image. Our research contributions are focused on these two stages, i.e., 'Feature extraction' and 'Feature analysis'. For these two stages, we present our 3-research pipeline. In the first pipeline, we implemented SIFT with multiple peak thresholds. The objective is to discover the optimal peak threshold value for SIFT on our dataset. The second research pipeline involves the evaluation of different local feature descriptors, namely SIFT (with optimal peak threshold), SURF, BRISK, MSER, and FAST. These descriptors were combined with RANSAC and tested against 6 typical image deformations, i.e., Blur, Illumination change, Viewpoint change, Scale change and Scale+Rotation. For the third pipeline, the proposed Iban mat motif classification method is outlined, incorporating adaptive smoothing and morphological dilation. The dataset prepared using this method will be utilized for Iban plaited mat motif classification, employing BRISK+RANSAC for feature detection and description.

3.3 Research Pipeline

In the first research experiment, the aim was to discover if a local feature descriptor can be used to classify Iban mat motifs. The chosen local feature descriptor is Lowe's (1999) Scale Invariant Feature Transform (SIFT), which was evaluated against six typical image deformations: Blur, Illumination change, Viewpoint change, Scale change and

Scale+Rotation across several peak threshold values, i.e., 0.02, 0.04, 0.06, and 0.08. Refer to Figure 3.2 for a visualization of research pipeline I.

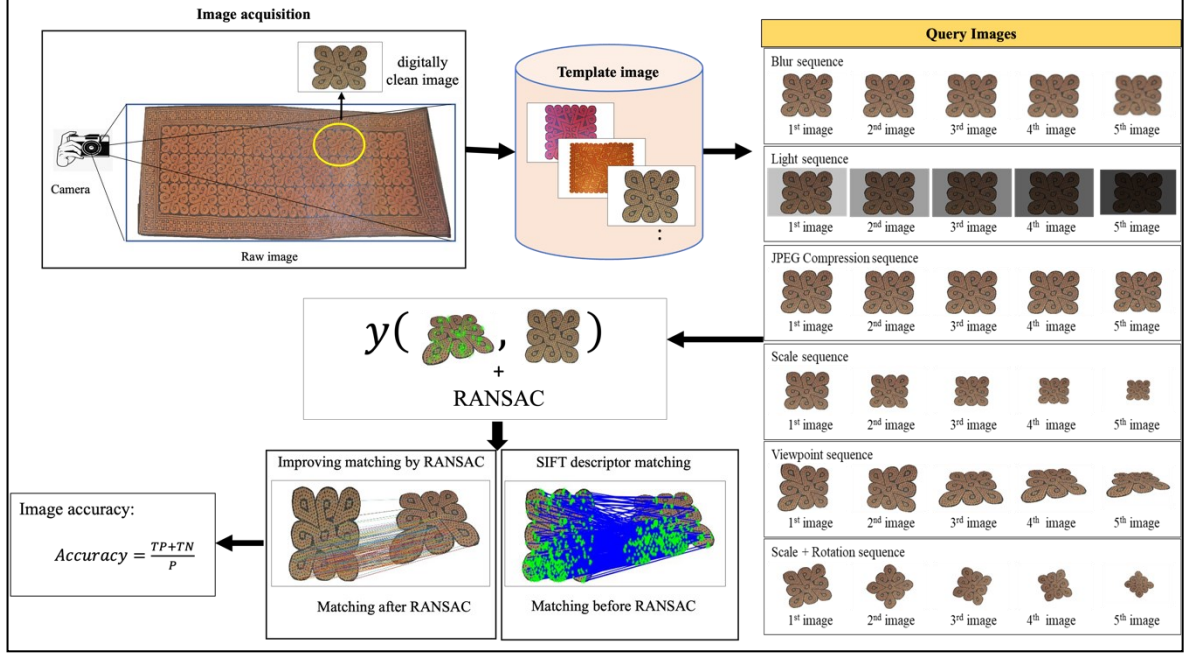


Figure 3.2: Graphical summary phases of the research pipeline I. The above image is adapted from (Joseph et al., 2021).

In the second phase of the research experiment, a comprehensive comparison of feature descriptors was conducted i.e., SIFT with an optimal PeakThr value of 0.02, SURF, BRISK, MSER, and FAST algorithm with RANSAC against 6 typical image deformations: Blur, Illumination change, Viewpoint change, Scale change, and Scale + Rotation. Refer to Figure 3.3 for a visualization of research pipeline II.

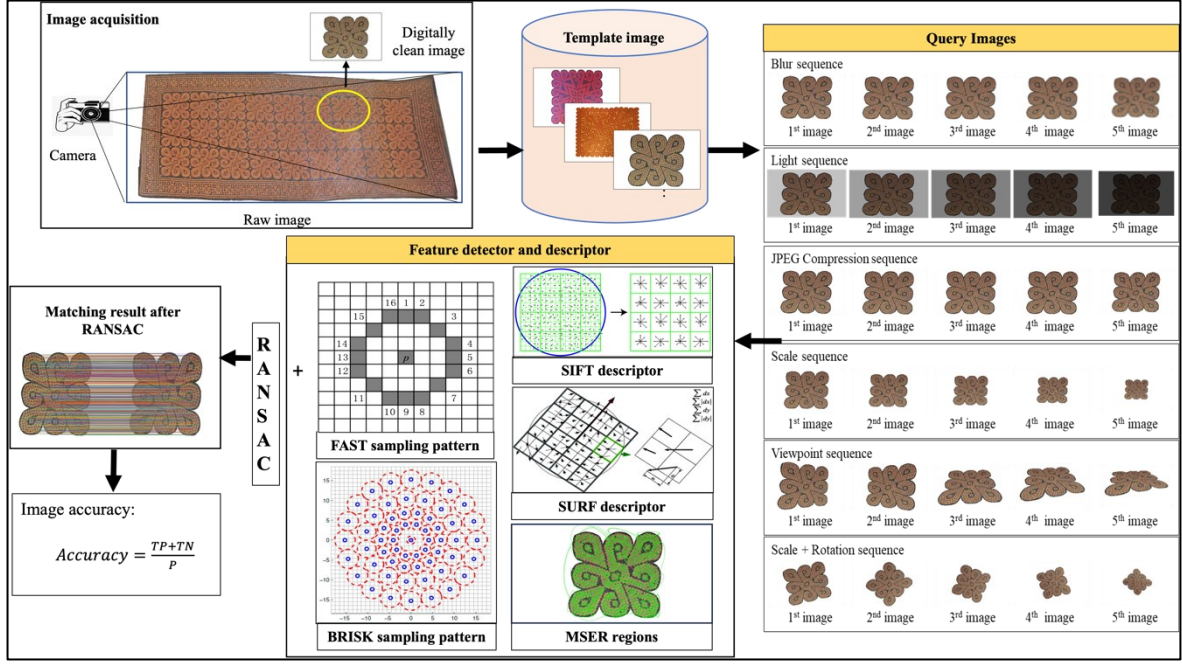


Figure 3.3: Graphical summary phases of the research pipeline II.

Next, our new Iban plaited mat motif classification method with adaptive smoothing was introduced. Adaptive smoothing was utilized to intelligently remove small structures from within an image while preserving larger and discriminative ones. This method corresponds to our third research question: “How to determine whether an image element is to be retained or discarded from the learned model?”. The work and findings reported in this chapter are detailed in the following journal article: "Iban plaited mat motif classification with adaptive smoothing" (Joseph et al., 2023). The proposed method utilizes the Canny edge detector to extract meaningful edges within an image. The focus is solely on the outline of a mat motif, disregarding its inner region. However, applying the Canny edge filter may result in thinned and broken edges. To address this issue, a modified Canny algorithm (ProHT PoRE Canny) with an adaptive lower threshold was proposed. The lower threshold increased until the percentage of remaining edges (PoRE) hits a

predetermined value. PoRE value was calculated as a ratio of the remaining edges over the edge count of the initial edge image (zero Gaussian smoothing). Once the predetermined PoRE value reached, morphological dilation is applied to the remaining edges to enhance their appearance. Subsequently, BRISK+RANSAC descriptors are learned from the final edge image. The framework is evaluated using accuracy, precision, and F1 score on our dataset. Figure 3.4 presents a graphical summary of the phases for the proposed methodology.

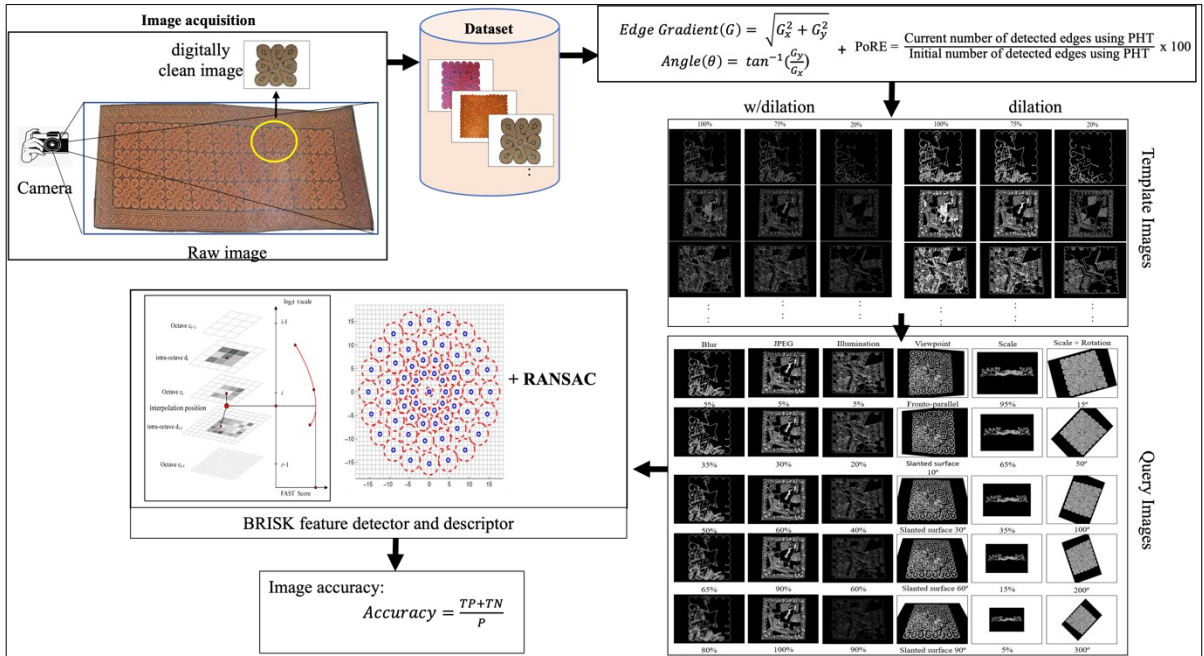


Figure 3.4: Graphical summary phases of proposed methodology. (Joseph et al., 2023).

3.4 Experimental Setup and Dataset

All experiments were conducted by implementing feature extraction with VLFeat in MATLAB and adaptive smoothing with OpenCV through API calls from Open-Source Computer Vision Library (OpenCV). Feature extraction, matching tasks and mathematical morphological operations were conducted using VLFeat Version 0.9.21 (Vedaldi &

Fulkerson, 2010) in MATLAB. Meanwhile, OpenCV's API calls facilitated adaptive smoothing techniques such as bilateral filtering and Gaussian smoothing for noise reduction and image enhancement. As an open-source library, it promotes collaboration and innovation, supported across multiple platforms and optimized for performance. Its accessibility, documentation, and efficiency make it a preferred choice for rapid development and scalability in various applications (Bradski, 2000). All input images (both reference and query) were converted to 8-bit greyscale image with a resolution of 512 x 384 pixels. By integrating these libraries, this research benefited from a comprehensive approach to computer vision tasks, capitalizing on the strengths of each library to achieve robust feature extraction and effective image smoothing.

3.4.1 Image Acquisition

The dataset, Iban's plaited mat motifs were collected from the following indigenous communities, i.e., Iban Batang Ai (from Rumah Temeling Ibai Bintung, Lubuk Antu, Sri Aman, Sarawak), and Iban Remun (from Kampung Sungai Engkabang). These communities were chosen due to existing relationships with expert plaiters and their preservation of traditional mats as personal collections. Digital photos were captured, as shown in Figure 3.5 with sample images of standard rectangular plaited mats. The photos were taken at Rumah Temeling Ibai Bintung, Lubok Antu, Sarawak. The camera setup is depicted in Figure 3.6 The photo was taken from one of the community houses at Kampung Sungai Engkabang, Serian, Sarawak. All images were taken indoors with adequate lighting.



Buah Dulang Sepandai



Buah Lintan Tanah

Figure 3.5: Sample photos of plaited mats captured at Rumah Temeling Ibai Bintong, Lubuk Antu, Sarawak.

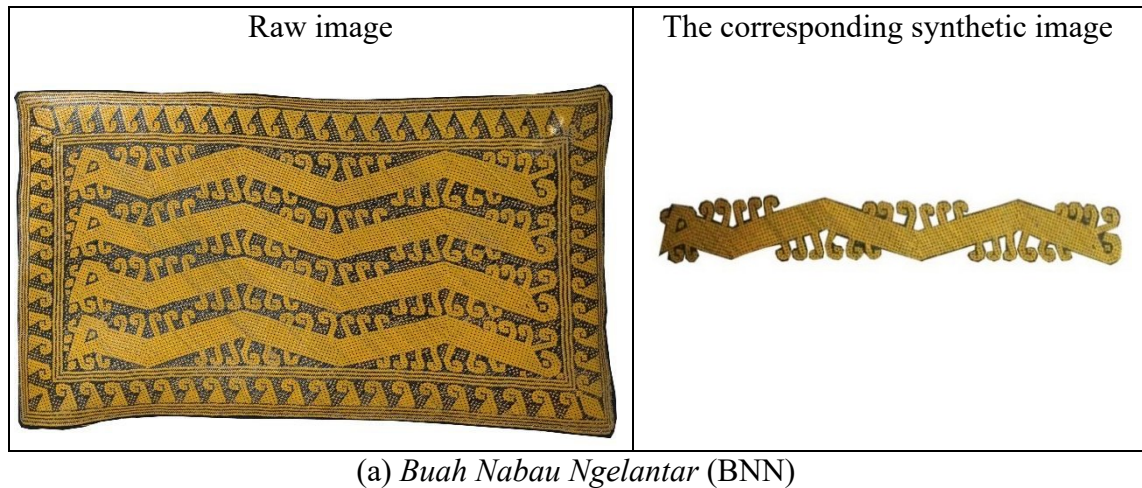


Figure 3.6: Our camera setup.

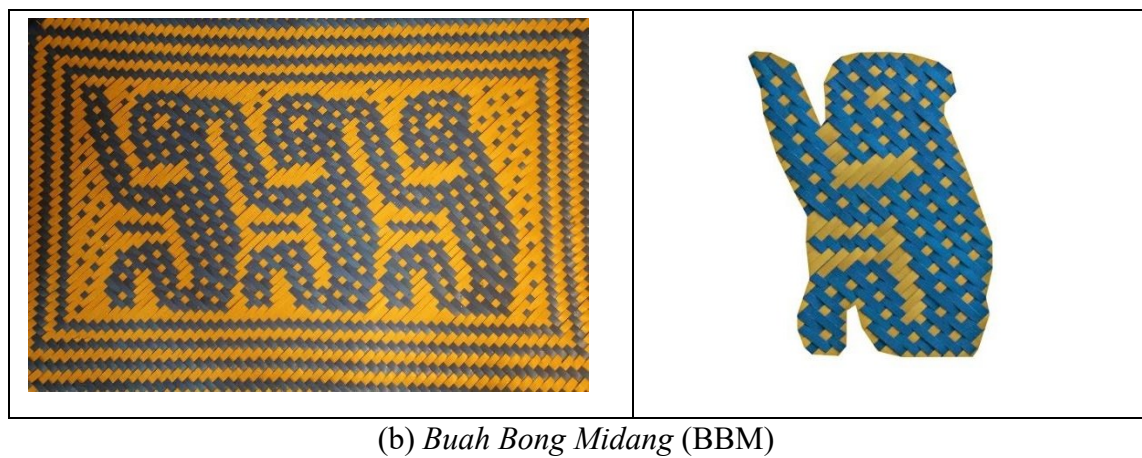
3.4.2 Image Pre-processing

In accordance with the decision made in previous work (Joseph et al., 2021), synthetic images were used instead of actual photographed images to ensure that the learned image descriptors are constructed from features on the mat motif itself, without interference from background noise. According to (Sarmah, 2019) and (Chawla, 2020), synthetic datasets improve the validation and training of machine learning models. Successful experiment in

various area conducted by (Anantrasirichai, 2019), (Ling & Jacobs, 2005), (Sapkota, et al., 2022) and (Eversberg & Lambrecht, 2024) had shown promising matching results and further improves detection performance without a significant increase in computational burden by using synthetic images. Preparation of the synthetic images was done using an image editing software. Through the use of image editing software, each motif undergoes meticulous adjustments such as cropping, perspective corrections, and fine-tuning of details to ensure accuracy and precision. Additionally, manual intervention allows for the application of filters to replicate various lighting conditions, angles, and environmental factors to replicate real-world settings contributing to the authenticity of the simulated scenarios. This human involvement not only guarantees quality control but also provides the flexibility to tailor the simulations to specific testing requirements and dynamic conditions. Furthermore, the manually processed synthetic images serve as invaluable reference data for validating algorithms and ultimately enhancing the reliability and performance of computer vision systems in analyzing Iban plaited mat motifs. Figure 3.7 shows side-by-side comparison of corresponding raw and synthetic images.



(a) *Buah Nabau Ngelantar* (BNN)



(b) *Buah Bong Midang* (BBM)



(c) *Buah Panchar Matahari* (BPM)

Figure 3.7: From left to right, (a) *Buah Nabau Ngelantar* (BNN), (b) *Buah Bong Midang* (BBM), and (c) *Buah Panchar Matahari* (BPM).

3.4.3 Dataset and entropy value

The determination of simple and complex label for Iban plaited mat motifs can be accurately assessed by examining the visual information intricacies represented as entropy value. Entropy serves as a quantitative measure of the richness and intricacy of patterns by assessing the uncertainty or randomness in pixel intensities. In Iban plaited mat motifs, simple patterns exhibit lower entropy values, indicating uniformity and predictability in pixel distributions, whereas complex motifs display higher entropy values, signifying greater variation and intricacy in the patterns. For our dataset, the midpoint of the resulting entropy values is used as the threshold to separate simple vs. complex motifs,

$$midpoint = \frac{\max + \min}{2.0} \quad \text{Equation 3.1}$$

To compute the entropy, by analyze the grayscale image of the Iban plaited mat motif, a histogram of pixel intensities is initially created. This histogram is then normalized to derive the probability distribution of pixel intensities. Using this probability distribution, the entropy of the image is calculated using a specific formula. The resulting entropy value serves as a measure of the information content and complexity of the grayscale Iban plaited mat motif. Higher entropy values indicate greater complexity in the patterns observed, while lower entropy values suggest more uniform or predictable patterns. The entropy, H , is given as,

$$H = -\sum_{i=0}^{L-1} p_i \log_2(p_i) \quad \text{Equation 3.2}$$

Where L is the number of possible intensity levels (typically 256 for 8-bit grayscale images), and p_i is the probability of occurrence of intensity level i in the image.

The resulting entropy values are tabulated in Table 3.1 Synthetic images and entropy value of simple motif. The threshold, i.e., midpoint, value is calculated as $\frac{6.51+1.28}{2.0}$ =3.90. Examples of synthetic images in the dataset are presented in Figure 3.8. The entropy values for each image deformation type are indicated below the images.

The sample size in the study is justified at twenty due to several reasons. Firstly, this study represents an initial experiment on the dataset, focusing on the motif of the plaited mat. Limited prior knowledge on this specific motif necessitates a cautious approach to experimentation, starting with a smaller sample size to understand the dataset's characteristics and intricacies. Additionally, referencing existing literature reveals that some studies also utilize small numbers of batik classes, indicating precedence for similar sample sizes in related research. By starting with a conservative sample size, the study can effectively assess the feasibility and potential challenges of the experimental design while minimizing resource expenditure. As the understanding of the motif plaited mat evolves and experimental techniques improve, future studies may explore larger sample sizes to further validate and refine the findings.

Table 3.1: Synthetic images and entropy value of simple motif.

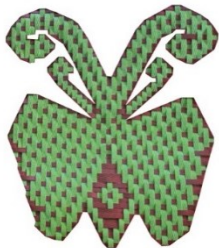
Simple Motif	
	
Buah Nabau Besundang (BNB) Entropy, $H = 1.28$	Buah Nabau Ngelantar (BNN) Entropy, $H = 1.87$
	
Buah Mayau (BM) Entropy, $H = 1.87$	Buah Burung Kenyalang Entropy, $H = 2.12$
	
Buah Bong Midang Entropy, $H = 2.44$	Buah Mata Punai (BMP) Entropy, $H = 2.9087$
	
Buah Kesulai (BK) Entropy, $H = 3.1877$	Buah Andu (BA) Entropy, $H = 3.5235$

Table 3.1: continued

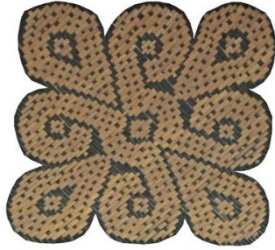
Complex Motif	
	
(a) Buah Bulan Bekarung (BBBekarung) Entropy, $H = 4.227$	Buah Tungku (BT) Entropy, $H = 4.5026$
	
Buah Pama (BP) Entropy, $H = 4.58$	Buah Tungku Lebur (BTL) Entropy, $H = 4.63$
	
Buah Lang Antu (BLA) Entropy, $H = 4.64$	Buah Burung Garuda (BBG) Entropy, $H = 4.74$
	
Buah Lang Menyarung (BLM) Entropy, $H = 4.787$	Buah Talam Kumang (BTK) Entropy, $H = 4.96$

Table 3.1: continued

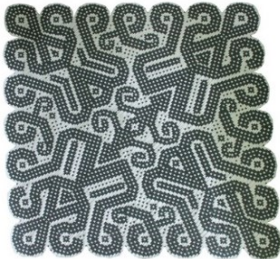
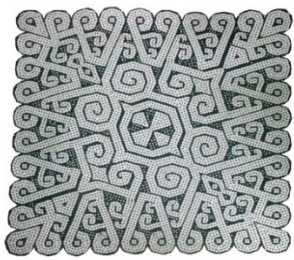
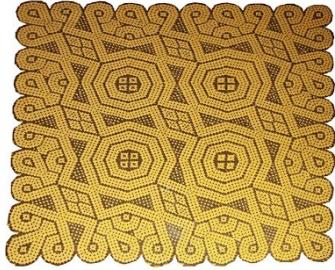
	
Buah Tangkai Gajai Besembah (BTGB) Entropy, $H = 5.0685$	Buah Kandung Nibung Berayah (BKNB) Entropy, $H = 5.0902$
	
Buah Sebayang (BS) Entropy, $H = 5.1028$	Buah Bulan Bepayung (BBBepayung) Entropy, $H = 5.107$
	
Buah Bandau (BB) Entropy, $H = 5.2416$	Buah Katak Tingkap Pama Merap (BKTPM) Entropy, $H = 5.28$
	
Buah Panchar Matahari Entropy, $H = 5.29$	Buah Lintan Tanah (BLT) Entropy, $H = 5.59$

Table 3.1: continued

	
Buah Bulan Sebayan (BBS) Entropy, $H = 5.93$	Buah Suri Ai (BSA) Entropy, $H = 6.512$

A complete image list is included in Appendix A.

3.4.4 Image Preprocessing

The Iban plaited mat motif dataset for analysis in experiments and proposed methods, images were carefully processed to ensure high-quality results. This involved a series of image preprocessing and data augmentation steps, including applying blur sequences, adjusting illumination, altering JPEG compression, changing scales, shifting viewpoints, and modifying scale and rotation simultaneously

3.4.4.1 Image preparation for the First and Second Experiment

To produce synthetic query images with varying levels of image deformation, the following software was utilized: Adobe Photoshop, PhotoScape, and a JPEG compressor software for editing. For the first and second experiment, a test sequence was prepared for each motif class for every type of image deformation. In total, the dataset comprises 10 motif classes multiplied by 6 image deformation types multiplied by 5 deformation levels, resulting in a total of 300 images. The precision of random categorization by chance is, for a total of 10 classes is $\frac{1}{10} = 0.1$. Meanwhile, for the second experiment, an extended

dataset comprising 20 motif classes of Iban Plaited mat motif multiplied by 6 image deformation types multiplied by 5 deformation levels was employed, resulting in a total of 600 images. The precision of random categorization by chance is, for a total of 20 classes is $\frac{1}{20} = 0.05$. The incremental values for each image deformation are set as follows: For the Scale + Rotate test sequences, images were captured by rotating the camera about its optical axis in the range of frontal-parallel area 10^0 degrees, Slanted surface 10^0 degrees to 90^0 degrees while varying the zoom levels of the camera. For the Viewpoint test sequences, the camera position was varied from a frontal-parallel view to a view with a significant foreshortening of the frontal area at about 50^0 to 60^0 from the camera. Test sequences for the scale + rotation, scale change, and viewpoint change were created using Adobe Photoshop software. In the Image blur test sequences, the Gaussian kernel was applied to the original image with a radius ranging from 0.5 to 8.0 (5% to 80%) using PhotoScape software. For the illumination test sequences, the gradual decrease in illumination was achieved by varying the camera aperture and post-processing with illumination level ranging from 5% to 90%. The JPEG compression test sequences were created by changing the compression parameter with a value between 5% and 100% using the JPEG compression software.

The gradual incremental values for each image deformation are determined through a process of randomized testing, involving systematic variations of parameters such as scale, rotation, or lighting conditions, while observing their effects on the images. By incrementally adjusting these parameters in a randomized manner, a broad range of potential variations was explored to identify optimal values that yield meaningful changes while preserving the image's essential features. This approach enables thorough experimentation, ensuring that the chosen incremental values accurately simulate real-

world variations encountered in practical applications especially in Iban plaited mat motif. The gradual incremental values for each image deformation are tabulated in Table 3.2.

Table 3.2: Incremental values for each image deformation type. (Joseph et al., 2021)

Image Blur	5%, 35%, 50%, 65%, 80%
Illumination	5%, 20%, 40%, 60%, 90%
JPEG compression	5%, 30%, 60%, 90%, 100%
Viewpoint	Fronto-parallel surface 10^0 ; Slanted surface $10^0, 30^0, 60^0, 90^0$
Scale+Rotation	$15^\circ, 50^\circ, 100^\circ, 200^\circ, 300^\circ,$
Scale	95%, 65%, 35%, 15%, 5%

The synthetic plaited mat motif images, as seen in Table 3.3 (a) to (f), were used as the query images during the matching task. Due to space limitation, we only show synthetic query images of the *Buah Bandau* (a) the blur sequence, (b) Illumination change sequence, (c) JPEG compression change sequence, (d) Scale change sequence (e) Viewpoint change sequence and (f) Scale+Rotation change sequence.

Table 3.3: Synthetic query images of *Buah Bandau* (a) the blur sequence, (b) Illumination change sequence, (c) JPEG compression change sequence, (d) Scale change sequence (e) Viewpoint change sequence and (f) Scale+Rotation change sequence.

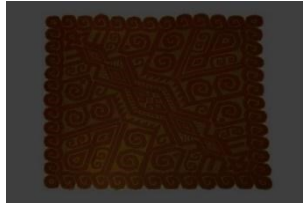
Level of image deformation	Blur	Level of image deformation	Illumination
Level 1 5%		Level 1 5%	
Level 2 35%		Level 2 20%	
Level 3 50%		Level 3 40%	
Level 4 65%		Level 4 60%	
Level 5 80%		Level 5 90%	
	(a)		(b)

Table 3.3 continued

Level of image deformation	JPEG Compression	Level of image deformation	Scale
Level 1 5%		Level 1 95%	
Level 2 30%		Level 2 65%	
Level 3 60%		Level 3 35%	
Level 4 90%		Level 4 15%	
Level 5 100%		Level 5 5%	
	(c)		(d)

Table 3.3 continued

Level of image deformation	Viewpoint	Level of image deformation	Scale + Rotation
Level 1 Fronto-parallel surface 10°		Level 1 5°	
Level 2 Slanted surface 10°		Level 2 50°	
Level 3 Slanted surface 30°		Level 3 100°	
Level 4 Slanted surface 60°		Level 4 200°	
Level 5 Slanted surface 90°		Level 5 300°	
	(e)		(f)

3.5 Feature Descriptor and Proposed Approach

Feature extraction involves selecting and isolating specific features from data for analysis and pattern classification, which plays a key role in determining the complexity and success of the process. For the first phase of feature extraction, the evaluation was conducted using the Scale-Invariant Feature Transform (SIFT) (Lowe, 1999) with multiple peak threshold values against our dataset.

The study also aims to compare the performance of several feature descriptor methods against an extended dataset to assess their accuracy, repeatability, and robustness. These methods include SIFT with the optimal parameter value, Speeded-Up Robust Features (SURF) (Bay et al., 2006), Binary Robust Invariant Scalable Keypoints (BRISK) by (Leutenegger et al. S., 2011), Maximally Stable Extremal Regions (MSER) (Matas et al., 2002) and Accelerated Segment Test (FAST) developed by (Rosten & Drummond, 2006). As a good feature descriptor should be computationally efficient and exhibit high repeatability, matching accuracy, and robustness. This evaluation is crucial to identify the most suitable algorithm for the classification of plaited Iban mat motifs.

Additionally, a new method involving adaptive smoothing is introduced to achieve a higher percentage of feature extraction on Iban plaited mat motifs. Adaptive smoothing is used to intelligently remove small structures from inside an image whilst preserving the larger and discriminative ones. This approach aids in effectively analyzing and comparing the motifs, as well as distinguishing between different patterns for further analysis or classification.

3.5.1 Feature Descriptor using Scale-Invariant Feature Transform (SIFT) algorithm Peak Thr parameter value of 0.02, 0.04, 0.06 and 0.08.

In the first research pipeline, the Lowe (1999) SIFT algorithm was selected as the local feature descriptor. This algorithm is capable of detecting and describing local features within images. An important parameter of the SIFT algorithm is the peak threshold, which establishes the minimum value required for a local feature to be considered a peak. This parameter's adjustment can significantly influence the algorithm's performance by affecting the quantity and quality of features detected (Zhou, 2016) and (Zhang, 2017). In this evaluation, Peak Thr parameter value of 0.02, 0.04, 0.06 and 0.08 will be evaluated.

First, SIFT feature descriptors was computed for a given image, and the number of detected features was recorded for both the target and query images. Query images were sorted in ascending order within a sequence according to the level of deformation.

It was observed that the number of detected keypoints increases with the level of deformation in blur, illumination change, scale change, and scale plus rotation change. In JPEG compression, the number of keypoints also increases as the deformation level rises. Correspondences are then found between the target and query images, and the RANSAC algorithm is applied to refine the matching results. The number of positive matches between the target and query images was used to determine the similarity score, assuming that a higher number of positive matches correlates with a higher score.

3.5.1.1 Scale-Invariant Feature Transform (SIFT) keypoint and descriptors.

When extracting image features in an Iban mat motif image, scale-invariant feature transformation (SIFT), works by identifying keypoints in the image that are distinctive and repeatable. SIFT works by identifying potential keypoints in the image at different scales.

Convolving the image with a Gaussian filter at different scales allows the identification of local extrema from the Difference-of-Gaussian (DoG) images, which are considered potential keypoints. The location of these keypoints is then refined to sub-pixel accuracy by fitting a quadratic function to the scale-space extrema. The next step involves orientation assignment, where each keypoint is given a dominant orientation based on the local image gradient directions within a neighborhood surrounding the keypoint. Finally, a descriptor was generated for each keypoint by building histograms of dominant gradient directions. This descriptor comprises a vector of 128 elements that encodes information about the local image structure around the keypoint. These steps are illustrated in Figure 3.8.

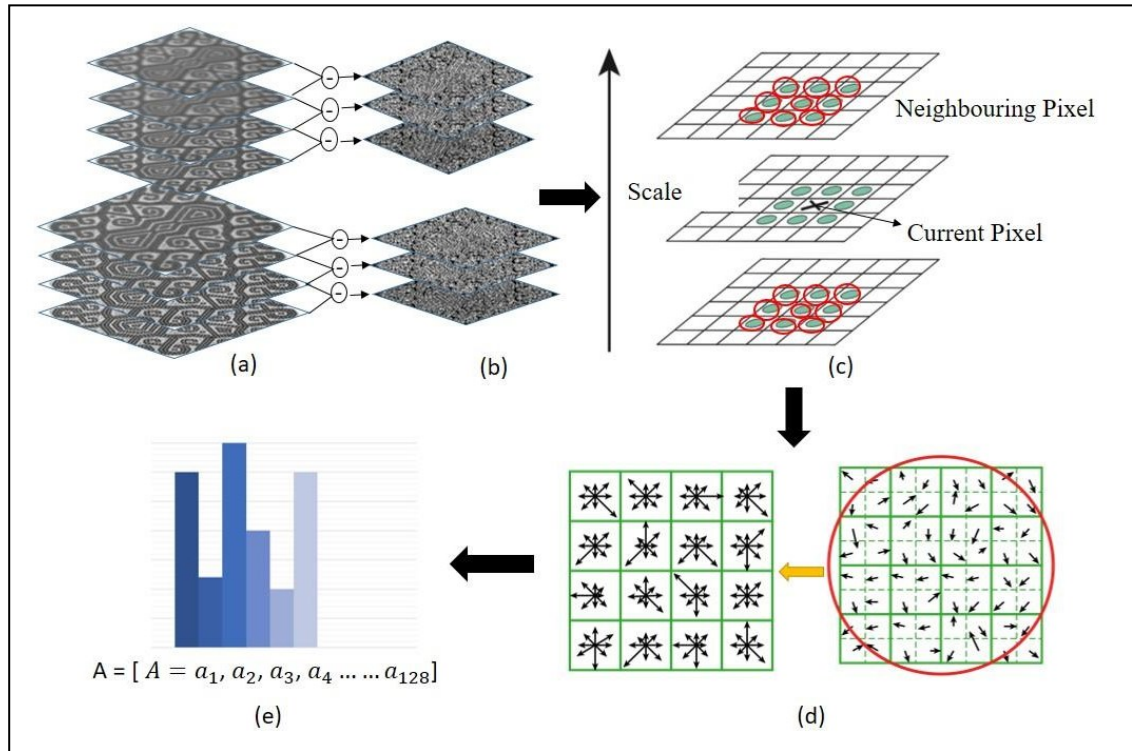


Figure 3.8: SIFT feature extraction; (a) Scale-space generation; (b) DoG image generation; (c) detection of local maximum and minimum; (d) gradient calculation and (e) histogram calculation and generation of 128-dimensional vectors. Image 3.7 (c) and (d) are sourced from (Lowe, 1999).

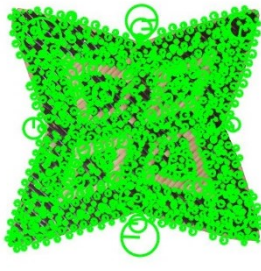
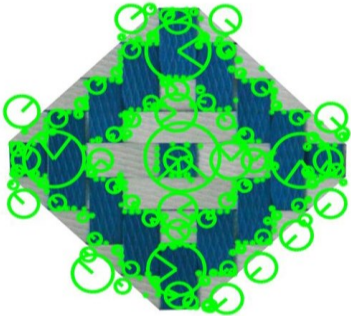
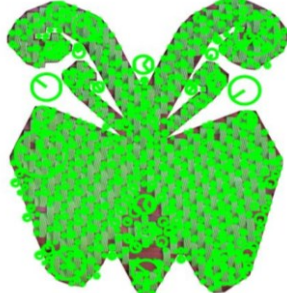
3.5.2 Feature Descriptor SIFT with Peak Thresholding parameter value of 0.02, SURF, BRISK, MSER AND FAST.

Having established that Iban plaited mat motifs can be distinguished using a local feature descriptor, the next step is to compare the performance of several methods against an extended dataset (20 different classes). The study aims to assess each feature descriptor's accuracy, repeatability, and robustness. There are many feature descriptors, each with its own advantages and disadvantages. In this study, the evaluation will focus on the Scale-Invariant Feature Transform (SIFT) with a PeakThr parameter value of 0.02, as introduced by (Lowe, 1999). Speeded-Up Robust Features (SURF) by (Bay et al., 2006), Binary Robust Invariant Scalable Keypoints (BRISK) by (Leutenegger et al., 2011), Maximally Stable Extremal Regions (MSER) by (Matas et al., 2002) and Accelerated Segment Test (FAST) developed by (Rosten & Drummond, 2006).

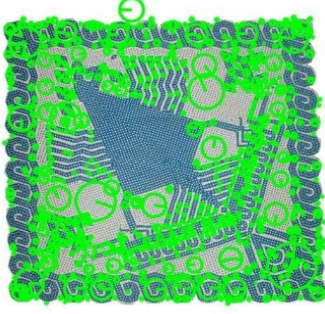
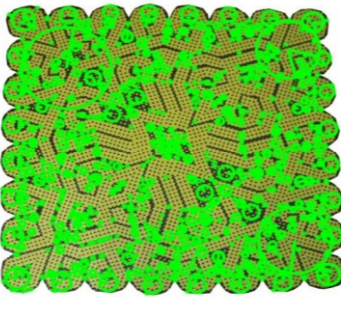
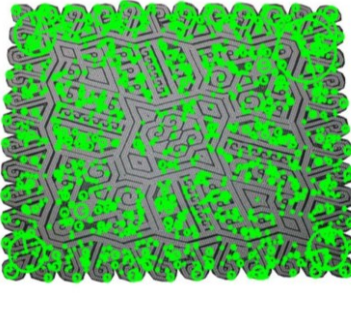
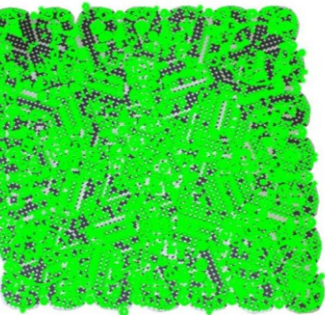
3.5.2.1 Scale-Invariant Feature Transform (SIFT) with Peak Thr parameter value of 0.02

In an earlier experiment, image matching was performed using the SIFT algorithm (Lowe, 1999) with various PeakThr values, with the optimal value reported to be 0.02. SIFT operates by identifying keypoints in the image that are distinctive and repeatable. The initial step involves identifying potential keypoints at different scales by convolving the image with a Gaussian filter and detecting local extrema from the Gaussian difference function. These extrema points are treated as potential keypoints. The next phase refines the keypoint locations to sub-pixel accuracy by fitting a quadratic function to the scale-space extrema. Orientation assignment follows, where each keypoint is given a dominant orientation based on the local image gradient direction of the surrounding neighborhood. Finally, a descriptor is generated for each keypoint by calculating the magnitude and

orientation of the local gradients. Figure 3.9 visualizes the distribution of SIFT keypoints detected (green color) in the synthetic images. Figure 3.10 illustrates the visualized SIFT feature descriptors on synthetic images belonging to both simple and complex motif categories.

		
$N_{tmp} = 1888$ (BA)	$N_{tmp} = 335$ (BMP)	$N_{tmp} = 1020$ (BK)

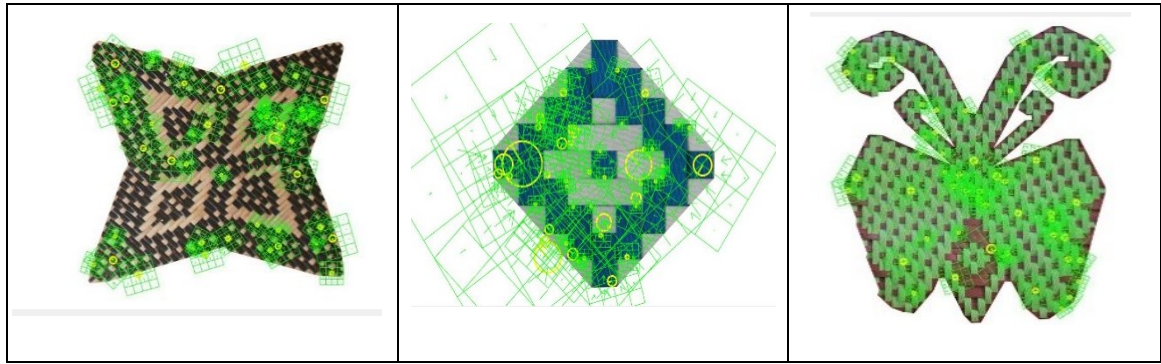
(a) Simple motif

		
$N_{tmp} = 949$ (BLA)	$N_{tmp} = 732$ (BB)	$N_{tmp} = 961$ (BBG)
		
$N_{tmp} = 1267$ (BT)	$N_{tmp} = 1519$ (BLT)	$N_{tmp} = 4394$ (BTGB)

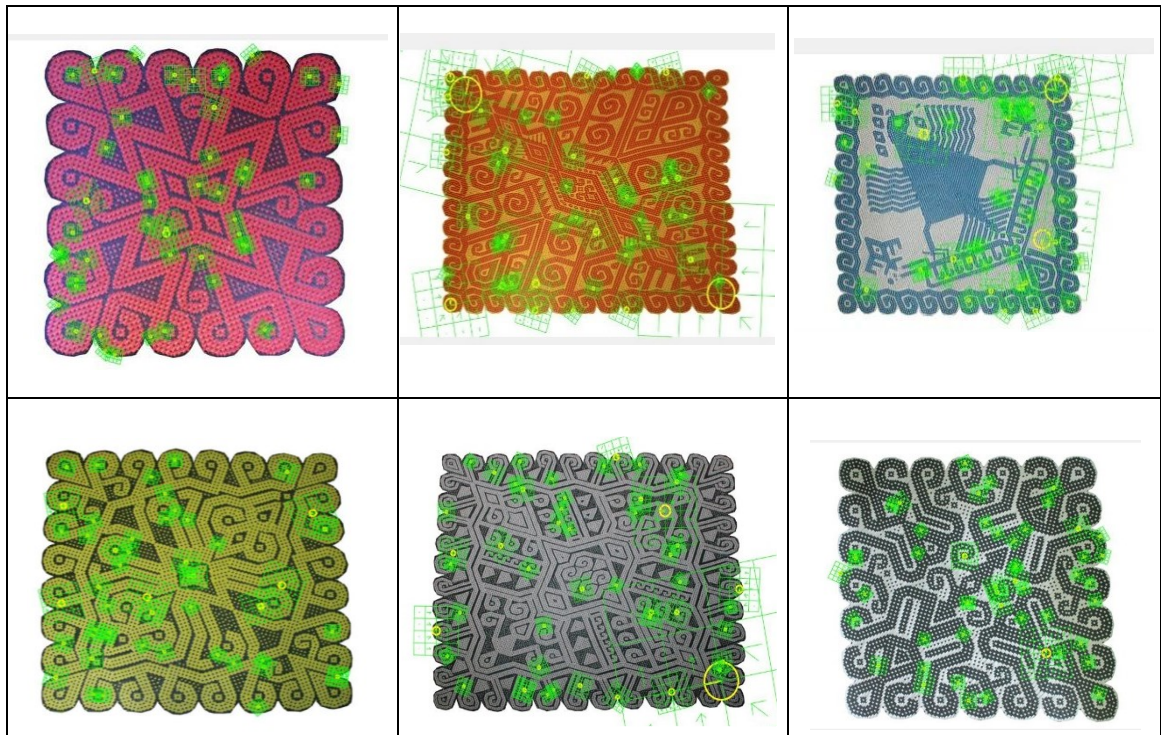
(b) Complex motif

Figure 3.9: The visualized SIFT PeakThr values 0.02 keypoints detected (green color) in the synthetic images of our dataset a) simple motifs and (b) complex motifs. The corresponding N_{tmp} are indicated below the images.

N_{tmp} = number of detected template image keypoints)



(a) Simple motif

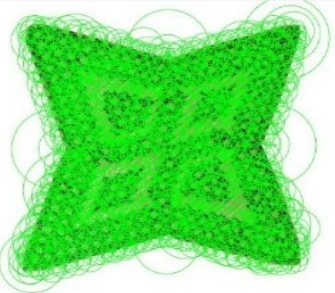
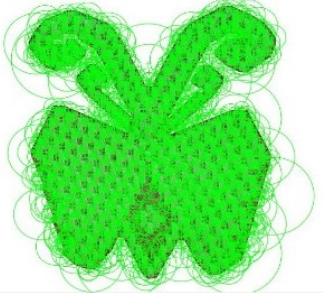


(b) Complex motif

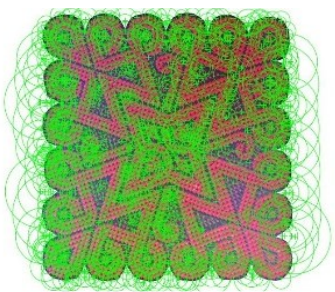
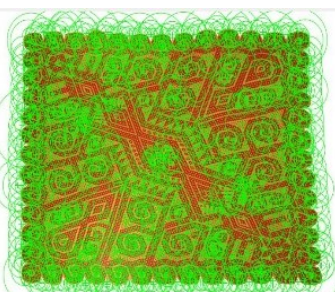
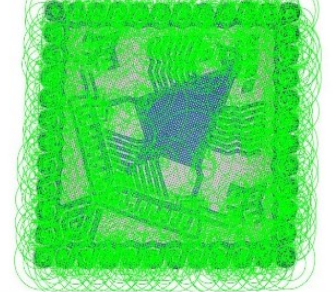
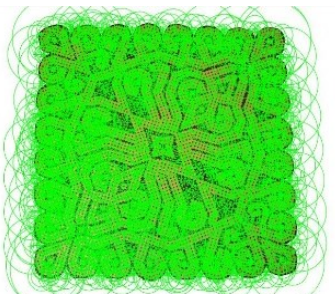
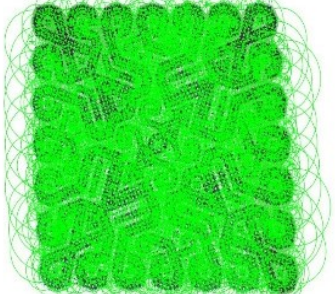
Figure 3.10: Visualized feature descriptors on selected synthetic images of our dataset (a) simple motifs and (b) complex motifs.

3.5.2.2 Speeded-Up Robust Features (SURF)

SURF (Bay et al., 2008) is the second feature descriptor used. The key steps in using SURF to extract features in Iban plaited mat motifs involve feature extraction and feature description (Bay et al., 2008). SURF was selected in the evaluation for its efficiency compared to SIFT, while maintaining comparable accuracy (Kang et al., 2015). SURF speeds up the keypoint detection process using integral images and square box filters for computation (Zhu, 201). Keypoint detection employs the Hessian matrix, while the Haar wavelet responses in the x and y directions provide rotational invariance. Visualized examples of SURF keypoints on synthetic images can be found in Figure 3.11, showing the keypoints detected on mat motif images in the simple motif category (i.e., *Buah Andu*, *Buah Mata Punai*, *Buah Kesulai*) and complex motif category (i.e., *Buah Lang Antu*, *Buah Bandau* and *Buah Burung Garuda*, *Buah Tungku Lebur*, *Buah Lintan Tanah* and *Buah Tangkai Gajai Besembah*).

		
$N_{tmp} = 970$	$N_{tmp} = 31$	$N_{tmp} = 1167$

(a) Simple motif

		
$N_{tmp} = 970$	$N_{tmp} = 1097$	$N_{tmp} = 1663$
		
$N_{tmp} = 1260$	$N_{tmp} = 2147$	$N_{tmp} = 1000$

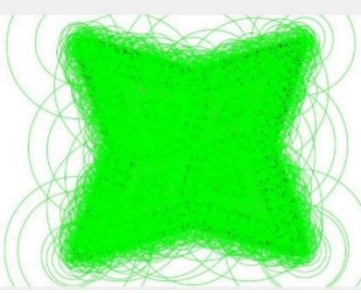
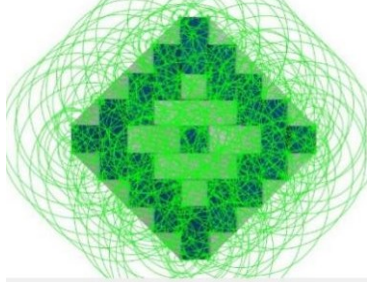
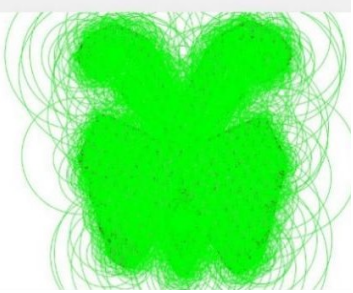
(b) Complex motif

Figure 3.11: Visualized SURF keypoints detected (green color) in the synthetic images belonging to our dataset. (a) Simple motifs and (b) complex motifs. The corresponding N_{tmp} are indicated below the images.

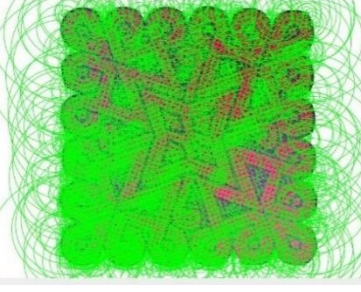
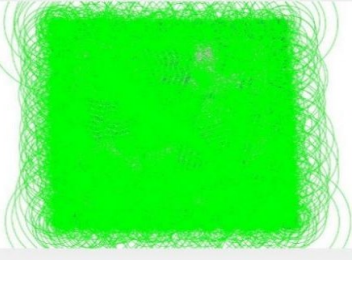
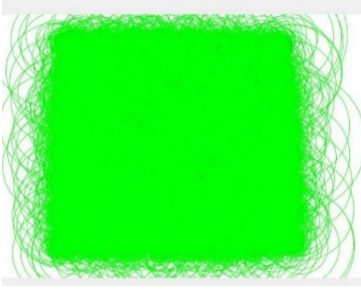
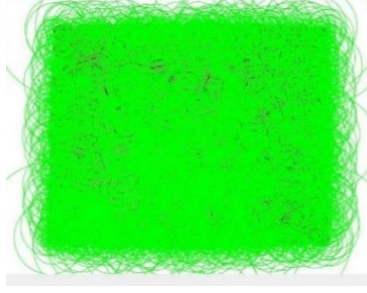
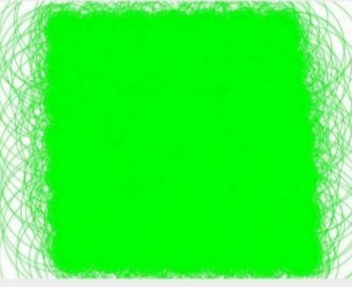
N_{tmp} = number of detected template image keypoints),

3.5.2.3 Binary Robust Invariant Scalable Keypoints (BRISK)

The third feature descriptor selected was Binary Robust Invariant Scalable Keypoints (BRISK) (Leutenegger et al., 2011). The BRISK algorithm consists of three main modules: keypoint detection, keypoint description, and descriptor matching. For keypoint detection, BRISK constructs a scale-space pyramid, where highly stable points of sub-pixel precision in continuous scale space are extracted. This approach is inspired by the Adaptive and Generic Accelerated Segment Test (AGAST), also known as an adaptive corner detection operator (Mair et al., 2010). The computational steps in the BRISK algorithm include the following: first, Gaussian smoothing is applied at each pixel sample point to determine the point value; next, three sets of pairs are created: long, short, and unused. The gradient between long pairs is computed and used to determine orientation, then short pairs are rotated based on the gradient orientation. Long pairs aid in orientation determination, while short pairs are used to build the descriptor through intensity comparisons. Ultimately, a binary descriptor is derived from point-wise comparisons of short pairs. Figure 3.12 illustrates visualized examples of BRISK keypoints on synthetic images.

		
$N_{tmp} = 3114$	$N_{tmp} = 252$	$N_{tmp} = 2538$

(a) Simple motif

		
$N_{tmp} = 7907$	$N_{tmp} = 2142$	$N_{tmp} = 97591$
		
$N_{tmp} = 10293$	$N_{tmp} = 5365$	$N_{tmp} = 10744$

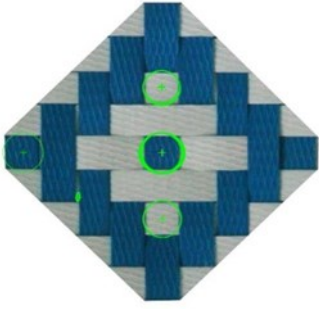
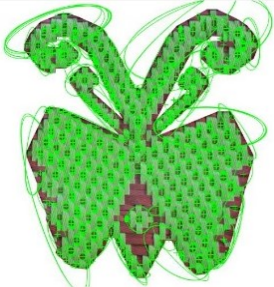
(b) Complex motif

Figure 3.12: The visualized BRISK keypoints detected (green color) in the selected synthetic images. (a) Simple motifs and (b) complex motifs. The corresponding N_{tmp} are indicated below the images.

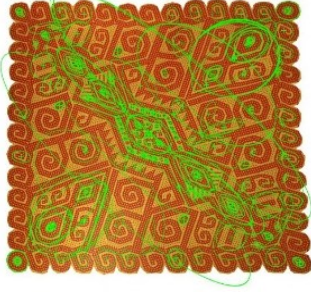
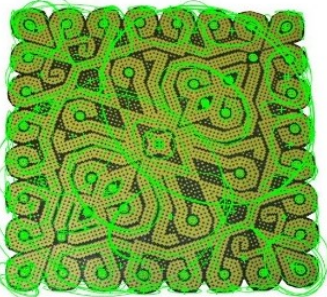
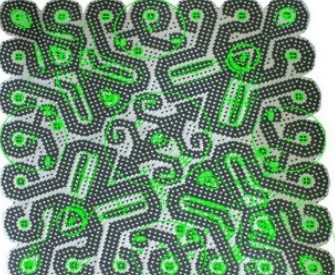
N_{tmp} = number of detected template image keypoints)

3.5.2.4 Maximally Stable Extremal Regions (MSER)

The fourth descriptor is Maximally Stable Extremal Regions (MSER) (Matas et al., 2002). MSER is an interest region/blob detector that serves as the basis for a shape descriptor and an alternative to morphological segmentation methods. MSER clusters pixels into regions based on binary intensity thresholding, forming connected components known as maximally stable regions, which contain similar pixel values across a range of threshold values. MSER is known for its strong performance on images with homogeneous regions, its efficacy with small regions, high repeatability, and affine invariance. MSER's feature extraction includes the following steps: first, sweeping the intensity threshold from minimum to maximum while retaining connected components at each threshold level; regions that maintain consistent size as intensity varies are considered maximally stable. The MSER descriptor records the positions of these maximal regions and their corresponding thresholds, along with the region descriptors as features. Figure 3.13 displays visualized MSER keypoints on synthetic images.

		
$N_{tmp} = 2119$	$N_{tmp} = 31$	$N_{tmp} = 1454$

Simple motif

		
$N_{tmp} = 198$	$N_{tmp} = 602$	$N_{tmp} = 694$
		
$N_{tmp} = 1260$	$N_{tmp} = 2147$	$N_{tmp} = 1000$

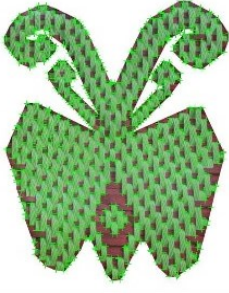
Complex motif

Figure 3.13: Visualized MSER ellipse keypoints detected (green color) in selected synthetic images. (a) Simple motifs and (b) complex motifs. The corresponding N_{tmp} are indicated below the images.

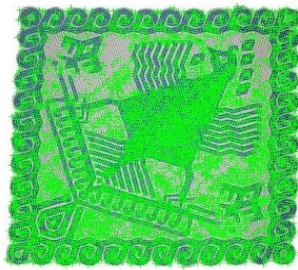
(N_{tmp} = number of detected template image keypoints)

3.5.2.5 Features from accelerated segment test (FAST)

In the fifth experiment, the dataset is evaluated using the Features from Accelerated Segment Test (FAST) descriptor, with code provided by Rosten and Drummond (2006). FAST is a corner detection method known for its computational efficiency. The method examines a pixel at the center of a candidate corner, referred to as P, and tests a circle of sixteen pixels around P to determine if it is an interesting point. Each pixel in the circle is labeled from 1 to 16 in a clockwise direction. The intensity of pixels at positions 1, 5, 9, and 13 in the circle is compared. If at least three of these four pixels meet the threshold, P is selected as an interesting point. FAST returns points if the neighboring pixels differ, and does not return keypoints on smooth backgrounds. Table 3.14 presents examples of detected keypoints on the template images.

		
$N_{tmp} = 1254$	$N_{tmp} = 33$	$N_{tmp} = 819$

(a) Simple motif

		
$N_{tmp} = 1508$	$N_{tmp} = 1534$	$N_{tmp} = 5957$

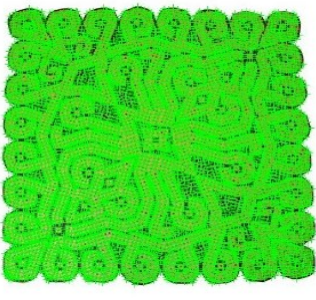
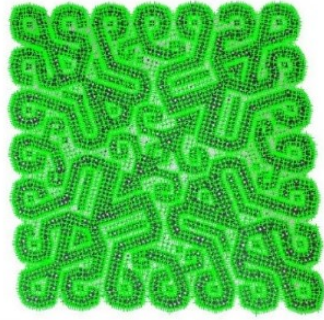
		
$N_{tmp} = 8141$	$N_{tmp} = 1836$	$N_{tmp} = 7554$
	(b) Complex motif	

Figure 3.14: The appearance and distribution of the FAST keypoint detected (green color) in the clean synthetic template images.

N_{tmp} = number of detected template image keypoints)

3.5.3 Proposed Method Adaptive Smoothing

The proposed method uses the Canny edge detector to extract meaningful edges within an image, focusing on the outline of a mat motif while ignoring its inner region. The application of the Canny edge filter can produce thinned and broken edges, so the lower threshold of the filter is dynamically increased until a specific percentage of retained edges (PoRE) is achieved. Probabilistic Hough Transform (ProHT) is utilized to count the remaining edges after each application of the Canny filter. The filter gradually reduces the number of edges by removing weaker ones through increasing the lower threshold value, thereby rejecting weaker edges. This process is applied to both the reference and query images. Once the process is complete for both, BRISK descriptors are searched for and built. The resulting matches are then filtered using RANSAC.

The proposed approach introduces several schemes utilizing combinations of the Canny edge detector, ProHT, and morphological dilation. Scheme 1 employs the standard Canny edge algorithm using default parameters from (Canny, 1986). In Scheme 2, the standard Canny edge algorithm is augmented with morphological dilation. For Scheme 3, Canny incorporates a dynamic lower threshold that increases after each iteration until reaching a Percentage of Remaining Edges (PoRE) value, termed the ProHT PoRE-Canny algorithm. PoRE values are set at 100.0%, 80.0%, 75.0%, and 70.0%. Scheme 4 replicates the setup of Scheme 3 but with a broader range of PoRE values, including 100.0%, 90.0%, 85.0%, 80.0%, 75.0%, 70.0%, 50.0%, and 20.0%. These thresholds are chosen heuristically to determine optimal values for the dataset. Additionally, Scheme 4 includes morphological dilation to enhance edge appearance. Detailed descriptions for each scheme are provided in Table 3.4. A flowchart outlining the general research workflow is depicted in Figure 3.15.

Table 3.4: Baseline and the 4 schemes.

Scheme	Implemented algorithm(s)	Target Percentage of Retained Edges (PoRE)	Morphological Dilation
Baseline	None (using synthetic RGB images)	Not Applicable	No
i.	Standard Canny edge	None. Using default parameters in (Canny, 1986)	No
ii.	Standard Canny edge	None. Using default parameters in (Canny, 1986)	Yes
iii.	Canny edge (dynamic lower threshold) + ProHT PoRE	100.0%, 80.0%, 75.0%, 70.0%	No
iv.	Canny edge (dynamic lower threshold) + ProHT PoRE	100.0%, 90.0%, 80.0%, 85.0%, 75.0%, 70.0%, 50.0% and 20.0%	Yes

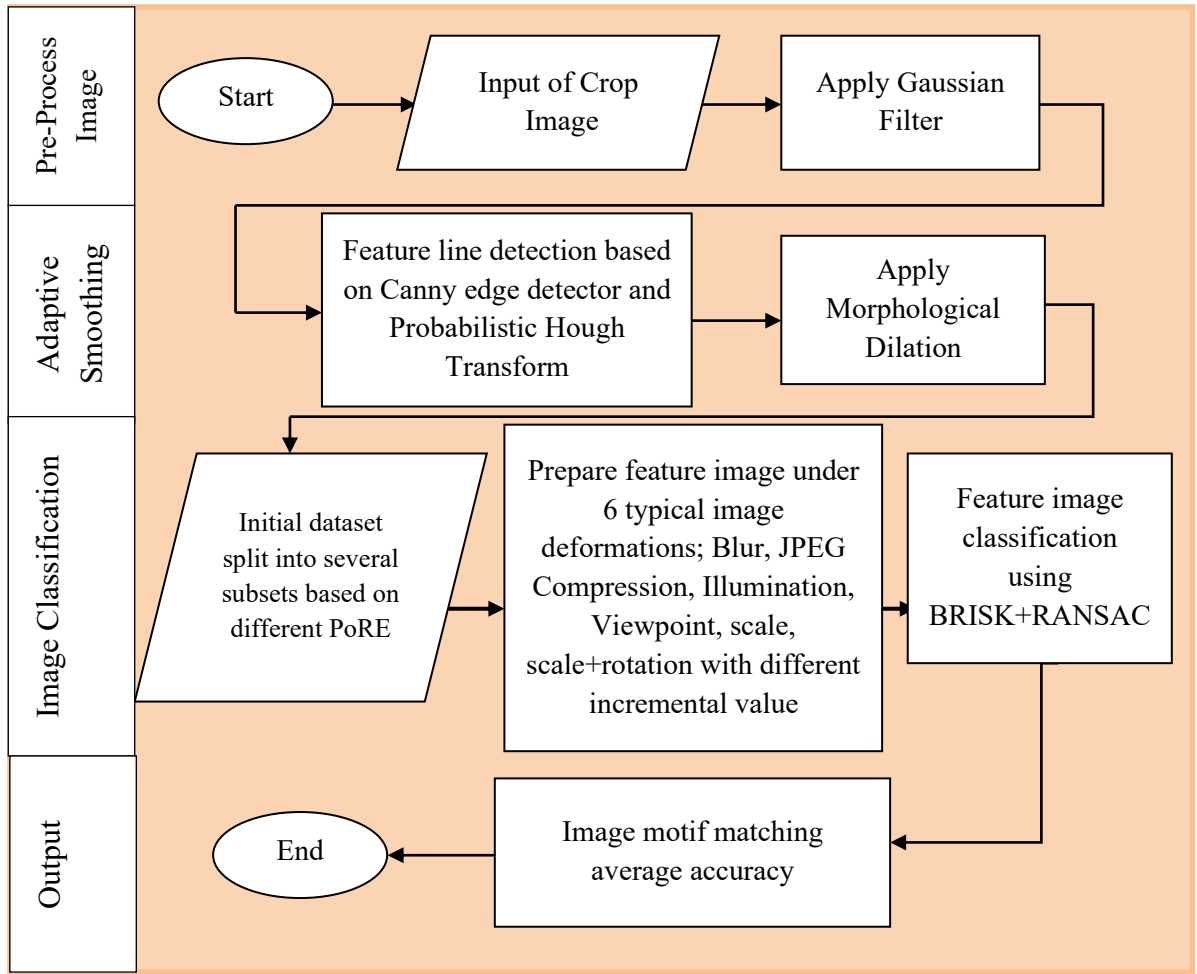


Figure 3.15: A flowchart describing our general research workflow.

3.5.3.1 Edge Extraction

The feature extraction process entails identifying and extracting strong edge features to represent the true outline of a mat motif. The inner region of the mat motif is not important features to our analysis and is therefore considered part of the background noise.

3.5.3.2 Gaussian Smoothing

To create the edge image, we first apply a 5x5 Gaussian filter to remove noise. This filter helps to eliminate high-frequency noise while retaining edges that are of interest

(Gonzalez & Woods, 2002). The coefficients of the filter are calculated using the Gaussian function with a standard deviation of 1.4 pixels. The Gaussian filter is defined as follows,

$$G(x,y) = \frac{1}{2\pi \sigma^2} \exp - \frac{x^2 + y^2}{2\sigma^2} \quad \text{Equation 3.3}$$

3.5.3.3 Image Gradient Calculation

The second step is to compute the magnitude and direction of the image gradients. The approach in the standard Canny filter is to use a 2x2 neighboring area to compute the magnitude and direction of the gradient, for both vertical direction (G_y) and horizontal direction (G_x). The edges are then marked in locations that have a large magnitude gradient. The image gradient magnitude is calculated as,

$$Edge_Gradient (G) = \sqrt{G_x^2 + G_y^2} \quad \text{Equation 3.4}$$

The direction of the image gradient (θ) at each pixel is computed as,

$$angle (\theta) = \tan^{-1} \left(\frac{G_y}{G_x} \right) \quad \text{Equation 3.5}$$

3.5.3.4 Non-maximum Suppression

Non-maximum suppression is a technique used in the standard Canny edge detection algorithm to thin out the edges into a single-pixel width and suppress all other gradient values that do not correspond to an edge. This is achieved by examining the gradient magnitude in a 3x3 window in the direction perpendicular to the edge. First, each pixel is

compared to its 2 neighboring pixels in the direction of the gradient. If the current pixel has a greater magnitude than its neighbors, it is considered a candidate edge pixel. To ensure that the edges are continuous, the algorithm performs edge thinning by preserving only those pixels which magnitude is the maximum in the direction of the gradient. Next, the gradient direction is rounded to the nearest 45° angle, and the magnitudes of the 2 pixels in that direction are checked. If the magnitude of the current pixel is more remarkable than both its neighbors, it is marked as an edge pixel. If not, it is suppressed or removed. This step results in a binary image where only the strongest edge pixels are retained.

Following the gradient direction, each pixel is examined for a local maximum in the nearest neighborhood. If a pixel lies on an edge, it will have a gradient direction that is normal to the edge.

3.5.3.5 Checking for the Connected Edges

The Canny algorithm adopts a double-threshold method to select edge points after non-maximum suppression. This stage uses 2 threshold values, high and low, to classify the candidate edge pixels into strong and weak edges. Weak edge pixels are then examined to check if they are connected to solid edge pixels using a connectivity test, and if they are, they are duly marked as part of the edge contour. This algorithm preserves the weak edges connected to solid edges while suppressing the weak edges that are not part of any edge contour. The result is a binary image where all the pixels belonging to the detected edges are retained.

Pixel selection relies on double threshold values: minVal and maxVal. Pixels with intensity gradient above maxVal are considered edges, while those below minVal are non-edges. Pixels between these thresholds are classified based on their connectivity. Those connected to "sure edge" pixels are considered part of edges, while disconnected ones are

discarded. Choosing appropriate minVal and maxVal values is therefore crucial to obtain accurate results. The process is illustrated in Figure 3.16, where edge A is a "sure-edge" above maximal, and edge C is connected to edge A. Hence it is considered valid, and edge B is above minimal but not connected to any "sure edge"; thus, it is discarded. Proper selection of high-threshold and low-threshold is important to ensure the correct result.

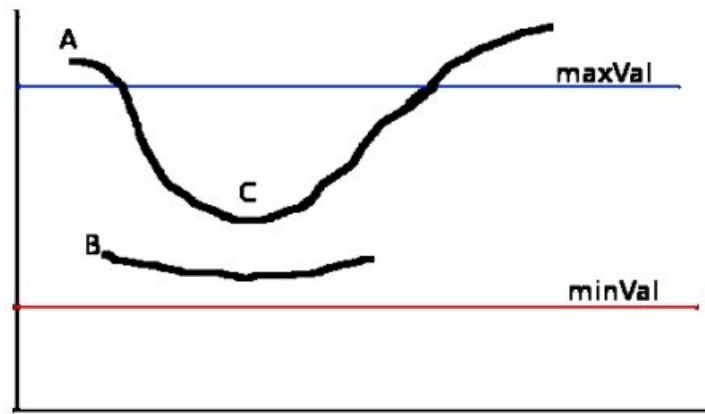


Figure 3.16: Two threshold values, minVal and maxVal. Image sourced from (Bradski, 2000).

3.5.3.6 Probabilistic Hough Transform

Probabilistic Hough Transform (ProHT) is a variant of the standard Hough Transform algorithm used in Image processing and Computer vision to detect lines or other simple shapes inside an image. The standard Hough Transform is computationally expensive due to its exhaustive search over all possible parameter values. In contrast, the probabilistic Hough Transform is a far more efficient approach that selectively samples the image space to detect the desired features. Probabilistic Hough Transform randomly selects a subset of edge points to fit a line instead of searching over all possible parameter values. The algorithm first sets a minimum line length and a maximum gap between line segments. It then selects a random point in the edge image and draws a short line segment in a

random direction. It then iteratively searches along the line segment for additional edge points. If enough points are found along the line, it is considered a valid line segment and added to the output.

3.5.3.7 Detail Process

In our proposed method, the process begins by converting both the reference and query images into Grayscale. Following this, Gaussian blur is applied with a 5x5 kernel to reduce noise. Subsequently, the Grayscale image is transformed into an edge image using the Canny filter. The calculation of the PoRE value follows. If the PoRE value does not meet the predetermined threshold, the lower threshold is incremented, and the Canny filter is reapplied to further eliminate weak edges from the motif image. A fixed increment of 5 units is utilized after each iteration. The iteration ceases once the PoRE value reaches or falls below the specified threshold, which includes values such as 100.0%, 90.0%, 85.0%, 80.0%, 75.0%, 70.0%, 50.0%, and 20.0%. The PoRE is computed using Equation 3.6 provided below.

$$PoRE = \frac{\text{Current number of detected edges using PHT}}{\text{Initial number of detected edges using PHT}} \times 100\% \quad \text{Equation 3.6}$$

During this stage, the adaptive smoothing approach removes small image structures on the assumption that important edges are larger and more prominent. The flowchart of the entire process is shown in Figure 3.17. Threshold parameter values for Canny edge detection are listed in Table 3.5 and the parameter values used for edge counting with Probabilistic Hough transform in Table 3.6.

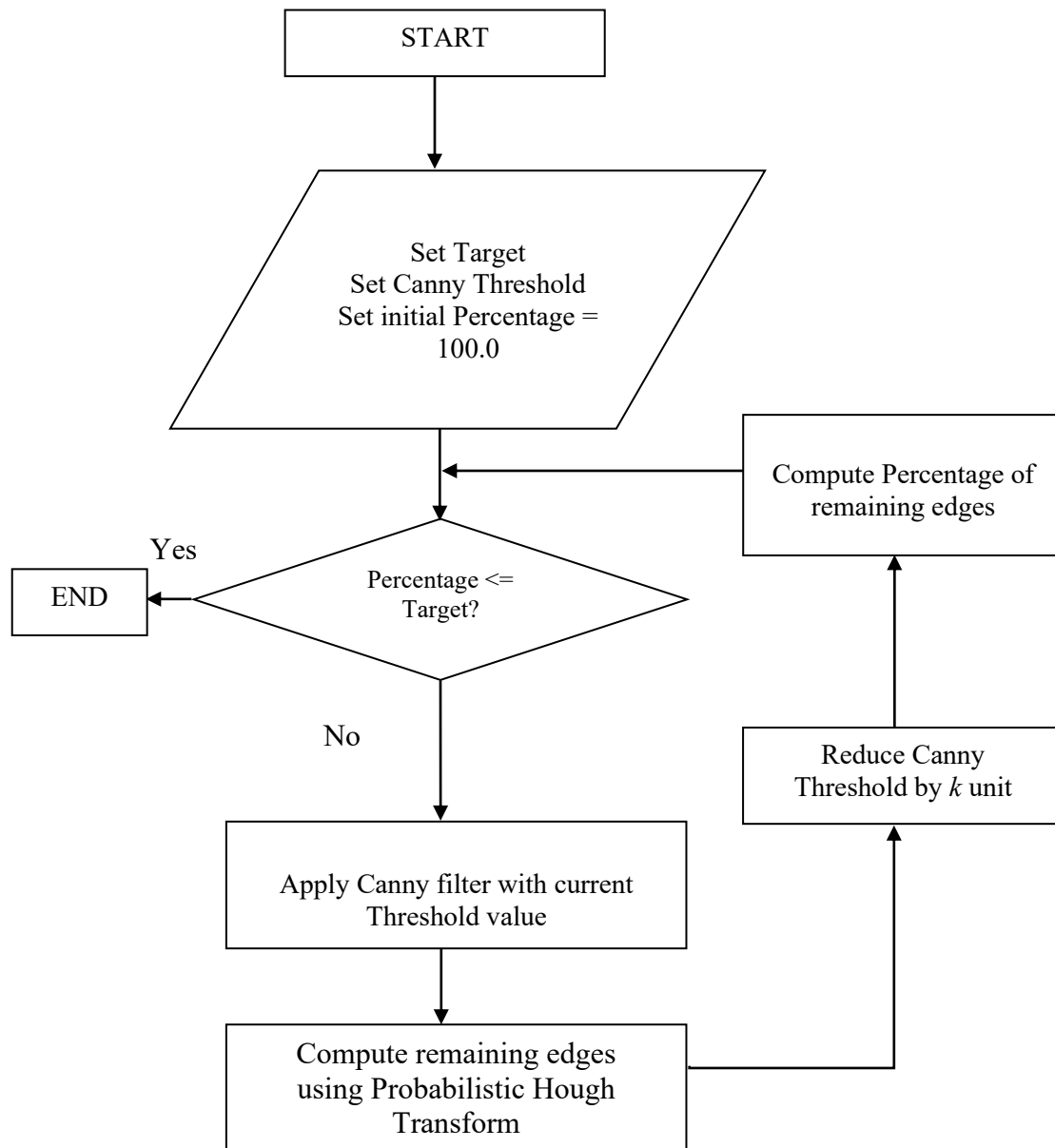


Figure 3.17: Flowchart of the adaptive smoothing process.

Table 3.5: Parameters used for Canny edge detection.

Parameter	Threshold Value	Parameter Explanation
Gaussian filter kernel size	5x5	Size of the filter window in Gaussian Blur function
Sigma (σ)	3	Size of the Sobel kernel used in gradient computation.
Lower (T_l)	5	The lower edge on the gradient values
Upper (T_h)	255	The upper edge on the gradient values

The following parameter values are used for edge counting with ProHT,

Table 3.6: Parameter values used for edge counting with ProHT.

Parameter	Value	Parameter Explanation
Threshold	100.0%, 90.0%, 80.0%, 85.0%, 75.0%, 70.0%, 50.0% and 20.0%	The percentage of remaining edges in the current edge image compared to the original edge image.
minLineLength	3	Minimum line length
maxLineGap	3	Maximum allowed the gap between points on the same line to link them

3.5.3.8 Edge Appearance Improvement

The adaptive smoothing feature may produce broken and/or thinned-out edges that fail to accurately represent the true outline of the mat motifs. Therefore, morphological dilation is used to add more pixels to the edge region, increasing the thickness of the edge pixels. Morphological dilation uses a structuring element placed at each pixel in a sliding window manner. If the structuring element overlaps with a group of adjacent pixels, the value of the center pixel is set to 1, indicating that the region has been expanded or dilated. See Figure 3.18 for examples of reference image produced using a standard Canny edge algorithm, with and without dilation.

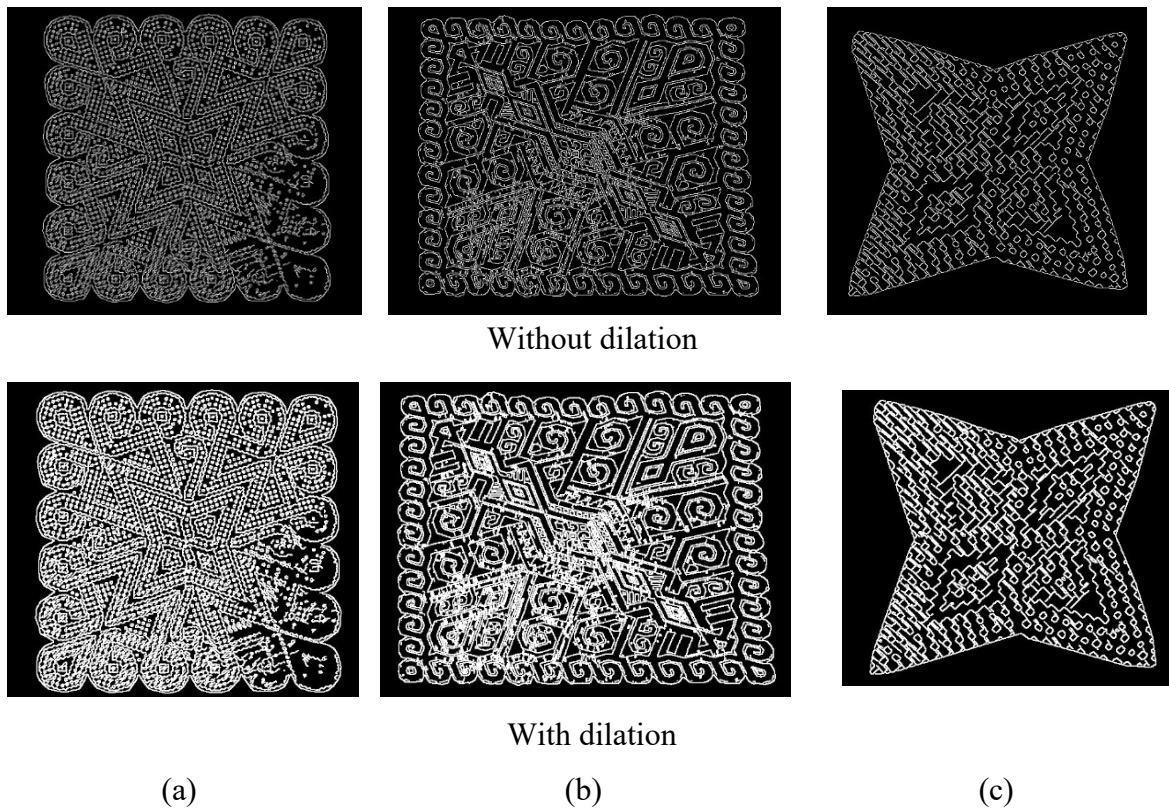


Figure 3.18: Reference images produced using standard Canny edge algorithm, without (top) and with dilation (bottom). The mat motifs are (a) *Buah Lang Antu*, (b) *Buah Bandau* and (c) *Buah Andu*.

3.5.3.9 Producing Edge Images at Different PoRE Values

All reference and query image pairs for each motif class were converted into edge images using different PoRE values. In the classification experiment, these edge images were utilized to determine the optimal PoRE value for our dataset. Figure 3.19 illustrates a sample query image generated at various PoRE values.

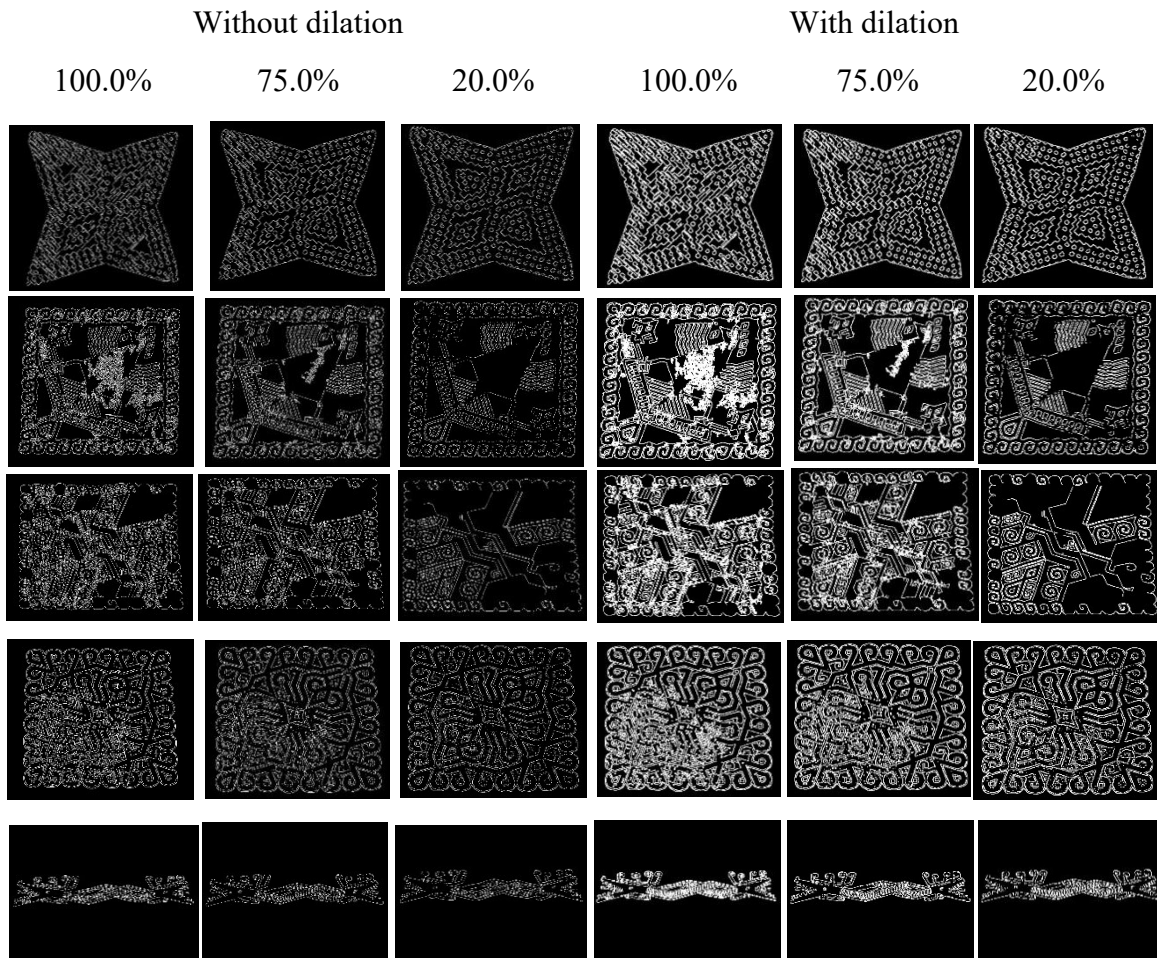


Figure 3.19: Images for the following motif classes (top to bottom row), from left to right, were created using PoRE values of 100.0%, 75.0%, and 20.0%: *Buah Andu*, *Buah Burung Garuda*, *Buah Bandau*, *Buah Tungku Lebur*, and *Buah Nabau Besundang*. The versions (a) without dilation and (b) with dilation are both displayed.

3.5.3.10 Preparation of Query Images (Test Sequences)

For each motif class, a test sequence was created in a manner similar to previous experiments. Each test sequence contains five images that exhibit a gradual increase in geometric and/or photometric transformations of the original image. Following the recommendations of Mikolajczyk (2005), the same six types of image deformations, each with five incremental levels, were used. A total of 9,600 query photos were generated due to the combination of 20 motif classes, 6 image deformation types, 5 deformation levels, and 8 sets of PoRE values (i.e., 100%, 90%, 85%, 80%, 75%, 70%, 50%, and 20%).

The optimal PoRE value for the dataset was determined through the utilization of a heuristic approach. Experimentation with a wider range of thresholds is conducted, with these values randomly chosen due to a lack of prior knowledge regarding the dataset's specific ideal value. By systematically altering the PoRE values, the objective is to evaluate their influence on the algorithm's performance, particularly regarding feature extraction and matching accuracy. Through this heuristic optimization process, the selection of the PoRE value is refined iteratively based on empirical observations, aiming to ensure its effectiveness in enhancing the algorithm's performance to align with the dataset's characteristics. Figure 3.20 shows several examples of the query images produced, i.e., *Buah Lang Antu* sequence for Blur, *Buah Burung Garuda* sequence for JPEG compression, *Buah Lintan Tanah* sequence for Illumination change, *Buah Tungku Lebur* sequence for Viewpoint change, *Buah Nabau Besundang* for Scale change, and *Buah Tangkai Gajai Besembah* sequence for Scale+Rotation change. The incremental values for each image deformation type are indicated below the images.

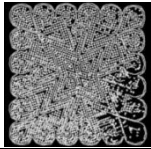
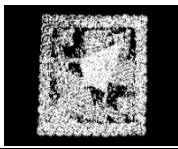
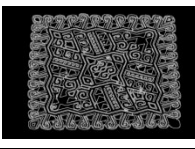
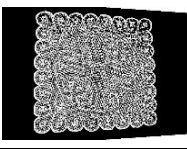
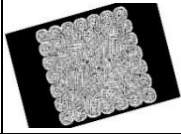
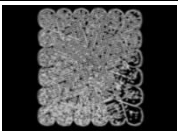
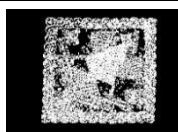
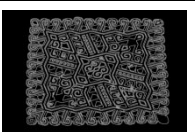
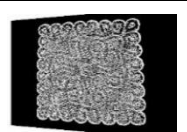
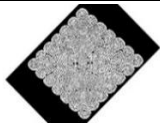
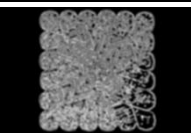
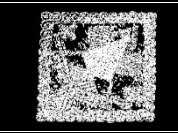
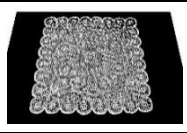
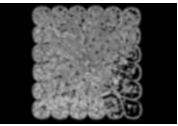
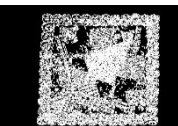
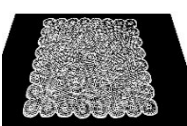
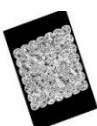
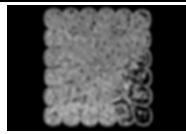
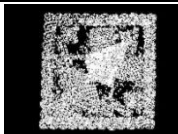
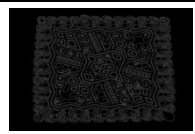
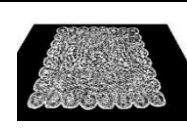
Blur	JPEG Compression	Illumination	Viewpoint	Scale	Scale+ Rotation
					
5.0%	5.0%	5.0%	Right fronto-parallel surface to the right 10°	95%	15°
					
35.0%	30.0%	20.0%	Left fronto-parallel surface to the left 10°	65.0%	50°
					
50.0%	60.0%	40.0%	Slanted surface 60°	35.0%	100°
					
60.0%	90.0%	60.0%	Slanted surface 40°	15.0%	200°
					
80.0%	100.0%	90.0%	Slanted surface 20°	5.0%	300°

Figure 3.20: Sample query images produced with Canny edge detection with varying degrees of deformation from top to bottom. Query images for the *Buah Lang Antu* sequence for blur, the *Buah Burung Garuda* sequence for JPEG compression, the *Buah Lintan Tanah* sequence for illumination change, the *Buah Tungku Lebur* sequence for viewpoint change, the *Buah Nabau Besundang* sequence for scale change, and the *Buah Tangkai Gajai Besembah* sequence for scale+rotation change is displayed in the column to the left.

3.6 Outlier Removal

In the study, feature matching on the Iban plaited mat motif will exclusively utilize Random Sample Consensus (RANSAC), an iterative method recognized for its efficient removal of outliers during model estimation, used to estimate parameters of a mathematical model from a set of observed data points that may contain outliers. RANSAC, as highlighted by (Wang, Li, & Xu, 2016), is robust and imposes a low computational load. The adoption of RANSAC is aimed at reducing the impact of spurious matches on the classification label. Due to its advantages, RANSAC was chosen to be employed during the matching process of the Iban plaited mat motif. RANSAC's robustness in handling outliers and its ability to efficiently estimate model parameters make it well-suited for this task. Its selection ensures that the matching process is more resilient to noise and inaccuracies, ultimately leading to more accurate and reliable results when identifying the motif within images.

3.7 Evaluation Approach

The methodologies for confirming the efficacy of the suggested feature extraction method and establishing classification are presented below. The performance evaluation of the feature detector and descriptor is based on the number of matching correspondences, using a confusion matrix. Table 3.7 shows the confusion matrix obtained. A confusion matrix is a useful tool in evaluating the performance of a classification model. It presents a tabular representation of the actual versus predicted classifications made by the model (Stehman & Stephen, 1997). It provides a summary of the predicted and actual class labels, and helps to determine the accuracy of the model's predictions. Our confusion matrix table contains three values:

- i. True Positive (TP): Number of correct matches with similarity score exceeding the threshold value.
- ii. False Positive (FP): Number of incorrect matches with similarity score exceeding the threshold value.
- iii. False Negative (FN): Number of correct matches with similarity score less than the threshold value.

False Negatives also apply in cases where our classification function returns multiple top matches or zero matches. The same evaluation criterion as proposed by (Mikolajczyk & Schmid, 2004) was utilized, relying on the correct and incorrect matches obtained from a pair of images. Each descriptor from the target images is compared with the descriptor from the query images.

Table 3.7: Possible Outcomes for a Binary Classification

		PREDICTED CLASS	
		True	False
ACTUAL CLASS	True	True Positive (TP)	False Positive (FP)
	False	False Negative (FN)	True Negative (TN)

Results from the confusion matrix, various metrics are calculated to evaluate the performance of the classification model, employing statistical measures such as accuracy, precision, recall, misclassification rate, and F1-score.

Precision is the ratio of true positive predictions to the total number of positive predictions made by the algorithm. It measures the ability of the algorithm to correctly

identify positive samples among all predicted positive samples. The value of precision is calculated as follows:

$$Precision = \frac{TP}{TP+FP} \quad \text{Equation 3.7}$$

Sensitivity (i.e., True Positive Rate) is the ratio of true positive predictions to the total number of actual positive samples in the dataset. It measures the ability of the model to retrieve all positive samples. The value of sensitivity is calculated as follows:

$$Sensitivity = \frac{TP}{TP+FN} \quad \text{Equation 3.8}$$

Accuracy measures the ability of the algorithm to make the correct. It is usually expressed as a percentage, and is calculated by dividing the number of correctly labelled images by the total number of images. The value of accuracy is defined as follows:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad \text{Equation 3.9}$$

The misclassification rate, also known as the error rate, quantifies the frequency of incorrect predictions made by a classification model relative to the total number of instances in the dataset. The resulting value represents the proportion of misclassified instances in the Iban plaited mat motif dataset. While the misclassification rate offers a

straightforward measure of overall accuracy, it does not provide insight into the specific types of errors made by the model. The misclassification rate can be calculated using the following formula:

$$\text{Misclassification Rate} = \frac{\text{Number of Misclassified Instance}}{\text{Total Number of Instance}} \quad \text{Equation 3.10}$$

The F1 score is a metric that combines precision and recall into a single value, offering a balanced assessment of a classification model's performance. It is calculated using the harmonic mean of precision and recall, providing equal weight to both measures. Ranging from 0 to 1, a higher F1 score indicates better model performance, making it particularly useful for evaluating models on imbalanced datasets or when the costs of false positives and false negatives need to be balanced. The formula for calculating the F1 score is:

$$F1 \text{ score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad \text{Equation 3.11}$$

3.8 Discussion and Conclusion

The research workflow was initially outlined to provide a comprehensive overview of the study. Following this, the evaluation compared well-cited feature descriptors with a newly introduced Iban plaited mat motif. It was essential to detail the framework's distinctive features to highlight the benefits of employing a feature extraction model for representing the Iban plaited mat motif dataset, as well as other cultural motif datasets

The proposed approach and model were also thoroughly detailed to provide a clearer picture of the study's primary contributions, utilizing adaptive smoothing for feature extraction in Iban plaited mat motifs. In addition, the experimental setup was presented to provide details on the platform employed. Furthermore, a comprehensive description of the dataset was provided to demonstrate the suitability of both simple and complex Iban plaited mat motifs for edge feature extraction. Lastly, the evaluation procedure is considered critical and warrants completion to validate the effectiveness of the proposed approach and model.

CHAPTER 4

TESTING AND IMPLEMENTATION

4.1 Overview

This chapter discusses the research work's experiments and results analysis of matching evaluation using SIFT with peak threshold values of 0.02, 0.04, 0.06, and 0.08. Furthermore, the evaluation involved assessing the SIFT PeakThr 0.02 (optimal parameter value), as well as SURF, BRISK, MSER, and FAST, along with image matching using the results of feature extraction from images employing Adaptive Smoothing (Proposed Method). The aim of the evaluation was to determine the algorithm's suitability for matching and classifying images of plaited Iban mat motifs at different deformation levels, such as blur change, JPEG compression, illumination change, scale change, and scale with rotation change. This advantage led to the second level of investigation, where the effects of each type of variation on recognition performance were discussed, with a focus on potential interaction effects in simple and complex Iban plaited mat motif variants.

4.2 Experiment 1 (SIFT with peak threshold value of 0.02, 0.04, 0.06 and 0.08)

The SIFT descriptors are matched using pairwise matching based on Nearest Neighbors Distance Ratio (NNDR). This method had been widely used in (Wang, Fan, & Wu, 2011) and (Lv et al., 2018). Due to its proven effectiveness in local feature matching task, it is applied in the experiment using Equation 4.1.

$$\frac{\|D_A - D_1\|}{\|D_A - D_2\|} \leq t \quad \text{Equation 4.1}$$

where, D_A denotes a descriptor of the query image, D_1 and D_2 are the nearest and second nearest neighbor to D_A respectively. The ratio value in Equation 4.1 is duly calculated and no match in the result if the ratio value is less than the PeakThr parameter value, $t = 0.02, 0.04, 0.06$ and 0.08 . Similarity scores are normalized to a range of 0.0 and 1.0 .

Matching results obtained with NNDR using PeakThr parameter values of $0.02, 0.04, 0.06$, and 0.08 often yield numerous mismatches. Random Sample Consensus (RANSAC) was employed to eliminate these mismatches. According to (Gioia et al., 2020) and (Tareen & Saleem, 2018) the RANSAC algorithm facilitates the discovery of a projection matrix and accurately identifies the keypoints that best fit the pairwise relationship.

4.2.1 Results and Analysis Experiment 1

The evaluation focuses on assessing SIFT's capability to differentiate plaited Iban mat motif classes. Additionally, an experiment was devised to identify the optimal peak threshold value for SIFT within the dataset. This optimal value hinges on factors including motif size and complexity, image noise levels, and the degree of deformation present. Comparison was made between the number of detected keypoints for each mat motif class when utilizing the optimal Peak Threshold value.

The recorded data includes the count of detected SIFT keypoints within the query versus reference image pairs, the correspondences tally, and the number of accurate matches post-RANSAC across various PeakThr parameter values ($0.02, 0.04, 0.06$, and 0.08) for each image deformation sequence. To enhance the likelihood of identifying suitable corresponding matches between two images, a significantly large number of keypoints is necessary in both images. See Table 4.1 for an example of matched keypoints

for an image pair from different mat motif classes, i.e., *Buah Bulan Sebayan* and *Buah Burung Kenyalang* at blur level 1 (lowest). Table 4.2 shows the matched keypoints for the same pair at blur level 5 (highest).

In both figures, the following statistics are presented, including important areas in the search image, the quantity of correspondences, accurate matches after RANSAC, and the number of rejected outliers. The report utilizes the following variables, i.e., the number of detected keypoints in the reference image, N_{tmp} , number of detected query image's keypoints, N_{qry} , the number of matches found, N_{crp} , and the number of correct matches after RANSAC, N_{mch} . However, for outliers, it represents keypoints that deviate significantly from the majority, often due to factors like noise or changes in viewpoint. The number of rejected keypoints after RANSAC reflects the algorithm's effectiveness in identifying and excluding inconsistent matches. A higher count suggests better outlier removal and a more accurate final set of correspondences, while a lower count may indicate potential issues with noise or parameter selection. Monitoring this count is vital for assessing the quality and reliability of the feature matching process.

Table 4.1: Number of found keypoints in query and reference image, correspondences, inliers and rejected outliers. Using SIFT + RANSAC at optimal peak threshold value of 0.02 on the Blur sequence (Level 1).

Bil	Threshold	Query Image (Image1)	N_{qry}	Reference Image (Image2)	N_{tmp}	N_{crp}	N_{mch}	Outlier
1	0.02	<i>Buah Bulan Sebayan</i> Blur1	996	<i>Buah Bulan Sebayan</i>	633	512	453	59
2			996	<i>Buah Burung Kenyalang</i>	1096	9	5	4
3			996	<i>Buah Engkatak Tingkap Pama Merap</i>	2683	40	8	32
4			996	<i>Buah Bong Midang</i>	514	13	5	8
5			996	<i>Buah Mata Punai</i>	335	21	7	14
6			996	<i>Buah Nabau Besundang</i>	198	3	3	0
7			996	<i>Buah Nabau Ngelantar</i>	124	1	1	0
8			996	<i>Buah Panchar Matahari</i>	775	33	9	24
9			996	<i>Buah Talam Kumang</i>	1825	19	9	10
10			996	<i>Buah Tungku</i>	2131	39	9	30

Table 4.1 continued

Bil	Threshold	Query Image (Image1)	N_{qry}	Reference Image (Image2)	N_{tmp}	N_{crp}	N_{mch}	Outlier
1	0.02	<i>Buah Burung Kenyalang</i> blur1	1487	<i>Buah Bulan Sebayan</i>	633	29	10	19
2			1487	<i>Buah Burung Kenyalang</i>	1096	905	889	16
3			1487	<i>Buah Engkatak Tingkap Pama Merap</i>	2683	36	7	29
4			1487	<i>Buah Bong Midang</i>	514	27	7	20
5			1487	<i>Buah Mata Punai</i>	335	9	7	2
6			1487	<i>Buah Nabau Besundang</i>	198	4	4	0
7			1487	<i>Buah Nabau Ngelantar</i>	124	56	18	38
8			1487	<i>Buah Panchar Matahari</i>	775	53	11	42
9			1487	<i>Buah Talam Kumang</i>	1825	16	10	6
10			1487	<i>Buah Tungku</i>	2131	53	18	35

Table 4.2: Number of found keypoints in query and template image, correspondences, inliers and rejected outliers. Using SIFT + RANSAC at optimal peak threshold value of 0.02 on the Blur sequence (Level 5).

Bil	Threshold	Query Image (Image1)	N_{qry}	Reference Image (Image2)	N_{tmp}	N_{crp}	N_{mch}	Outlier
1	0.02	<i>Buah Bulan Sebayan blur5</i>	83	<i>Buah Bulan Sebayan</i>	633	31	25	6
2			83	<i>Buah Burung Kenyalang</i>	1096	2	2	0
3			83	<i>Buah Engkatak Tingkap Pama Merap</i>	2683	7	5	2
4			83	<i>Buah Bong Midang</i>	514	11	9	2
5			83	<i>Buah Mata Punai</i>	335	17	11	6
6			83	<i>Buah Nabau Besundang</i>	198	0	0	0
7			83	<i>Buah Nabau Ngelantar</i>	124	0	0	0
8			83	<i>Buah Panchar Matahari</i>	775	8	5	3
9			83	<i>Buah Talam Kumang</i>	1825	13	9	4
10			83	<i>Buah Tungku</i>	2131	4	4	0

Table 4.2 continued

Threshold	Query Image (Image1)	N_{qry}	Reference Image (Image2)	N_{tmp}	N_{crp}	N_{mch}	Outlier
0.02	<i>Buah Burung Kenyalang</i> blur5	56	<i>Buah Bulan Sebayan</i>	633	16	10	6
		56	<i>Buah Burung Kenyalang</i>	1096	49	37	12
		56	<i>Buah Engkatak Tingkap Pama Merap</i>	2683	74	42	32
		56	<i>Buah Bong Midang</i>	514	55	31	24
		56	<i>Buah Mata Punai</i>	335	12	6	6
		56	<i>Buah Nabau Besundang</i>	198	14	12	2
		56	<i>Buah Nabau Ngelantar</i>	124	55	42	13
		56	<i>Buah Panchar Matahari</i>	775	27	20	7
		56	<i>Buah Talam Kumang</i>	1825	21	18	3
		56	<i>Buah Tungku</i>	2131	50	27	23

The visualized keypoints selected target images at the optimal PeakThr parameter value of 0.02 is shows in Table 4.3. Table 4.4 shows the corresponding visualized SIFT descriptors.

Table 4.3: Visualized keypoints detected (green color) in the reference images (no deformation) at the optimal PeakThr parameter value of 0.02.
(N_{tmp} = number of detected template keypoints).

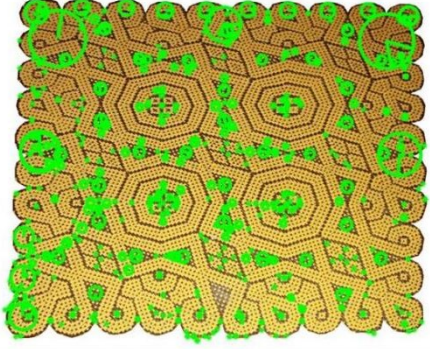
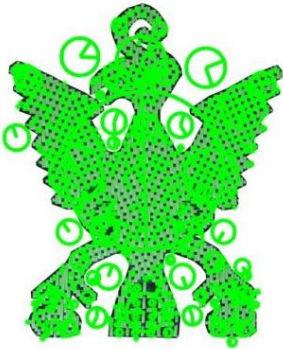
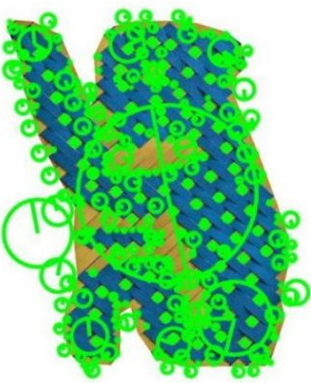
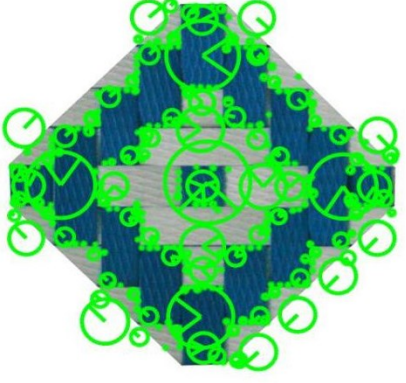
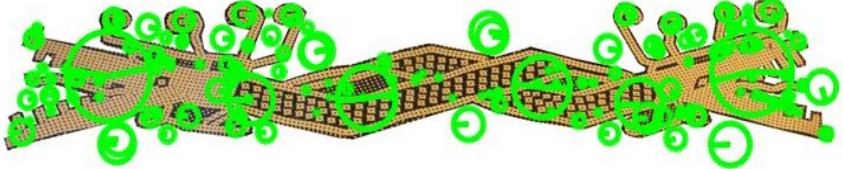
	
Buah Bulan Sebayan (BBS) $N_{tmp}=633$	Buah Burung Kenyalang (BBK) $N_{tmp}=1096$
	
Buah Bong Midang (BBM) $N_{tmp}= 514$	Buah Mata Punai (BMP) $N_{tmp}=335$
	
Buah Nabau Besundang (BNB)) $N_{tmp}=198$	

Table 4.3 continued

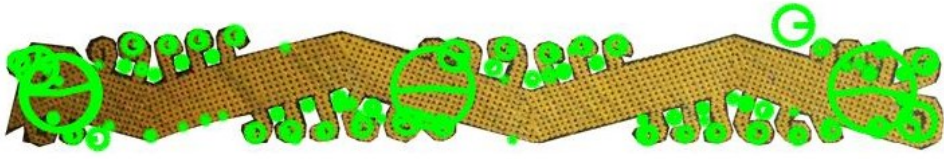
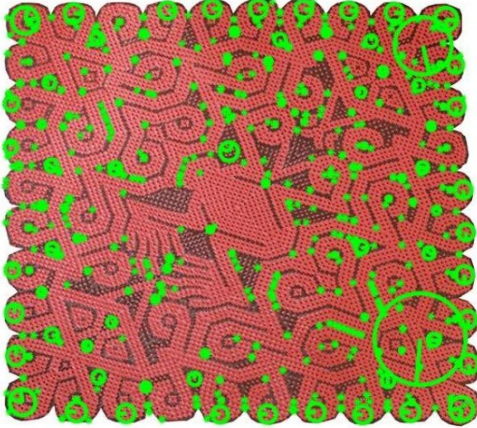
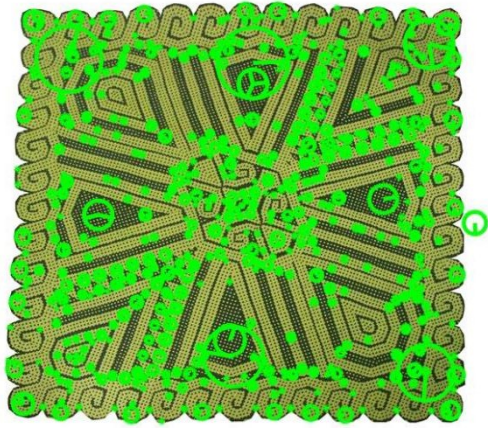
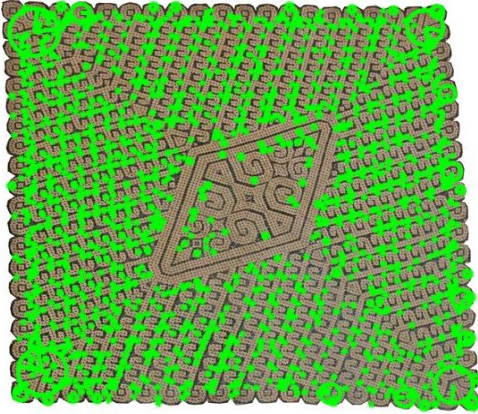
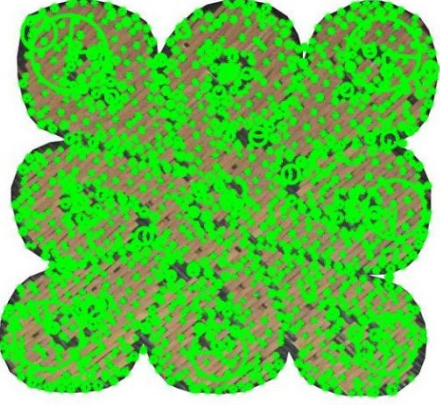
	
Buah Nabau Ngelantar (BNN)) $N_{tmp}=124$	
	
Buah Enkatak Tingkap Pama Merap (BKTPM) $N_{tmp}=693$	Buah Panchar Matahari (BPM) $N_{tmp}=775$
	
Buah Talam Kumang (BTK) $N_{tmp}=1825$	Buah Tungku (BT) $N_{tmp}=2131$

Table 4.4: Visualized distribution of SIFT build feature descriptor detected in the clean synthetic template images at the PeakThr parameter value of 0.02.

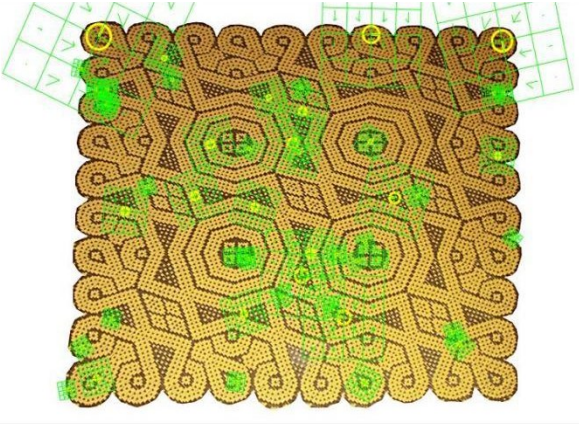
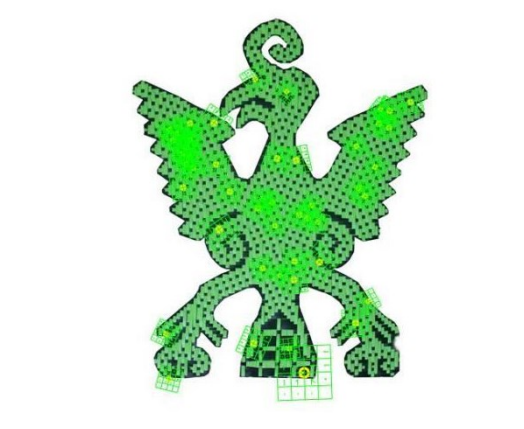
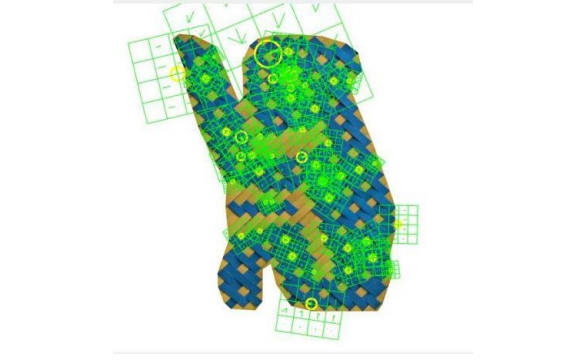
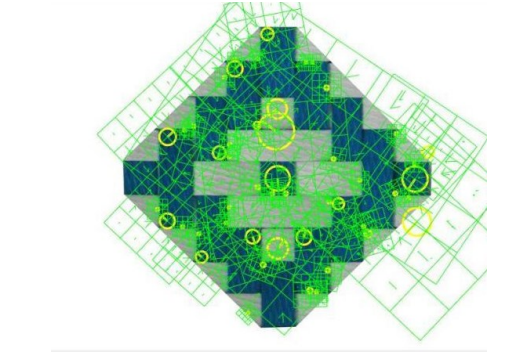
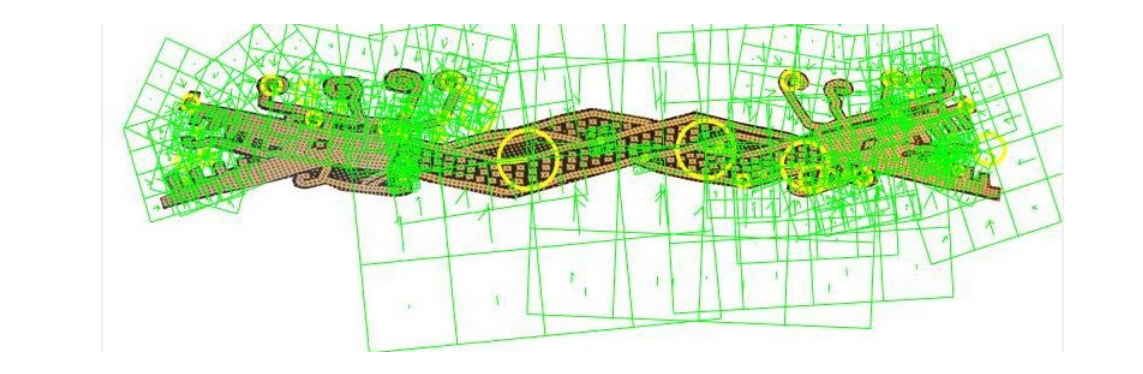
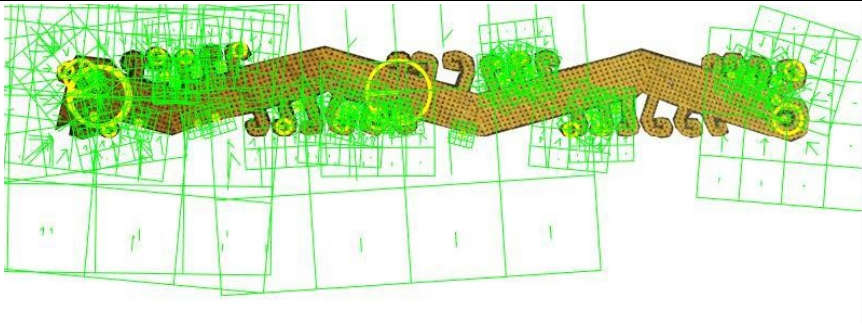
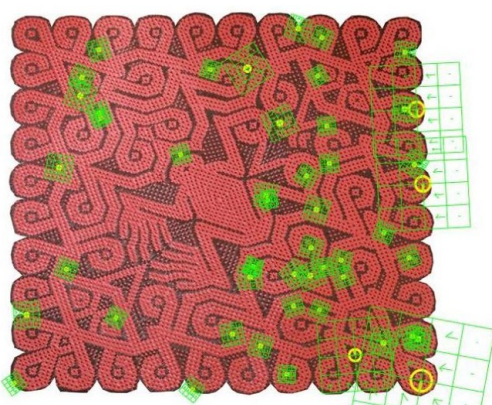
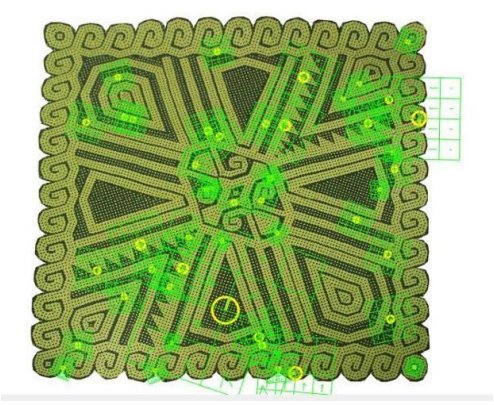
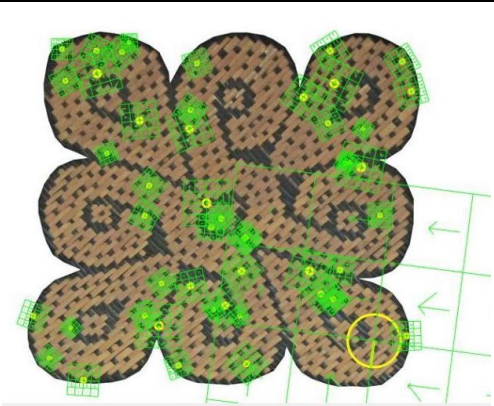
	
Buah Bulan Sebayan (BBS)	Buah Burung Garuda (BBG)
	
Buah Bong Midang (BBM)	Buah Mata Punai (BMP)
	
Buah Nabau Ngelantar (BNN)	

Table 4.4 continued

	
<i>Buah Nabau Besundang (BNB)</i>	
	
<i>Buah Katak Tingkap Pama Merap (BKTPM)</i>	<i>Buah Panchar Matahari (BPM)</i>
	
<i>Buah Talam Kumang (BTK)</i>	<i>Buah Tungku (BT)</i>

4.2.2 Comparing the Matching Quality of Each Mat Motif Class When Using Peak Threshold Value SIFT with RANSAC performance against common image deformations.

Matching quality as the level of distortion increases, the number of detected SIFT keypoints decreases for blurring, particularly when employing a PeakThr parameter value of 0.02. Nevertheless, the low number of detected keypoints does not correlate with a loss in accuracy. Regarding illumination changes, the number of detected SIFT keypoints decreases from the first to the fifth level of deformation. SIFT demonstrates poor performance with images featuring front parallel surfaces and slanted surfaces, particularly in cases of viewpoint change ranging from 30° to 90°. However, SIFT reliably detects an adequate number of keypoints, even at higher levels of deformation for scale and scale combined with rotation, which aligns with its rotation invariance property. Furthermore, SIFT performs effectively in scenarios involving JPEG compression with a PeakThr parameter value of 0.02. Nonetheless, increasing the PeakThr parameter value leads to a significant decrease in the number of detected keypoints. Table 4.5 shows the example of *Buah Bulan Sebayon* comparison results in the number of SIFT matches between deformation first level vs. fifth level at PeakThr parameter value of 0.02 0.04, 0.06, and 0.08.

Table 4.5: Classification statistics of PeakThr parameter values of 0.02, 0.04, 0.06, and 0.08 for every image deformation sequences, belonging to *Buah Bulan Sebayan*.

						
<i>Buah Bulan Sebayan</i>						
	0.02			0.04		
	N_{gry}	N_{crp}	N_{mch}	N_{gry}	N_{crp}	N_{mch}
Blr1	996	512	453	454	242	207
Blr2	653	137	104	68	13	12
Blr3	257	90	73	14	11	10
Blr4	151	63	59	8	34	29
Blr5	83	31	25	8	6	5
	0.06			0.08		
	N_{gry}	N_{crp}	N_{mch}	N_{gry}	N_{crp}	N_{mch}
Blr1	145	3	3	0	0	0
Blr2	4	4	4	0	0	0
Blr3	2	6	6	0	0	0
Blr4	2	6	6	0	0	0
Blr5	0	0	0	0	0	0
	0.02			0.04		
	N_{gry}	N_{crp}	N_{mch}	N_{gry}	N_{crp}	N_{mch}
Light 1	556	525	461	315	294	264
Light 2	491	465	406	189	219	149
Light 3	438	406	356	45	48	mismatch
Light 4	311	310	246	0	0	0
Light 5	26	92	57	0	0	0
	0.06			0.08		
	N_{gry}	N_{crp}	N_{mch}	N_{gry}	N_{crp}	N_{mch}
Light 1	36	45	32	0	0	0
Light 2	2	9	9	0	0	0
Light 3	0	0	0	0	0	0
Light 4	0	0	0	0	0	0
Light 5	0	0	0	0	0	0

Table 4.5 continued

	0.02			0.04		
	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}
JPEG1	657	623	613	393	375	370
JPEG2	633	598	584	387	362	354
JPEG3	648	572	531	388	347	322
JPEG4	626	539	499	373	326	301
JPEG5	614	178	38	246	93	mismatch
	0.06			0.08		
	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}
JPEG1	76	71	69	11	11	10
JPEG2	70	72	65	10	11	10
JPEG3	70	69	60	10	11	9
JPEG4	73	65	57	12	11	10
JPEG5	80	18	mismatch	9	2	2

	0.02			0.04		
	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}
Scale1	348	322	213	125	167	88
Scale2	249	237	165	68	97	50
Scale3	231	205	148	60	62	34
Scale4	215	182	146	41	33	30
Scale5	197	176	121	24	25	15
	0.06			0.08		
	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}
Scale1	21	32	17	2	33	32
Scale2	10	15	mismatch	0	0	0
Scale3	6	20	mismatch	0	0	0
Scale4	7	4	mismatch	0	0	0
Scale5	5	5	mismatch	0	0	0

Table 4.5 continued

	0.02			0.04		
	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}
View1	431	331	195	188	178	95
View2	421	300	163	192	177	96
View3	409	240	20	173	152	57
View4	343	152	27	153	5	21
View5	324	144	10	160	34	mismatch
	0.06			0.08		
	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}
View1	21	22	mismatch	1	22	mismatch
View2	27	38	17	4	5	mismatch
View3	29	10	mismatch	4	7	mismatch
View4	23	5	mismatch	6	14	mismatch
View5	23	3	mismatch	5	15	mismatch

	0.02			0.04		
Scale + rotation	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}
Level1	331	355	205	123	170	86
Level2	244	285	151	65	114	25
Level3	203	256	139	50	94	35
Level4	177	164	112	38	38	27
Level5	142	128	76	21	21	15
	0.06			0.08		
Scale + rotation	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}
Level1	13	45	mismatch	0	0	0
Level2	8	13	mismatch	0	0	0
Level3	5	6	mismatch	0	0	0
Level4	4	20	mismatch	0	0	0
Level5	6	7	mismatch	0	0	0

A comparison of SIFT matches before and after RANSAC reveals that a satisfactory number of SIFT keypoints were detected, even at the most severe deformation level for blurring, illumination change, and viewpoint change. The average reduction in the number of SIFT keypoints with and without RANSAC from first level to fifth level exceeded 90% across all classes. In the case of JPEG compression, there was an average decrease of 87.14% in the number of SIFT keypoints with RANSAC from first level to fifth level. Regarding scale change and scale combined with rotation change, the average reduction in the number of SIFT keypoints from first level to fifth level was less than 70% across all classes, both before and after applying RANSAC, see Table 4.6.

Table 4.6: Comparison in the number of SIFT matches between deformation first level to fifth level at Optimal PeakThr parameter value of 0.02.

Image deformation	SIFT matches		Average drop in number (%)	
	w/o RANSAC	w/ RANSAC	w/o RANSAC	w/ RANSAC
Illumination1	607	555	95.86	96.72
Illumination5	25	18		
Image Blur1	625	582	93.53	95.86
Image Blur5	41	24		
Viewpoint1	507	471	85.62	94.91
Viewpoint5	93	22		
JPEG_Compression1	784	774	76.46	87.14
JPEG_Compression5	185	100		
Scale+rotation1	524	452	65.63	69.53
Scale+rotation5	180	138		
Scale1	540	471	66.98	69.48
Scale5	178	144		

The matching results of the reference image versus query image pairs were generated both with and without RANSAC. For example, *Buah Bulan Sebayang* (a complex motif) shows a dramatic improvement using SIFT matching without and with RANSAC under PeakThr parameter value 0.02 for blur change in Table 4.7. As the level of blurring increases, there is a decreasing trend in the number of detected feature points. However, even at the fifth deformation level of image blur, SIFT still manages to detect feature points and produce correct matches. At a PeakThr parameter value of 0.04, as shown in Table 4.8, no match was found at the fifth level of illumination changes. However, with a higher peak threshold value of 0.06, as indicated in Table 4.9, incorrect matches were generated at the fifth deformation level of Scale Changes. A similar occurrence transpired with Viewpoint Changes when the peak threshold value was set to 0.08, as show in Table 4.10.

Table 4.7: SIFT matching result between target vs. query image pairs belonging to the Blur sequences, without (a) and with (b) RANSAC. The results were generated using the optimal peak threshold value of 0.02.

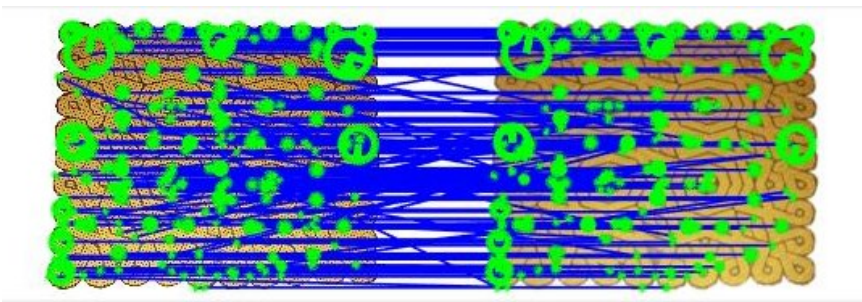
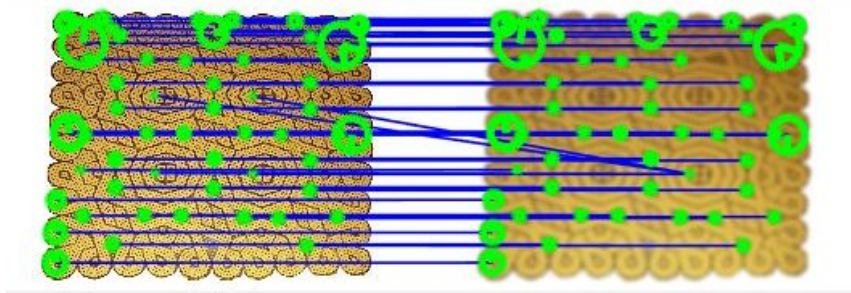
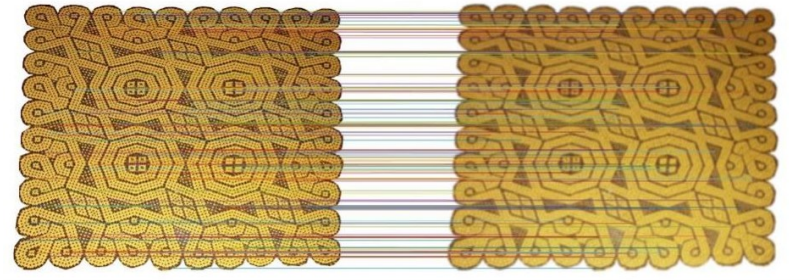
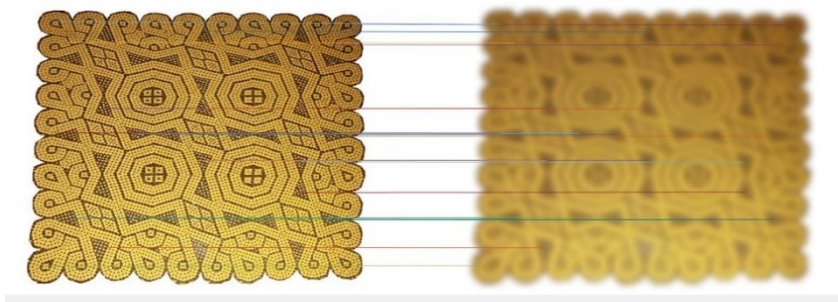
Level of deformation	(a) Matching before RANSAC
Level 1	
Level 5	
	(b) Matching after RANSAC
Level 1	
Level 5	

Table 4.8: Example of SIFT matching result of the template image vs. query image without RANSAC (a) and with RANSAC (b) at the PeakThr parameter value of 0.04. (Illumination change).

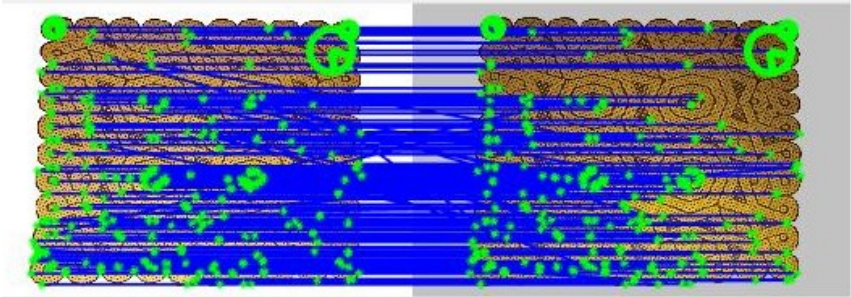
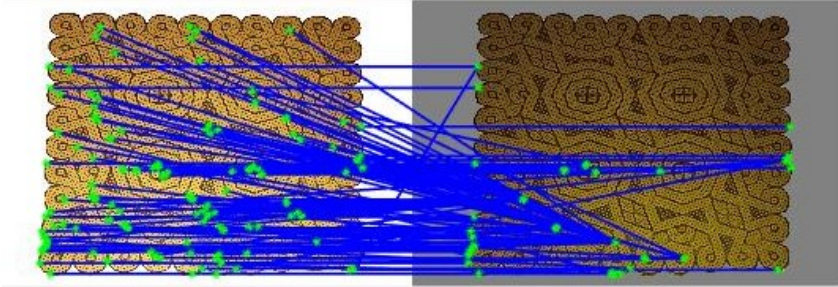
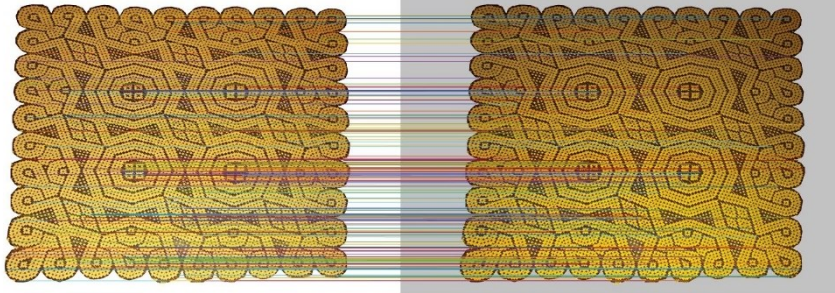
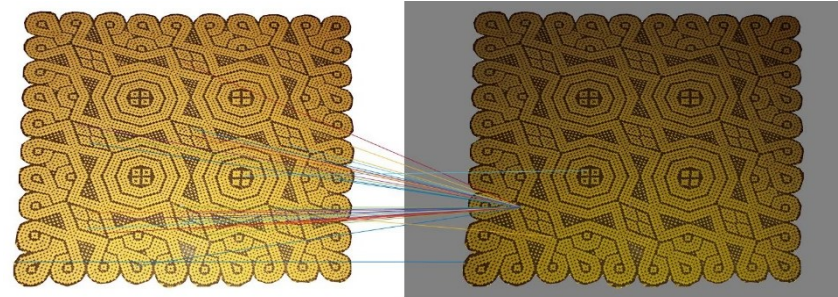
Level of deformation	(a) Matching before RANSAC
Level 1	 This image shows the SIFT matching results at Level 1 before RANSAC. It displays two square images side-by-side: a template image on the left and a query image on the right. Both images feature a complex, repeating geometric pattern. Numerous green dots, representing SIFT keypoints, are scattered across both images. A dense web of blue lines connects corresponding keypoints between the two images, indicating a high number of potential matches.
Level 4	 This image shows the SIFT matching results at Level 4 before RANSAC. Similar to the Level 1 view, it shows the template and query images with their SIFT keypoints (green dots) and potential matches (blue lines). The blue lines are more concentrated and appear thicker than at Level 1, suggesting a higher confidence in the matches at this finer scale.
	(b) Matching after RANSAC
Level 1	 This image shows the SIFT matching results at Level 1 after RANSAC. The template and query images are shown. In contrast to the 'before RANSAC' results, the number of blue lines (potential matches) is significantly reduced. Only the most reliable matches, which have survived the RANSAC outlier rejection process, are displayed.
Level 4	 This image shows the SIFT matching results at Level 4 after RANSAC. The template and query images are shown. The number of blue lines is further reduced compared to the Level 1 view, representing the most accurate and reliable matches at the finest scale.

Table 4.9: SIFT matching result between target vs. query image pairs belonging to the Scale change sequences, without (a) and with (b) RANSAC. The results were generated using a non-optimal peak threshold value of 0.06.

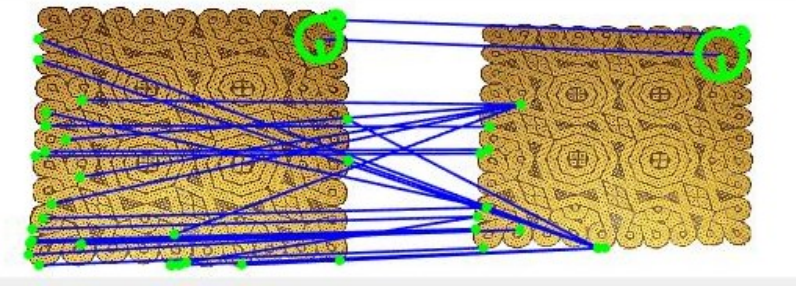
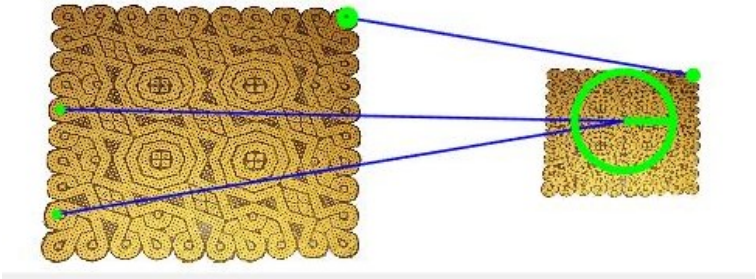
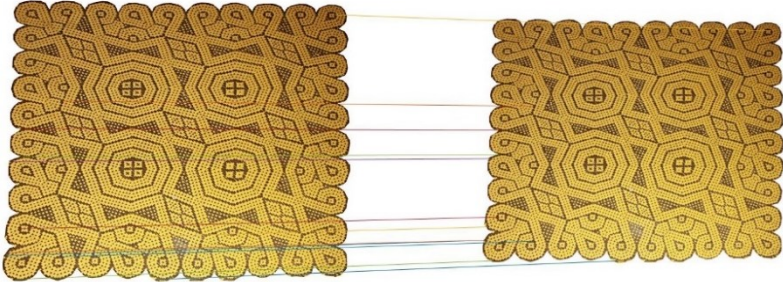
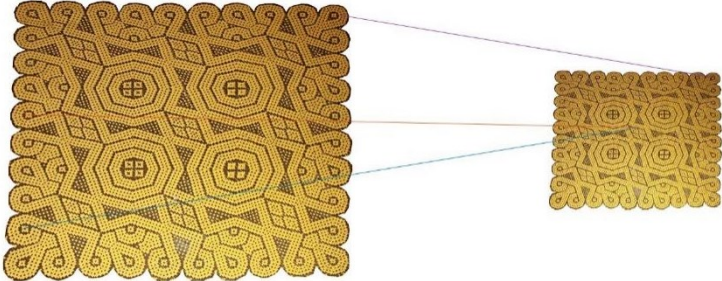
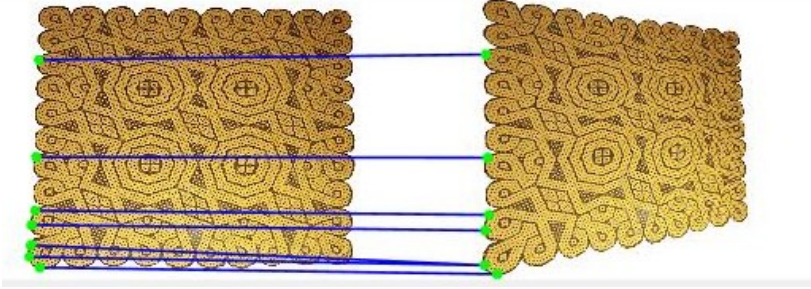
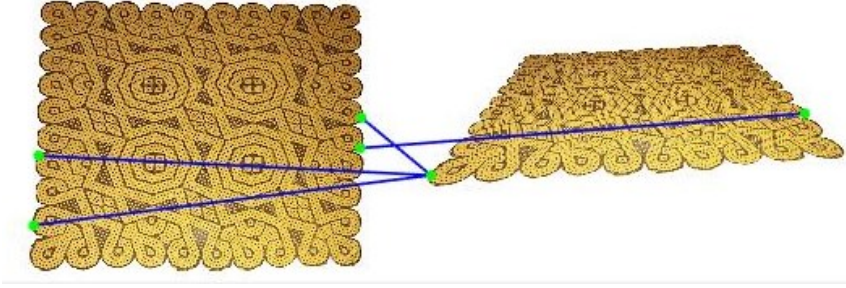
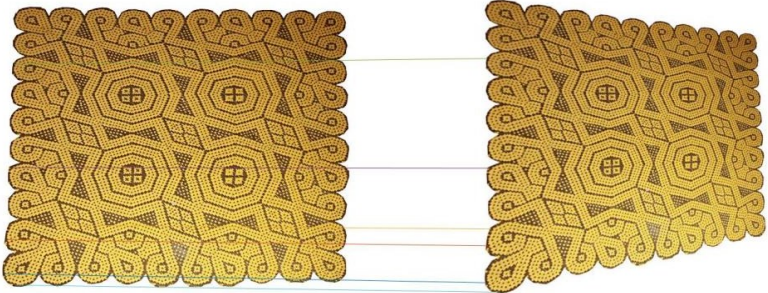
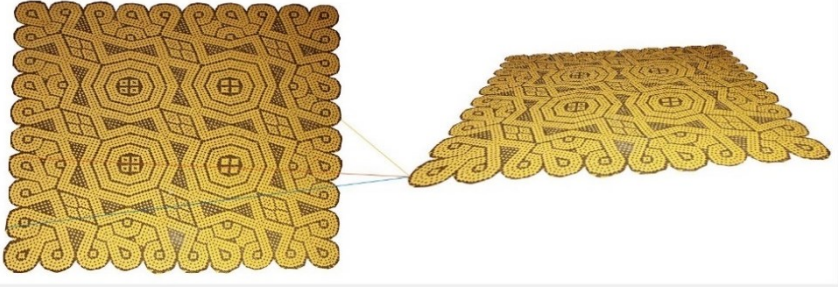
Level of deformation	(a) Matching before RANSAC
Level 1	
Level 5	
	(b) Matching after RANSAC
Level 1	
Level 5	

Table 4.10: SIFT matching result between target vs. query image pairs belonging to the Viewpoint change sequences, without (a) and with (b) RANSAC. The results were generated using a non-optimal peak threshold value of 0.08.

Level of deformation	(a) Matching before RANSAC
Level 1	
Level 5	
	(b) Matching after RANSAC
Level 1	
Level 5	

From the result it was also observed that the number of SIFT keypoints was higher on complex mat motifs (i.e., *Buah Bulan Sebayang* (BBS), *Buah Panchar Matahari* (BPM), *Buah Talam Kumang* (BTK) and *Buah Tungku* (BT)) compared to their non-geometric motif counterparts (i.e., *Buah Burung Kenyalang* (BBK), *Buah Nabau Besundang* (BNB), *Buah Nabau Ngelantar* (BNN), *Buah Bung Midang* (BBM)) and *Buah Mata Punai* (BMP). The reason being complex motifs possess more corner-like structures hence resulting to more keypoints being detected as show in Figure 4.1 to Figure 4.5, average matching accuracy for each mat motifs at PeakThr parameter value of 0.02, 0.04, 0.06, and 0.08 (blur change, JPEG compression, illumination change, scale change and scale+rotation change) respectively.

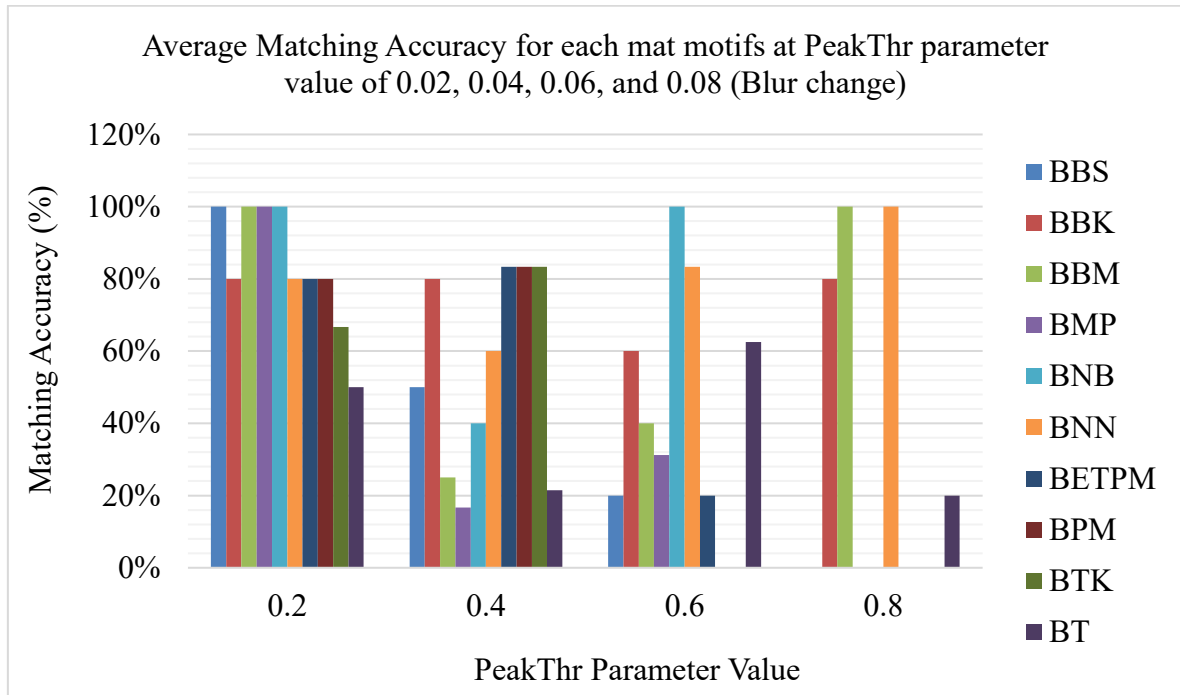


Figure 4.1: Average Matching Accuracy for each mat motifs at PeakThr parameter value of 0.02, 0.04, 0.06, and 0.08 (Blur change).

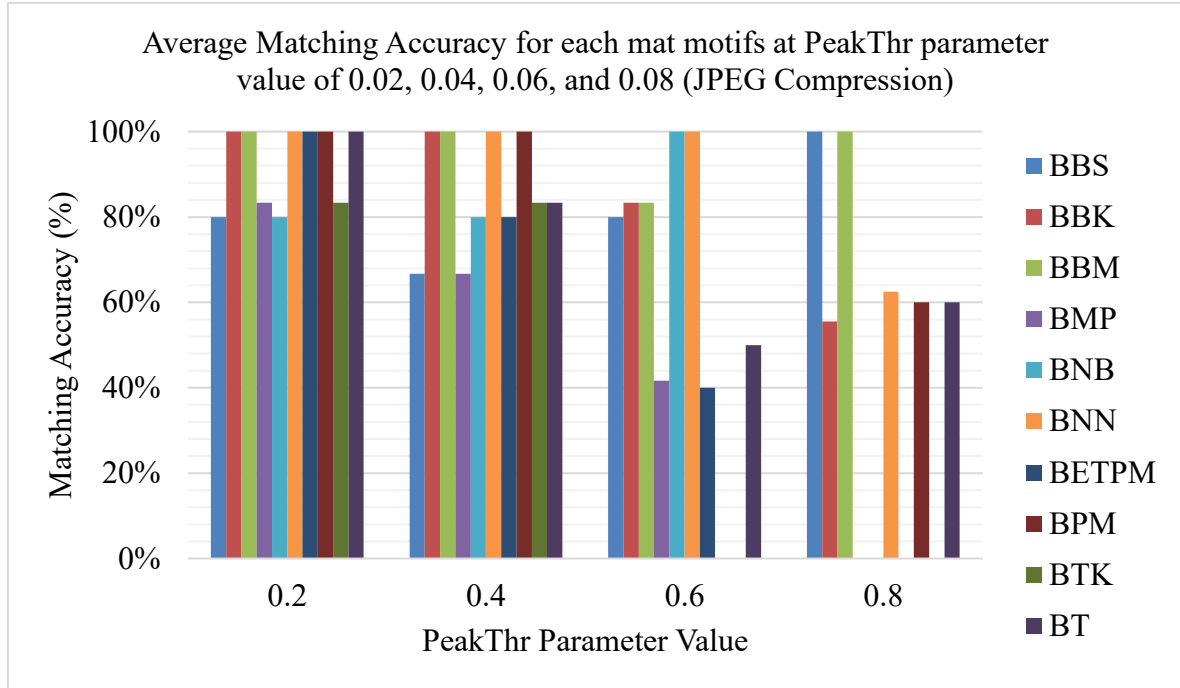


Figure 4.2: Average Matching Accuracy for each mat motifs at PeakThr parameter value of 0.02, 0.04, 0.06, and 0.08 (JPEG Compression).

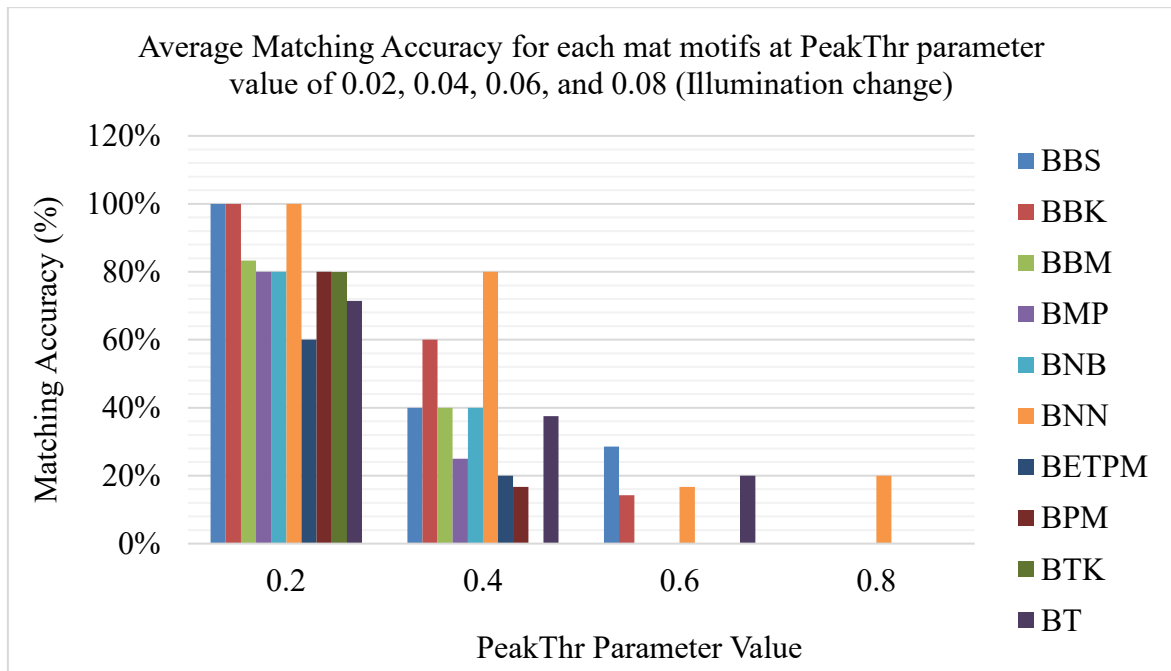


Figure 4.3: Average Matching Accuracy for each mat motifs at PeakThr parameter value of 0.02, 0.04, 0.06, and 0.08 (Illumination change).

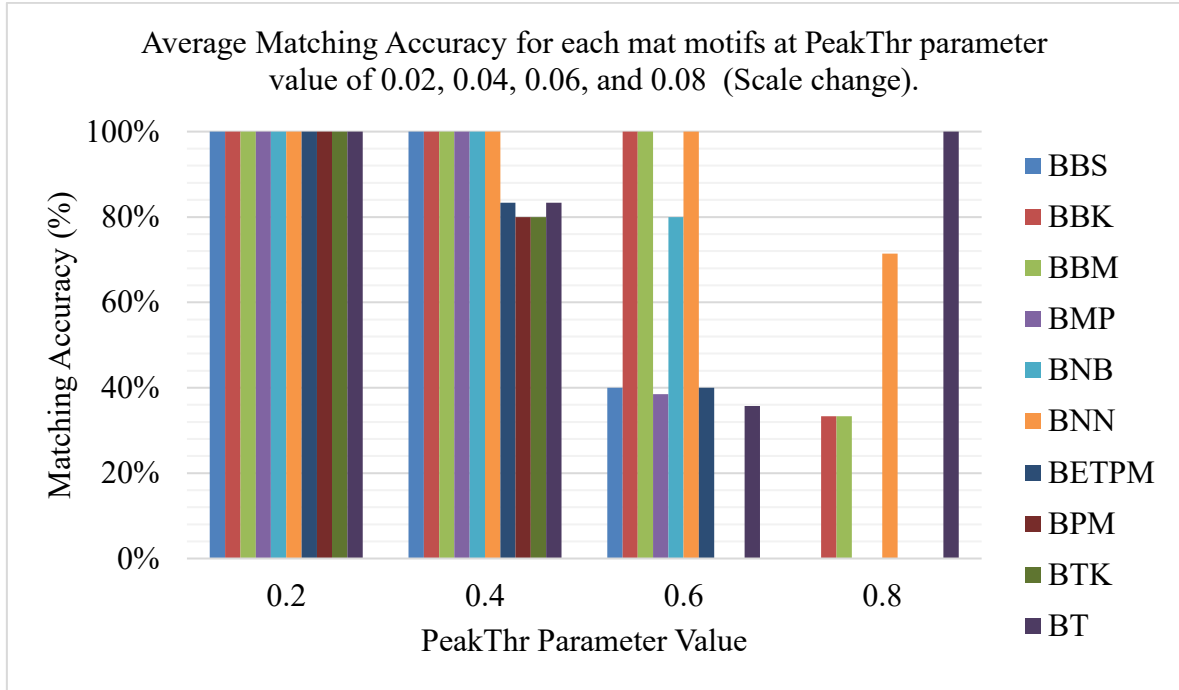


Figure 4.4: Average Matching Accuracy for each mat motifs at PeakThr parameter value of 0.02, 0.04, 0.06, and 0.08 (Scale change).

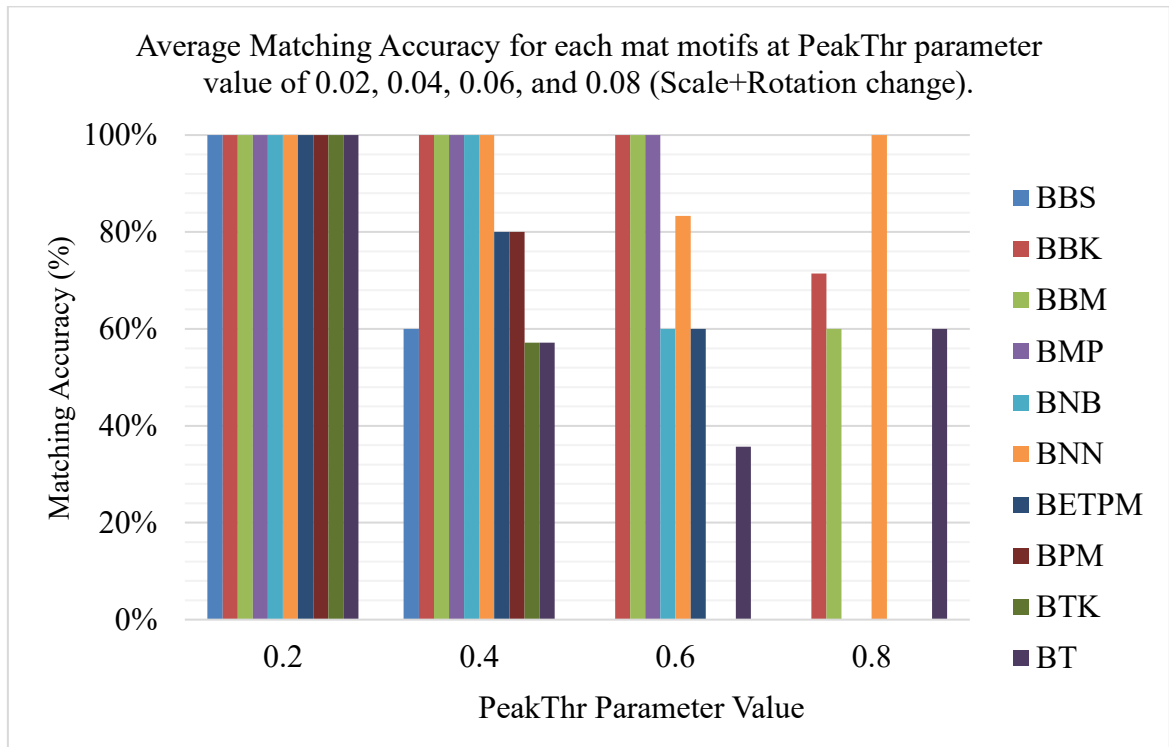


Figure 4.5: Average Matching Accuracy for each mat motifs at PeakThr parameter value of 0.02, 0.04, 0.06, and 0.08 (Scale+Rotation change).

On the other hand, non-geometric-shaped motifs may not have distinct corner-like structures, resulting in fewer keypoints being detected. As in some cases, when there are complex and highly repetitive motifs in an image with higher level of image deformation (i.e., Viewpoint change), the SIFT algorithm can face challenges in accurately matching keypoints. This can lead to multiple similar keypoints being detected in different regions of the image. As a result, SIFT algorithm may struggle to determine the correct matches between keypoints, leading to ambiguous or incorrect matches.

The poor performance of SIFT in the viewpoint sequence, could be attributed to several factors. Firstly, the intricate and complex nature of the plaited mat motif might pose challenges for SIFT in accurately detecting and matching keypoints across different viewpoints. Additionally, variations in lighting conditions, occlusions, and perspective changes inherent in the viewpoint sequence could further hinder the ability of SIFT to robustly match keypoints. Moreover, the geometric transformations involved in the viewpoint changes may lead to significant distortions in the appearance of the motif, making it difficult for SIFT to establish reliable correspondences between keypoints. Overall, these factors collectively contribute to the diminished performance of SIFT in the viewpoint sequence evaluation, particularly when analyzing the Iban plaited mat motif. Average matching accuracy for each mat motifs at PeakThr parameter value of 0.02, 0.04, 0.06, and 0.08 under viewpoint change, see Figure 4.6. Example of complex motifs that had a low average matching accuracy shown in Figure 4.7 (a) *Buah Engkatak Tingkap Pama Merap* (BETPM) and (b) *Buah Talam Kumang* (BTK).

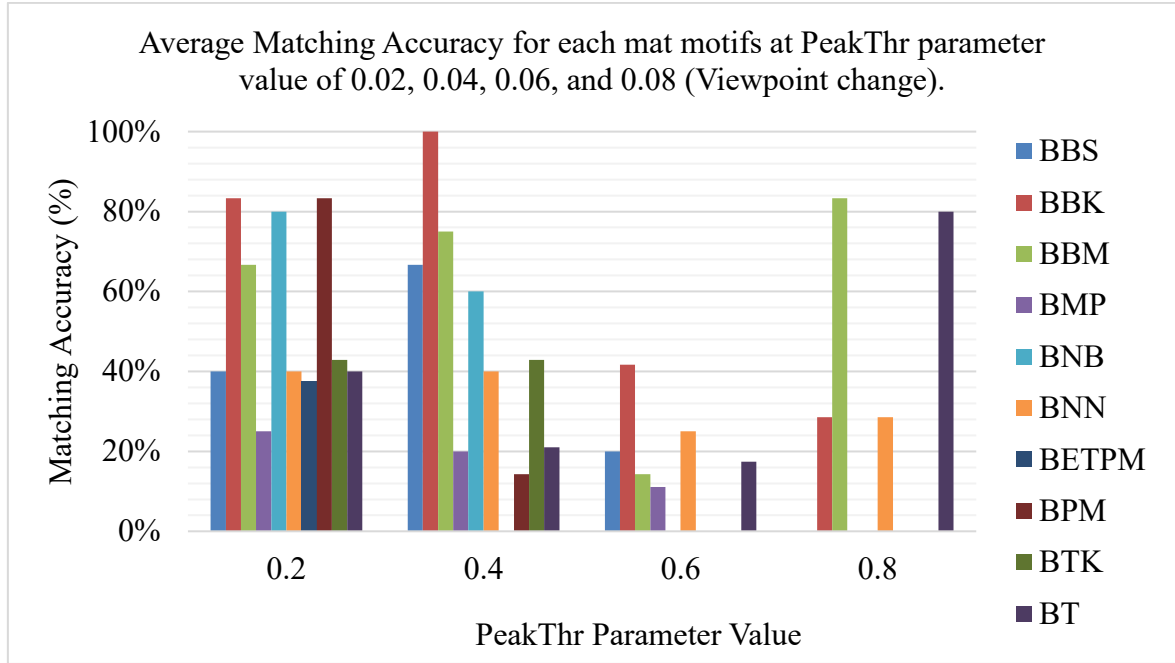


Figure 4.6: Average Matching Accuracy for each mat motifs at PeakThr parameter value of 0.02, 0.04, 0.06, and 0.08 (Viewpoint change).

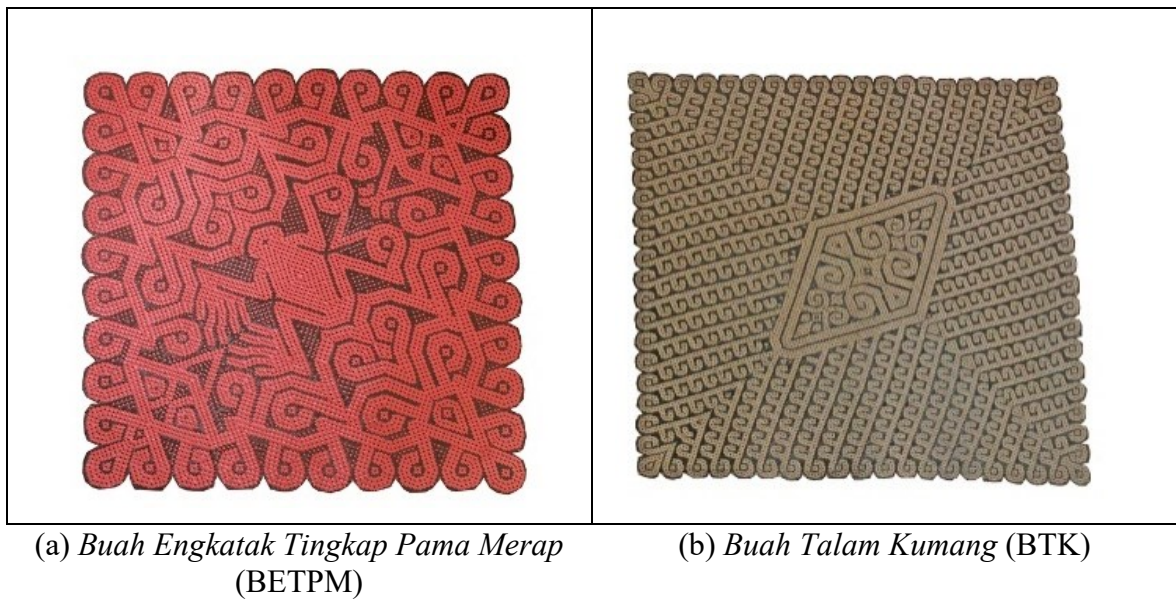


Figure 4.7: Visualized of geometric and highly repetitive motifs that had a low average matching accuracy.

However, SIFT algorithm face the limitations in detecting meaningful keypoints on simple motifs. SIFT was designed to identify distinctive and repeatable features, which can be challenging to detect on images with low complexity or uniform regions. SIFT exhibits poor performance on motifs with less intricate details and variations due to several factors. Firstly, its reliance on detecting local extrema in scale-space means that in simpler motifs, there may be fewer distinctive features or areas of significant intensity change to serve as keypoints, leading to a dearth of robust keypoints for accurate description and matching. Secondly, the limited discriminative information provided by local gradients in simpler motifs results in less distinctive feature descriptors, reducing the accuracy of keypoint matching. Thirdly, the increased likelihood of ambiguous matches between keypoints in simpler motifs contributes to higher rates of false matches and decreased overall matching accuracy. Finally, SIFT's scale invariance may falter in simpler motifs, leading to inaccuracies in scale estimation and further hindering keypoint matching. Overall, SIFT's performance struggles in scenarios lacking intricate details and variations, highlighting its limitations in handling simpler patterns effectively. Figure 4.8 shows an example of simple motif that have lack intricate details and variations (i.e., *Buah Mata Punai*).



Buah Mata Punai (BMP)

Figure 4.8: Visualized of simple motif *Buah Mata Punai* (BMP) that have less intricate details and variations.

4.2.3 Finding the Optimal Peak Threshold for SIFT

The prediction results of all reference versus query pairs for each image deformation type were tabulated within a confusion matrix. Each column represents the instances in the predicted (query) classes, while each row represents the instances in the actual (reference) classes. Our confusion matrix contains 10 actual classes and 10+1 predicted classes. The additional class for the predicted set is the unresolved class. This class represents cases where classification yielded several top matches (of equal similarity score) or a no match. Both cases were considered as False Negatives to penalize the configuration, given that all query images had correct matches within the learned set.

From analyzing the confusion matrices, it becomes evident that the optimal SIFT at PeakThr parameter value with RANSAC stands at 0.02, primarily due to its ability to achieve a higher true positive rate. However, it's noteworthy that this threshold value results in a higher number of false positives, particularly under the condition of viewpoint change. Conversely, when the peak threshold value was set to 0.04, there was an increase in false positives across various conditions, including JPEG compression, viewpoint change, scale+rotation, scale, blur, and illumination, as well as for unresolved classes. Additionally, a threshold value of 0.06 exhibits even higher false positives across these same conditions. While a threshold value of 0.08 had the highest unresolved class. The "unresolved class" refers to scenarios where the classification process yields multiple top matches with equal similarity scores or no match at all. In such cases, both scenarios are considered as false negatives to penalize the configuration, especially since all query images were expected to have correct matches within the learned set.

The confusion matrix for SIFT+RANSAC at PeakThr parameter value of (a) 0.02, (b) 0.04, (c) 0.06, (d) 0.08, for each image deformation type are shown in Figure 4.9 for Blur, Figure 4.10 for Illumination change, Figure 4.11 for JPEG Compression, Figure 4.12 for Scale change, Figure 4.13 for Viewpoint change, and lastly Figure 4.14 for Scale+Rotation.

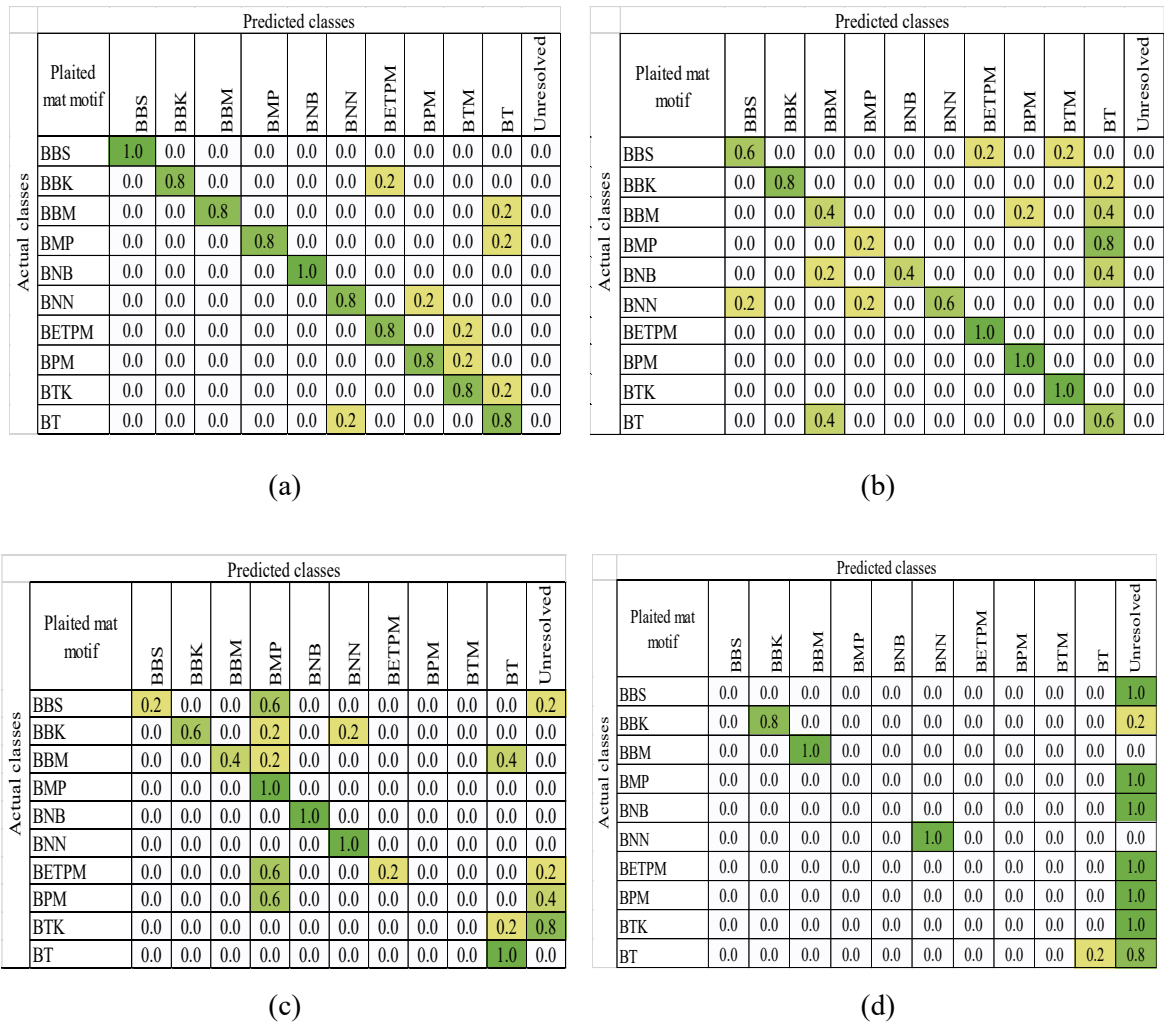


Figure 4.9: Confusion Matrix for SIFT+RANSAC, at PeakThr parameter value of (a) 0.02, (b) 0.04, (c) 0.06, (d)0.08. (Blur change).

		Predicted classes											
		Plaited mat motif	BBS	BBK	BBM	BMP	BNB	BNN	BETPM	BPM	BTM	BT	Unresolved
Actual classes	BBS	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
	BBK	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
	BBM	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
	BMP	0.0	0.0	0.0	0.8	0.0	0.0	0.0	0.0	0.0	0.0	0.2	
	BNB	0.0	0.0	0.0	0.0	0.8	0.0	0.0	0.0	0.0	0.0	0.2	
	BNN	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	
	BETPM	0.0	0.0	0.2	0.0	0.0	0.0	0.6	0.0	0.0	0.2	0.0	
	BPM	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.8	0.0	0.2	0.0	
	BTK	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.8	0.0	0.2	
	BT	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	

(a)

		Predicted classes											
		Plaited mat motif	BBS	BBK	BBM	BMP	BNB	BNN	BETPM	BPM	BTM	BT	Unresolved
Actual classes	BBS	0.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.4
	BBK	0.0	0.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.4
	BBM	0.0	0.0	0.4	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.4
	BMP	0.0	0.0	0.0	0.4	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.4
	BNB	0.0	0.0	0.0	0.0	0.4	0.0	0.0	0.0	0.0	0.0	0.0	0.6
	BNN	0.0	0.0	0.0	0.0	0.0	0.8	0.0	0.0	0.0	0.0	0.0	0.2
	BETPM	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.2	0.0	0.0	0.2	0.4
	BPM	0.0	0.0	0.0	0.4	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.4
	BTK	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.6
	BT	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.6	0.4

(b)

Actual classes	Predicted classes												
	Plaited mat motif	BBS	BBK	BBM	BMP	BNB	BNN	BETPM	BPM	BTM	BT	Unresolved	
	BBS	0.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.6	
	BBK	0.0	0.2	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.6	
	BBM	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.8	
	BMP	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.8	
	BNB	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.8	
	BNN	0.0	0.2	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.6	
	BETPM	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.8	
	BPM	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.8	
	BTK	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	
	BT	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.8	

(c)

Actual classes	Predicted classes												
	Plaited mat motif	BBS	BBK	BBM	BMP	BNB	BNN	BETPM	BPM	BTM	BT	Unresolved	
	BBS	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	
	BBK	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	
	BBM	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	
	BMP	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	
	BNB	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	
	BNN	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.8	
	BETPM	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	
	BPM	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	
	BTM	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	
	BT	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	

(d)

Figure 4.10: Confusion Matrix for SIFT+RANSAC, at PeakThr parameter value of (a) 0.02, (b) 0.04, (c) 0.06, (d)0.08 (Illumination change).

Actual classes	Predicted classes											
	Plaited mat motif	BBS	BBK	BBM	BMP	BNB	BNN	BETPM	BPM	BTM	BT	Unresolved
BBS		0.8	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0
BBK		0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
BBM		0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
BMP		0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
BNB		0.0	0.0	0.0	0.0	0.8	0.0	0.0	0.0	0.2	0.0	0.0
BNN		0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0
BETPM		0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0
BPM		0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0
BTM		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0
BT		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0

(a)

Actual classes	Predicted classes											
	Plaited mat motif	BBS	BBK	BBM	BMP	BNB	BNN	BETPM	BPM	BTM	BT	Unresolved
BBS		0.8	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0
BBK		0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
BBM		0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
BMP		0.2	0.0	0.0	0.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0
BNB		0.0	0.0	0.0	0.0	0.8	0.0	0.0	0.0	0.2	0.0	0.0
BNN		0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0
BETPM		0.0	0.0	0.0	0.0	0.0	0.0	0.8	0.0	0.2	0.0	0.0
BPM		0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0
BTM		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0
BT		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0

(b)

Actual classes	Predicted classes											
	Plaited mat motif	BBS	BBK	BBM	BMP	BNB	BNN	BETPM	BPM	BTM	BT	Unresolved
BBS		0.8	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0
BBK		0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
BBM		0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
BMP		0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
BNB		0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0
BNN		0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0
BETPM		0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.0	0.0	0.6	0.0
BPM		0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
BTM		0.0	0.2	0.2	0.2	0.0	0.0	0.0	0.0	0.4	0.0	0.0
BT		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0

(c)

Actual classes	Predicted classes											
	Plaited mat motif	BBS	BBK	BBM	BMP	BNB	BNN	BETPM	BPM	BTM	BT	Unresolved
BBS		1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
BBK		0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
BBM		0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
BMP		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
BNB		0.0	0.0	0.0	0.0	0.4	0.0	0.0	0.0	0.0	0.0	0.6
BNN		0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0
BETPM		0.0	0.4	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.4
BPM		0.0	0.2	0.0	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.2
BTM		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
BT		0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.6	0.2	0.0

(d)

Figure 4.11: Confusion Matrix for SIFT+RANSAC, at PeakThr parameter value of (a) 0.02, (b) 0.04, (c) 0.06, (d) 0.08 (JPEG compression).

		Predicted classes											
		Plaited mat motif	BBS	BBK	BBM	BMP	BNB	BNN	BETPM	BPM	BTM	BT	Unresolved
Actual classes	BBS	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
	BBK	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
	BBM	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
	BMP	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
	BNB	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	
	BNN	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	
	BETPM	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	
	BPM	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	
	BTK	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	
	BT	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	

(a)

		Predicted classes											
		Plaited mat motif	BBS	BBK	BBM	BMP	BNB	BNN	BETPM	BPM	BTM	BT	Unresolved
Actual classes	BBS	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	BBK	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	BBM	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	BMP	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	BNB	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	BNN	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0
	BETPM	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0
	BPM	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.8	0.0	0.0	0.0	0.0
	BTM	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.8	0.2	0.0	0.0
	BT	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0

(b)

		Predicted classes											
		Plaited mat motif	BBS	BBK	BBM	BMP	BNB	BNN	BETPM	BPM	BTM	BT	Unresolved
Actual classes	BBS	0.4	0.0	0.0	0.4	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0
	BBK	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	BBM	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	BMP	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	BNB	0.0	0.0	0.0	0.0	0.8	0.0	0.0	0.0	0.0	0.0	0.2	0.0
	BNN	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0
	BETPM	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.0	0.0	0.0	0.6	0.0
	BPM	0.0	0.0	0.0	0.4	0.0	0.0	0.0	0.0	0.0	0.0	0.6	0.0
	BTM	0.0	0.0	0.0	0.8	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0
	BT	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0

(c)

		Predicted classes											
		Plaited mat motif	BBS	BBK	BBM	BMP	BNB	BNN	BETPM	BPM	BTM	BT	Unresolved
Actual classes	BBS	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.8
	BBK	0.0	0.6	0.0	0.0	0.0	0.4	0.0	0.0	0.0	0.0	0.0	0.0
	BBM	0.0	0.6	0.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	BMP	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
	BNB	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
	BNN	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0
	BETPM	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
	BPM	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
	BTM	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.8
	BT	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0

(d)

Figure 4.12: Confusion Matrix for SIFT+RANSAC, at PeakThr parameter value of (a) 0.02, (b) 0.04, (c) 0.06, (d) 0.08 (Scale change).

Actual classes	Plaited mat motif	Predicted classes											
		BBS	BBK	BBM	BMP	BNB	BNN	BETPM	BPM	BTM	BT	Unresolved	
	BBS	0.4	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.4	0.0	
	BBK	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
	BBM	0.0	0.0	0.8	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	
	BMP	0.0	0.0	0.0	0.4	0.0	0.0	0.2	0.0	0.0	0.4	0.0	
	BNB	0.0	0.0	0.2	0.0	0.8	0.0	0.0	0.0	0.0	0.0	0.0	
	BNN	0.0	0.2	0.0	0.4	0.0	0.4	0.0	0.0	0.0	0.0	0.0	
	BETPM	0.0	0.0	0.0	0.0	0.0	0.0	0.6	0.0	0.2	0.2	0.0	
	BPM	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	
	BTK	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.0	0.6	0.0	0.0	
	BT	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.8	0.0	

(a)

Actual classes	Plaited mat motif	Predicted classes											
		BBS	BBK	BBM	BMP	BNB	BNN	BETPM	BPM	BTM	BT	Unresolved	
	BBS	0.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0	
	BBK	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
	BBM	0.0	0.0	0.8	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	
	BMP	0.0	0.0	0.0	0.2	0.0	0.0	0.2	0.2	0.0	0.4	0.0	
	BNB	0.0	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.0	0.4	0.0	
	BNN	0.0	0.0	0.0	0.0	0.0	0.4	0.2	0.0	0.2	0.2	0.0	
	BETPM	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.8	0.0	
	BPM	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.8	0.0	
	BTK	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.6	0.0	0.0	
	BT	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.8	0.0	

(b)

Actual classes	Plaited mat motif	Predicted classes											
		BBS	BBK	BBM	BMP	BNB	BNN	BETPM	BPM	BTM	BT	Unresolved	
	BBS	0.2	0.2	0.0	0.2	0.0	0.0	0.2	0.0	0.0	0.2	0.0	
	BBK	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
	BBM	0.0	0.0	0.2	0.2	0.0	0.0	0.0	0.0	0.0	0.6	0.0	
	BMP	0.0	0.2	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.6	0.0	
	BNB	0.0	0.0	0.2	0.0	0.0	0.4	0.0	0.0	0.0	0.4	0.0	
	BNN	0.0	0.2	0.0	0.0	0.0	0.4	0.0	0.0	0.0	0.4	0.0	
	BETPM	0.0	0.4	0.0	0.0	0.2	0.2	0.0	0.0	0.0	0.2	0.0	
	BPM	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.8	0.0	
	BTK	0.0	0.4	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.4	0.0	
	BT	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.8	0.0	

(c)

Actual classes	Plaited mat motif	Predicted classes											
		BBS	BBK	BBM	BMP	BNB	BNN	BETPM	BPM	BTM	BT	Unresolved	
	BBS	0.0	0.6	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.2	
	BBK	0.0	0.8	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	
	BBM	0.0	0.0	0.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	
	BMP	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.8	
	BNB	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	
	BNN	0.0	0.6	0.0	0.0	0.0	0.4	0.0	0.0	0.0	0.0	0.0	
	BETPM	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.8	
	BPM	0.6	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	
	BTK	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	
	BT	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.8	0.2	

(d)

Figure 4.13: Confusion Matrix for SIFT+RANSAC, at PeakThr parameter value of (a) 0.02, (b) 0.04, (c) 0.06, (d)0.08 (Viewpoint change).

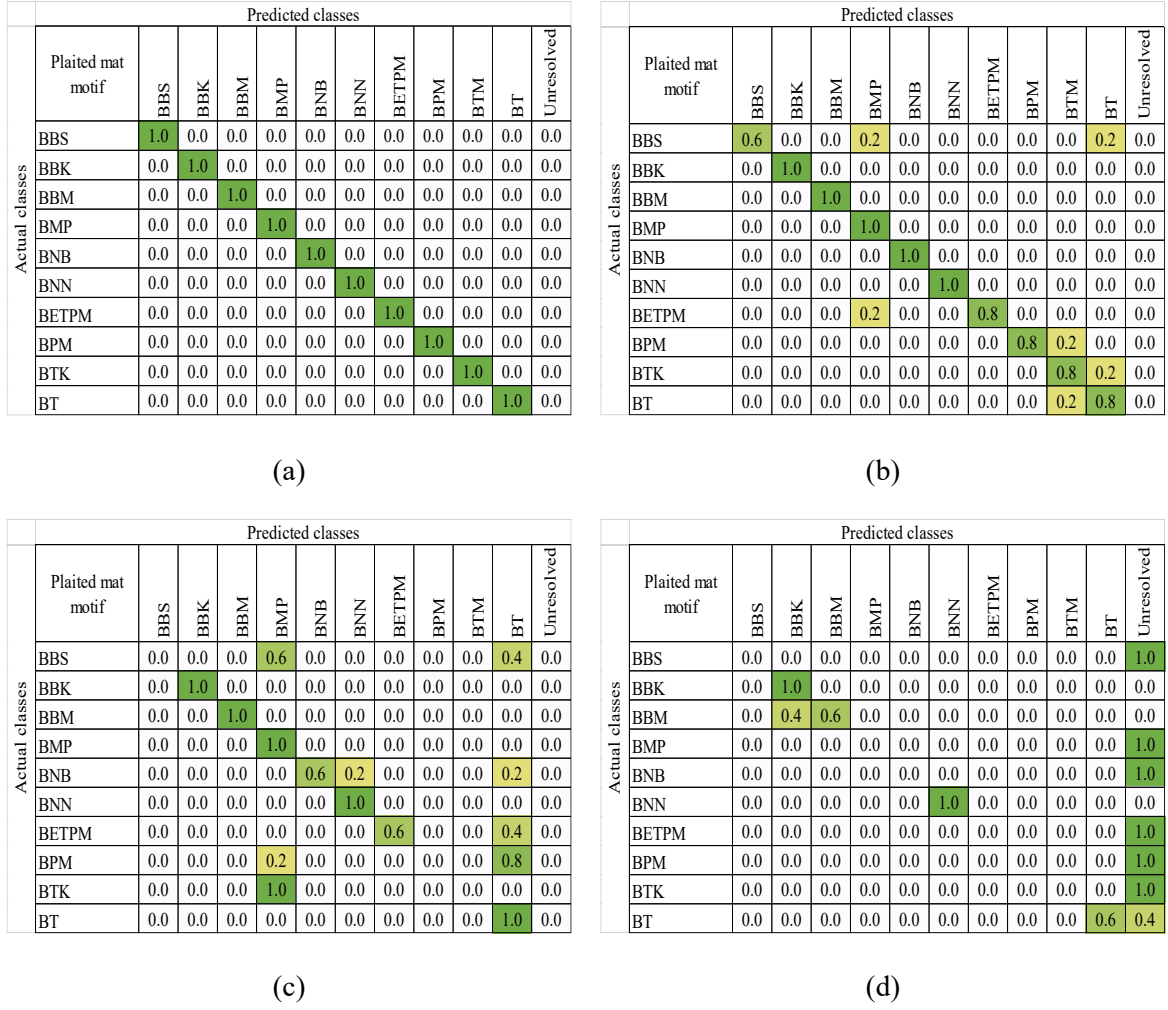


Figure 4.14: Confusion Matrix for SIFT, at PeakThr parameter value of (a) 0.02, (b) 0.04, (c) 0.06, (d) 0.08 (Scale + Rotation).

From the confusion matrixes, it is clear that the optimal peak threshold value is 0.02 as it returned the highest average accuracy of 88.0% across all mat motif compared to the rest followed by peak threshold value of 0.04, 0.06 and 0.08, the average accuracy is 66.0%, 38.0% and 25.0% respectively as shown in Figure 4.15.

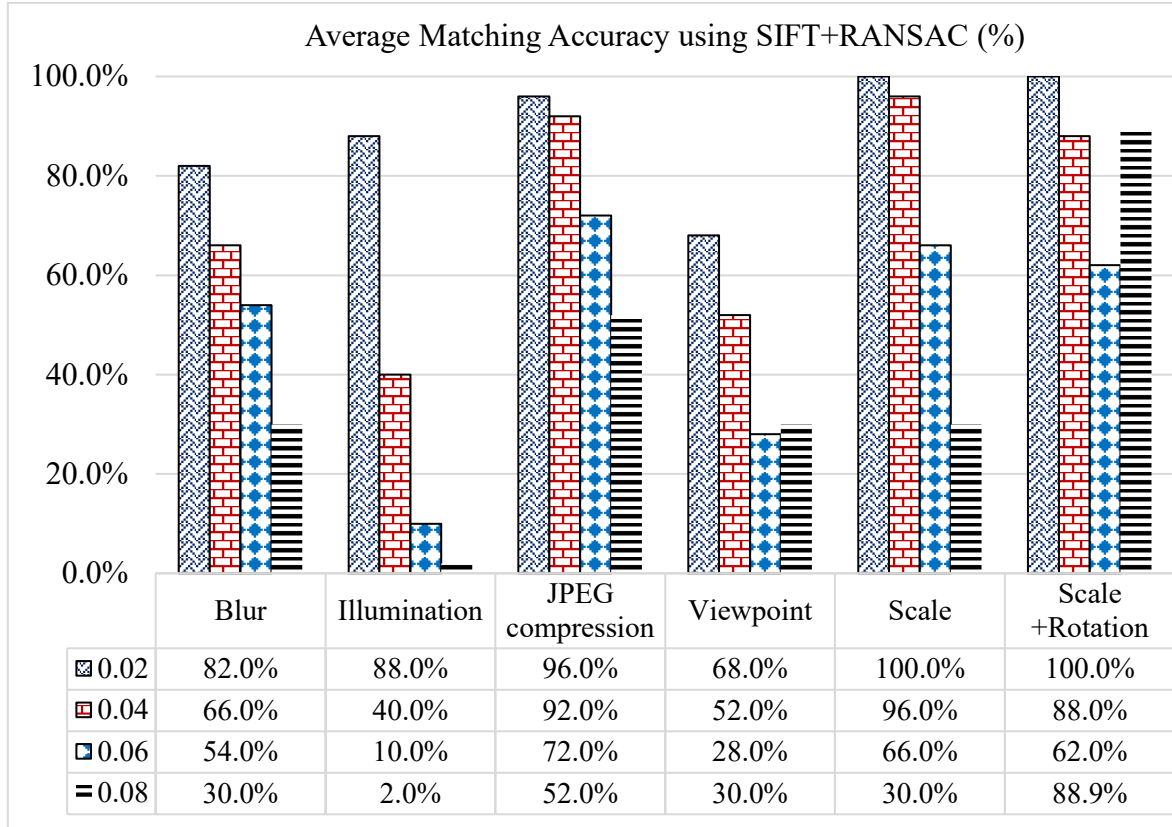


Figure 4.15: Average matching accuracy of SIFT+RANSAC, at PeakThr parameter value of 0.02, 0.04, 0.06, and 0.08; following six image deformations.

The precision graph is summarized in Figure 4.16, while true positive rate or sensitivity graph is summarized in Figure 4.17, where the optimal threshold value is observed to be 0.02 produced more accurate and reliable results. The PeakThr parameter value of 0.02 following six image deformations also shows a higher F1 score as in Figure 4.18. Finally, Figure 4.19 shows that the PeakThr parameter value of 0.08 following six image deformations has the highest misclassification rate.

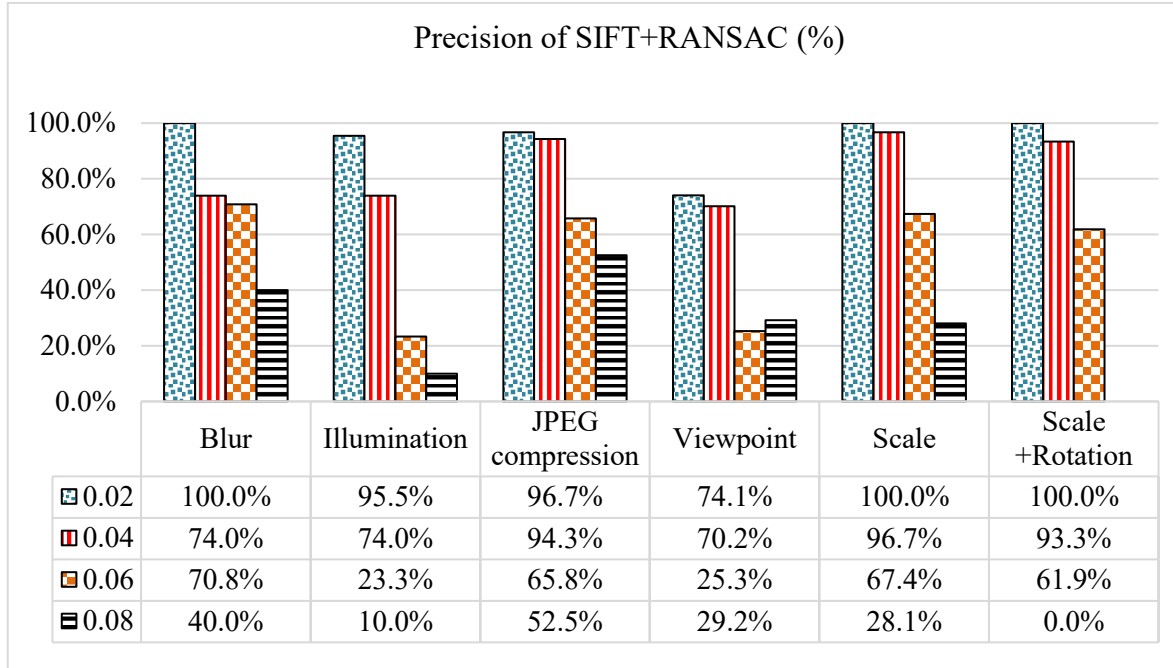


Figure 4.16: Precision of SIFT+RANSAC, at PeakThr parameter value of 0.02, 0.04, 0.06, and 0.08; following six image deformations.

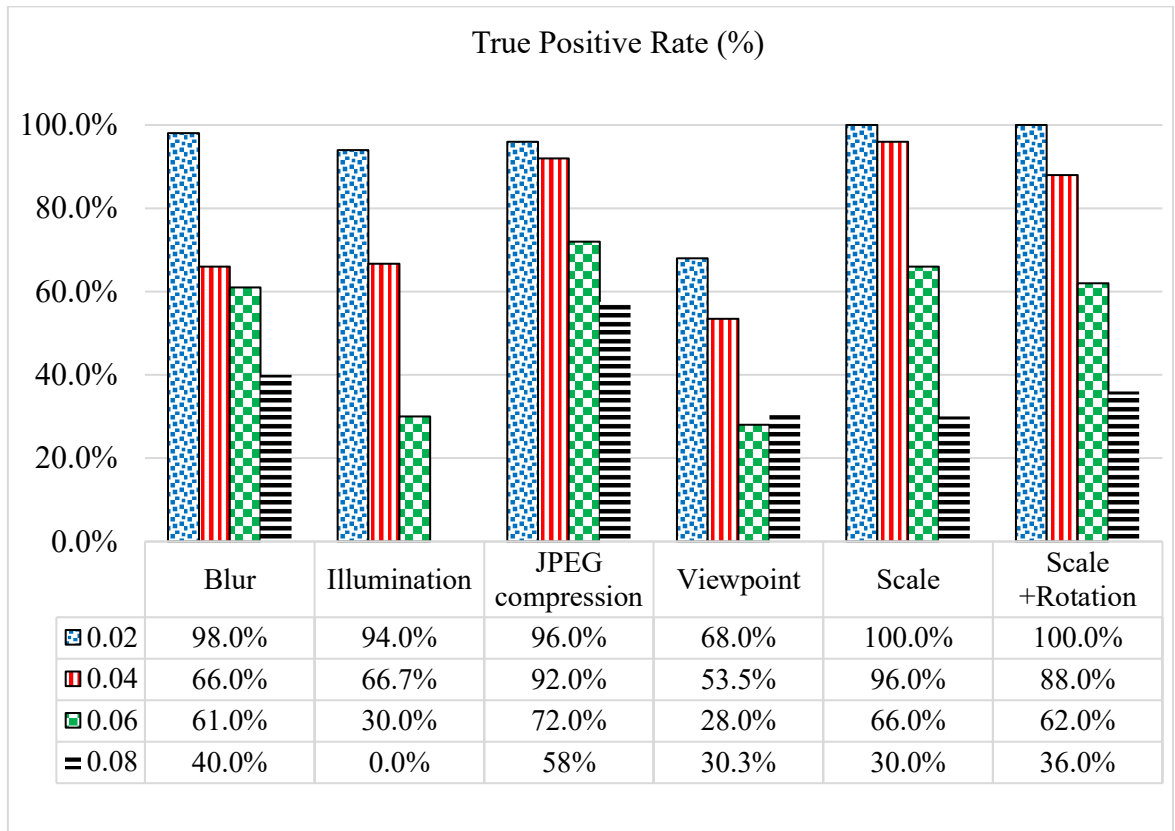


Figure 4.17: True Positive Rate or sensitivity of SIFT+RANSAC, at PeakThr parameter value of 0.02, 0.04, 0.06, and 0.08; following six image deformations.

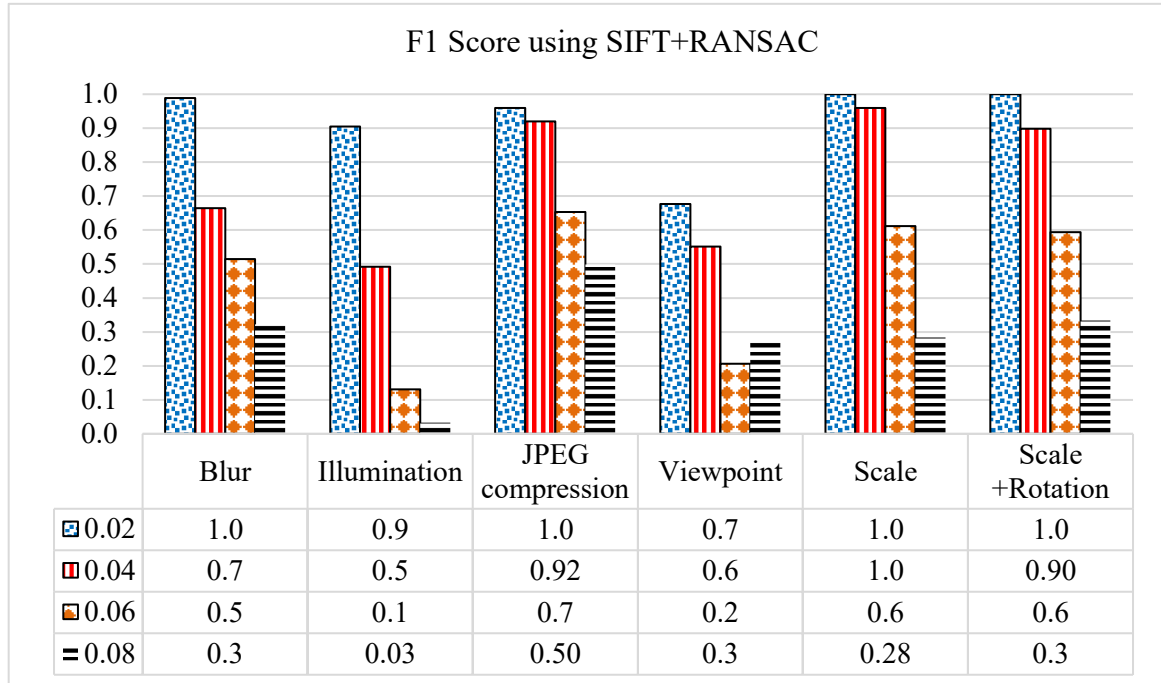


Figure 4.18: F1 Score of SIFT+RANSAC, PeakThr parameter value of 0.02, 0.04, 0.06, and 0.08; following six image deformations.

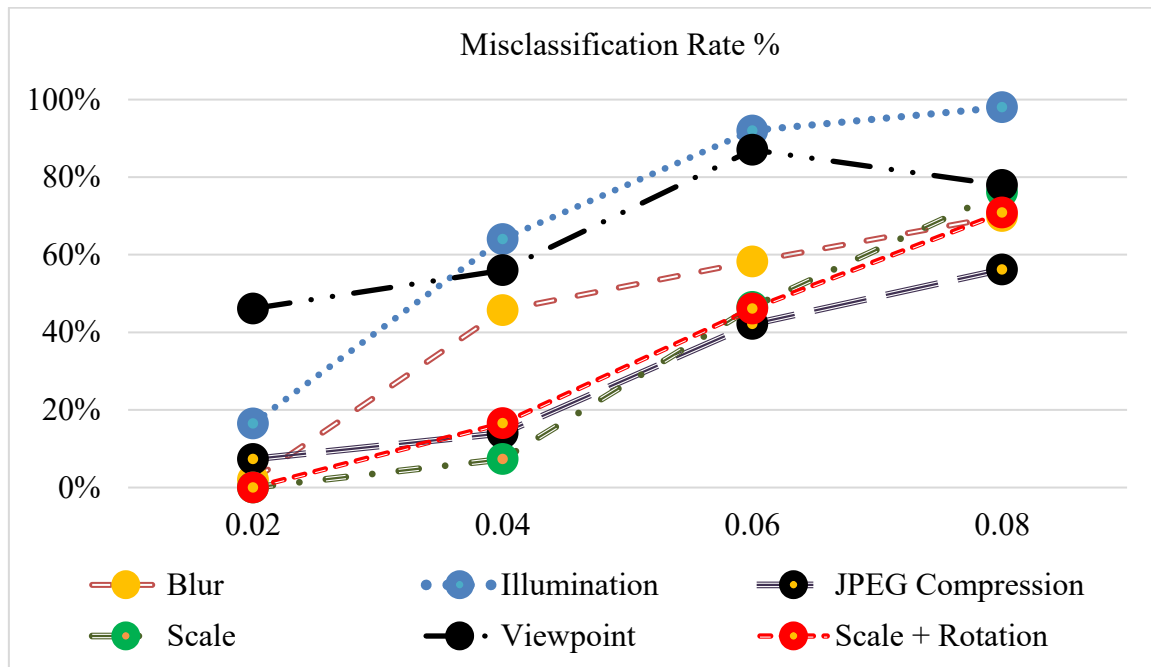


Figure 4.19: Misclassification rate of SIFT+RANSAC, PeakThr parameter value of 0.02, 0.04, 0.06, and 0.08; following six image deformations.

In our experiment, a comparison was made of SIFT+RANSAC failure points for each image deformation type under PeakThr parameter value of 0.02, as shown in Table 4.11. Viewpoint change is the most challenging with the greatest number of False Positives. As expected, SIFT+RANSAC performed well against the other deformation types, especially against Scale and Scale+Rotation. Comparison of SIFT+RANSAC matching results with PeakThr parameter value of 0.04 are shown in Table 4.12. For JPEG Compression, false matches only started at the fifth deformation level. While for image blurring and scale+rotation, false matches started at the second deformation level. SIFT+RANSAC failed to yield any True Positives at each deformation level using peak threshold values of 0.06 and 0.08, as shown in Table 4.13 and 4.14, respectively. Across all deformation types, SIFT+RANSAC yielded zero True Positives.

Table 4.11: The failure point of SIFT+RANSAC, at optimal PeakThr parameter value of 0.02, for each image deformation category.

Level of image deformation	Blur	Illumination	JPEG _Compression	Viewpoint	Scale + rotation	Scale
Image1	TP	TP	TP	FP	TP	TP
Image2	TP	TP	TP	TP	TP	TP
Image3	TP	TP	TP	FP	TP	TP
Image4	TP	TP	TP	FP	TP	TP
Image5	FP	FP	FP	FP	TP	TP

Table 4.12: Failure point of SIFT+RANSAC, at PeakThr parameter value of 0.04, for each image deformation category.

Level of image deformation	Blur	Illumination	JPEG _Compression	Viewpoint	Scale + rotation	Scale
Image1	TP	FP	TP	FP	TP	FP
Image2	FP	FP	TP	FP	FP	FP
Image3	FP	FN	TP	FP	FP	FP
Image4	FP	FN	TP	FP	FP	FP
Image5	FP	FN	FP	FP	FP	FP

Table 4.13: Failure point of SIFT+RANSAC, at PeakThr parameter value of 0.06, for each image deformation category.

Level of image deformation	Blur	Illumination	JPEG _Compression	Viewpoint	Scale + rotation	Scale
Image1	FP	FP	FP	FP	FP	FP
Image2	FP	FN	FP	FP	FP	FP
Image3	FN	FN	FP	FP	FP	FP
Image4	FN	FN	FP	FP	FP	FP
Image5	FN	FN	FP	FP	FP	FP

Table 4.14: The failure point of SIFT+RANSAC, at PeakThr parameter value of 0.08, for each image deformation category.

Level of image deformation	Blur	Illumination	JPEG _Compression	Viewpoint	Scale + rotation	Scale
Image1	FN	FN	FN	FN	FN	FN
Image2	FN	FN	FN	FN	FN	FN
Image3	FN	FN	FN	FN	FN	FN
Image4	FN	FN	FN	FN	FN	FN
Image5	FN	FN	FN	FN	FN	FN

To summarize, increasing the threshold value in SIFT leads to the detection of fewer keypoints within the Iban plaited mat motif, especially in areas with lower contrast. This reduction occurs because the algorithm becomes more selective in its choice of keypoints, prioritizing those with higher contrast levels.

Instances where the classification function yields either no match or multiple matches are classified as False Negatives, as they indicate a failure to identify the correct match, which does indeed exist within the database.

4.2.4 Summary

The robustness of the SIFT features algorithm hinges on the PeakThr parameter, dictating the total number of keypoints identified. Reducing the PeakThr parameter leads to the elimination of keypoints, diminishing the number of features and resulting in lower average matching accuracy in pairwise matching across six-image deformations. Additionally, a higher threshold value in SIFT contributes to fewer keypoints being detected in the Iban plaited mat motif. This heightened selectivity is particularly notable in regions with lower contrast, where fewer keypoints are identified due to SIFT's preference for areas with distinct contrast levels. Consequently, this leads to a decrease in the overall number of keypoints detected, especially in motif with uniform texture.

In summary, SIFT+RANSAC demonstrates strong performance and yields optimal results when employed with a PeakThr parameter value of 0.02, particularly in scenarios involving scale change and rotation combinations. This performance holds across all image deformation sequences at varying levels (i.e., degrees), with an average accuracy of 88.0%. The finding indicates that SIFT with a PeakThr parameter value of 0.02 is optimal for feature extraction in both simple and complex Iban plaited mat motifs. SIFT +RANSAC is

renowned for its ability to detect keypoints invariant to scale, rotation, and illumination changes, making it suitable for analyzing images with varying complexities. The PeakThr parameter controls the threshold for identifying keypoint peaks in the image's scale-space representation, and a value of 0.02 strikes a balance between capturing motif details and filtering out noise. This optimal setting demonstrates consistent performance across different motif complexities, underscoring its effectiveness in capturing relevant features while maintaining robustness to variations in scale and texture.

In evaluating the Iban plaited mat motif, SIFT+RANSAC demonstrates poor performance attributed to its difficulty in handling motifs with fewer intricate details and variations. Similarly, in the viewpoint sequence evaluation, SIFT+RANSAC also exhibits subpar performance.

4.3 Experiment II (Matching evaluation SIFT, SURF, BRISK, MSER and FAST)

In the second experiment, the following algorithms will be thoroughly evaluated: Scale-Invariant Feature Transform (SIFT) by (Lowe, 1999) with the PeakThr parameter value of 0.02, Speeded-Up Robust Features (SURF) by (Bay et al., 2006), Binary Robust Invariant Scalable Keypoints (BRISK) by (Leutenegger et al., 2011), Maximally Stable Extremal Regions (MSER) by (Matas et al., 2002), and Accelerated Segment Test (FAST) developed by (Rosten & Drummond, 2006). This evaluation aims to determine which algorithm is best suited for matching and classifying plaited Iban mat motifs images at different deformation level.

4.3.1 SIFT PeakThr parameter value of 0.02 and SURF descriptor matching

Both SIFT and SURF descriptors were matched using pairwise matching based on Nearest Neighbor's Distance Ratio (NNDR). NNDR was chosen due to its proven effectiveness for the local feature-matching task. NNDR was implemented utilizing Equation 4.2.

$$\frac{\|F_A - F_1\|}{\|F_A - F_2\|} \leq t \quad \text{Equation 4.2}$$

Where F_A denotes a descriptor of the query image, F_1 and F_2 are the nearest and second-nearest neighbors from the reference set to F , respectively.

4.3.2 BRISK and FAST descriptor matching

Hamming distance was used for feature matching in BRISK and FAST by comparing the similarities between descriptors of two feature points. The descriptors were composed of binary bits (1 or 0) describe the extracted feature points. If the corresponding bits are the same, the result will return “0”, otherwise it returns “1”. The similarity between two descriptors was determined by counting the occurrences of '0's and '1's.

Assuming X and Y are two BRISK descriptors, where the value of x_i and y_i represent “1” and “0” respectively:

$$X = x_1 x_2 \dots x_i \dots x_N \quad \text{Equation 4.3}$$

$$Y = y_1 y_2 \dots y_i \dots y_N \quad \text{Equation 4.4}$$

The Hamming distance calculation was implemented using a bitwise XOR operation. The Hamming distance equation was thus calculated as:

$$\text{HD}(X, Y) = \sum_{i=1}^N X_i \oplus Y_i = \sum_{i=1}^n b(X_i, Y_i) \quad \text{Equation 4.5}$$

where $b(X_1 Y_1)$ denotes the bit inequality. The greater the value of the Hamming distance, the lower the similarity of the descriptors.

4.3.3 MSER descriptor matching

For the matching of MSER, regions are first generated from each tile. Then MSER region tile X_1 inside reference image T_1 is compared with MSER region of in a tile X_2 inside query image T_2 . Matching MSER regions are stored while unmatched MSER regions are considered as potential change regions.

4.3.4 Matching Verification

Geometric verification using RANSAC is a step in ensuring the accuracy and reliability of feature matches, particularly in noisy background as in Iban plaited mat motifs. After initial matching using algorithms, such as SIFT, SURF, BRISK, MSER, and FAST, RANSAC is employed to estimate the geometric transformation between matched keypoints in the reference and query images. Through an iterative process, RANSAC

selects subsets of matched keypoints to form candidate models and evaluates their consistency with the estimated transformation. By filtering out outlier matches and retaining only geometrically consistent keypoints, RANSAC helps improve the accuracy and robustness of feature matching algorithms, ultimately enhancing the effectiveness of motif recognition across different level of image deformation.

4.4 Performance Results and Discussion

In this section, the experimental results are presented and discussed. The recorded statistics include the number of detected features, i.e., results of number of detected features in the reference image, N_{tmp} , in the query image, N_{qry} , number of positive matches found, N_{crp} , number of positive matches after RANSAC, N_{mch}

4.4.1 Blur Sequence

Table 4.15 shows a summarized statistics of *Buah Lang Antu* and *Buah Nabau Besundang* for each feature descriptor. These two motifs are considered as complex motifs. SIFT PeakThr parameter value of 0.02, BRISK and SURF detect the most keypoints, and MSER detects keypoints only up to Blur level 2. Meanwhile FAST only detect keypoint up to blur first level. As for the quality of correspondences, SIFT returned the highest false positives while FAST performed the worst with zero correspondences returned for Blur at any level.

Table 4.15: Classification statistics of Blur sequences belonging to *Buah Lang Antu* and *Buah Nabau Besundang*.

	SIFT			SURF			BRISK		
	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}
Blr1	196	266	mismtch	252	54	34	177	23	19
Blr2	142	173	mismtch	198	35	23	143	16	11
Blr3	100	91	mismtch	68	13	8	103	6	2
Blr4	73	31	mismtch	26	multi	multi	85	2	0
Blr5	36	57	mismtch	19	2	0	59	0	0
	MSER			FAST					
	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}			
Blr1	15	3	3	13	0	0			
Blr2	6	1	0	2	0	0			
Blr3	0	0	0	0	0	0			
Blr4	0	0	0	0	0	0			
Blr5	0	0	0	0	0	0	<i>Buah Lang Antu</i>		
	SIFT			SURF			BRISK		
	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}
Blr1	346	122	114	280	4	mismtch	220	58	47
Blr2	176	95	91	209	4	mismtch	147	37	29
Blr3	95	177	65	100	0	0	89	19	10
Blr4	66	142	mismatch	0	0	0	59	11	7
Blr5	51	106	mismatch	0	0	0	28	3	3
	MSER			FAST					
	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}			
Blr1	107	4	4	5	0	0			
Blr2	56	2	0	0	0	0			
Blr3	13	0	0	0	0	0			
Blr4	9	0	0	0	0	0			
Blr5	0	0	0	0	0	0	<i>Buah Nabau Besundang</i>		

Figure 4.20 shows visualized keypoints detected when using SURF descriptor on the Blur sequence. Results of image pair matching in Figure 4.21, shows no image pair was found after image matching of blur sequence for *Buah Lang Antu* and *Buah Nabau Besundang* at level 3 and below.

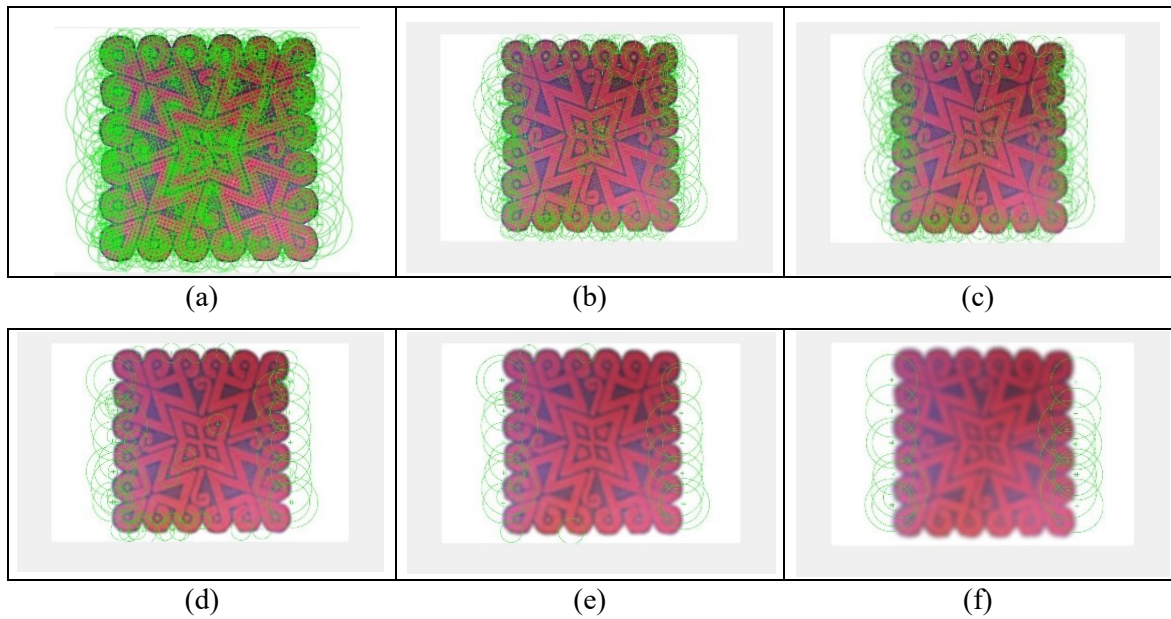


Figure 4.20: Visualized SURF keypoints in reference image of (a) *Buah Lang Antu*, and query image with blur (b) level 1, (c) level 2, (d) level 3, (e) level 4 and (f) level 5.

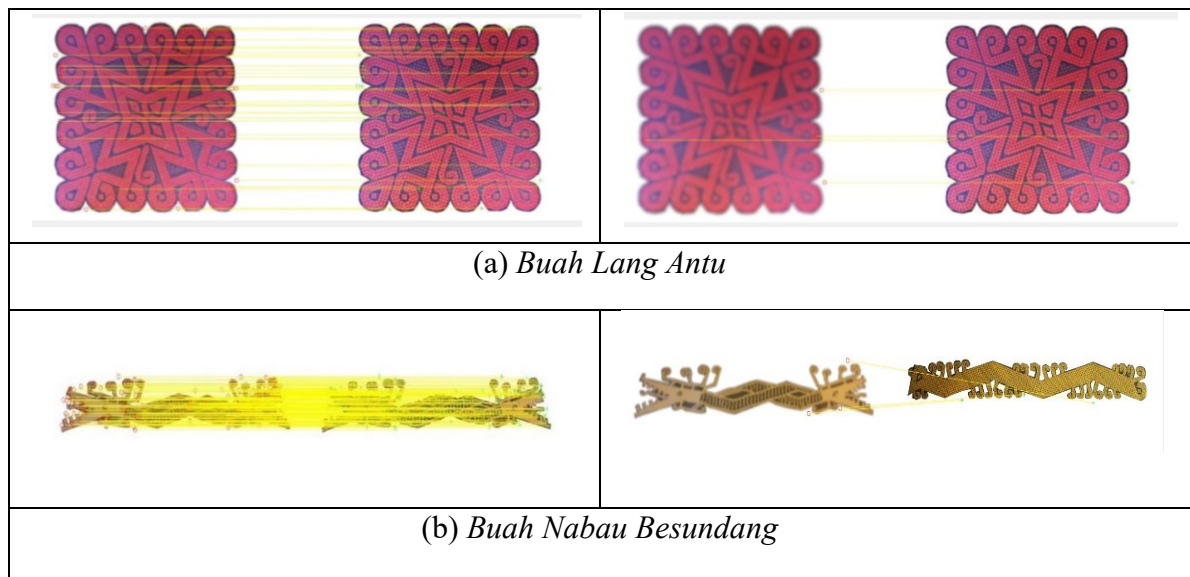


Figure 4.21: Matching results of (a) *Buah Lang Antu* and (b) *Buah Nabau Besundang* using SURF+RANSAC at deformation of blur change first level vs. third level (left to right column)

4.4.2 JPEG Compression

JPEG compression is a commonly used method for compressing digital images. It works by reducing the amount of information stored in an image while attempting to maintain the visual quality of the image. However, the compression process can result in a change of appearance of the image, particularly in terms of the image's sharpness and colour accuracy. Table 4.16 shows a summarized statistics for a complex motif, i.e., *Buah Lintan Tanah* and a simple motif of *Buah Mata Punai* for each feature descriptor. The results show that for JPEG compression, SIFT PeakThr parameter value of 0.02, BRISK SURF, MSER and FAST obtained a sufficient number of detected keypoint and correct matches.

Table 4.16: Classification statistics of JPEG Compression sequences belonging to *Buah Lintan Tanah* and *Buah Mata Punai*.

	SIFT			SURF			BRISK		
	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}
JPEG1	1523	1454	1404	2177	1851	1793	4189	2161	2154
JPEG2	1540	1404	1354	2211	1725	1647	4233	1665	1660
JPEG3	1539	1335	1230	2250	1524	1396	4401	1146	1135
JPEG4	1625	1276	1153	2244	1310	1185	4503	881	871
JPEG5	1613	361	171	2366	134	66	6465	13	11
	MSER			FAST					
	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}			
JPEG1	1988	740	711	1880	1318	1313			
JPEG2	1813	538	506	1861	1084	1072			
JPEG3	1570	390	343	2039	783	772			
JPEG4	1541	322	276	2200	577	563			
JPEG5	2788	21	8	3102	5	3	<i>Buah Lintan Tanah</i>		

Table 4.16 continued

	SIFT			SURF			BRISK		
	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}
JPEG1	332	333	mismatch	227	197	186	251	183	181
JPEG2	333	368	mismatch	216	182	173	253	179	177
JPEG3	338	362	mismatch	211	159	148	259	159	155
JPEG4	330	272	mismatch	212	135	120	254	138	136
JPEG5	246	271	mismatch	201	39	15	534	33	27
	MSER			FAST					
	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}			
JPEG1	38	20	20	36	23	23			
JPEG2	36	16	16	37	24	24			
JPEG3	37	17	17	41	20	19			
JPEG4	32	7	7	37	12	11			
JPEG5	109	2	0	138	1	0	<i>Buah Mata Punai</i>		

Figure 4.22 shows visualized keypoints detected when using BRISK on the JPEG Compression sequences. A side-by-side comparison of the matching outcomes utilizing BRISK+RANSAC is presented in Figure 4.23.

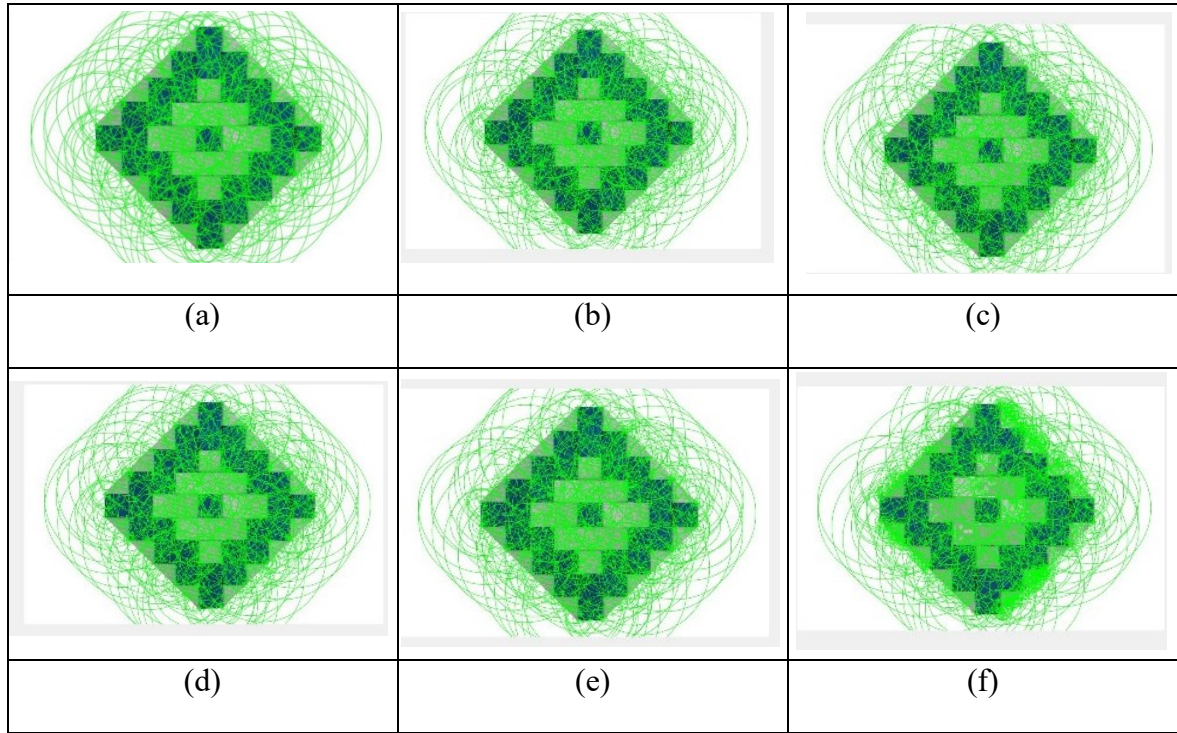


Figure 4.22: Visualized BRISK keypoints in reference image of (a) *Buah Mata Punai*, and query image belonging to JPEG Compression sequence: (b) level 1, (c) level 2, (d) level 3, (e) level 4 and (f) level 5.

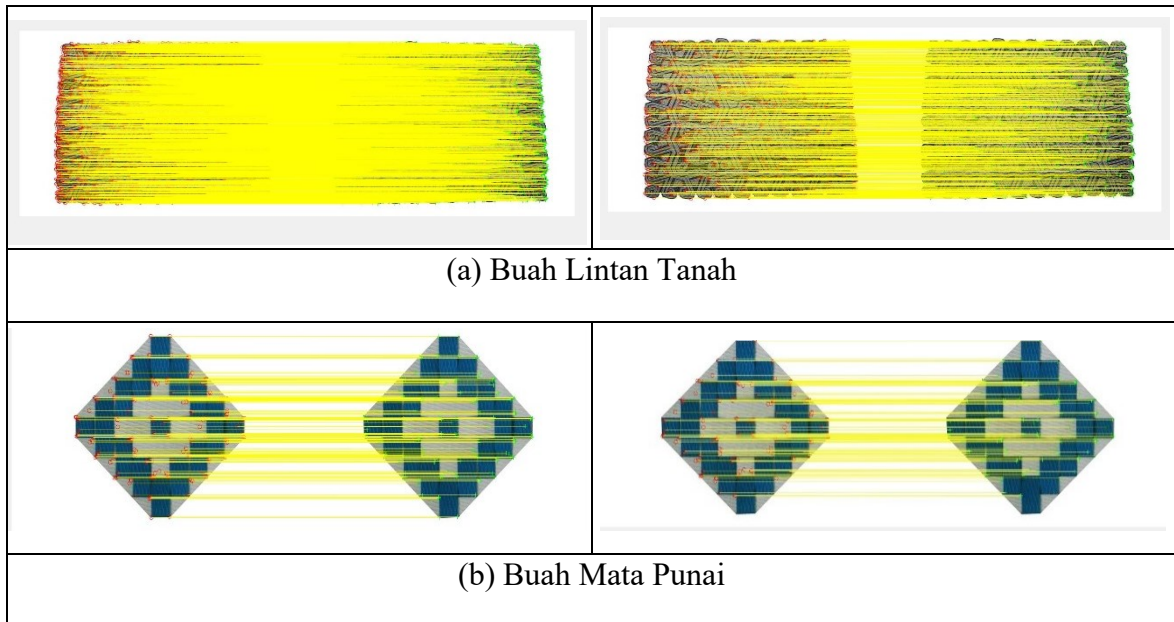


Figure 4.23: Matching results of (a) *Buah Lintan Tanah* and (b) *Buah Mata Punai* using BRISK + RANSAC for JPEG Compression comparing first level (left column) and fifth (right column).

4.4.3 Illumination change

Illumination change in image processing refers to a change in the amount of light or brightness within an image. This deformation can occur for various reasons, such as changes in lighting conditions, shadows, reflections, or camera settings. Table 4.17 shows summarized statistic for a complex motif of *Buah Sebayan* and a simple motif of *Buah Andu* for each feature descriptor. With decreasing illumination conditions in the image, the number of detected feature points also shows a decreasing trend. BRISK+RANSAC detects the most feature points and matches at deformation Level 1 and Level 2.

Table 4.17: Classification statistics of Illumination sequences belonging to *Buah Sebayan* and *Buah Andu*.

	SIFT			SURF			BRISK		
	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}
Light 1	785	824	758	1404	1266	1243	2546	1850	1849
Light 2	634	659	615	913	809	801	1216	827	826
Light 3	300	458	292	623	535	523	570	332	331
Light 4	34	78	16	265	218	210	217	114	113
Light 5	0	0	0	6	5	5	4	1	0
	MSER			FAST					
	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}			
Light 1	1342	669	663	1559	1369	1363			
Light 2	1006	472	467	738	626	623			
Light 3	697	315	314	240	185	185			
Light 4	175	67	65	82	53	53			
Light 5	18	4	4	4	1	0	Buah Sebayan		

Table 4.17 continued									
	SIFT			SURF			BRISK		
	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}
Light 1	1618	851	849	1346	1196	1179	2528	2005	2005
Light 2	1237	600	598	1195	997	982	1896	1367	1365
Light 3	923	414	413	1053	880	868	1145	798	796
Light 4	500	213	213	693	592	583	77	45	45
Light 5	35	10	10	224	197	191	3	0	0
	MSER			FAST					
	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}			
Light 1	1618	851	849	857	758	758			
Light 2	1237	600	598	503	407	407			
Light 3	923	414	413	175	131	131			
Light 4	500	213	213	7	5	5			
Light 5	35	10	10	0	0	0	Buah Andu		

Figure 4.24 shows visualized keypoints detected using the MSER descriptor on the Illumination sequences, where the last image is darker than the first image. A side-by-side comparison of the matching outcomes utilising MSER+RANSAC is shown in Figure 4.25.

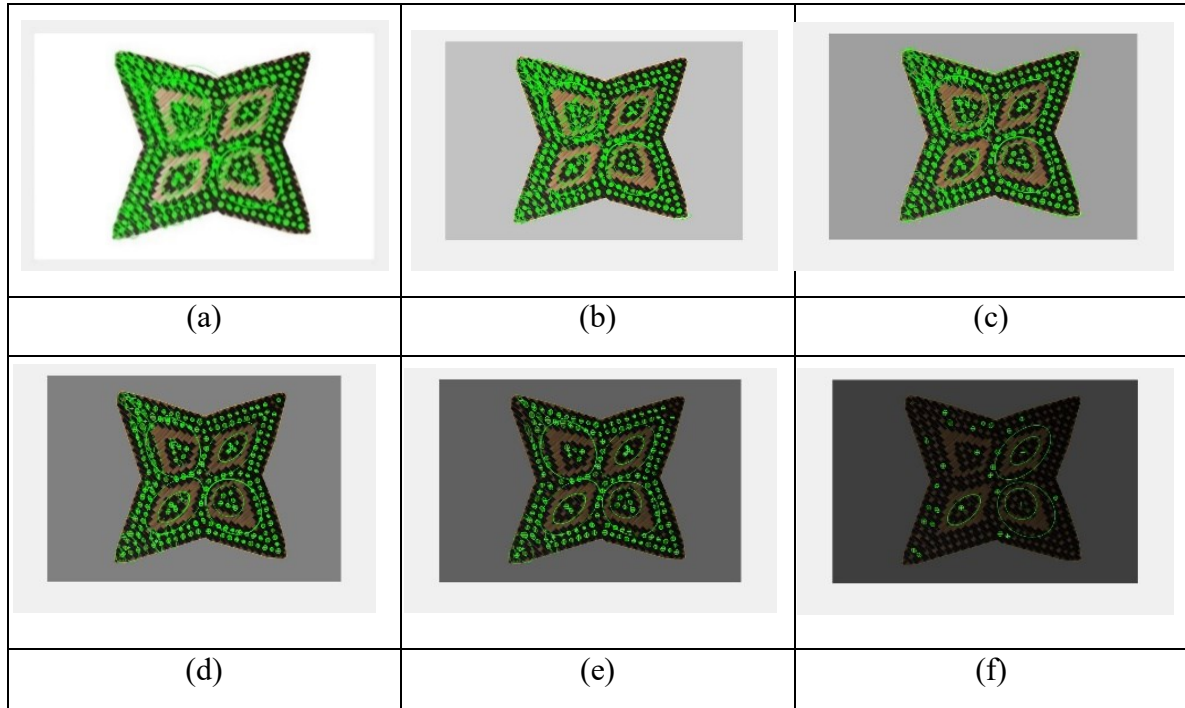


Figure 4.24: Visualized MSER keypoints in reference image of (a) *Buah Andu*, and query images belonging to Illumination sequences, (b) level 1, (c) level 2, (d) level 3, (e) level 4 and (f) level 5.

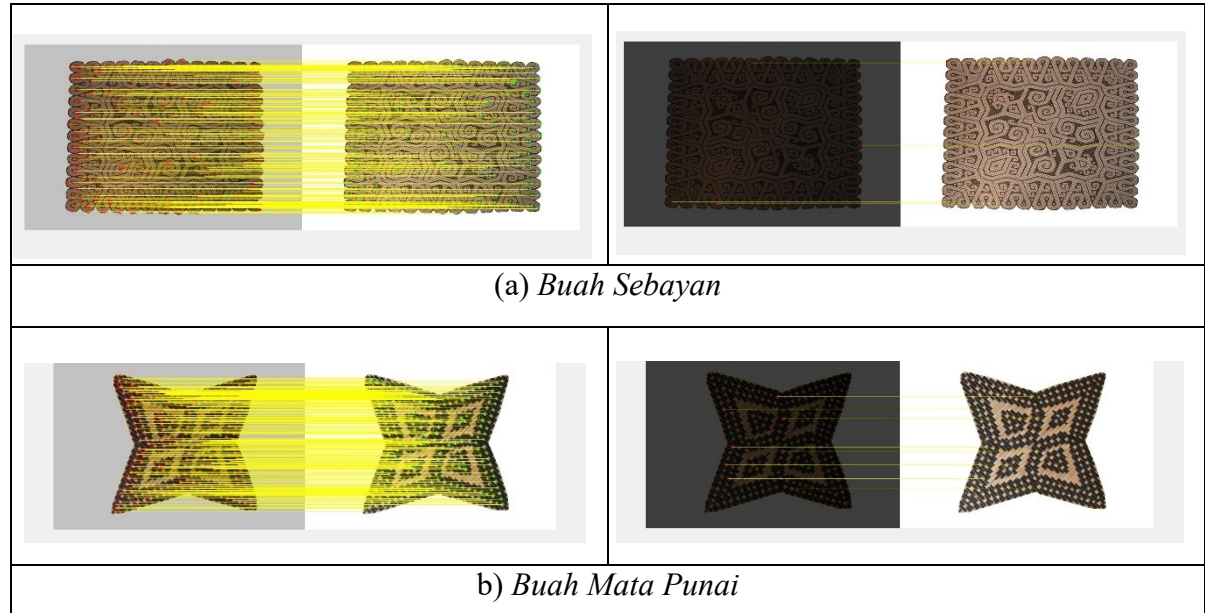


Figure 4.25: Matching results of (a) *Buah Sebayan* and (b) *Buah Mata Punai* utilising test sequences from Illumination change levels 1 and 5 (left to right column) with MSER + RANSAC

4.4.4 Scale change

Scale change in image processing refers to a change in the size or resolution of an image. This can occur for various reasons, such as image cropping, resizing, or resampling. Table 4.18 shows a summarized statistics for a complex motif of *Buah Bandau* and a simple motif of *Buah Mayau*, for each feature descriptor. SIFT PeakThr parameter value of 0.02, SURF, BRISK and MSER obtain a sufficient number of correct matches. Meanwhile FAST descriptor performed the worst with hardly any correct matches for *Buah Bandau*.

Table 4.18: Classification statistics of Scale change sequences belonging to *Buah Bandau* and *Buah Mayau*.

	SIFT			SURF			BRISK		
	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}
Scale1	587	460	385	803	219	120	739	12	9
Scale2	523	430	379	648	185	125	703	8	4
Scale3	429	409	303	530	189	140	635	9	5
Scale4	355	361	279	445	123	59	571	4	3
Scale5	254	246	200	245	117	75	516	4	3
	MSER			FAST					
	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}			
Scale1	308	55	52	340	7	3			
Scale2	263	45	39	306	0	0			
Scale3	239	25	20	255	1	0			
Scale4	223	18	6	239	0	0			
Scale5	246	13	8	244	0	0	<i>Buah Bandau</i>		

Table 4.18 continued									
	SIFT			SURF			BRISK		
	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}
Scale1	844	738	720	774	308	259	2570	146	136
Scale2	821	748	724	559	216	176	2069	52	42
Scale3	486	442	412	378	130	105	1749	36	29
Scale4	194	212	180	264	59	29	1506	28	23
Scale5	58	160	mismatch	170	68	53	1160	41	35
	MSER			FAST					
	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}			
Scale1	853	116	108	1457	86	84			
Scale2	604	51	46	1188	7	7			
Scale3	484	35	27	1025	5	4			
Scale4	306	25	19	891	0	0			
Scale5	191	13	11	768	0	0	<i>Buah Mayau</i>		

Figure 4.26 shows visualized keypoints detected when using BRISK on the Illumination change sequences. In Figure 4.27, a side-by-side comparison of the matching results obtained through BRISK+RANSAC is depicted.

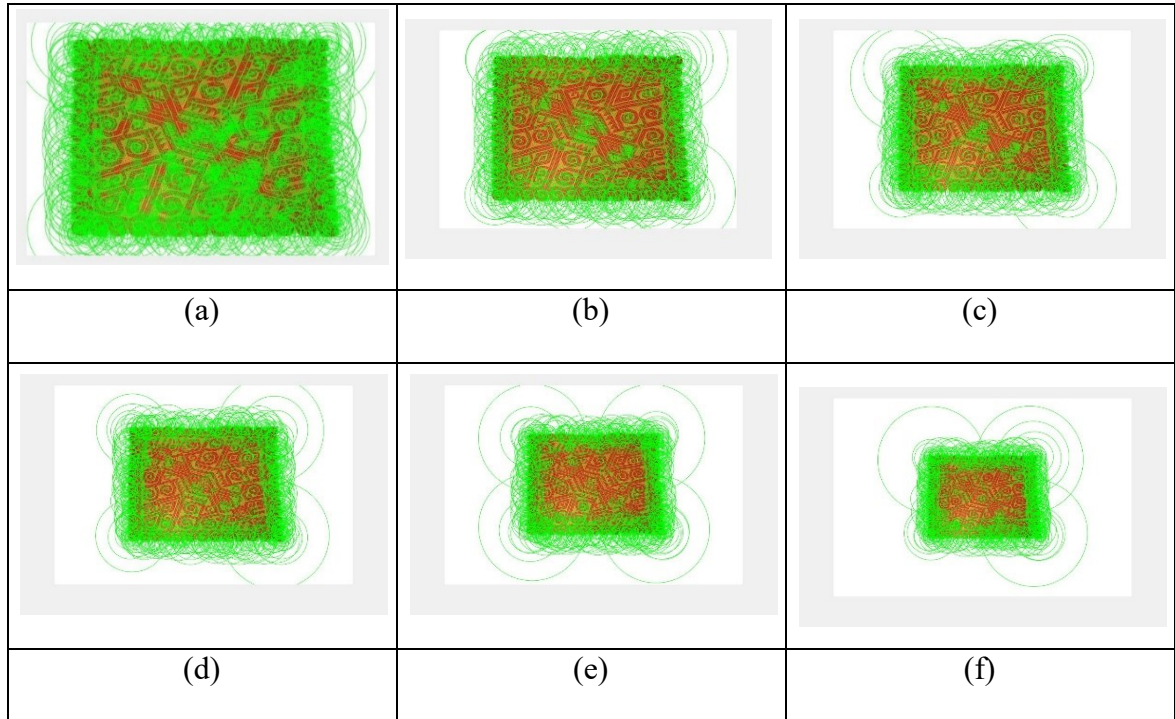


Figure 4.26: Visualized BRISK keypoints in the reference image of (a) *Buah Bandau* and query images belonging to the Scale change sequences, (b) level 1, (c) level 2, (d) level 3, (e) level 4 and (f) level 5.

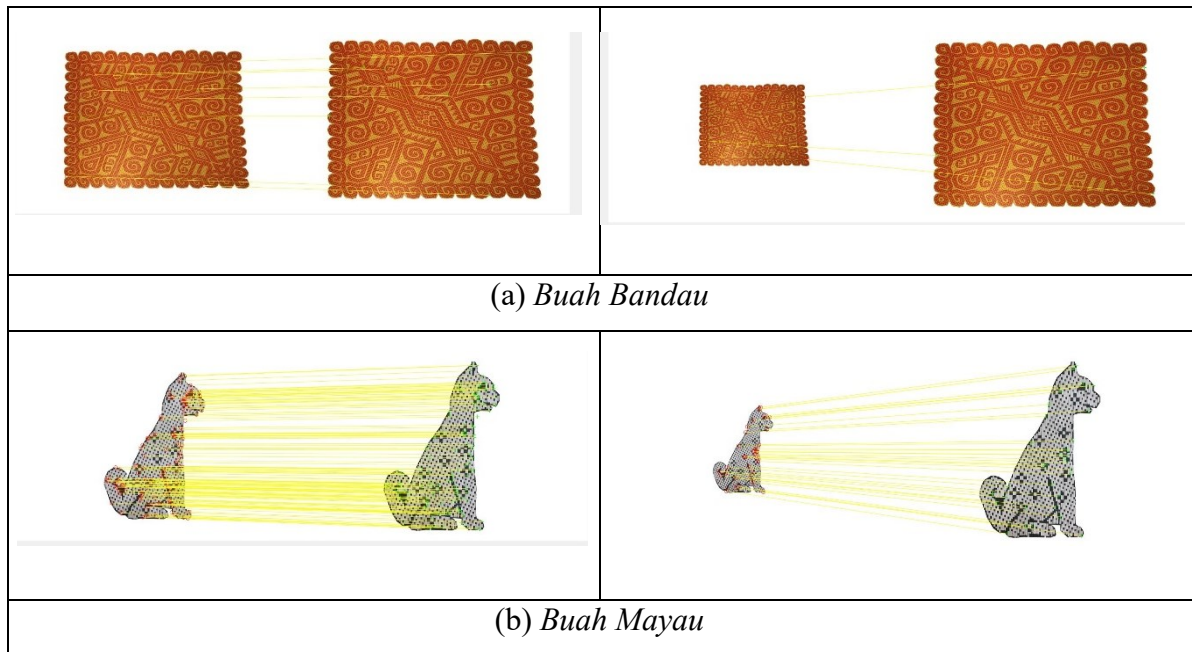


Figure 4.27: Matching results of (a) *Buah Bandau* and (b) *Buah Mayau* utilising Scale change level 1 (left column) vs. level 5 (right column) test sequences with BRISK + RANSAC.

4.4.5 Viewpoint change

Viewpoint change in image processing refers to a change in the position or perspective from which an image is captured. View change can occur due to changes in camera position, orientation, or focal length. Table 4.19 shows a summarized statistics for a complex motif i.e., *Buah Kandung Nibung Berayah* and *Buah Nabau Ngelantar* for each feature descriptor. BRISK+ RANSAC discovered the most feature points, and the most correct matches, even on the last image pair, which is the most difficult to match because of the substantial view angle change. SIFT PeakThr parameter value of 0.02 performed the worst, due to the repetitive and non-geometric patterns in *Buah Nabau Ngelantar*.

Table 4.19: Classification statistics of Viewpoint change sequences belonging to *Buah Kandung Nibung Berayah* and *Buah Nabau Ngelantar*.

	SIFT			SURF			BRISK		
	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}
View1	1758	1459	902	1666	306	65	8629	100	35
View2	2106	1548	1053	1870	347	56	8900	144	41
View3	1493	795	383	1490	99	15	7385	26	6
View4	1148	380	mismatch	1256	47	7	6176	6	4
View5	926	208	mismatch	1100	25	mismatch	5271	5	3
	FAST			MSER					
	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}			
View1	6486	145	59	829	24	16			
View2	6571	119	36	953	38	11			
View3	5316	29	12	810	15	mismatch			
View4	4405	3	3	772	22	mismatch			
View5	0	0	0	652	5	mismatch			

Table 4.19 continued

	SIFT			SURF			BRISK		
	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}
View1	153	159	mismatch	289	59	12	995	26	9
View2	175	427	mismatch	322	65	13	1219	32	7
View3	113	113	mismatch	262	28	7	794	9	5
View4	118	90	mismatch	247	9	mismatch	701	1	0
View5	118	62	mismatch	226	11	mismatch	691	1	0
	FAST			MSER					
	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}			
View1	579	20	11	198	19	9			
View2	735	5	4	236	40	16			
View3	407	4	4	190	5	3			
View4	401	0	0	152	2	0			
View5	0	0	0	121	2	0	Buah Nabau Ngelantar		

Figure 4.28 shows visualized keypoints detected when using FAST on images belonging to the Viewpoint change sequences. Figure 4.29 presents a visual comparison of the matching results obtained using FAST+RANSAC, displayed side by side.

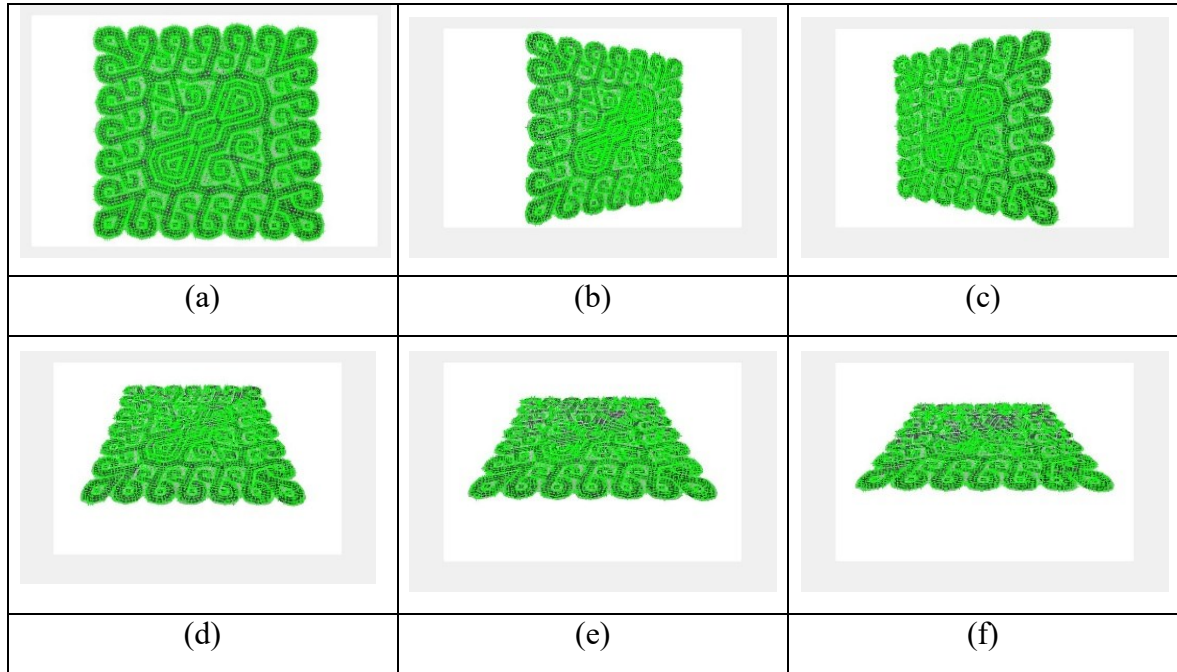


Figure 4.28: Visualized FAST keypoints in the reference image of (a) *Buah Kandung Nibung Berayah*, and query images belonging to the Viewpoint change sequences (b) level 1, (c) level 2, (d) level 3, (e) level 4 and (f) level 5.

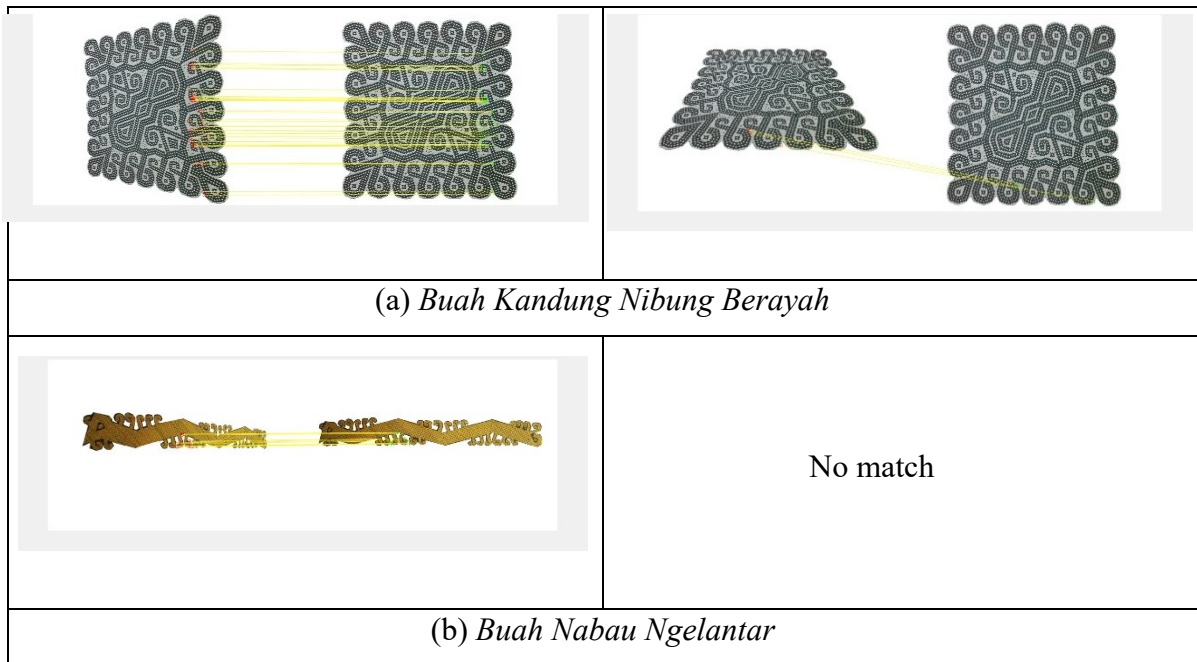


Figure 4.29: Matching results of (a) *Buah Kandung Nibung Berayah* and (b) *Buah Nabau Ngelantar* level 1 vs. level 4 (left to right column) utilising FAST + RANSAC at Viewpoint.

4.4.6 Scale + Rotation change

Combination of scale and rotation refers to changes in the scale and orientation of an image. These changes occur due to image cropping, resizing, resampling, as well as camera orientation or perspective changes. Table 4.20 shows a summarized statistics for the following motifs, i.e., *Buah Tungku* and the *Buah Suri Ai* when classifying their Scale+Rotations sequences. This is arguably the most challenging image deformation type. SIFT PeakThr parameter value of 0.02, SURF, BRISK, and MSER managed to detect sufficient keypoints and find correct matches for test sequences images of *Buah Suri Ai*, while FAST did not find any correct matches starting at deformation level 3.

Table 4.20: Classification statistics of Scale+Rotation change sequences belonging to *Buah Tungku* and *Buah Suri Ai*.

Scale + rotation	SIFT			SURF			BRISK		
	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}
L1	1764	1562	1485	1492	486	392	2451	135	123
L2	1356	1267	1166	1123	292	232	1980	42	34
L3	952	927	799	931	262	139	1955	33	18
L4	620	631	522	731	183	64	1760	25	13
L5	384	382	319	338	85	28	1183	12	8
	FAST			MSER					
	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}			
L1	847	6	6	1526	81	72			
L2	756	3	3	800	27	23			
L3	959	3	mismtch	580	14	mismtch			
L4	952	0	0	298	19	mismtch			
L5	726	1	0	160	14	mismtch	<i>Buah Tungku</i>		

Table 4.20 continued

Scale + rotation	SIFT			SURF			BRISK		
	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}
L1	892	735	624	1837	338	77	6179	89	33
L2	808	666	562	1542	265	51	3469	59	23
L3	682	596	459	1102	281	30	2093	32	8
L4	601	540	414	1007	161	21	1837	30	7
L5	507	446	333	545	104	13	1515	18	5
	FAST			MSER					
	N_{qry}	N_{crp}	N_{mch}	N_{qry}	N_{crp}	N_{mch}			
L1	4682	31	7	987	104	37			
L2	2161	3	3	887	92	29			
L3	1021	0	0	743	76	30			
L4	822	1	0	633	54	19			
L5	747	0	0	481	24	12	<i>Buah Suri Ai</i>		

Figure 4.30 shows visualized keypoints detected when using SIFT descriptor with peak threshold of 0.02 on selected images from the test sequences of Scale+Rotation (95%, 15° to 5%, 300°). A side-by-side comparison of the matching outcomes utilising SIFT+RANSAC is shown in Figure 4.31. The SIFT descriptor with a peak threshold of 0.02, coupled with RANSAC, demonstrates the ability to detect keypoints even at high levels of deformation, specifically in cases of Scale+Rotation Change. This combination proves robust in maintaining feature detection capabilities despite significant distortions introduced by scale changes and rotation variations in the images.

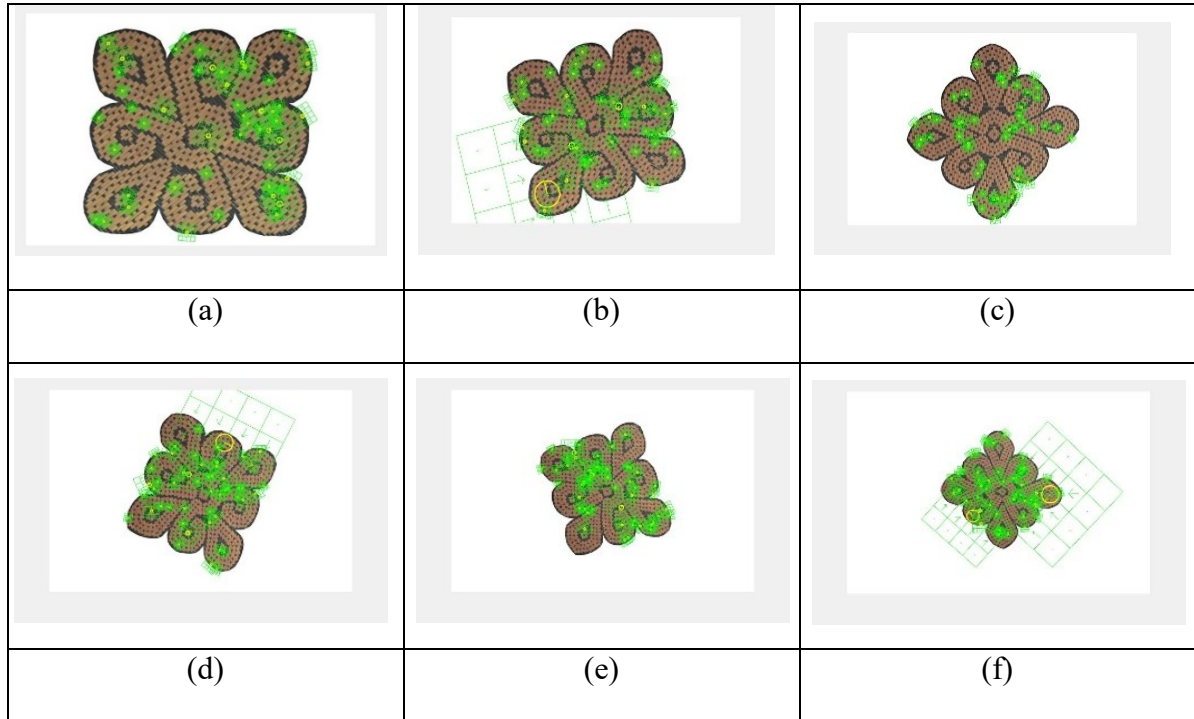


Figure 4.30: Visualized SIFT+RANSAC keypoint in reference image of (a) *Buah Tungku*, and query images belonging to the Scale+Rotation sequences (b) level 1, (c) level 2, (d) level 3, (e) level 4 and (f) level 5.

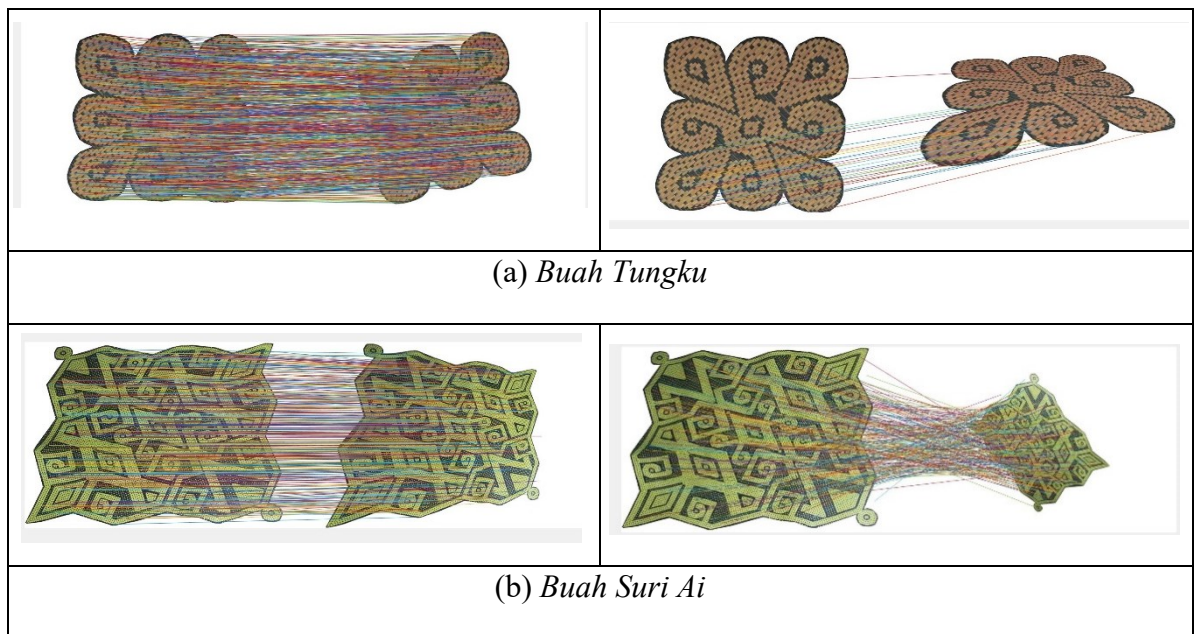


Figure 4.31: Matching results of (a) *Buah Tungku* and (b) *Buah Suri Ai* utilising test sequences from Scale+Rotation Change first level and fifth level (left to right column) using SIFT + RANSAC.

4.4.7 Confusion matrix results

Confusion matrices for each feature descriptor combined with RANSAC are presented. The values were averaged across different deformation types with varying degrees of complexity. The confusion matrixes of SIFT with PeakThr value of 0.02 +RANSAC are shown in Figure 4.32 (a) to (f). This combination shows promising results for Scale Change and Scale+Rotation Change. However, this combination performed poorly on test sequences belonging to Blur and Viewpoint change where most of the classified motifs turned out to be incorrect.

Actual classes	Predicted classes																					
	Plaited mat motif	BLA	BB	BA	BBBekarung	BBBepayung	BBG	BKNB	BP	BK	BLM	BLT	BMP	BM	BNB	BNN	BS	BSA	BTGB	BTL	BT	Unresolved
	BLA	0.00	0.20	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.20	0.00	0.00	0.00	0.20	0.00
	BB	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BA	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20
	BBBekarung	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BBBepayung	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BBG	0.00	0.00	0.20	0.00	0.00	0.40	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00
	BKNB	0.00	0.00	0.20	0.20	0.00	0.00	0.60	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BK	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.60	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	0.00	0.00
	BLM	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.60	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BLT	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BMP	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.60	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BM	0.00	0.00	0.00	0.40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.60	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BNB	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	0.00	0.00	0.40	0.00	0.00	0.00
	BNN	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	0.00	0.40	0.00	0.00	0.00	0.00
	BS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
	BSA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00
	BTGB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
BTL	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	
BT	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.60	0.00	

(a)

		Predicted classes																						
		Plaited mat motif	BLA	BB	BA	BBBekarung	BBBepayung	BBG	BKNB	BP	BK	BLM	BLT	BMP	BM	BNB	BNN	BS	BSA	BTGB	BTL	BT	unresolved	
Actual classes	BLA	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		
	BB	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		
	BA	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		
	BBBekarun	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		
	BBBepayur	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		
	BBG	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		
	BKNB	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		
	BP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		
	BK	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		
	BLM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		
	BLT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		
	BMP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		
	BM	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		
	BNB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		
	BNN	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00		
	BS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00		
BSA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00			
BTGB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00			
BTL	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00			
BT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00			

(f)

Figure 4.32: Confusion matrixes from SIFT+RANSAC classification results (with PeakThr value of 0.02), under the following image deformation type, i.e., (a) Blur (b) JPEG Compression (c) Illumination change (d) Viewpoint change (e) Scale change, and (f) Scale+Rotation.

While the confusion matrixes in Figure 4.33 (a) to (f) show the results of the SURF descriptor matching + RANSAC. The following test sequences, comprising JPEG compression, illumination change, and even the worst deformation level of scale change, show good performance for this combination. However, SURF performed poorly under viewpoint change and blur change as it returned a higher number of mismatched classes.

Actual classes	Predicted classes																					
	Plaited mat motif	BLA	BB	BA	BBBekarung	BBBepayung	BBG	BKNB	BP	BK	BLM	BLT	BMP	BM	BNB	BNN	BS	BSA	BTGB	BTL	BT	Unresolved
	BLA	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20
	BB	0.20	0.40	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BA	0.00	0.00	0.40	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.40	0.00	0.00	0.00	0.00	0.00
	BBBekarung	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BBBepayung	0.00	0.00	0.00	0.00	0.60	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20
	BBG	0.00	0.00	0.20	0.00	0.00	0.40	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00
	BKNB	0.20	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20
	BK	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00
	BLM	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.60	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00
	BLT	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.20	0.60	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BMP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.60	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.20
	BNB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.20	0.00	0.00	0.00	0.00	0.00	0.60
	BNN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
	BS	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.40	0.00	0.00	0.00	0.00	0.20
	BSA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00
	BTGB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
	BTL	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.20
	BT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	0.00	0.00	0.00	0.60	0.00

(a)

Actual classes	Predicted classes																					
	Plaited mat motif	BLA	BB	BA	BBBekarung	BBBepayung	BBG	BKNB	BP	BK	BLM	BLT	BMP	BM	BNB	BNN	BS	BSA	BTGB	BTL	BT	unresolved
	BLA	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BB	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BA	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BBBekarung	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BBBepayung	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BBG	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BKNB	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BK	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BLM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BLT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BMP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BNB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BNN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
	BS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
	BSA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00
	BTGB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
	BTL	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00
	BT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00

(b)

Actual classes	Plaited mat motif	Predicted classes																				
		BLA	BB	BA	BBBekarung	BBBepayung	BBG	BKNB	BP	BK	BLM	BLT	BMP	BM	BNB	BNN	BS	BSA	BTGB	BTL	BT	Unresolved
BLA	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BB	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BA	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BBBekarung	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BBBepayung	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BBG	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BKNB	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20
BP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BK	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BLM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20
BLT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BMP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20
BM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BNB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BNN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
BSA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
BTGB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00
BTL	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
BT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00

(c)

Actual classes	Plaited mat motif	Predicted classes																				
		BLA	BB	BA	BBBekarung	BBBepayung	BBG	BKNB	BP	BK	BLM	BLT	BMP	BM	BNB	BNN	BS	BSA	BTGB	BTL	BT	unresolved
BLA	0.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
BB	0.0	0.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.4	0.0	0.0	0.0	0.0	0.0	0.0
BA	0.0	0.0	0.6	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
BBBekarung	0.0	0.0	0.0	0.6	0.2	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
BBBepayung	0.0	0.0	0.0	0.0	0.8	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
BBG	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
BKNB	0.0	0.0	0.0	0.0	0.0	0.0	0.8	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
BP	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.8	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
BK	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.6	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
BLM	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.8	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0
BLT	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.8	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0
BMP	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.0	0.0	0.0
BM	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
BNB	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
BNN	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.6	0.2	0.0	0.0	0.0	0.0	0.0	0.0
BS	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.0	0.0	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.0	0.0	0.0
BSA	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.0	0.0	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.0	0.0
BTGB	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0
BTL	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.8	0.0	0.0	0.0
BT	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.8	0.0	0.0

(d)

	Predicted classes																						
	Plaited mat motif	BLA	BB	BA	BBBekarung	BBBepayung	BBG	BKNB	BP	BK	BLM	BLT	BMP	BM	BNB	BNN	BS	BSA	BTGB	BTL	BT	unresolved	
Actual classes	BLA	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	BB	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	BA	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	BBBekarung	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	BBBepayung	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	BBG	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	BKNB	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	BP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	BK	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	BLM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	BLT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	BMP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	BM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	BNB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	BNN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	
	BS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	
	BSA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	
BTGB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00		
BTL	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00		
BT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00		

(e)

	Plaited mat motif	Predicted classes																				
		BLA	BB	BA	BBBekarung	BBBepayung	BBG	BKNB	BP	BK	BLM	BLT	BMP	BM	BNB	BNN	BS	BSA	BTGB	BTL	BT	Unresolved
Actual classes	BLA	0.60	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	0.00	0.00	0.00	0.00	0.00	0.00
	BB	0.20	0.40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.20	0.00	0.00
	BA	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BBBekarung	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BBBepayung	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BBG	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BKNB	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BK	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BLM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BLT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BMP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BNB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BNN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
	BS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
	BSA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00
	BTGB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
	BTL	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00
	BT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00

(f)

Figure 4.33: Confusion matrixes from the SURF+RANSAC classification outcomes, i.e., (a) Blur (b) JPEG Compression (c) Illumination change (d) Viewpoint change (e) Scale change, and (f) Scale+Rotation.

The confusion matrixes in Figure 4.34 show the results of the BRISK descriptor +RANSAC. BRISK+ RANSAC performed well on test sequences of JPEG Compression, Scale Change, and Scale+Rotation. However, BRISK+RANSAC returned a high number of unresolved classes of blur, illumination change and viewpoint change. Cases where there are multiple top matches or a zero match are considered unresolved. The combination returning these two results is penalized by counting the classification result as a False Negative.

	Plaited mat motif	Predicted classes																				
		BLA	BB	BA	BBBekarung	BBBepayung	BBG	BKNB	BP	BK	BLM	BLT	BMP	BM	BNB	BNN	BS	BSA	BTGB	BTL	BT	Unresolved
Actual classes	BLA	0.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.4
	BB	0.0	0.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.6
	BA	0.0	0.0	0.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2
	BBBekarung	0.0	0.0	0.0	0.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2
	BBBepayung	0.0	0.0	0.0	0.0	0.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2
	BBG	0.0	0.0	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.4
	BKNB	0.0	0.0	0.0	0.0	0.0	0.0	0.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2
	BP	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2
	BK	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	BLM	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2
	BLT	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.8
	BMP	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	BM	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2
	BNB	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	BNN	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.8	0.0	0.0	0.0	0.0	0.0	0.2
	BS	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.0	0.4
	BSA	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.8	0.0	0.0	0.0	0.2
	BTGB	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0
	BTL	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.6	0.0	0.4
	BT	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.8	0.2

(a)

	Plaited mat motif	Predicted classes																				
		BLA	BB	BA	BBBekarung	BBBepayung	BBG	BKNB	BP	BK	BLM	BLT	BMP	BM	BNB	BNN	BS	BSA	BTGB	BTL	BT	Unresolved
Actual classes	BLA	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20
	BB	0.00	0.20	0.00	0.00	0.00	0.60	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00
	BA	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BBBekarung	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BBBepayung	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BBG	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BKNB	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BK	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BLM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20
	BLT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BMP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BNB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BNN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
	BS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
	BSA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00
	BTGB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
	BTL	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00
	BT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00

(f)

Figure 4.34: Confusion matrixes from the classification results using BRISK+RANSAC, under the following image deformation type, i.e., (a) Blur (b) JPEG Compression (c) Illumination change (d) Viewpoint change (e) Scale change, and (f) Scale+Rotation.

The confusion matrixes in Figure 4.35 shows the results of the MSER descriptor + RANSAC. The combination performed well under Scale Change but performed poorly against other image deformation categories.

[illegible]

Actual classes	Predicted classes																					
	Plaited mat motif	BLA	BB	BA	BBBekarung	BBBepaying	BBG	BKNB	BP	BK	BLM	BLT	BMP	BM	BNB	BNN	BS	BSA	BTGB	BTL	BT	Unresolved
	BLA	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00
	BB	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00
	BA	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BBBekarung	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BBBepaying	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BBG	0.00	0.20	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BKNB	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BK	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BLM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20
	BLT	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BMP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20
	BM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BNB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BNN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
	BS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
	BSA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00
	BTGB	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00
BTL	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	
BT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	

Actual classes	Plaited mat motif	Predicted classes																			
		BLA	BB	BA	BBBekarung	BBBepayung	BBG	BKNB	BP	BK	BLM	BLT	BMP	BM	BNB	BNN	BS	BSA	BTGB	BTL	BT
	BLA	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BB	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BA	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BBBekarung	0.20	0.00	0.00	0.60	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00
	BBBepayung	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BBG	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BKNB	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BK	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.60	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BLM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BLT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BMP	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BNB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BNN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
	BS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
	BSA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00
	BTGB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
	BTL	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00
	BT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00

(e)

Actual classes	Predicted classes																					
	Plaited mat motif	BLA	BB	BA	BBBekarung	BBBepayung	BBG	BKNB	BP	BK	BLM	BLT	BMP	BM	BNB	BNN	BS	BSA	BTGB	BTL	BT	unresolved
	BLA	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BB	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20
	BA	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BBBekarung	0.20	0.00	0.20	0.40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00
	BBBepayung	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BBG	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BKNB	0.00	0.00	0.00	0.00	0.00	0.60	0.40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BK	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	0.40	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BLM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BLT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BMP	0.00	0.00	0.60	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20
	BM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BNB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.20
	BNN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.60	0.00	0.00	0.00	0.00	0.00	0.40
	BS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
	BSA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00
	BTGB	0.00	0.00	0.00	0.00	0.20	0.40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	0.00	0.00	0.00
BTL	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	
BT	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	0.00	

(f)

Figure 4.35: Confusion matrixes from the classification results using MSER+RANSAC, under the following image deformation type, i.e., (a) Blur (b) JPEG Compression (c) Illumination change (d) Viewpoint change (e) Scale change, and (f) Scale+Rotation.

Finally, in Figure 4.36, the confusion matrixes show the results of the FAST descriptor + RANSAC. This combination performed poorly under Blur change, where zero correspondences were found. FAST also has the highest number of unresolved classes for the rest of the image deformation types.

Actual classes	Plaited mat motif	Predicted classes																			
		BLA	BB	BA	BBBekarung	BBBepayung	BBG	BKNB	BP	BK	BLM	BLT	BMP	BM	BNB	BNN	BS	BSA	BTGB	BTL	BT
	BLA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BBBekarung	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BBBepayung	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BBG	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BKNB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BK	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BLM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BLT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BMP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BNB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BNN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BSA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BTGB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BTL	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

(a)

		Predicted classes																					
		BLA	BB	BA	BBBekarung	BBBepayung	BBG	BKNB	BP	BK	BLM	BLT	BMP	BM	BNB	BNN	BS	BSA	BTGB	BTL	BT	Unresolved	
Actual classes	Plaited mat motif																						
	BLA	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	BB	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	
	BA	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	BBBekarung	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	BBBepayung	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	BBG	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	
	BKNB	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	BP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	BK	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	BLM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	
	BLT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	BMP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	
	BM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	BNB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	
	BNN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.20	
	BS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.20	
	BSA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	
	BTGB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	
	BTL	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	
BT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.20	0.00		

(b)

[illegible]

Actual classes	Predicted classes																						
	Plaited mat motif	BLA	BB	BA	BBBekarang	BBBepaying	BBG	BKNB	BP	BK	BLM	BLT	BMP	BM	BNB	BNN	BS	BSA	BTGB	BTL	BT	Unresolved	
	BLA	0.40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.60	
	BB	0.00	0.60	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	
	BA	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	
	BBBekarang	0.00	0.00	0.00	0.60	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.20	0.00
	BBBepaying	0.00	0.00	0.00	0.00	0.40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.40
	BBG	0.00	0.00	0.00	0.00	0.00	0.60	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40
	BKNB	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00
	BP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.60	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.20
BK	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	
BLM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.60	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	
BLT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.60	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	
BMP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	
BM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	
BNB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.60	
BNN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.60	0.00	0.00	0.00	0.00	0.00	0.00	0.40	
BS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.20	
BSA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.20	
BTGB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.20	
BTL	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.40	0.00	0.40	
BT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.20	

Actual classes	Plaited mat motif	Predicted classes																				
		BLA	BB	BA	BBBekarung	BBBepayung	BBG	BKNB	BP	BK	BLM	BLT	BMP	BM	BNB	BNN	BS	BSA	BTGB	BTL	BT	Unresolved
BLA	0.40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.20	0.00	0.20
BB	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80
BA	0.00	0.00	0.40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.60
BBBekarung	0.60	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00
BBBepayung	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	0.00	0.00	0.00	0.00	0.40
BBG	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80
BKNB	0.00	0.00	0.00	0.00	0.00	0.60	0.20	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BP	0.40	0.00	0.00	0.20	0.00	0.00	0.00	0.40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BK	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.60	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40
BLM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.60
BLT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.60
BMP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.60	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40
BNB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.60	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40
BNN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	0.00	0.00	0.00	0.00	0.00	0.00	0.60
BS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	0.00	0.00	0.00	0.00	0.00	0.60
BSA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.20	0.00	0.00	0.00	0.00	0.60
BTGB	0.00	0.20	0.00	0.00	0.00	0.40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.20
BTL	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	0.00	0.00	0.20	0.00	0.00	0.20
BT	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.60	0.20	0.20

(e)

Actual classes	Plaited mat motif	Predicted classes																				
		BLA	BB	BA	BBBekarung	BBBepayung	BBG	BKNB	BP	BK	BLM	BLT	BMP	BM	BNB	BNN	BS	BSA	BTGB	BTL	BT	Unresolved
BLA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
BB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
BA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
BBBekarung	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BBBepayung	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80
BBG	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80
BKNB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80
BP	0.40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20
BK	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.60
BLM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80
BLT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80
BMP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.60
BM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80
BNB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.80
BNN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.80
BS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
BSA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	0.00	0.00	0.00	0.00	0.60
BTGB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80
BTL	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.80
BT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.40	0.40	0.40

(f)

Figure 4.36: Confusion matrixes from the classification results using FAST+RANSAC, under the following image deformation type, i.e., (a) Blur (b) JPEG Compression (c) Illumination change (d) Viewpoint change (e) Scale change, and (f) Scale+Rotation.

4.4.8 Failure point for each image descriptor

Each feature detector's failure point at each image deformation level is reported in Table 4.21 to Table 4.25. It is observed that BRISK+RANSAC performed quite well for all deformation types, with false matches only starting at the fifth level of illumination change compared to SIFT PeakThr 0.02 +RANSAC and SURF+RANSAC. SIFT+RANSAC's failure point was identified at the first level of blur, JPEG Compression, and viewpoint change. Both MSER+RANSAC and FAST+RANSAC descriptors failed to return any True Positive for all deformation categories, except for JPEG Compression. FAST+RANSAC performed the worst, particularly under Blur and Scale+Rotation. Overall, BRISK+RANSAC demonstrated the best performance by returning a True Positive for all deformation types at almost all degrees of complexity. However, the reported failure points do not serve as an indicator of overall matching accuracy (Joseph et al., 2021).

Table 4.21: The failure point of SIFT + RANSAC (with Peak Thr value of 0.02), for each image deformation category.

Level of image deformation	Blur	Illumination	JPEG _Compression	Scale	Viewpoint	Scale + rotation
Img1	FP	TP	FP	TP	FP	TP
Img2	FP	FP	FP	TP	FP	TP
Img3	FP	FP	FP	TP	FP	TP
Img4	FP	FP	FP	TP	FP	FP
Img5	FP	FP	FP	TP	FN	FP

Table 4.22: The failure point of SURF + RANSAC for each image deformation category.

Level of image deformation	Blur	Illumination	JPEG _Compression	Scale	Viewpoint	Scale + rotation
Img1	TP	TP	TP	TP	FP	TP
Img2	TP	TP	TP	TP	FP	FP
Img3	FP	TP	TP	TP	FP	FP
Img4	FN	TP	TP	TP	FP	FP
Img5	FN	FN	FP	TP	FP	FN

Table 4.23: The failure point of BRISK + RANSAC for each image deformation category.

Level of image deformation	Blur	Illumination	JPEG _Compression	Scale	Viewpoint	Scale + rotation
Img1	TP	TP	TP	TP	TP	TP
Img2	TP	TP	TP	TP	TP	TP
Img3	TP	TP	TP	TP	FP	FP
Img4	TP	TP	TP	TP	FP	FP
Img5	FP	FN	TP	TP	FP	FP

Table 4.24: The failure point of MSER + RANSAC for each image deformation category.

Level of image deformation	Blur	Illumination	JPEG _Compression	Scale	Viewpoint	Scale + rotation
Img1	FP	FP	TP	FP	FP	FP
Img2	FN	FP	TP	FP	FP	FP
Img3	FN	FN	TP	FP	FP	FP
Img4	FN	FN	TP	FP	FP	FP
Img5	FN	FN	FP	FP	FN	FN

Table 4.25: The failure point of FAST + RANSAC for each image deformation category.

Level of image deformation	Blur	Illumination	JPEG _Compression	Scale	Viewpoint	Scale + rotation
Img1	FN	FP	TP	FP	FP	FN
Img2	FN	FP	TP	FN	FP	FN
Img3	FN	FN	TP	FN	FN	FN
Img4	FN	FN	TP	FN	FN	FN
Img5	FN	FN	FP	FN	FN	FN

4.4.9 Performance Measures

Based on the Precision (positive Predicted Value) graph shown in Figure 4.37. BRISK+RANSAC has the highest precision, which shows that the algorithm had performed well on our dataset of plaited Iban mat motifs. SURF + RANSAC, SIFT PeakThr 0.02 + RANSAC and MSER+RANSAC achieved a lower precision than BRISK+RANSAC. FAST+RANSAC had the poorest precision performance, especially for Blur test sequences.

The FAST+RANSAC combination may demonstrate poorer precision performance in blur test sequences due to several interrelated factors. Firstly, the blurring of images can significantly degrade the distinctiveness of corners and edges that FAST relies on for keypoint detection, leading to inaccuracies in keypoint localization. Additionally, the smoothing effect of blurring can diminish the discriminative power of feature descriptors, making it challenging for RANSAC to accurately match keypoints between blurry images. Moreover, blurring introduces spatial correlations and reduces texture details, increasing the likelihood of false positives as nearby keypoints may erroneously match. Furthermore, the distortion of geometric structures caused by blurring complicates the estimation of accurate geometric transformations by RANSAC, resulting in a higher number of incorrect correspondences. Collectively, these challenges contribute to the poorer precision performance observed when using FAST+RANSAC in blur test sequences in Iban plaited mat motif.

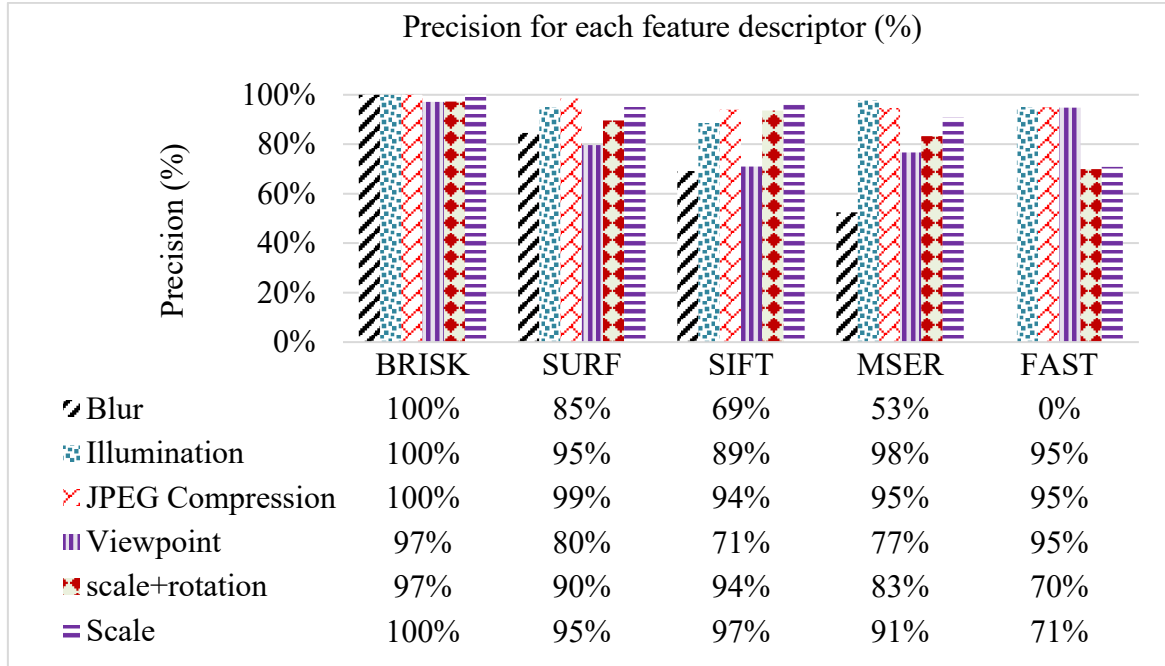


Figure 4.37: Precision for each feature descriptor against 6 typical image deformations.

Figure 4.38 shows the percentage of true positive rate or sensitivity. BRISK+RANSAC performed well in finding the correct matches based on the detected features' descriptions. The higher the TPR value, the better the performance of the descriptors. The high true positive rate (74%) observed with the BRISK+RANSAC combination in blur test sequences and its perfect sensitivity (100%) in JPEG compression for Iban plaited mat motifs can be attributed to several key factors. Firstly, the robustness of BRISK descriptors to image deformations, including blurring and compression artifacts, ensures that distinctive representations of keypoints are maintained even in challenging conditions. Additionally, RANSAC's accurate estimation of geometric transformations between matched keypoints further enhances the reliability of correspondences, effectively filtering out outlier matches. The effectiveness of BRISK descriptors in handling noise and small ornaments, coupled with RANSAC's adaptability to different types and levels of image distortions, contributes to the combination's excellent performance across various

deformation scenarios. These factors collectively underscore the strength of the BRISK+RANSAC approach in achieving high true positive rates and sensitivity in matching keypoints across Iban plaited mat motif images affected by different types of image deformations.

However, FAST+RANSAC combination exhibit a 0% true positive rate or sensitivity in blur test sequences for Iban plaited mat motifs due to several factors. Firstly, the blurring effect reduces the distinctiveness of keypoints, making it challenging for FAST to detect discernible keypoints in the blurred regions. Even if keypoints are detected, the degradation of feature descriptors computed around these keypoints in blurred areas diminishes their discriminative power, hindering RANSAC's ability to accurately match keypoints between reference and query images. Additionally, the increased visual similarity of nearby image regions caused by blurring leads to a higher number of false positives, further complicating the matching process. Moreover, the distortion of geometric structures in blurred images presents challenges for RANSAC in accurately estimating geometric transformations between keypoints, resulting in a lack of true correspondences. Consequently, these challenges collectively contribute to the 0% true positive rate observed when using FAST+RANSAC in blur test sequences for Iban plaited mat motifs.

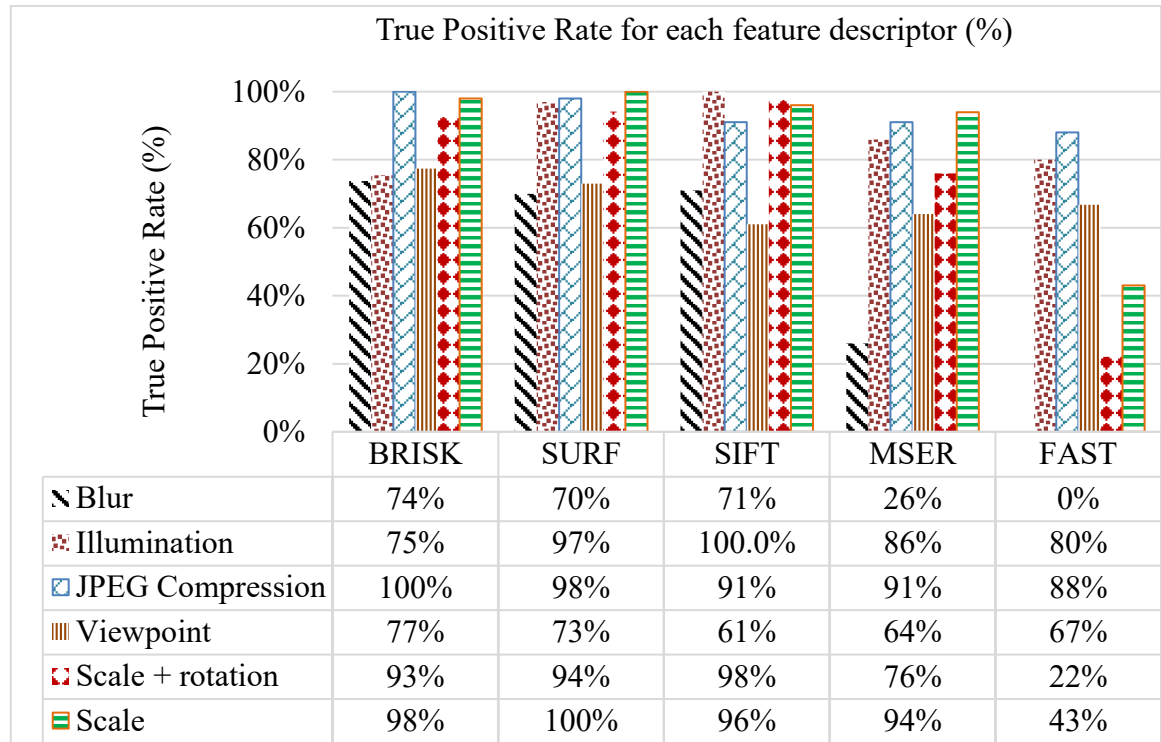


Figure 4.38: True positive rate for each feature descriptor against 6 typical image deformations.

BRISK+RANSAC was reported to have an F1 scores of 0.9, and followed by SURF + RANSAC (0.8), SIFT PeakThr 0.02 + RANSAC (0.8), MSER+ RANSAC (0.7), and FAST+RANSAC (0.5), against each image deformation type, respectively as show in Figure 4.39. The reported high F1 score (0.9) achieved by the BRISK+RANSAC combination when applied to Iban plaited mat motifs stems from its robustness to image deformations, including changes in scale, rotation, and illumination. BRISK descriptors, designed to capture distinctive local image structures in a binary format, provide reliable keypoints for RANSAC to accurately estimate geometric transformations between matched keypoints in the reference and query images. This accurate estimation ensures high precision in matching keypoints and effectively filters out incorrect correspondences, contributing to the high F1 score. Additionally, BRISK+RANSAC demonstrates robust

performance across various deformation types encountered in Iban plaited mat motifs, maintaining a balance between precision and recall and effectively capturing relevant keypoints while minimizing false positives and false negatives. Overall, the combination's ability to handle diverse variations of the motif with accuracy and reliability underscores its effectiveness in achieving a high-quality performance assessment.

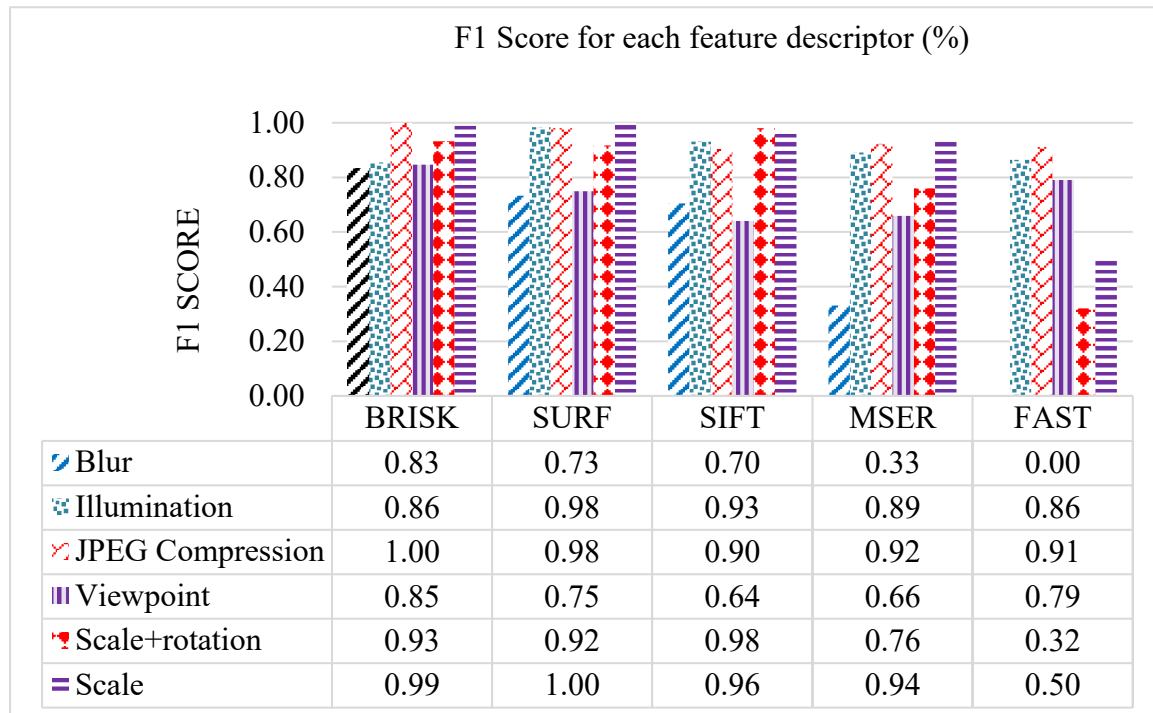


Figure 4.39: F1 Score for each feature descriptor against 6 typical image deformations.

In contrast, FAST+RANSAC had an average of 51% misclassification rate compared to BRISK + RANSAC, which only had an average of 15% misclassification rate, as seen in Figure 4.40. This is due to several factors. Firstly, the limited robustness of FAST keypoints to various image deformations, such as changes in scale, rotation, and illumination, may result in inaccurate keypoint detection and localization. Additionally, challenges in descriptor matching, combined with susceptibility to noise and artifacts, further contribute to misclassifications. Ineffective geometric transformation estimation by RANSAC exacerbates the problem, as inaccuracies in keypoint localization and descriptor

matching hinder the establishment of reliable correspondences between keypoints. Moreover, FAST's limited adaptability to diverse image deformations may result in significant performance degradation under complex conditions, ultimately leading to a higher misclassification rate. Overall, these factors collectively underscore the challenges associated with the FAST+RANSAC combination in accurately matching keypoints across Iban Plaited mat motifs affected by various image deformations.

Second highest misclassification rate is using MSER+RANSAC for matching in Iban plaited mat motifs, regardless of complexity, may encounter limitations resulting in high failure rates. These limitations encompass sensitivity to texture and contrast, where MSER might struggle to detect stable extremal regions accurately, particularly in areas with subtle texture variations or low contrast, leading to missed features or erroneous matches. Additionally, in intricate motifs, MSER may fail to capture fine details, resulting in incomplete feature representation and inaccurate matching. Scale variations in Iban plaited mat motifs pose another challenge, as MSER's stability criteria may struggle to handle such variations, leading to mismatches or failure to detect relevant features across different sizes. Moreover, MSER's fixed algorithmic approach may not adequately adapt to the diverse structural characteristics of these motifs, limiting its effectiveness in accurately representing and matching features. Furthermore, noise interference can also impede MSER's performance, particularly in simpler motifs, where noise patterns might be mistaken for stable extremal regions, leading to incorrect feature detection and matching.

Overall, the lower misclassification rate observed with BRISK+RANSAC highlights its effectiveness and robustness compared to the other feature descriptor in handling image deformations and achieving accurate keypoint matching.

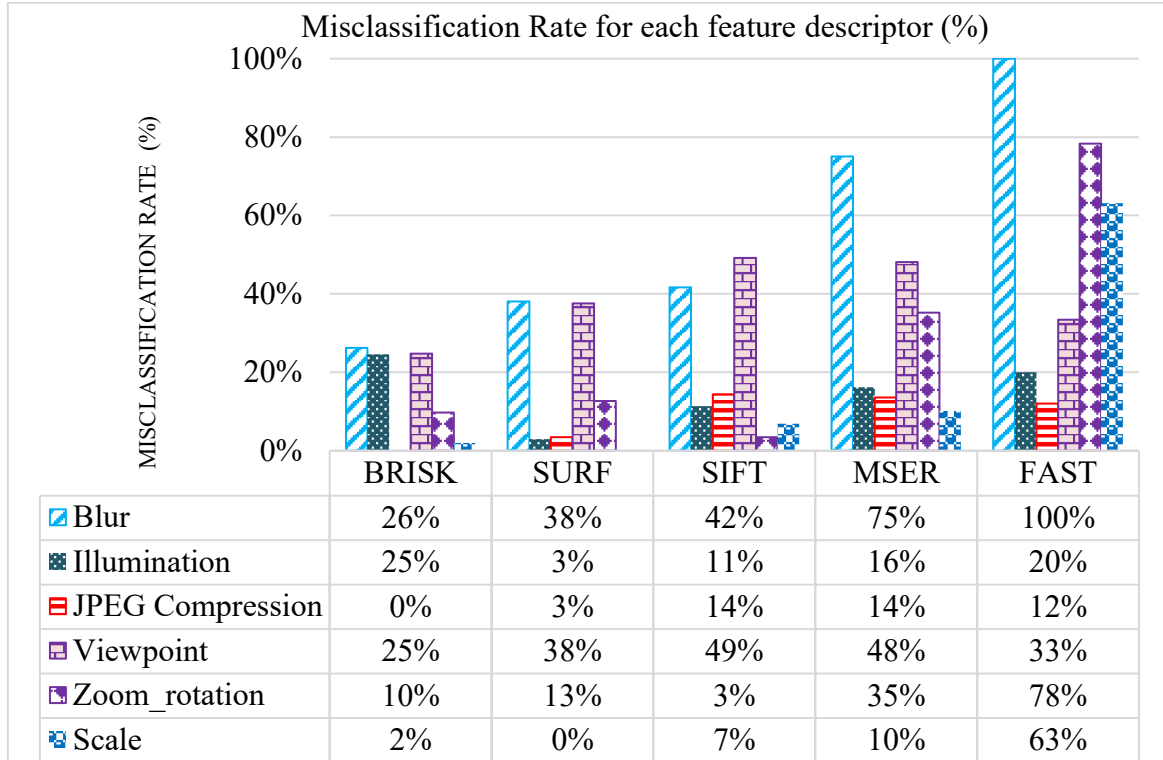


Figure 4.40: Misclassification rate for each feature detector and descriptor against 6 typical image deformations.

Finally for matching accuracy, the use of BRISK + RANSAC led to a higher average, i.e., 85.5% compared to SURF + RANSAC (84.2%), SIFT + RANSAC (78.8%), MSER + RANSAC (66.9%) and FAST + RANSAC (48.9%), across all Iban plaited mat motif classes, see Figure 4.41. The higher average matching accuracy achieved with the BRISK+RANSAC combination, ranging from 73.8% to 100% across various image deformation types, can be attributed to its robustness to transformations such as JPEG compression, scale changes, rotation, illumination, viewpoint variations, and blur. BRISK descriptors, known for their resilience to image distortions, facilitate accurate keypoint detection and matching, even in challenging scenarios. Additionally, the precise geometric transformation estimation provided by RANSAC ensures the retention of true

correspondences while filtering out erroneous matches. This adaptability to diverse deformations, coupled with the combination's robust matching process, underscores its superior performance in accurately establishing correspondences between keypoints of our dataset.

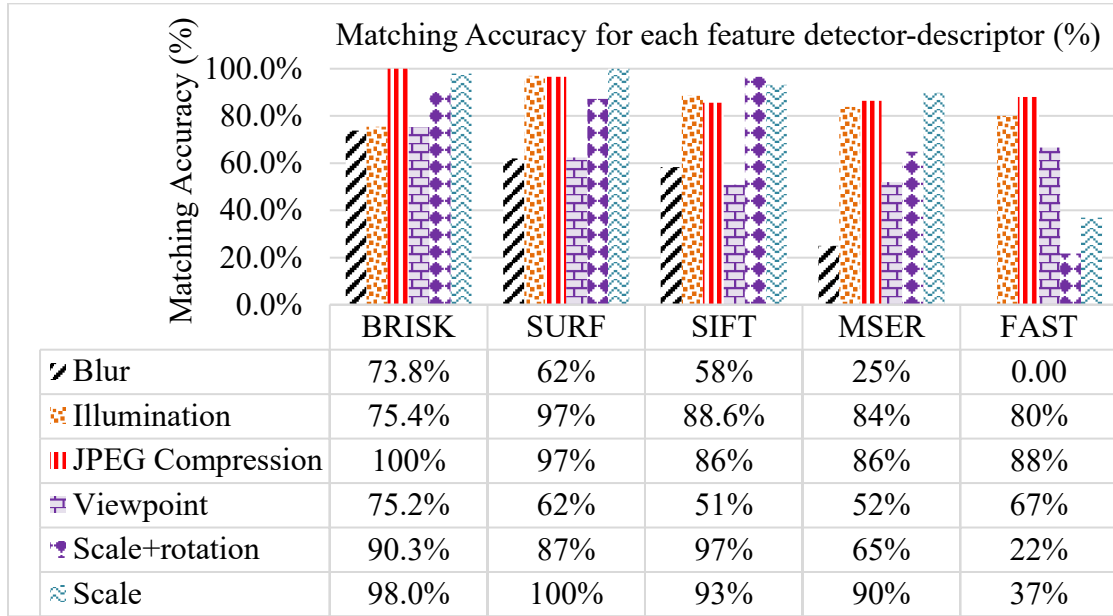


Figure 4.41: Matching accuracy for each feature detector and descriptor against 6 typical image deformations.

4.4.10 Summary

In this chapter, the performance of the following feature descriptors, namely SIFT PeakThr 0.02, SURF, BRISK, MSER, and FAST combined with RANSAC, was evaluated on the plaited Iban mat motifs dataset. The objective is to ascertain the most effective algorithm among them across 20 classes of simple and complex plaited Iban mat motifs. Overall, BRISK + RANSAC demonstrated superior performance compared to other feature descriptors when subjected to challenges such as JPEG compression, viewpoint change, scale change, and scale+rotation.

BRISK, in combination with RANSAC, surpassed other feature descriptors when dealing with JPEG compression, changes in viewpoint, scale, and rotation due to its binary nature, which makes it less sensitive to image alterations, and its robust matching capabilities. However, it exhibited lower accuracy in recognizing blur and illumination changes in the Iban plaited mat motif. This discrepancy could be attributed to the motif's intricate textures and the limited discrimination ability of BRISK's binary descriptors, potentially hindering its effectiveness in these scenarios. Additionally, RANSAC might not always effectively filter outliers or handle noise, further impacting BRISK's performance.

Hence, it was observed that most of the false matches resulted from the spurious matching of small motifs present in the image as decorative fillers. To address this challenge, a feature extraction approach was introduced, integrating adaptive smoothing to retain prominent and discriminative image structures while filtering out smaller features, thereby enhancing the overall accuracy of image matching. This methodology was elaborated in the next experiment.

4.5 Motif Classification using Adaptive Smoothing (Proposed Method)

The steps involved in the mat motif matching using edge images that have undergone adaptive smoothing are as follows: Firstly, the detection of BRISK keypoints was initiated, where distinctive points in the smoothed edge images were identified. Subsequently, descriptors were constructed for these keypoints, capturing their local image structures. Then, nearest neighbor distance ratio matching of BRISK descriptors was performed, assessing the similarity between keypoints based on the Hamming distance. A small Hamming distance value indicates a close match, signifying similarity between descriptors, while a large value suggests a poor match. To address potential false matches,

Random Sample Consensus (RANSAC) is employed. RANSAC randomly selects an initial subset of correspondences and iteratively estimates a transformation matrix that aligns the reference image with the query image. Correspondences that consistently adhere to the transformation matrix are considered inliers, ensuring the robustness of the matching process despite potential outliers or noise in the data. This methodology, integrated with adaptive smoothing, enhances the accuracy and reliability of mat motif matching by effectively handling variations in edge images that representations of Iban plaited mat motif where only the outlines or boundaries are highlighted.

In this section, all four schemes and their results are presented and discussed. The classification statistic report utilizes the following variables for analysis, i.e., number of detected reference image's keypoints, N_{tmp} , number of detected query image's keypoints, N_{qry} , the number of matches found, N_{crp} , and the number of correct matches after RANSAC, N_{mch} .

4.5.1 Detected Keypoints

Figure 4.42 depicts the visualization of BRISK descriptors alongside the count of detected keypoints within the reference image generated using the standard Canny filter. It's evident that complex motifs exhibit a higher number of detected keypoints compared to simple mat motifs, which show fewer detected keypoints. The provided sample edge images illustrate that BRISK successfully captured a substantial number of keypoints within the mat motif images from our dataset.

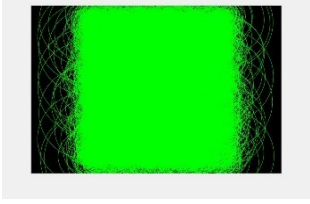
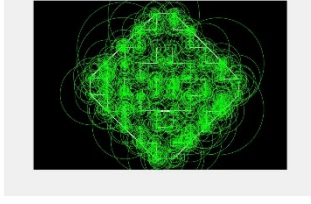
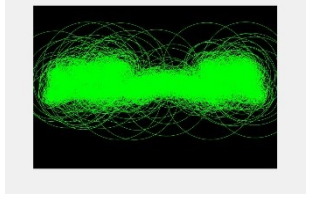
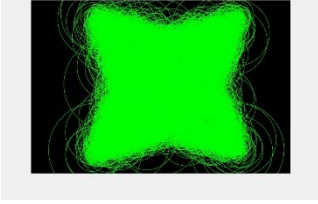
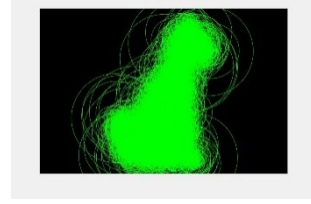
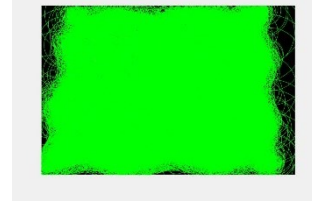
<i>Buah Lang Antu</i>	<i>Buah Mata Punai</i>	<i>Buah Nabau Besundang</i>
		
$N_{tmp} = 16214$	$N_{tmp} = 813$	$N_{tmp} = 2834$
<i>Buah Andu</i>	<i>Buah Mayau</i>	<i>Buah Suri Ai</i>
		
$N_{tmp} = 8060$	$N_{tmp} = 4943$	$N_{tmp} = 20623$

Figure 4.42: Visualized BRISK descriptors (green color) on reference images produced using standard Canny edge detection.

Figure 4.43 shows visualized BRISK descriptors inside a set of edge images belonging to *Buah Mata Punai*, produced using ProHT PoRE-Canny algorithm. The edge images were produced using the following PoRE values, i.e., 100.0%, 75.0%, 70.0%, 50.0%, and 20.0%, without dilation. A trend emerged where the number of detected keypoints decreased as the PoRE value became more stringent. Specifically, with a PoRE value of 100.0% (no adaptive smoothing), the number of keypoints totaled 646. However, this count diminished to 453 when employing a PoRE value of 70.0%, attributed to the removal of weaker edges from the initial edge image.

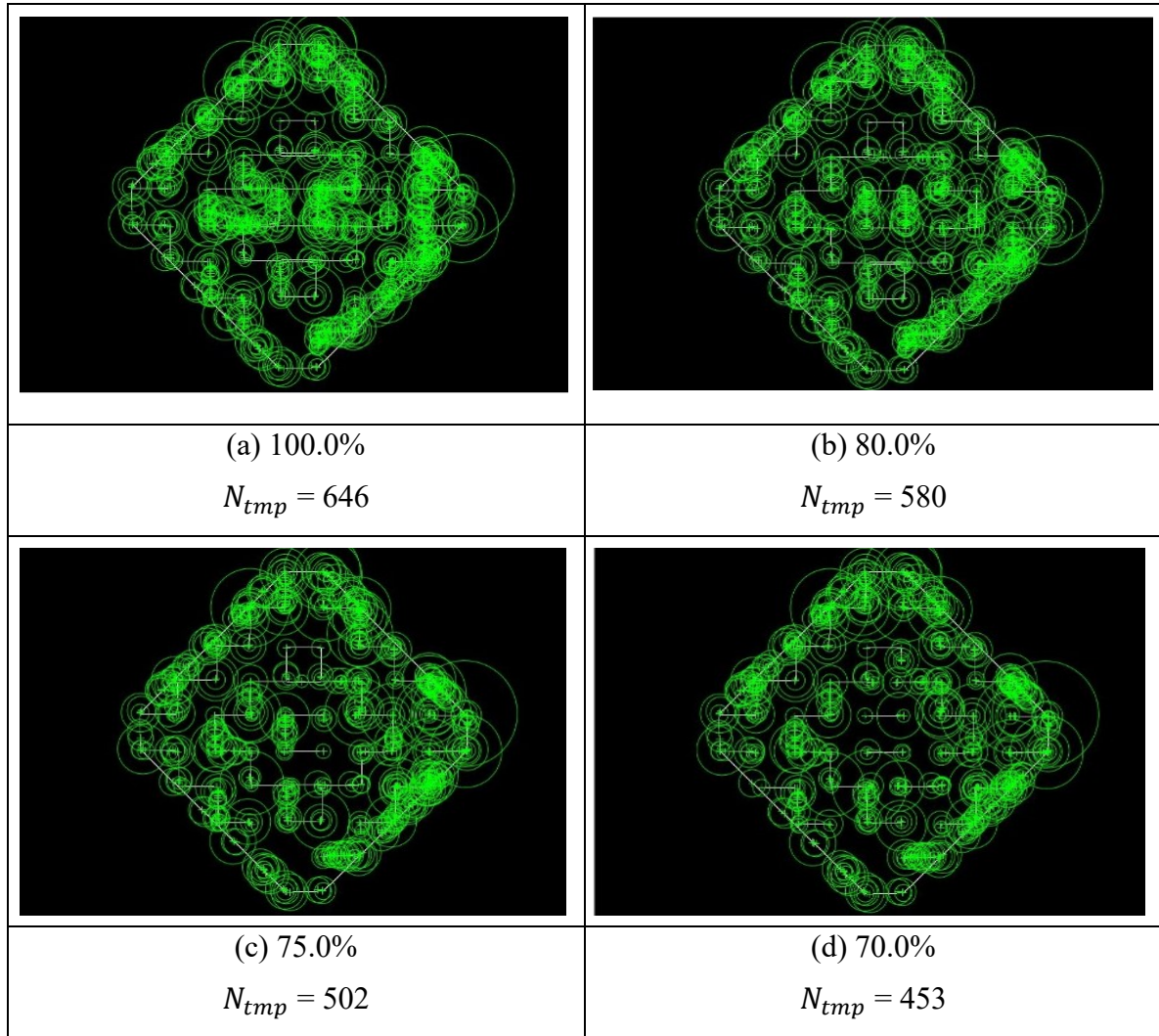


Figure 4.43: Visualized BRISK descriptors (green color) in reference images of *Buah Mata Punai* produced using ProHT PoRE-Canny algorithm with PoRE values of (a) 100.0%, (b) 75.0%, (c) 70.0%, (g) 50.0%, and (h) 20.0%. No dilation.

Figure 4.44 shows visualized BRISK descriptors inside a set of edge images belonging to *Buah Mata Punai*, produced using ProHT PoRE-Canny algorithm. The edge images were produced using the following PoRE values, i.e., 100.0%, 90.0%, 80.0%, 85.0%, 75.0%, 70.0%, 50.0%, and 20.0%, with dilation. Following dilation, there was an augmentation in the count of detected keypoints.

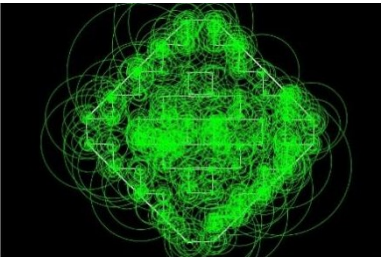
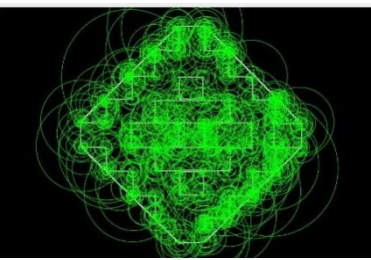
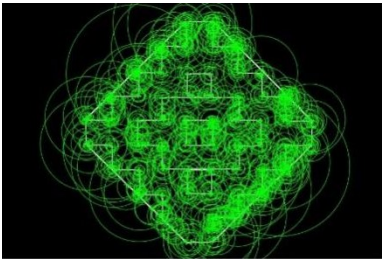
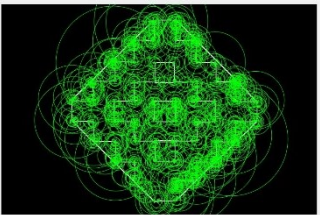
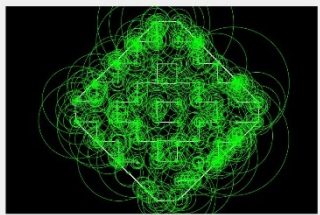
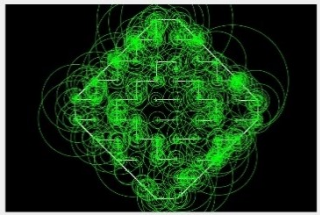
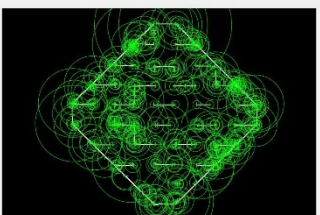
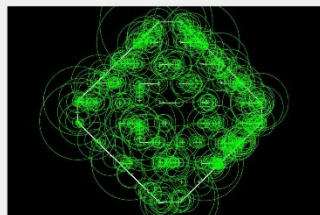
		
<i>Buah Mata Punai</i>	(a) 100% $N_{tmp} = 906$	(b) 90% $N_{tmp} = 868$
		
(c) 85 % $N_{tmp} = 817$	(d) 80% $N_{tmp} = 820$	(e) 75% $N_{tmp} = 683$
		
(f) 70% $N_{tmp} = 603$	(g) 50% $N_{tmp} = 418$	(h) 20% $N_{tmp} = 566$

Figure 4.44: Visualized BRISK descriptors (green color) in reference images of *Buah Mata Punai* produced using ProHT PoRE-Canny algorithm with PoRE values of (a) 100.0%, (b) 90.0%, (c) 80.0%, (d) 85.0%, (e) 75.0%, (f) 70.0%, (g) 50.0% and (h) 20.0%. With dilation.

Further evidence demonstrating the positive impact of dilation on the quantity of detected keypoints is presented. Table 4.26 shows the number of found BRISK keypoints

in *Buah Lang Antu* in query images, i.e., deformation first level vs. deformation fifth level, with and without dilation. For instance, the percentage increase in the number of detected keypoints inside the first dilated query image versus the non-dilated one from the Blur's test sequence is 1164.8%, rising from 344 to 4,351 keypoints.

Table 4.26: Comparison between deformations Level 1 vs. Level 5 regarding the number of detected BRISK keypoints in *Buah Lang Antu*. The query images were generated using the PoRE value of 75.0%, for every image deformation category, with and no morphological dilation.

Image deformation	w/o Dilation		w/ Dilation	
	First level	Fifth level	First level	Fifth level
Blur	344	0	4351	92
Illumination	4641	3002	5963	4087
Viewpoint	6728	5955	6321	6137
JPEG compression	5113	7195	6140	7937
Scale+Rotation	5206	2230	5348	2350
Scale	4831	2014	5067	2022

4.5.2 Matching Results

Selected matching results are displayed in Figure 4.45 (a) *Buah Bandau* with blurring, (b) *Buah Tungku Lebur* with viewpoint change, (c) *Buah Nabau Ngelantar* with scale change, (d) *Buah Tungku* with scale and rotation (e) *Buah Mayau* with illumination change, (f) *Buah Bulan Bekarung* with JPEG compression, compare query images produced using the first level of deformation (left column) vs. the fifth level (right column).

Illustrating that with the proposed method, sufficient correspondences are found, even at the fifth deformation level. While a large number of correspondences is typically preferred for robustness, the extreme nature of transformations at this level anticipates a smaller number. However, despite this expectation, the proposed method still manages to yield an adequate number of correspondences, which is essential for tasks like correct label classification. This success contrasts with other matching results, which often produce either zero or minimal correspondences, highlighting the superiority of the proposed method in handling complex image transformations and generating meaningful results even in challenging scenarios.

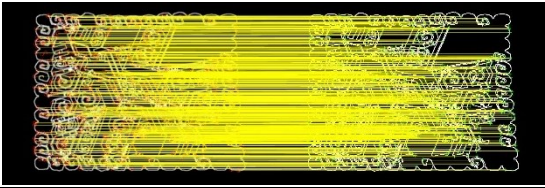
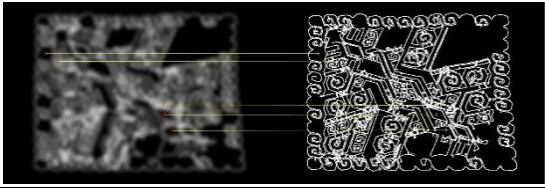
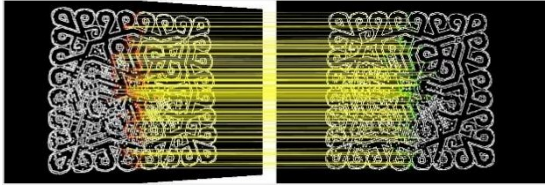
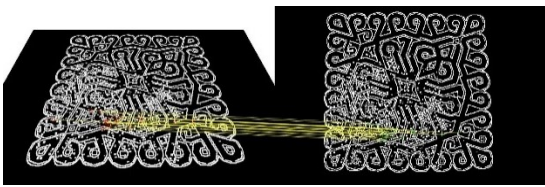
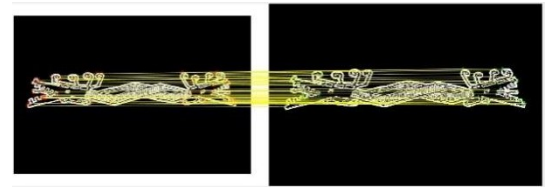
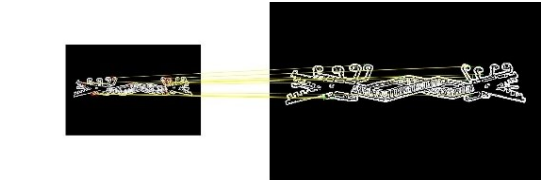
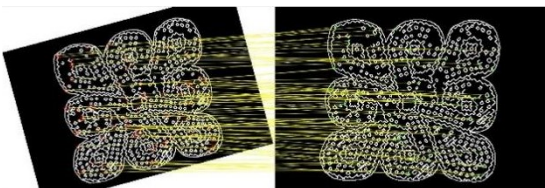
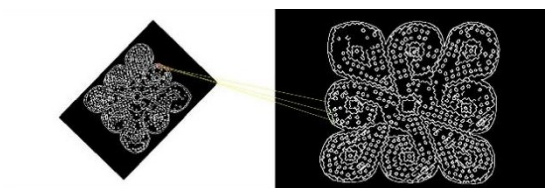
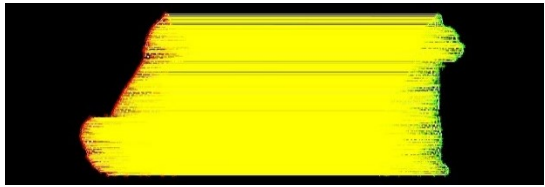
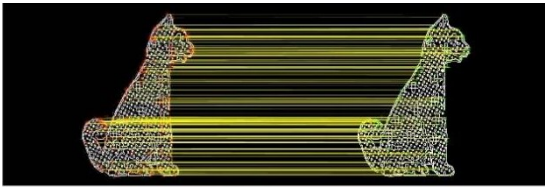
	Level 1	Level 5
(a)		
	$N_{mch} = 813$	$N_{mch} = 5$
(b)		
	$N_{mch} = 217$	$N_{mch} = 19$
(c)		
	$N_{mch} = 70$	$N_{mch} = 13$
(d)		
	$N_{mch} = 89$	$N_{mch} = 3$
(e)		
	$N_{mch} = 2628$	$N_{mch} = 153$
(f)		
	$N_{mch} = 9272$	$N_{mch} = 4546$

Figure 4.45: Matching results using BRISK+RANSAC

N_{mch} = The number of correct matches after RANSAC)

4.5.3 Confusion Matrix Results, Using Scheme 4

The confusion matrices of the classification results obtained using Scheme 4, with a PoRE value of 75.0% and dilation, are presented in Figure 4.46 (a) Blur change, Illumination change, (c) JPEG Compression, (d) Scale change, (e) Viewpoint change. The confusion matrix has 20 actual classes and 20+1 predicted classes. The additional presented class, class Unresolved, serves to address situations where classification system registers zero matches, particularly concerning the blur change deformation. The inclusion of this class denotes instances where the algorithm struggles to establish significant correspondences between keypoints in both reference and query images amid conditions of blur change. This difficulty could arise from the blurring effect obscuring critical structural features of the motif, thereby complicating the algorithm's ability to identify appropriate matches.

While for scale+rotation see Figure 4.46 (f) scale+rotation refers to a deformation scenario where the motif undergoes both scaling (resizing) and rotation transformations. In a situation where a motif is uniform and relatively simple, such transformations may not significantly impact its appearance, allowing for accurate classification. However, for complex motifs, especially those with intricate patterns or details, the combination of scale and rotation transformations can distort the motif's structure, making it challenging for the classification system to accurately identify and classify it. In such cases, the complexity of the motif may lead to misclassification, where the system incorrectly assigns it to the wrong class or fails to classify it altogether. This underscores the importance of robust classification algorithms capable of effectively handling various deformation scenarios, particularly for motifs with intricate designs e.g. *Buah Tangkai Gajai Besembah (BTGB)*

[illegible][illegible]

4.5.4 Comparative Failure Points for each Scheme

The failure points were documented for each image deformation category across the four schemes. Table 4.27 presents Scheme 4 (with a PoRE value of 75.0%) incorporating morphological dilation, demonstrating superior performance in handling Illumination change, JPEG compression, and Viewpoint change. For comparison, Table 4.28 illustrates Scheme 3 (also with a PoRE value of 75.0%), which is identical to Scheme 4 except for the absence of the morphological dilation step. The implementation of morphological dilation effectively enhances the detection of true positive keypoints across different deformation levels in Iban plaited mat motifs, contributing to more accurate and reliable feature extraction results.

Table 4.27: Failure points, obtained using Scheme 4.

Scheme 4: BRISK+RANSAC, ProHT PoRE-Canny algorithm with PoRE value of 75.0%, and morphological dilation						
Level of image deformation	Blur	Illumination	JPEG _Compression	Viewpoint	Scale	Scale + rotation
Img1	TP	TP	TP	TP	TP	TP
Img2	TP	TP	TP	TP	TP	FN
Img3	FN	TP	TP	TP	TP	TP
Img4	FN	TP	TP	TP	TP	FN
Img5	FN	TP	TP	TP	FN	FN

Table 4.28: Failure points, obtained using Scheme 3.

Scheme 3: BRISK+RANSAC, ProHT PoRE-Canny algorithm with PoRE value of 75.0%. without morphological dilation						
Level of image deformation	Blur	Illumination	JPEG _Compression	Viewpoint	Scale	Scale + rotation
Img1	FN	TP	TP	TP	FN	FN
Img2	FN	TP	TP	TP	FN	FN
Img3	FN	TP	TP	TP	FN	FN
Img4	FN	TP	TP	FN	FN	FN
Img5	FN	TP	TP	FN	FN	FN

For comparison purposes, the failure points encountered when using Scheme 1 are also reported, see Table 4.29, and Scheme 2, see Table 4.30.

Table 4.29: Failure points, obtained using Scheme 1.

Scheme 1: BRISK+RANSAC, using standard Canny filter						
Level of image deformation	Blur	Illumination	JPEG _Compression	Viewpoint	Scale	Scale + rotation
Img1	TP	TP	TP	TP	TP	TP
Img2	FN	TP	TP	TP	TP	FN
Img3	FN	TP	TP	TP	TP	FN
Img4	FN	TP	TP	FN	FN	FN
Img5	FN	TP	TP	FN	FN	FN

Table 4.30: Failure points, obtained using Scheme 2.

Scheme 2: BRISK+RANSAC, using standard Canny filter, and morphological dilation						
Level of image deformation	Blur	Illumination	JPEG _Compression	Viewpoint	Scale	Scale + rotation
Img1	TP	TP	TP	TP	TP	TP
Img2	TP	TP	TP	TP	TP	FN
Img3	FN	TP	TP	TP	TP	FP
Img4	FN	TP	TP	TP	TP	FN
Img5	FN	TP	TP	TP	FN	FN

From our observation, some of the failure cases are due to visually-similar mat motifs, as well as the motifs being complex in nature. *Buah Bulan Bepayung* and *Buah Tangkai Gajai Bersembah* are two examples of a highly complex motif. These motifs contain repetitive patterns and shapes, see Figure 4.47 (a) and (b). *Buah Bulan Bepayung* and *Buah Tangkai Gajai Bersembah* exemplify highly complex motifs due to their intricate and repetitive patterns and shapes. These motifs feature elaborate designs characterized by the repetition of intricate elements, such as curves, loops, and intersecting lines, which contribute to their complexity. The presence of repetitive patterns and shapes poses a significant challenge for the classification function, as it increases the likelihood of false correspondences being produced during the matching process. False correspondences occur when keypoints in one image erroneously match with keypoints in another image due to the similarities in their patterns, but they do not actually represent the same visual feature. This issue is exacerbated in highly complex motifs like *Buah Bulan Bepayung* and *Buah Tangkai Gajai Bersembah*, where the abundance of intricate details can lead to numerous false matches. However, false correspondences are later identified and rejected

by the Random Sample Consensus (RANSAC) algorithm during the verification stage. RANSAC iteratively estimates a transformation matrix that best aligns the keypoints between the reference and query images, and it identifies correspondences that deviate from this estimated matrix as outliers.

Failure cases may also occur when the motif is too simple or overly simplistic. An overly simplistic pattern refers to design that lacks complexity or intricacy, often comprising basic shapes or repetitive elements without much variation or detail. An example of such a motif is *Buah Mata Punai*, see Figure 4.47 (c). *Buah Mata Punai* is homogeneous in appearance, with few distinctive features and strong edges. It can easily be mistaken with another motif due to this reason. Moreover, *Buah Mata Punai*, characterized by its homogeneity in appearance, exhibits few distinctive features and strong edges. This uniformity in its visual characteristics poses challenges for accurate identification, as it shares similarities with other motifs. Due to its homogeneous nature, the motif lacks unique attributes that could distinguish it from similar motifs. Additionally, the presence of few edge features further complicates its recognition, as there is limited information available for distinguishing it from other motifs during feature extraction processes. Figure 4.48 shows the graph of average accuracy for the three motifs.

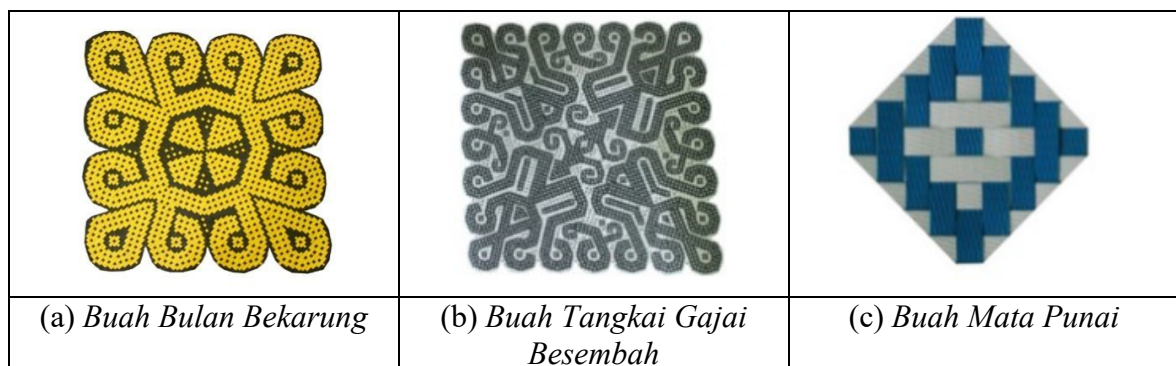


Figure 4.47: Three motifs with a high rate of misclassification.

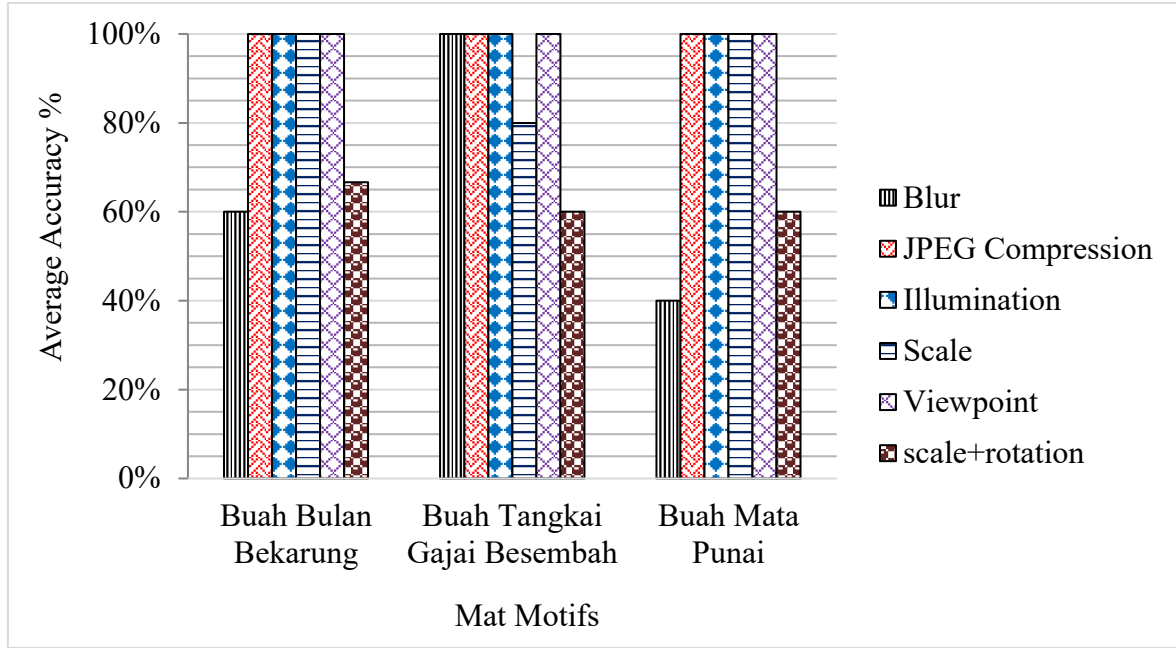


Figure 4.48: Three motifs that with failure cases under blur, scale and scale+rotation.

4.5.5 Optimal Scheme and Optimal PoRE Value

The classification accuracy was assessed by comparing the performance of the four schemes outlined previously. Table 4.31 presents the mean accuracy attained by each scheme, indicating that Baseline achieved an average accuracy of 85.5%, Scheme 1 attained 84.5%, Scheme 2 reached 94.9%, Scheme 3 achieved 78.6%, and Scheme 4 obtained 95.7%. Notably, Scheme 4 emerges as the optimal scheme due to its highest average accuracy compared to the other schemes.

Scheme 4 with PoRE value of 75.0% consistently produces higher average accuracy across all deformation types compared to alternative PoRE settings. The PoRE value represents the proportion of retained edges post-dilation, pivotal in determining feature matching quality. A higher PoRE implies better edge retention post-dilation, yielding more robust features for matching. Specifically, a 75.0% PoRE preserving critical features and enhancing matching accuracy. In contrast, other PoRE values like 100.0%,

90.0%, 80.0%, 85.0%, 70.0%, 50.0%, and 20.0% often result in lower average accuracy across deformation types due to either excessive edge loss or inadequate preservation, compromising matching quality. Therefore, analyzing matching accuracy at various PoRE values, with emphasis on the superiority of 75.0% PoRE, provides insights into the efficacy of the BRISK+RANSAC algorithm in addressing different deformation types and optimizing matching accuracy.

Table 4.31: The mean accuracy achieved by each scheme against different image deformation category. The PoRE value for Scheme 3 and 4 is 75.0%.

Scheme	Blur	Illumination	JPEG Compression	Viewpoint	Scale+Rotation	Scale	Average Matching Accuracy
Baseline	73.8%	75.4%	100.0%	75.2%	90.3%	98.0%	85.5%
Scheme 1	47.0%	100.0%	100.0%	95.0%	73.0%	92.0%	84.5%
Scheme 2	82.0%	100.0%	100.0%	100.0%	89.0%	98.2%	94.9%
Scheme 3	29.0%	100.0%	100.0%	89.0%	63.8%	90.0%	78.6%
Scheme 4	83.0%	100.0%	100.0%	100.0%	92.3%	99.0%	95.7%

Observations revealed that enabling dilation (Scheme 4) resulted in a 17.1% increase in average accuracy compared to no dilation (Scheme 3). The optimal scheme, i.e., Scheme 4, achieved an increase of 11.2% over the Scheme 1. The introduction of adaptive smoothing (Scheme 4 vs. Scheme 2) definitely increases the average accuracy, albeit small at only 0.8%. Our optimal scheme, i.e., Scheme 4 exhibits an average

improvement of 10.2% in classification accuracy compared to the evaluation using synthetic RGB images (i.e., Baseline scheme).

Figure 4.49 provides a comparative analysis between the Baseline approach and Scheme 4, showcasing the average accuracy for each type of image deformation.

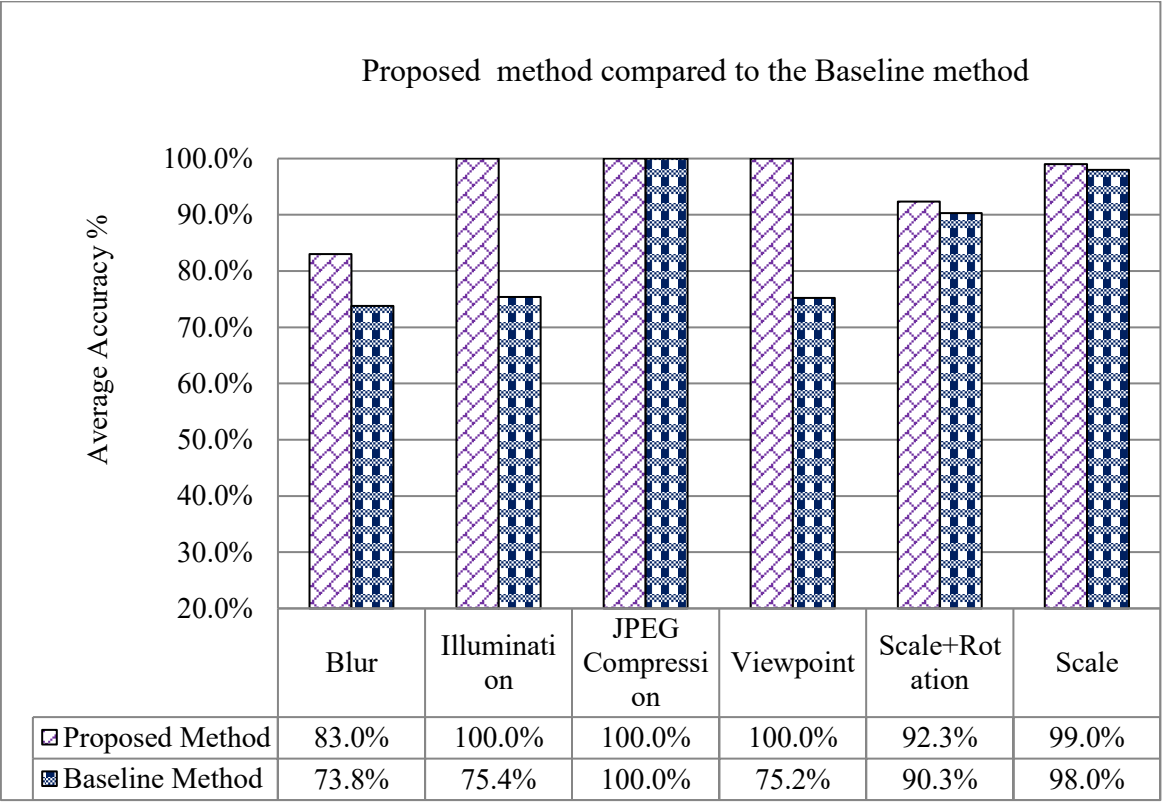


Figure 4.49: Baseline vs. Scheme 4 (PoRE value of 75.0%). Average accuracy obtained for each image deformation category.

Figure 4.50 shows a spider chart comparing the average accuracy obtained by each scheme under all image deformation categories. Scheme 4 appears to be the optimal scheme as it outperformed or matched the other schemes for all image deformation categories.

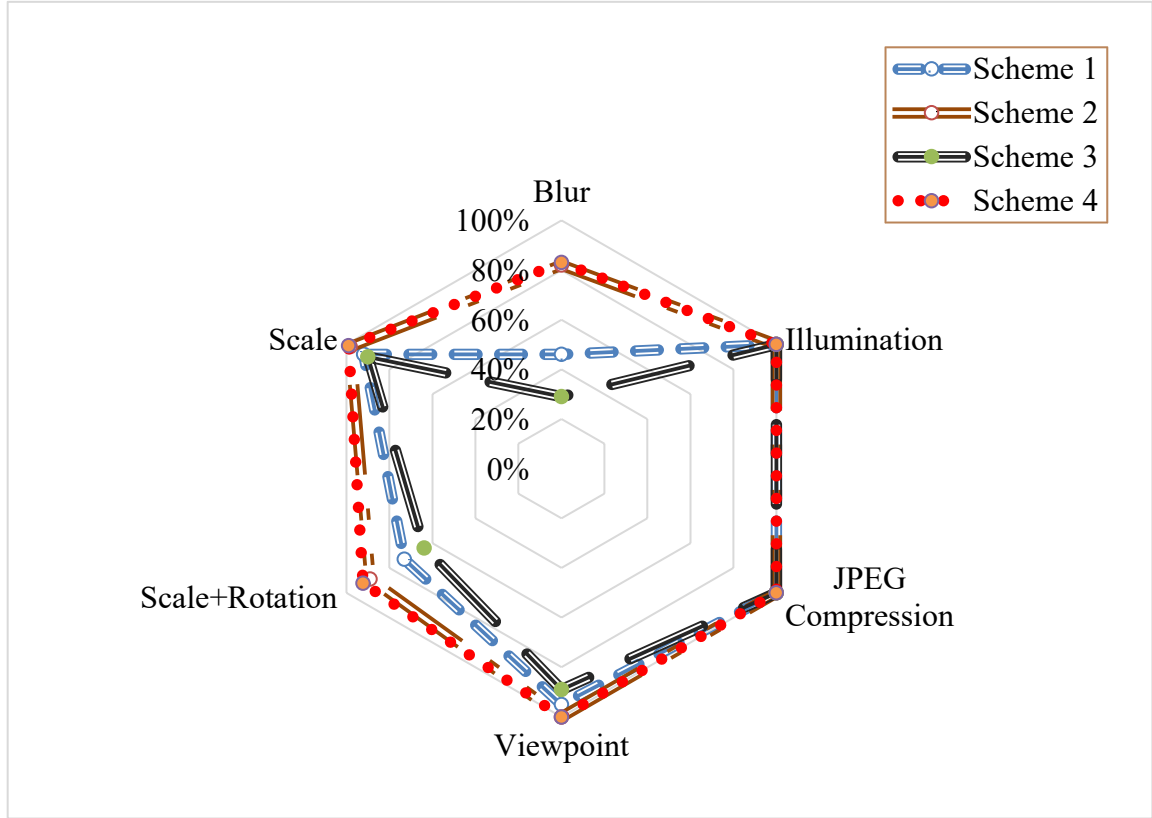


Figure 4.50: Average matching accuracy obtained by each scheme under each deformation category.

Figure 4.51 illustrates the average matching accuracy achieved using BRISK+RANSAC at different PoRE values. Notably, a PoRE value of 75.0% results in a relatively higher average accuracy across all deformation types. Specifically, the average accuracy per deformation type stands at 83.0% for Blur, 100.0% for Illumination, 100.0% for JPEG compression, 100.0% for Viewpoint, 92.0% for Scale+Rotation, and 99.0% for Scale.

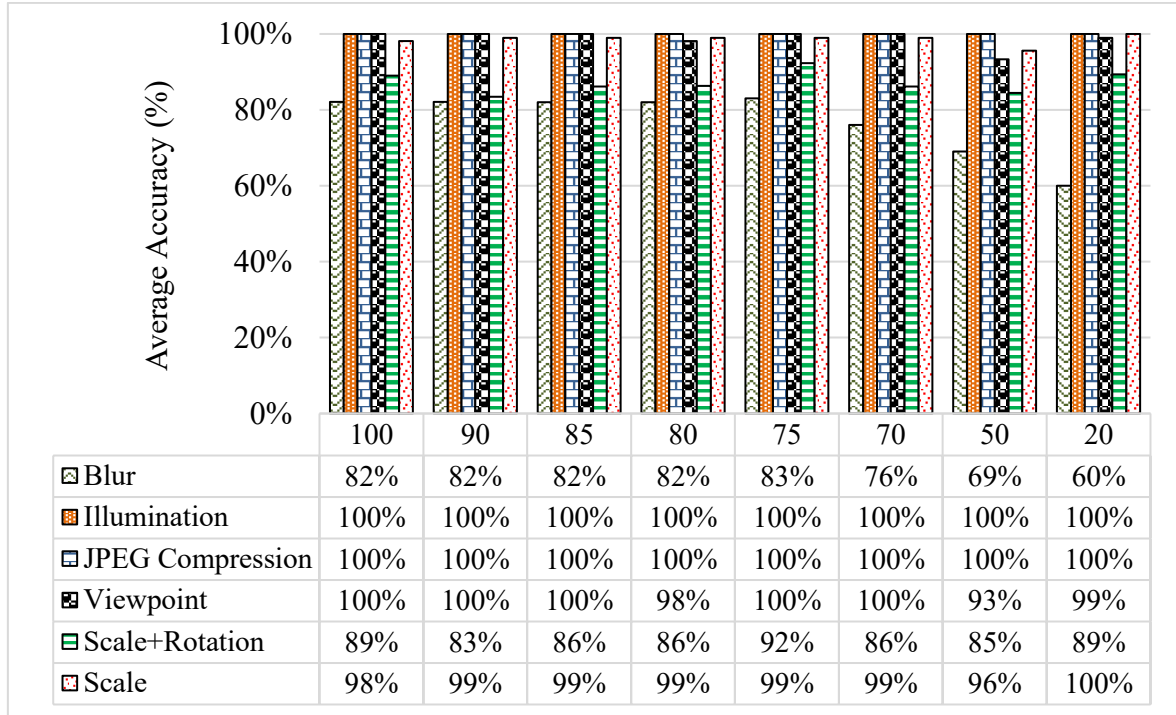


Figure 4.51: Average matching accuracy while using Scheme 4 at various PoRE values.

4.5.6 Summary

Four schemes were presented for classifying Iban mat motifs. Scheme 4, utilizing a PoRE value of 75.0% coupled with morphological dilation, demonstrated notably superior performance compared to the others. The incorporation of adaptive smoothing resulted in an average accuracy increase of 0.8% when comparing Scheme 4 to Scheme 2, a modest yet statistically significant improvement. Adaptive smoothing played a crucial role in mitigating false matches by eliminating small image structures (i.e., filler motifs), thereby enhancing label classification accuracy. Opting for morphological dilation yielded a substantial increase of 17.1% in accuracy when comparing Scheme 4 to Scheme 3. Remarkably, the combined approach in Scheme 4 outperformed both Scheme 1 and the Baseline method by 11.2% and 10.2%, respectively, showcasing its efficacy in classification accuracy enhancement.

4.6 Conclusion

This chapter provides background studies on the effectiveness of the SIFT features algorithm, highlighting its dependence on the PeakThr parameter. Lowering the PeakThr parameter reduces keypoints, diminishing feature count and resulting in lower average matching accuracy across six-image deformations. Conversely, a higher threshold value leads to fewer keypoints detected, especially in regions of lower contrast within motifs like the Iban plaited mat. SIFT+RANSAC performs well with a PeakThr parameter of 0.02, particularly in scale change and rotation scenarios, achieving an average accuracy of 88.0% across all deformation sequences. However, it struggles in evaluating the Iban plaited mat motif and viewpoint sequence, encountering difficulty with motifs lacking intricate details and variations.

Encouraged by the intriguing outcome from the first experiment, it was of interest to assess how well other feature descriptors i.e., SIFT PeakThr 0.02, SURF, BRISK, MSER, and FAST combined with RANSAC on plaited Iban mat motifs dataset. Results presented that, BRISK+RANSAC demonstrated lower accuracy in recognizing blur and illumination changes due to its binary nature and limited discrimination ability against intricate features in the Iban plaited mat motif. False matches often arose from small motifs serving as decorative fillers, leading to the introduction of an adaptive smoothing feature extraction approach involves the application of a modified Canny algorithm combined with PHT and PoRE. This method specifically targets the outline of a mat motif, while disregarding its inner region, thereby enhancing the clarity and prominence of the motif's edges for more effective feature extraction.

Through rigorous experimentation and analysis, it had been conclusively demonstrated that the adaptive smoothing feature extraction approach significantly enhances matching accuracy. This method had showed a remarkable ability to discern and preserve essential motif features while effectively filtering out extraneous noise and filler elements. By intelligently adjusting the smoothing parameters based on the characteristics of the motif images, the adaptive smoothing approach optimizes the extraction of discriminative features, leading to more precise matching results. The higher matching accuracy achieved with this approach underscores its efficacy in addressing the challenges posed by noisy backgrounds and decorative fillers in motif classification research, thereby validating its superiority in feature extraction for motif recognition tasks.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusion

The aim of this research is to assess the performance of existing local feature descriptors when applied to the classification of Iban plaited mat motifs within a designated dataset. It seeks to devise a new classification method equipped with adaptive smoothing capabilities, intended to eliminate small and repetitive image elements, such as ornaments, while retaining essential features. This method was designed to enhance the accuracy of edge detection within the motifs. Finally, the research endeavours to evaluate the efficacy of the proposed method across a range of scenarios, specifically against six common image deformations: Blur, JPEG compression, Illumination change, Viewpoint change, Scale change, and Scale combined with Rotation (Scale+Rotation). Through these comprehensive evaluations, the research aims to contribute to the advancement of techniques for motif classification and image processing, particularly in the context of Iban plaited mat motifs.

The motif classification research conducted by (Yulianto, Hariadi, & Purnomo, 2012), (Gultom, Masikome, & Arymurthy, 2018), and (Meranggi, 2022) has investigated factors influencing recognition performance, particularly noisy backgrounds and decorative fillers. These factors remain significant challenges in image recognition, where the objective was to extract features from the main motif while filtering out background noise without losing crucial feature information. However, these studies did not delve further into the edge effects of robust features, a method that intelligently removes small

structures within an image while preserving larger and discriminative ones within the motif. This study can therefore be seen as an extension of their findings, aiming to address this gap in research. As a result, this research adds to the existing body of knowledge.

5.2 Summary of Contributions

Our contributions are:

This study presents a newly introduced dataset, namely the Iban plaited mat motif dataset, with the primary purpose of serving as a valuable resource for future research endeavours within this field. The dataset encompasses of 20 simple and complex motifs. By providing a comprehensive and diverse dataset, it is anticipated to facilitate further investigations by fellow researchers in this domain.

Reported a comprehensive performance analysis of a selected set of feature descriptors, evaluated against our dataset. Firstly, our investigation had successfully demonstrated that a local feature descriptor could effectively be used to classify Iban mat motifs under varying common image deformations. Secondly, this study provided empirical proofs that the BRISK feature descriptor, when combined with RANSAC, performed the best on our dataset. The effectiveness of BRISK+RANSAC in this study lies in its robustness, efficiency, accuracy, and adaptability. BRISK descriptors offer robustness to JPEG Compression, illumination variations, viewpoint change and scale change. When combined with RANSAC, which excels in robust parameter estimation from noisy data, the resulting algorithm proves adept at accurately identifying and matching motifs in the Iban plaited mat motif dataset. The empirical evidence provided in the study showcases the superior performance of BRISK+RANSAC over other feature descriptor

and matching algorithms tested, affirming its suitability for motif recognition tasks. This combination's adaptability to different data types and noise levels further enhances its effectiveness in handling various challenges encountered in motif recognition, such as blur and scale + rotation changes.

Image classification method incorporating of adaptive smoothing that selectively removes smaller image structures while preserving the larger and more discriminative ones. The integration of adaptive smoothing utilizing Canny edge detection with Probabilistic Hough Transform (PHT) and Percentage of Retained Edges (PoRE) into the motif recognition process represents a comprehensive approach to enhance accuracy and robustness. By applying adaptive smoothing techniques, such as Canny edge detection, the method effectively extracts prominent image structures while minimizing noise and irrelevant details, thereby improving the quality of edge information crucial for motif recognition. The subsequent incorporation of PHT allows for the detection of geometric patterns and shapes within the pre-processed images, facilitating the identification of motifs with well-defined structures. Moreover, the utilization of PoRE as a metric enables the systematic evaluation of edge retention quality, ensuring that essential motif details are preserved while irrelevant information is discarded. By dynamically adjusting smoothing thresholds and edge retention parameters based on PoRE values, the framework optimizes its adaptability to varying image conditions, enhancing accuracy and resilience to noise, occlusion, and other challenges inherent in motif recognition tasks. This integrated approach not only enhances motif recognition performance but also offers a comprehensive solution for analyzing complex motif datasets with diverse visual attributes.

5.3 Limitation and Challenges

The proposed method was thoroughly evaluated using a series of experiments. The evaluations can be extended in the following ways.

5.3.1 Dataset Size

Training a descriptor on a small dataset, such as in this study, may lead to over fitting or poor generalization of new data. Images of plaited Iban mats are scarce and rarely available to the public. Our dataset is probably the first of its kind with a systematic approach in collecting the images. A larger dataset will improve the generalization of our classification model since the training set is larger and more diverse. Furthermore, the classification framework can be evaluated against a greater number of classes, thereby enhancing the credibility and conclusiveness of the results.

5.3.2 Limited Knowledge on Iban Plaited Mat Motifs.

Locating expert weavers or plaiters capable of elucidating the intricate meanings of Iban plaited mats presents challenges. It entails extensive fieldwork and numerous visits to remote communities where weaving or plaiting remains prevalent. Additionally, fostering relationships with local weavers and earning their trust to facilitate knowledge sharing is essential. This necessitates proficiency in the local language and familiarity with local customs and traditions. An approach marked by sensitivity and respect for local cultures is crucial, alongside collaboration with local partners or organizations possessing established community ties.

5.3.3 Enhance Matching Accuracy in Homogenous Motif Image.

The combination of homogeneity in appearance, few distinctive features, and strong edges presents challenges for accurately identifying simple motifs such as the *Buah Mata Punai motif*, as it shares similarities with other motifs and lacks unique attributes for differentiation. This uniformity makes it prone to being mistaken for other motifs, complicating accurate identification. Furthermore, the motif's strong edges contribute to its uniform appearance, but they also present a challenge. While strong edges can enhance the motif's definition, they may not provide enough variation or distinctive features for accurate recognition. As a result, during feature extraction processes, there was limited information available to differentiate *Buah Mata Punai* from other motifs, highlighting areas where further improvements may be necessary to enhance matching accuracy in homogenous motif images.

5.3.4 Challenges of False Correspondences in Highly Complex Motifs: Implications for Recognition and Classification.

Challenge lies in the presence of false correspondences within highly complex motifs, even after discarding those that do not conform to the estimated transformation matrix. Although the rejection process aims to ensure that only true correspondences influence the final similarity score, the intricate designs of complex motifs can still lead to an abundance of false correspondences. These false correspondences may arise due to similarities between different parts of the motif that do not accurately represent matches. Consequently, even with rigorous rejection mechanisms in place, the persistence of false correspondences can result in a lower overall similarity score than what the motif truly deserves. This underscores the difficulty inherent in motif classification tasks, particularly when dealing with motifs characterized by intricate and elaborate designs. Despite efforts

to mitigate the impact of false correspondences, their prevalence in highly complex motifs remains a significant challenge, requiring further refinement and optimization of recognition algorithms to accurately assess motif similarity.

5.4 Future Work

Based on the study that had been conducted, there are still some limitations and suggestions for future work to be evaluated against the Iban plaited mat motif dataset.

5.4.1 Enhancing Deep Learning Model Training: Expanding the Iban Plaited Mat Motif Dataset

Expanding the dataset of Iban plaited mat motif images for training deep learning models presents a promising avenue for future research, offering opportunities to enhance the robustness and generalization capabilities of these models. By collecting additional images from diverse sources and contexts, including different regions, communities, and historical periods, researchers can enrich the dataset with a wider variety of motifs, patterns, and designs. Collaborations with local communities and artisans can facilitate the documentation and digitization of traditional and contemporary interpretations of Iban motifs, while annotating the dataset with rich metadata can provide valuable context for cultural understanding, facilitating more nuanced and culturally sensitive interpretations. This expanded dataset will not only enable the development of more accurate and culturally sensitive deep learning models for motif recognition but also contribute to the preservation and appreciation of Iban cultural heritage.

5.4.2 Assessing Computational Efficiency: Evaluating Matching Speed in Motif Classification Algorithms

In research on Iban plaited mat motif classification, evaluating the matching speed is crucial to ensure that the developed classification algorithms are not only accurate but

also computationally efficient. Given the complexity and diversity of motifs within the Iban plaited mat dataset, it's essential to develop classification algorithms that can handle large volumes of data while providing timely results. By incorporating an evaluation of matching speed into the research methodology, researchers can assess how quickly the classification algorithms can process and classify motifs, particularly in real-world applications where time is a critical factor. This evaluation helps identify algorithms that strike a balance between accuracy and computational efficiency, ensuring that the classification system is not only reliable but also practical for use in various scenarios, such as cultural heritage preservation, art analysis, and digital archiving. Moreover, by optimizing the matching speed, researchers can enhance the scalability and applicability of the classification system, making it accessible to a broader range of users and applications.

5.4.3 Expanding the Multi-Material Dataset

Future work involves expanding the dataset to include motifs weaving, carved, or embossed on different materials, such as beads, wood carving, and ritual textiles. This multi-material dataset would enable testing on a more diverse range of images, potentially enhancing the robustness and versatility of the motif classification approach. Additionally, it could offer insights into the distinctions among cultural art motifs crafted from various materials and their impact on the classification process. Furthermore, evaluating our proposed method on other cultural motifs is warranted to assess its applicability and effectiveness across different cultural contexts.

This adaptability allows researchers and practitioners to explore its performance and applicability in a wide range of edge image classification problems beyond the specific domain of Iban Plaited mat motifs.

REFERENCES

- Dubey, P., Dubey, P. K., & Changlani, S. (2020). A Hybrid Technique for Digital Image Edge Detection by Combining Second Order Derivative Techniques Log and Canny. *2nd International Conference on Data, Engineering and Applications (IDEA)*, 1-6.
- Ghosh, M., Obaidullah, S., Gherardini, F., & Zdimalova, M. (2021). Classification of Geometric Forms in Mosaics Using Deep Neural Network. *Journal of Imaging*, 149.
- Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. USA: MIT Press.
- Jamil, N., Bakar, Z. A., & Sembok, T. T. (2006). Image Retrieval of Songket Motifs Using Simple Shape Descriptors. *Institute of Electrical and Electronics Engineers (IEEE)*, 171-176.
- Kasim, A. A., Wardoyo, R., & Harjoko, A. (2017). Batik Classification with Artificial Neural Based on Texture-Shape Feature of Main Ornament. *I.J. Intelligent Systems and Applications*, 55-65.
- Abed, E. A., Mohammed, R. J., & Shihab, D. T. (2021). Intelligent Multimodal Identification System Based On Local Feature Fusion Between Iris and Finger Vein. *Indonesian Journal Of Electrical Engineering and Computer Science*, 224-232.
- Agus, M. &. (2017). Pattern Recognition of Balinese Carving Motif Using Learning Vector Quantization (LVQ). *International Conference on Soft Computing in Data Science*, 43-55.

- Ahmad, R., Naz, S., & Razzak, I. (2021). Efficient skew detection and correction in scanned document images through clustering of probabilistic hough transforms. *Pattern Recognition Letters*, 93-99.
- Ahmed, A. S. (2018). Comparative Study Among Sobel, Prewitt And Canny Edge Detection Operators Used In Image Processing. *Journal of Theoretical and Applied Information Technology*, 6517-6525 .
- Albert, F., Gomis, J. M., Blasco, J., & González, J. V. (2014). A new method to analyse mosaics based on Symmetry Group theory applied to Islamic Geometric Patterns. *Computer Vision and Image Understanding*.
- Anantrasirichai, N., Biggs, J., Albino, F., & Bull, D. (2019). A Deep Learning Approach To Detecting Volcano Deformation From Satellite Imagery Using Synthetic Datasets. *Computer Vision and Pattern Recognition*.
- Andrei, M.-A., Boiană, C.-A., Tarbă, N., & Văncilă, M.-L. (2022). Robust Lane Detection and Tracking Algorithm for Steering Assist Systems. *MDPI*, 1(10).
- Ansari, M. A., Kurchaniya, D., & Dixit, M. (2017). A Comprehensive Analysis of Image Edge Detection Techniques. *International Journal of Multimedia and Ubiquitous Engineering*, 1-12.
- Arandjelović, Y. M. (2020). Classification of Ancient Roman Coins by Denomination Using Colour, a Forgotten Feature in Automatic Ancient Coin Analysis. *MDPI*, 2(2).
- Artani, F., Delorme, A., & Makeig, S. (2018). Applying dimension reduction to EEG data by Principal Component Analysis reduces the quality of its subsequent Independent Component decomposition. *NeuroImage*, 176-187.

- Azhar, R., Tuwohingide, D., Kamudi, D., Sarimuddin, & Nanik, S. (2015). Batik Image Classification Using SIFT Feature Extraction, Bag of Features and Support Vector Machine. *The Third Information Systems International Conference 2015*, 24-30.
- Bachofer, F., Quénéhervé, G., Zwiener, T., Maerker, M., & Hochschild, V. (2017). Comparative analysis of Edge Detection techniques for SAR images. *European Journal of Remote Sensing*, 205-224.
- Balntas, V. K. (2017). A Benchmark and evaluation of Handcrafted and Learned Local Descriptor. *Conference on Computer Vision and Pattern Recognition*.
- Bay, H., Tuytelaars, T., & Gool, L. V. (2006). Speeded-up Robust Features. *European Conference on Computer Vision*, 404-417.
- Bay, H., Tuytelaars, T., & Gool, L. (2008). Speeded-up Robust Features (SURF). *Computer Vision and Image Understanding (CVIU)*, 110(3), 346-359.
- Bhardwaj, S., & Mittal, A. (2012). A Survey on Various Edge Detector Techniques. *Procedia Technology*, 220-226.
- Bharodiya, A. K. (2022). Feature Extraction Methods for CT-Scan Images Using Image Processing. *Computed-Tomography (CT) Scan. IntechOpen. doi: 10.5772/intechopen.102573*.
- Bishop, C. M. (2006). *Pattern recognition and machine learning*. New York: Springer.
- Blake, J. (2014). Convention for the Safeguarding of Intangible Cultural Heritage (2003). In *Encyclopedia of Global Archaeology* (pp. 1706-1711). New York: Springer New York.

- Boudraa, O., Hidouci, W. K., & Michelucci, D. (2020). Using skeleton and Hough transform variant to correct skew in historical documents. *Mathematics and Computers in Simulation*, 389-403.
- Bradski, G. (2000). The OpenCV Library. *Dr. Dobb's Journal of Software Tools*.
- Brown, M. (2007). Automatic Panoramic Image Stitching Using Invariant Features. *International Journal of Computer Vision*, 59-73.
- Bu, X., & Jiang, M. (2022). Extraction of Intangible Cultural Heritage Visual Elements by Deep Learning and Its Application in Grassland Tourism of the Silk Road Culture. *Computational Intelligence and Neuroscience*.
- Buyer, L. (2017, June 7). *How to Optimize for Next-Level Image Search*. (kepios.com) Retrieved January 15, 2021, from Search Engine Journal - SEO, Search Marketing News and Tutorials: <https://www.searchenginejournal.com/optimize-google-lens-pinterest-lens/200638/>
- C. Leng, H. Z. (2019). Local Feature Descriptor for Image Matching: A Survey. *IEEE Access*, 6424-6434.
- Canny, J. (1986). IEEE Transactions on Pattern Analysis and Machine Intelligence. *A Computational Approach to Edge Detection, PAMI-8(6)*, 679-698.
- Cao, J., Chen, L., Wang, M., & Tian, Y. (2018). Implementing a Parallel Image Edge Detection Algorithm Based on the Otsu-Canny Operator on the Hadoop Platform. *Computational Intelligence and Neuroscience*.
- Chawla, V. (2020, August 1). *Analyticsindiamag.com*. (Analytics India Magazine PVT LTD) Retrieved December 5, 2020, from How Synthetic Data Sets Can Improve

Computer Vision Models: <https://analyticsindiamag.com/how-synthetic-data-sets-can-improve-computer-vision-models/>

Chen, C. H. (2013). *Pattern Recognition and Artificial Intelligence*. Elsevier.

Chih Chen, Wei Hsieh, Yan, & Yu Chen. (2015). Vehicle make and model recognition using sparse representation and symmetrical SURFs. *Pattern Recognition*, 1979-1998.

Chin, L. (1983). Our Heritage And The Need To Preserve It. *Sarawak Museum Journal Vol XXXII*, 61-69.

Copeland, T. (2004). *Presenting Archaeology To The Public 1st Edition*. London: Routledge.

Cosovic, M., Amelio, A., & Junuz, M. (2019). Classification Methods in Cultural Heritage. *Visual Pattern Extraction and Recognition for Cultural Heritage*.

Das, S. (2016). Comparison of Various Edge Detection Technique. *International Journal of Signal Processing, Image Processing and Pattern Recognition*, 143-158.

David G. Lowe. (1999). Object recognition from local scale invariant features. *Proceedings of the Seventh IEEE International Conference on Computer Vision*, 2, 1150-1157.

Ding, L., & Goshtasby, A. (2001). On The Canny Edge Detector. *Pattern Recognition*, 721-725.

Donoser, M., & Horst, B. (2006). Efficient Maximally Stable Extremal Region (MSER) Tracking. *IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'06)*, 553-560.

- Dougherty, G. (2012). *Pattern Recognition and Classification: An Introduction*. Springer Science & Business Media.
- Duda, R. O., & Hart, P. E. (1972). Use of the Hough transformation to detect lines and curves in pictures. *Commun. ACM*, 11-15.
- Durin, A. (2014). *Tikar Bemban*. Kota Samarahan Sarawak: Universiti Malaysia Sarawak.
- El-gayar, M. e. (2013). A Comparative Study Of Image Low Level Feature Extraction Algorithm. *Egyptian Informatics Journal*, 175-181.
- Elmar Mair, G. D. (2010). Adaptive and Generic Corner Detection Based. *In Proceedings of the European Conference on Computer Vision*.
- Eversberg, L., & Lambrecht, J. (2024). Combining Synthetic Images and Deep Active Learning: Data-Efficient Training of an Industrial Object Detection Model. *Journal of Imaging*.
- Fahmi, H., Zen, R. A., Sanabila, H., Nurhaida, I., & Arymurthy, A. (2016). Feature Selection and Reduction for Batik Image Retrieval. *Proceedings of the Fifth International Conference on Network, Communication and Computing*, 47–52.
- Fanani, A., Yuniarti, A., & Suciati, N. (2014). Geometric Feature Extraction of Batik Image Using Cardinal Spline Curve Representation. *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, 397-404.
- Fischler, M. A., & Bolles, R. C. (1981). Random sample consensus: A paradigm for model fitting with applications to image analysis and automated cartography. *Communications of the ACM*, 24(6), 381-395.
- Gavin, T. (2003). *Iban Ritual Textiles*. Leiden: KITLV Press.

- Gioia, F. d., Meoni, G., Giuffrida, G., Donati, M., & Fanucci, L. (2020). A Robust RANSAC-Based Planet Radius Estimation for Onboard Visual Based Navigation. *Sensors* 2020, 20, 1-13.
- Girsang, N. D., & Muhathir. (2021). Classification Of Batik Images Using Multilayer Perceptron With Histogram Of Oriented Gradient Feature Extraction. *Proceeding International Conference on Science and Engineering*, 197–204.
- Gonzalez, R. C., & Woods, R. E. (2002). *Digital Image Processing, Fourth Edition, Global Edition*. New York: Prentice Hall.
- Goodfellow et al., I. B. (2016). *Deep Learning*. MIT Press.
- Gultom, Y., Masikome, R. J., & Arymurthy, A. M. (2018). Batik Classification using Deep Convolutional Network Transfer Learning. *Journal of a Science and Information*, 59-66.
- Han & Jain. (2013). Tattoo Based Identification: Sketch to Image Matching. *The 6th IAPR International Conference on Biometrics (ICB)*.
- Han, S., Shi, Z., & Shi, Y. (2022). Cultural and Creative Product Design and Image Recognition. *Computational Intelligence and Neuroscience*.
- Hassaballah et. al. (2016). *Image Features Detection, Description*. Springer International Publishing.
- Heppell, M. (2006). Women's War. An Update of the Literature on Iban Textiles. *Borneo Research Bulletin Volume 37*, 143-153.
- Hidayattullah, M. F., Nishom, M., Wiyono, S., & Hapsari, Y. (2020). Feature Extraction In Batik Image Geometric Motif Using Canny. *Jounal Informatika*, 1-6.

- Hipiny, I. M.-C. (2012). Recognising Egocentric Activities from Gaze. *CTIT technical reports series*.
- Hipiny, I., Ujir, H., Mujahid, A., & Yahya, N. K. (2019). Towards Automated Biometric Identification of Sea Turtles (*Chelonia mydas*). *Journal of ICT Research and Applications*, 256-266.
- Jamil, N., & Sembok, T. (2003). Gradient-Based Edge Detection of Songket Motifs. *Digital Libraries: Technology and Management of Indigenous Knowledge for Global Access.*, 456–467.
- Jamil, N., Sembok, T. T., & Bakar, Z. A. (2012). Digital archiving of traditional songket motifs using image processing tool. *Semantic Scholar*.
- Janković, R. (2020). Machine Learning Models for Cultural Heritage Image Classification: Comparison Based on Attribute Selection. *Special Issue Visual Pattern Extraction and Recognition for Cultural Heritage Understanding*.
- Jian Wu, Z. C. (2013). A Comparative Study of SIFT and its Variants. *IEEE*.
- Joseph, S., Hipiny, I., & Ujir, H. (2023). Iban plaited mat motif classification with adaptive smoothing. *IAES International Journal of Artificial Intelligence (IJ-AI)*, 1-11.
- Joseph, S., Hipiny, I., Ujir, H., Juan, S., & Minoi, J.-L. (2021). Performance Evaluation of SIFT Againsts Common Image Deformations on Iban Plaited Mat Motif Images. *Indonesian Journal of Electrical Engineering and Computer Science*, 23(3).
- Joseph, S., Ujir, H., & Hipiny, I. (2017). Unsupervised Classification of Intrusive Igneous Rock Thin Section Images Using Edge Detection and Color Analysis. *IEEE International Conference on Signal and Image Processing Applications (ICSIPA)*, 530-534.

- Joshi, M., & Vyas, A. (2018). Comparison of Canny edge detector with Sobel and Prewitt edge detector using different image formats. *International Journal of Engineering Research & Technology (IJERT)*, 133-137.
- Juwita, A. R., & Solichin, A. (2014). Batik Pattern Identification Using GLCM and Artificial Neural Netork Backpropagation.
- K. A. M. Said et al. (2016). A study on image processing using mathematical morphological. *3rd International Conference on Electronic Design (ICED)*, 507-512.
- Kälviäinen, H., Hirvonen, P., Xu, L., & Oja, E. (1994). Comparisons Of Probabilistic And Non-Probabilistic Hough Transforms. *Third European Conference on Computer Vision*, 350–360.
- Kälviäinen, H., Hirvonen, P., Xu, L., & Oja, E. (1995). Probabilistic And Non-Probabilistic Hough Transforms: Overview And Comparisons. *Image and vision computing*, 239-252.
- Kang, T.-K., Choi, I.-H., & Lim, M.-T. (2015). MDGHM SURF: A robust local image descriptor based on modified discrete Gaussian–Hermite moment. *Elsevier, Pattern Recognition*, 670-684.
- Kasim, A. H. (2016). Feature extraction methods for batik pattern recognition: A review. *ADVANCES OF SCIENCE AND TECHNOLOGY FOR SOCIETY: Proceedings of the 1st International Conference on Science and Technology 2015 (ICST-2015)*.
- Kasiselvanathan, M., Sangeetha, V., & Kalaiselvi, A. (2020). Palm pattern recognition using scale invariant feature transform. *International Journal of Intelligence and Sustainable Computing*, 1, 44.

- Ke, Y., & Sukthankar. (2004). PCA-SIFT: a more distinctive representation for local image descriptors. *Proceedings of the 2004 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2, II-II.
- Khan, N., McCane, B., & Wyvill, G. (2011). SIFT and SURF performance evaluation againts various image deformations on benchmark dataset. *International Conference on Digital Image Computing Techniques and Applications, DICTA*, 501-506.
- Kim, J., Li, H., Yue, J., & Delp, E. (2016). Tattoo image retrieval for region of interest. *IEEE Symposium on Technologies for Homeland Security (HST)*, 1-6.
- Kiryati , N., Kälviäinen, H., & Alaoutinen, S. (2000). Randomized or Probabilistic Hough Transform: Unified Performance Evaluation. *Pattern Recognition Letters* 21, 1157-1164.
- Kiryati, N., Eldar, Y., & Bruckstein, A. (1991). A Probabilistic Hough Transform. *Pattern Recognition*, 303-316.
- Kuila, S., Dhanda, N., & Joardar, S. (2020). Feature extraction of electrocardiogram signalusingmachine learning classification. *International Journal of Electrical and Computer Engineering (IJECE)*, 10(6), 6598-6605.
- Kumar, K. K. (2017). Indian Classical Dance Mudra Classification Using HOG Features and SVM Classifier. *International Journal of Electrical and Computer Engineering (IJECE)*, 7(5), 2537-2546.
- Kumar, V., Singh, R., & Dua, Y. (2022). Morphologically dilated convolutional neural network for hyperspectral image classification. *Signal Processing: Image Communication*.

- Kuntitan, P., & Chaowalit, O. (2021). Using Deep Learning for the Image Recognition of Motifs on the Center of Sukhothai Ceramics. *MDPI*, 22(2).
- Kusanti, J., & Suprpto, A. (2019). Combination of Otsu and Canny Method to Identify the Characteristics of Solo Batik as Surakarta Traditional Batik. *2nd International Conference of Computer and Informatics Engineering (IC2IE)*, 63-68.
- Lapušinskij, A., Suzdalev, I., Goranin, N., Janulevičius, J., Ramanauskaitė, S., & Stankūnavičius, G. (2021). The Application of Hough Transform and Canny Edge Detector Methods for the Visual Detection of Cumuliform Clouds. *sensors*, 21(17).
- Leutenegger, S., Chli, M., & Siegwart, R. (2011). Binary Robust Invariant Scalable Key points (BRISK). *IEEE International Conference Compututer Vision*, 2548-2555.
- Li, H., Qin, J., Xiang, X., Pan, L., Ma, W., & Xiong, N. N. (2018). An Efficient Image Matching Algorithm Based on Adaptive Threshold and RANSAC. *IEEE*, 6, 66963-66971.
- Li, Y., & Liu, B. (2022). Improved Edge Detection Algorithm for Canny Operator. *IEEE 10th Joint International Information Technology and Artificial Intelligence Conference (ITAIC)*, 1-5.
- Liang, X. (2022). Traditional Pattern Feature Extraction and Cultural Creative Design Application Based on Multilevel Histogram Shape Segmentation. *Mobile Information System*, 1-10.
- Lindeberg, T. (2012). Scale Invariant Feature Transform. *Scholarpedia*, 7, 10491.
- Ling, H., & Jacobs, D. (2005). Deformation Invariant Image Matching. *Tenth IEEE International Conference on Computer Vision (ICCV'05)*, 1466-1473.

- Liu, H., Luo, S., Lu, J., & Dong, J. (2019). Method for fused phase and PCA Direction Based on a SIFT framework for multi-modal image matching. *IEEE Access*, 7, 165356-165364.
- Liu, K., Xiao, K., & Xiong, H. (2017). An Image Edge Detection Algorithm Based on Improved Canny. *5th International Conference on Machinery, Materials and Computing Technology (ICMMCT)*, 533-537.
- Lowe. (1999). Object recognition from local scale-invariant features. *Proceedings of the International Conference on Computer Vision.*, 1150–1157.
- Lowe, D. G. (2004). Distinctive image features from scale invariant keypoint. *International Journal of Computer Vision*, 91-110.
- Lv, G., Teng, S., & Lu, G. (2018). Enhancing image registration performance by incorporating. *Pattern Recognition*, 103, 46–52.
- M Trombini, F. F. (2021). Camera Color Correction for Cultural Heritage Preservation Based on Clustered Data. *Journal of Imaging*, 7.
- M. Marzougui, A. A. (2020). A Lane Tracking Method Based on Progressive Probabilistic Hough Transform. *IEEE*, 8, 84893 - 84905.
- Mahawan, I. M., & Harjoko, A. (2017). Pattern Recognition of Balinese Carving Motif Using Learning Vector Quantization (LVQ). *International Conference on Soft Computing in Data Science*, 43-55.
- Mahfudi, I., Sarosa, M., Asmara, R., & Gustalika, M. (2018). Indonesian Sign Language Number Recognition. *The 2nd International Conference on Vocational Education and Electrical Engineering (ICVEE)*.

- Mahfudi, I., Sarosa, M., Asmara, R., & Gustalika, M. (2018). Indonesian Sign Language Number Recognition using SIFT Algorithm. *IOP Conference Series: Materials Science and Engineering*, 336.
- Mair, E., Hager, G., Burschka, D., Suppa, M., & Hirzinger, G. (2010). Adaptive and Generic Corner Detection Based on the Accelerated Segment Test. *European Conference on Computer Vision*.
- Maragos, P. (1996). Differential Morphology and Image Processing. *IEEE Transactions on Image Processing*, 922 - 937.
- Martínez-Otzeta, J. M.-M. (2015). A new method to analyse mosaics based on Symmetry Group theory applied to Islamic Geometric Patterns. *Computer Vision and Image Understanding*, 54-70.
- Matas, J., Chum, O., Urban, M., & Pajdla, T. (2002). Robust Wide Baseline Stereo from Maximally Stable Extremal Regions. *Proc. of British Machine Vision Conference*, 384-396.
- Meranggi, D. G., Yudistira, N., & Sari, Y. A. (2022). Batik Classification Using Convolutional Neural Network with Data Improvements. *International Journal On Informatics Visualization*, 6-11.
- Meyer-Baese, A., & Schmid, V. (2014). *Pattern Recognition and Signal Analysis in Medical Imaging*. Elsevier Inc.
- Mikolajczyk, K., & Schmid, C. (2005). A performance evaluation of local descriptors. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 27(10), 1615-1630.

- Mikolajczyk, & Schmid. (2004). Scale & Affine Invariant Interest Point Detectors. *International Journal of Computer Vision*, 60, 63–86.
- Mikolajczyk, K., & Schmid, C. (2004). Comparison Of Affine Invariant Local Detectors and Descriptors. *2004 12th European Signal Processing Conference*, 1729-1732.
- Minarno, A. E., Azhar, Y., Sumadi, F. D., & Munarko, Y. (2020). A Robust Batik Image Classification using Multi Texton Co-Occurrence Descriptor and Support Vector Machine. *3rd International Conference on Intelligent Autonomous Systems (ICoIAS)*, 51-55.
- Minarno, A. E., Maulani, A. S., Kurniawardhani, A., Bimantoro, F., & Suciati, N. (2018). Comparison of Methods for Batik Classification Using Multi Texton Histogram. *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, 1358-1366.
- Minarno, A. E., Munarko, Y., Kurniawardhani, A., & Bimantoro, F. (2014). Texture Feature Extraction Using Co-Occurrence. *IEEE, 2nd International Conference on Information and Communication technology (ICoICT)*, 249-254.
- Minarno, A. E., Soesanti, I., & Nugroho, H. A. (2024). Batik Classification using Microstructure Co-occurrence Histogram. *International Journal On Informatics Visualization*, 134-140.
- Mittal , H., Pandey, A. C., Saraswat , M., Kumar, S., Pal, R., & Modwel, G. (2022). A Comprehensive Survey Of Image Segmentation: Clustering Methods, Performance Parameters, And Benchmark Datasets. *Multimedia Tools and Applications*, 1-26.

- Mohd Noor, N., & Abd Aziz, A. (2018). Safeguarding Intangible Cultural Heritage In Malaysia: A Legal Analysis On The National Heritage Act 2005. *European Proceedings of Social and Behavioural Sciences*, 841-848.
- Mukhopadhyay, P., & Chaudhuri, B. (2015). A survey of Hough Transform. *Pattern Recognition*, 993-1010.
- Murinto, & Aribowo, E. (2016). IMAGE SEGMENTATION USING HIDDEN MARKOV TREE. *Journal of Theoretical and Applied Information Technology*.
- Nadernejad, E., Sharifzadeh, S., & Hassanpour, H. (2008). Edge Detection Techniques Evaluations and Comparisons. *Applied Mathematical Sciences*, 1507-1520.
- Nahum Kiryati, H. K. (2000). Randomized or Probabilistic Hough Transform: Unified Performance Evaluation. *Pattern Recognit. Lett.*, 21, 1157-1164.
- Nister, D., & Stewenius, H. (2008). Linear maximally stable extremal regions. *European Conference on Computer Vision*, 183-196.
- Nugrowati, A. D., Barakbah, A. R., Ramadijanti, N., & Setiowati, Y. (2014). Batik Image Search System with Extracted. *International Conference on Imaging and Printing*.
- Nurhaida, I., Manurung, R., & Arymurthy, A. M. (2012). Performance comparison analysis features extraction methods for Batik recognition. *International Conference on Advanced Computer Science and Information Systems (ICACSIS)*, 207-212.
- Nurhaida, I., Noviyanto, A., Manurung, R., & Arymurthy, A. (2015). Automatic Indonesian's Batik Pattern Recognition Using SIFT Approach. *International Conference on Computer Science and Computational Intelligence*, 567 – 576.

- Nurhaida, I., Wei, H., Zen, R. A., & Manurung, R. (2016). Texture Fusion for Batik Motif Retrieval System. *International Journal of Electrical and Computer Engineering*, 6(6), 3174-3187.
- Parmar, J. D. (2019). Feature Extraction in Augmented Reality.
- Pedro J. Garcia-Pardo & Pascual Campoy. (2003). *On the goodness of two classical, fast implementations of the Hough Transform: Randomized and Multiresolution*.
pedrojgarcia.files.wordpress.com.
- Prewitt, J. (1970). *Object Enhancement and Extraction*. Picture processing and Psychopictorics. Academic Press.
- Priyanto, D., & Heriwati, S. H. (2022). Java Traditional Delivery Ritual Instruments In The Work of Dodot Batik. *Ekspresi Seni : Jurnal Ilmu Pengetahuan dan Karya Seni Vol24*, 50-66.
- Qiang, S., Guoying, L., Jingqi, M., & Hongmei, Z. (2016). An edge-detection method based on adaptive canny algorithm and iterative segmentation threshold. *IEEE*, 64-67.
- Qiaoling, Z., Lee, M., & Juhyun, E. (2023). Digital Design Method Of Cultural Heritage Using Ancient Egyptian Theological Totem. *Elsevier*.
- Rafael C. Gonzalez, R. E. (1992). *An Introduction to Morphological Image Processing* . SPIE-International Society for Optical Engineering.
- Ramadevi, Y., Sridevi, T., Poornima, B., & Kalyani, B. (2010). Segmentation And Object Recognition Using Edge Detection Techniques. *AIRCC's International Journal of Computer Science and Information Technology*, 153-161.

- Rangkuti, A. H., Bahaweres, R. B., & Harjoko, A. (2012). Batik image retrieval based on similarity of shape and texture characteristics. *International Conference on Advanced Computer Science and Information Systems (ICACSIS)*, 267-273.
- Rangkuti, A. H., Harjoko, A., & Putra, A. (2021). A Novel Reliable Approach For Image Batik Classification That Invariant With Scale And Rotation Using MU2ECS-LBP Algorithm. *5th International Conference on Computer Science and Computational Intelligence 2020*, 863-870.
- Rangkuti, A. H., Rasjid, Z. E., & Santoso, D. (2015). Batik Image Classification Using Treeval and Treefit as Decision Tree Function in Optimizing Content Based Batik Image Retrieval. *International Conference on Computer Science and Computational Intelligence (ICCSCI)*, 577-583.
- Rangkuti, A., Harjoko, A., & Putra, A. (2019). Improvement Of Accuracy in Batik Image Classification Due To Scale and Rotation Changes Using M2ECS-LBP Algorithm. *Journal of Theoretical And Applied Information Technology*, 97(14), 3859-3870.
- Rasyidi, M. A., & Bariyah, T. (2020). Batik Pattern Recognition Using Convolutional Neural Network. *Bulletin of Electrical Engineering and Informatics*, 9(4), 1430-1437.
- Rizzi, A., & Vichi, M. (1995). Representation, Synthesis, Variability and Data Preprocessing of a Three-way Data Set. *Computational Statistics & Data Analysis, Elsevier*, 203-222.
- Roberts, L. (1965). *Machine Perception of Three Dimensional Solids*. MIT Press.
- Rosenfeld, K.-S. F. (1976). Pattern Recognition and Image Processing. *IEEE Transactions on Computers*, 1336-1346.

- Rosten, E., & Drummond, T. (2006). Features From Accelerated Segment Test (FAST). *9th European Conference on Computer Vision, 1*, 430–443.
- Rosten, E., Porter, R., & Drummond, T. (2010). Faster and better: A machine learning approach to corner detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 105-119.
- Said, K. A., Jambek, A. B., & Sulaiman, N. (2016). A Study Of Image Processing Using Morphological Opening And Closing Processes. *International Journal of Control Theory and Applications*, 15-21.
- Sanabila, H. R., & Manurung , R. (2009). Recognition of Batik Motifs using the Generalised Hough Transform. *Proceedings of the International Conference on Advanced Computer Science and Information Systems, (ICACSIS)*, 1-6.
- Sapkota, B., Popescu, S., Rajan, N., Leon, R., Horton, C., Mirsky, S., & Bagavathiannan, M. (2022). Use Of Synthetic Images For Training A Deep Learning Model For Weed Detection And Biomass Estimation In Cotton. *Nature Communications*.
- Sarmah, H. (2019, October 17). *Analyticsindiamag.com*. (Analytics India Magazine PVT LTD) Retrieved January 3, 2021, from Synthetic Data Is Making It Easy For Data Scientists To Create & Train AI Algorithms: <https://analyticsindiamag.com/synthetic-data-is-making-it-easy-for-data-scientists-to-create-train-ai-algorithms/>
- Sasikala, N., Swathipriya, V., Ashwina, M., Preethi, V., Pranavi, A., & Ranjith, M. (2020). Feature Extraction of Real-Time Image Using SIFT Algorithm. *European Journal ofElectricalEngineeringand ComputerScience (EJECE)*, 4(3).

- Sellato, B. (2012). *Plaited Arts From The Borneo Rainforest*. Jakarta Indonesia, Singapore: Jakarta : Lontar Foundation.
- Sellato, B. (2017). Names Meanings and Referents In Borneo Basketry Decoration. *Borneo Research Bulletin*, 48.
- Sellato, B., & Fogel, J. M. (2013). Decorated Mats of the Peoples of the Borneo Hinterland. *Researchgate*, 17(4), 126-137.
- Septiarini, A., Saputra, R., Tedjawati, A., Wati, M., & Hamdani, H. (2022). Pattern Recognition of Sarong Fabric Using Machine Learning Approach Based. *International Journal of Intelligent Engineering and Systems*.
- Setyawan, I., Timotius, I., & Calvin, M. (2015). Automatic batik motifs classification using various combinations of SIFT features moments and k-Nearest Neighbor. *7th International Conference on Information Technology and Electrical Engineering (ICITEE)*, 269-274.
- Sha, N., Mehra, R., & Sharma, L. (2015). Comparative Analysis of Canny and Prewitt Edge Detection Techniques used in Image Processing. *International Journal of Engineering Trends and Technology*, 48-53.
- Shi, e. a. (2013). SIFT Feature Point Matching Based on Improved RANSAC Algorithm. *Interntional Conference on Intelligent Human- Machine Systems and Cybernetics*, 474-477.
- Shi, G., Xu, X., & Dai, Y. (2013). SIFT Feature Point Matching Based on Improved RANSAC Algorithm. *Interntional Conference on Intelligent Human- Machine Systems and Cybernetics*, 474-477.

- Shidi, T. A., & Suyoto. (2011). New Edge Detection Method for Indonesian Batik. *Jurnal Buana Informatika*, 55-62.
- Shrivakshan, G., & Chandrasekar, C. (2012). A Comparison of various Edge Detection Techniques used in Image Processing. *International Journal of Computer Science*, 269-276.
- Shwetha.V; C.H.Renu Madhavi. (2020). Design Techniques For Improvement of Canny Edge Detection Algorithm. *International Journal of Creative Research Thoughts (IJCRT)*, 1224-1231.
- Sobel, I. E. (1970). *Camera Models and Machine Perception*. Stanford University.
- Song, R., Zhang, Z., & Liu, H. (2017). Edge connection based Canny edge detection algorithm. *Pattern Recognition and Image Analysis*, 740–747.
- Stehman & Stephen. (1997). Selecting and interpreting measures of thematic classification accuracy. *Remote Sensing of Environment*, 77-89.
- Suciati, N., Herumurti, D., & Wijaya, A. Y. (2017). Feature extraction using gray-level co-occurrence matrix of wavelet coefficients and texture matching for batik motif recognition. *Eighth International Conference on Graphic and Image Processing (ICGIP 2016)*, 10225.
- Sulistianingsih, N., Soesanti, I., & Hartant, R. (2018). Classification of Batik Image using Grey Level Co-occurrence Matrix Feature Extraction and Correlation Based Feature Selection. *International Seminar on Research of Information Technology and Intelligent Systems (ISRITI)*, 492-497.

- Tao, Y., Skubic, M., Han, T., Xia, Y., & Chi, X. (2010). Performance Evaluation of SIFT-Based Descriptors for Object Recognition. *Proceedings of the International MultiConference of Engineers and Computer Scientists (IMECS)*, 2.
- Tareen, S. A., & Saleem, Z. (2018). A Comparative Analysis of SIFT, SURF, KAZE, AKaze, ORB and BRISK. *2018 International Conference on Computing, Mathematics and Engineering Technologies (iCoMET)*, 1-10.
- The MathWorks Inc. (2017). *MATLAB version 9.3.0.713579 (R2017b)*. United State: Natick, Massachusetts.
- Tiing, C. L. (2013, March 31). *Borneopost online*. Retrieved from Sarawak handicrafts: Preserving a heritage threatened by extinction: <http://www.theborneopost.com>
- Tristante, J., Hendryli, J., & Herwindiati, D. (2018). Classification of Batik Motifs Using Convolutional Neural Networks. *International Conference on Information Technology, Engineering, Science and its Applications*.
- Ulku, I., & Akagunduz, E. (2022). A Survey on Deep Learning-based Architectures for Semantic Segmentation on 2D images. *Applied Artificial Intelligence*.
- Varshney, S., Lakshmi, C., & Patvardhan, C. (2023). Madhubani Art Classification using transfer learning with deep feature fusion and decision fusion based techniques. *Engineering Applications of Artificial Intelligence*.
- Vedaldi, A., & Fulkerson, B. D. (2010). VLFeat: An open and portable library of computer vision algorithms. *Proceedings of the 18th International Conference on Multimedia 2010*, (pp. 1469-1472). Firenze, Italy.

- Volkov, V. Y., Germer, R., Oneshko, A., & Oralov, D. (2010). Straight Edge Segments Localization on Noisy Images. *Proceedings of the 2010 International Conference on Image Processing, Computer Vision, & Pattern Recognition*, 512-518.
- Walsh, D., & Raftery, A. (2002). Accurate And Efficient Curve Detection In Images: The Importance Sampling Hough Transform. *Pattern Recognition*, 1421-1431.
- Wang, K., Li, X., & Xu, T. (2016). A Novel Improved Probability-Guided RANSAC Algorithm for Robot 3D Map Building. *Journal of Sensors*, 2016, 1-18.
- Wang, Q., Gao, X., Wang, F., Ji , Z., & Hu, X. (2020). Feature Point Matching Method Based on Consistent Edge Structures for Infrared and Visible Images. *Applied Sciences*.
- Wang, Z., Fan, B., & Wu, F. (2011). Local intensity order pattern for feature description. *International Conference on Computer Vision (ICCV)*, 1, 603–610.
- Widiaty, I., Yustiawan, I., Wibisono, Y., Abdullah, A. G., Abdullah, C. U., & Riza, L. S. (2018). Implementation of Markerless Augmented Reality Method to Visualise Philosophy of Batik Based on Android. *SCIENCE & TECHNOLOGY - Pertanika Journal*, 1383 - 1400.
- Won, I. &. (2016). Adaptive Image Matching Using Discrimination of Deformable Objects. *Symmetry*, 68.
- Xin He & Yushi Chen. (2021). Modifications of the Multi-Layer Perceptron for Hyperspectral Image Classification. *Remote Sensing*.
- Xing, D., & Patel, V. M. (2016). Deep Tattoo Recognition. *IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, 119-126.

- Yang, Y., & Yang, B. (2024). Benchmarking and Analysis of Unsupervised Object Segmentation from Real-World Single Images. *International Journal of Computer Vision*, 1-37.
- Yang, Z., Shen, D., & Yap, P.-T. (2017). Image Mosaicking Using SURF Features of Line Segment. *Computational and Mathematical Methods in Medicine*.
- Yarlott, W., & Finlayson, M. (2016). Learning a Better Motif Index: Toward Automated Motif Extraction. *7th Workshop on Computational Models of Narrative*.
- Yasir, M., Hossain, M., Nazir, S., Khan, S., & Thapa, R. (2011). Object Identification Using Manipulated Edge Detection. *Science Development*, 1-6.
- Yu, Y., Wang, C., Fu, Q., Kou, R., Huang, F., Yang, B., . . . Gao, M. (2023). Techniques and Challenges of Image Segmentation: A Review. *Recent Advances in Computer Vision: Technologies and Applications*, 1199.
- Yuhandri, Y., Madenda, S., Prasetyo, E., & Karmilasari, K. (2017). Object Feature Extraction of Songket Image Using Chain Code Algorithm. *International Journal on Advanced Science, Engineering and Information Technology (IJASEIT)*, 235-241.
- Yulianto, R., Hariadi, M., & Purnomo, M. (2012). Fractal Based on Noise for Batik Coloring using Normal Gaussian Method. *The Journal for Technology and Science*, 34-40.
- Yunari, N., Yuniarno, E. M., & Purnomo, M. H. (2018). Indonesian Batik Image Classification Using Statistical Texture Feature Extraction Gray Level Co-occurrence Matrix (GLCM) and Learning Vector Quantization (LVQ). *Telecommunication, Electronic and Computer Engineering (JTEC)* , 67-71.

- Zang, Y., Li, B., Xiao, X., Zhu, J., & Meng, F. (2020). An Efficient Probabilistic Registration Based on Shape Descriptor for Heritage Field Inspection. *International Journal of Geo-Information*, 1-23.
- Zhang, B. (2017). Design of mobile Augmented Realty Game Based on Image Recognition. *EURASIP Journal on Image and Video Processing*, 2-20.
- Zhang, D., Islam, M., & Lu, G. (2012). A Review On Automatic Image Annotation Techniques. *Pattern Recognition*, 346-362.
- Zhou, M., Zhang, G., Hu, X., Sun, D., & Xiao, J. (2017). SAR real-time guidance system based on multi-scale FAST-BRISK. *13th IEEE International Conference on Control & Automation (ICCA)*, 425-430.
- Zhou, X., Wang, K., & Fu, J. (2016). A Method of SIFT Simplifying and Matching Algorithm Improvement. *International Conference on Industrial Informatics*, 73-77.

APPENDICES

Appendix A:

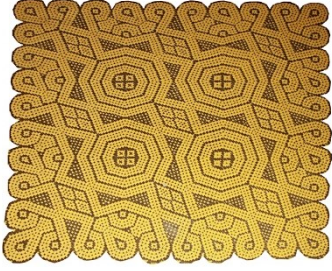
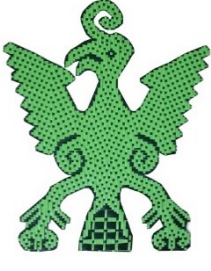
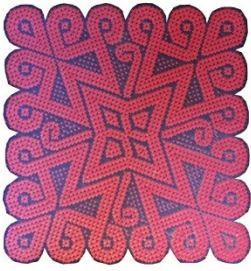
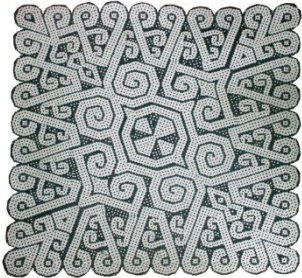
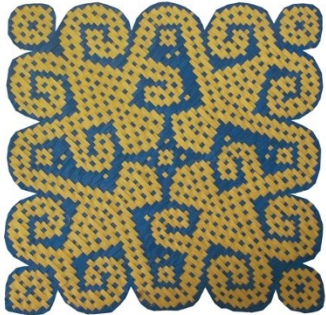
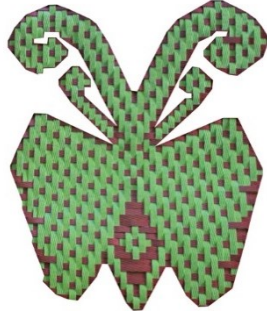
		
Buah Bulan Sebayang (BBS)	Buah Burung Kenyalang (BBK)	Buah Bong Midang (BBM)
		
Buah Mata Punai (BMP)	Buah Katak Tingkap Pama Merap (BKTPM)	Buah Panchar Matahari (BPM)
		
Buah Talam Kumang (BTK)	Buah Nabau Ngelantar (BNN)	
		
Buah Tungku (BT)	Buah Nabau Besundang (BNB)	

Figure 1: Dataset use during first experiment.

		
Buah Lang Antu (BLA)	Buah Bandau (BB)	Buah Andu (BA)
		
Buah Bulan Bekarung (BBBekarung)	Buah Bulan Bepayung (BBBepayung)	Buah Burung Garuda (BBG)
		
Buah Kandung Nibung Berayah (BKNB)	Buah Pama (BP)	Buah Kesulai (BK)
		
Buah Lang Menyarung (BLM)	Buah Lintan Tanah (BLT)	Buah Mata Punai (BMP)

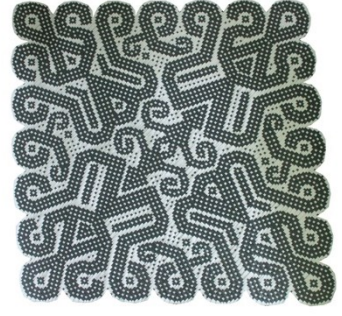
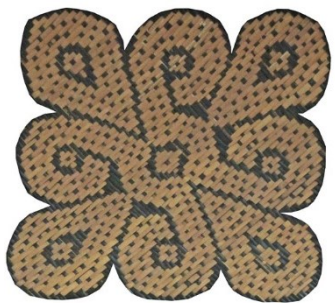
		
Buah Mayau (BM)	Buah Sebayon (BS)	Buah Tangkai Gajai Besembah (BTGB)
		
Buah Nabau Besundang (BNB)	Buah Nabau Ngelantar (BNN)	
		
Buah Suri Ai (BSA)	Buah Tungku Lebur (BTL)	Buah Tungku (BT)

Figure 2: Dataset use for second and proposed method experiment.