



**Faculty of Computer Science and Information Technology**

## **Identification of Image Features for Skin Burn Depth Classification**

**Kuan Pei Nei**

**Master of Science  
2018**

# Identification of Image Features for Skin Burn Depth Classification

Kuan Pei Nei

A thesis submitted

In fulfilment of the requirements for the degree of Master of Science

(Computer Science)

Faculty of Computer Science and Information Technology  
UNIVERSITI MALAYSIA SARAWAK

2018

## **DECLARATION**

I declare that the work in this thesis was carried out in accordance with the regulations of Universiti Malaysia Sarawak. It is original and is the result of my work, unless otherwise indicated or acknowledged as referenced work. This thesis has not been accepted for any degree and is not concurrently submitted in candidature for any other degree.

Student Name: Kuan Pei Nei

Matric No.: 16020107

Faculty: Faculty of Computer Science and Information Technology,  
Universiti Malaysia Sarawak

Date: October 2018

## **ACKNOWLEDGEMENT**

I would like to express my greatest gratitude to all who have contributed towards the success of this research work. Firstly, a special thanks to my supervisor, Dr. Stephanie Chua, who has been guiding, assisting and advising me throughout my study. My thanks also go to my first co-supervisor, Dr. Wang Hui Hui, who has been guiding and assisting me with the knowledge in image processing. I would also like to convey my thanks to my second co-supervisor, Dr. Ehfa binti Bujang Safawi and her colleague, Dr. William Tiong, both of whom are from the Faculty of Medicine and Health Science, UNIMAS, for providing the valuable skin burn images for this research work. Last but not least, I would like to thank my friends and my beloved family for their constant support, encouragement and understanding all this while.

## ABSTRACT

A correct first evaluation of burn injury is critical as the first treatment given to the patient based on the evaluation can lead to a better healing process. However, sometimes mistakes on the first evaluation of the burn injury can happen especially when a specialist is not available on site. Besides that, even an experienced doctor may sometimes be confused with the depth of burn through visual examination. In this thesis, a process of evaluating the burn depths to assist inexperienced doctors and to complement the diagnosis of the doctors and specialists is presented. This research specifically investigates the features that can characterise the burn depths in order to more accurately classify skin burn images. Thus, the main focus in this thesis is to propose a feature extraction process to extract features that can specifically characterise each burn depth. In this study, an image mining approach, specifically image classification process, is used to evaluate the skin burn images and classify the burn images into one of the burn depths. The burns depths studied in this thesis are superficial partial thickness burn (SPTB), deep partial thickness burn (DPTB) and full thickness burn (FTB). The proposed feature extraction process extracted six image features that represent the skin burn depths. These features, when used with common image features, were able to improve the performance in the classification of skin burn depths with an accuracy of 87.88% when tested on unseen data.

**Keywords:** Image classification, skin burn depths, feature extraction, classification of skin burn depths, features, colour, texture.

## ***Pengenalpastian Ciri-Ciri Imej Untuk Pengkelasan Tahap Kebakaran Kulit***

### **ABSTRAK**

*Penilaian awal tahap kecederaan kebakaran yang betul adalah kritikal kerana rawatan pertama yang diberikan kepada pesakit boleh menyumbang kepada proses penyembuhan yang lebih baik. Walau bagaimanapun, kadang kala kesilapan pada penilaian awal tahap kecederaan kebakaran boleh berlaku terutamanya apabila tiada pakar di tempat kejadian. Selain itu, doktor yang berpengalaman kadang kala akan keliru dengan tahap kebakaran yang dinilai secara visual. Dalam tesis ini, satu proses yang menilai tahap kebakaran untuk membantu doktor yang tidak berpengalaman dan untuk menambahbaik diagnosis doktor dan pakar disampaikan. Penyelidikan ini secara khusus menyelidik ciri-ciri yang boleh mencirikan tahap kebakaran untuk mengklasifikasikan imej kebakaran kulit dengan lebih tepat. Oleh itu, tumpuan utama dalam tesis ini adalah untuk mencadangkan proses pengestrakan ciri untuk mengekstrak ciri-ciri yang dapat mencirikan setiap tahap kebakaran. Dalam kajian ini, pendekatan perlombongan imej, khususnya proses klasifikasi imej, digunakan untuk menilai imej kebakaran kulit dan mengklasifikasikan imej kebakaran ke salah satu tahap kebakaran. Tahap kebakaran yang dikaji dalam tesis ini adalah luka bakar derajet II dangkal (SPTB), luka bakar derajet II dalam (DPTB) dan luka bakar derajet III (FTB). Proses pengestrakan ciri yang dicadangkan telah mengekstrak enam ciri imej yang mewakili tahap kebakaran kulit. Ciri-ciri ini, apabila digunakan dengan ciri-ciri imej biasa, dapat meningkatkan prestasi klasifikasi tahap kebakaran kulit dengan ketepatan 87.88% apabila diuji dengan imej yang baru.*

**Kata kunci:** *Klasifikasi imej, tahap kebakaran kulit, pengestrakan ciri, klasifikasi tahap kebakaran kulit, ciri, warna, tekstur.*

## TABLE OF CONTENT

|                                                               | <b>Page</b> |
|---------------------------------------------------------------|-------------|
| <b>DECLARATION</b>                                            | i           |
| <b>ACKNOWLEDGEMENT</b>                                        | ii          |
| <b>ABSTRACT</b>                                               | iii         |
| <b>ABSTRAK</b>                                                | iv          |
| <b>TABLE OF CONTENT</b>                                       | v           |
| <b>LIST OF TABLES</b>                                         | viii        |
| <b>LIST OF FIGURES</b>                                        | x           |
| <b>CHAPTER 1 : INTRODUCTION</b>                               | 1           |
| 1.1 Overview                                                  | 1           |
| 1.2 Human Skin Structure and Burn Injury                      | 3           |
| 1.3 Histological tools for clinical assessment of burn depths | 6           |
| 1.4 Motivation                                                | 7           |
| 1.5 Research Problems                                         | 8           |
| 1.6 Research Objectives                                       | 9           |
| 1.7 Expected Contributions                                    | 9           |
| 1.8 Structure of Thesis                                       | 10          |
| 1.9 Summary                                                   | 11          |
| <b>CHAPTER 2 : LITERATURE REVIEW</b>                          | 12          |
| 2.1 Introduction                                              | 12          |
| 2.2 Image Mining                                              | 12          |
| 2.2.1 Image Mining Process                                    | 14          |
| 2.3 Colour Model                                              | 23          |

|                                                          |                                        |    |
|----------------------------------------------------------|----------------------------------------|----|
| 2.3.1                                                    | CIE 1976 L*a*b* Colour Space           | 24 |
| 2.4                                                      | Texture Analysis Function              | 27 |
| 2.5                                                      | Grey-Level Co-Occurrence Matrix (GLCM) | 28 |
| 2.6                                                      | Pattern Search Algorithm               | 29 |
| 2.7                                                      | Related Works                          | 31 |
| 2.8                                                      | Burn Depth Characteristics             | 49 |
| 2.9                                                      | Literature Analysis                    | 51 |
| 2.10                                                     | Summary                                | 55 |
| <b>CHAPTER 3 : METHODOLOGY</b>                           |                                        | 57 |
| 3.1                                                      | Introduction                           | 57 |
| 3.2                                                      | Image Acquisition                      | 58 |
| 3.3                                                      | Image Pre-Processing                   | 59 |
| 3.4                                                      | Image Feature Extraction               | 60 |
| 3.4.1                                                    | Feature Set A – Global Features        | 65 |
| 3.4.2                                                    | Feature Set B – Blister Features       | 67 |
| 3.4.3                                                    | Feature Set C – Image Features         | 71 |
| 3.5                                                      | Image Classification                   | 89 |
| 3.6                                                      | Results Interpretation and Evaluation  | 90 |
| 3.7                                                      | Summary                                | 90 |
| <b>CHAPTER 4 : IMPLEMENTATION AND RESULTS DISCUSSION</b> |                                        | 91 |
| 4.1                                                      | Introduction                           | 91 |
| 4.2                                                      | Image Acquisition                      | 91 |
| 4.3                                                      | Image Pre-Processing                   | 92 |
| 4.4                                                      | Image Feature Extraction               | 93 |

|                                                |                                                  |     |
|------------------------------------------------|--------------------------------------------------|-----|
| 4.4.1                                          | Feature Set A – Global Features                  | 93  |
| 4.4.2                                          | Feature Set B – Blister Features                 | 93  |
| 4.4.3                                          | Feature Set C – Image Features                   | 94  |
| 4.5                                            | Image Classification                             | 100 |
| 4.5.1                                          | Experiment Using 10-Fold Cross Validation Method | 102 |
| 4.5.2                                          | Experiment Using Supplied Test Set Method        | 104 |
| 4.6                                            | Results Interpretation and Evaluation            | 106 |
| 4.7                                            | Summary                                          | 108 |
| <b>CHAPTER 5 : CONCLUSION AND FUTURE WORKS</b> |                                                  | 109 |
| 5.1                                            | Introduction                                     | 109 |
| 5.2                                            | Summary of Research                              | 109 |
| 5.3                                            | Objective Achievement and Contributions          | 111 |
| 5.4                                            | Research Work Limitations                        | 112 |
| 5.5                                            | Future Works                                     | 113 |
| 5.6                                            | Summary                                          | 114 |
| <b>REFERENCES</b>                              |                                                  | 115 |
| <b>APPENDIX</b>                                |                                                  | 123 |

## LIST OF TABLES

|           |                                                                                                                                                                      | Page |
|-----------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------|------|
| Table 2.1 | Confusion matrix                                                                                                                                                     | 21   |
| Table 2.2 | General Delta E value                                                                                                                                                | 26   |
| Table 2.3 | Burn depths characteristics defined in different previous research works                                                                                             | 50   |
| Table 2.4 | Summary of previous works                                                                                                                                            | 51   |
| Table 2.5 | Summary of colour and texture features extracted by previous works                                                                                                   | 53   |
| Table 3.1 | Total images collected for training and testing sets                                                                                                                 | 59   |
| Table 3.2 | Colour definition for each burn depth                                                                                                                                | 60   |
| Table 3.3 | Reference white point, D <sub>65</sub> values                                                                                                                        | 62   |
| Table 4.1 | Average and standard deviation colour values of the L*, a* and b* channels of the training images in the dataset for each of the burn depths                         | 94   |
| Table 4.2 | Optimum x values                                                                                                                                                     | 95   |
| Table 4.3 | Values computed from average and standard deviation colour ranges calculation process and optimum weightage generation process                                       | 97   |
| Table 4.4 | Values in colour ranges refining process                                                                                                                             | 97   |
| Table 4.5 | Proposed feature set combination                                                                                                                                     | 101  |
| Table 4.6 | Classification measures for proposed feature set combination using 10-fold cross validation method                                                                   | 101  |
| Table 4.7 | Classification measures for proposed feature set combination using supplied test set method                                                                          | 102  |
| Table 4.8 | Comparison of classification measures between the proposed feature set and the feature set proposed by previous research works using 10-fold cross validation method | 103  |
| Table 4.9 | Comparison of classification measures between the proposed feature set and the feature set proposed by previous research works using supplied test set method        | 105  |

|           |                                                 |
|-----------|-------------------------------------------------|
| Table 5.1 | Limitations of the research work in this thesis |
|-----------|-------------------------------------------------|

|     |
|-----|
| 112 |
|-----|

## LIST OF FIGURES

|                                                                                            | <b>Page</b> |
|--------------------------------------------------------------------------------------------|-------------|
| Figure 1.1 Human skin structure                                                            | 3           |
| Figure 1.2 Jackson's burn model                                                            | 4           |
| Figure 2.1 Image mining process                                                            | 14          |
| Figure 2.2 Image classification architecture                                               | 19          |
| Figure 2.3 Image mining process used in the classification of skin burn depths images      | 22          |
| Figure 2.4 Image mining process used in the classification of skin cancer and skin allergy | 23          |
| Figure 2.5 Image mining process used in the classification of skin burn depths images      | 23          |
| Figure 2.6 CIE L*a*b* colour chart                                                         | 26          |
| Figure 3.1 Proposed image classification process for skin burn depths                      | 57          |
| Figure 3.2 Proposed feature extraction process                                             | 64          |
| Figure 3.3 Blister region detection process                                                | 67          |
| Figure 3.4 Average and standard deviation colour ranges calculation process                | 71          |
| Figure 3.5 Optimum weightage generation process using pattern search algorithm             | 77          |
| Figure 3.6 Colour ranges refining process                                                  | 85          |
| Figure 3.7 Colour area percentage process                                                  | 88          |
| Figure 4.1 SPTB images                                                                     | 91          |
| Figure 4.2 DPTB images                                                                     | 91          |
| Figure 4.3 FTB images                                                                      | 92          |
| Figure 4.4 Cropped SPTB images                                                             | 92          |
| Figure 4.5 Cropped DPTB images                                                             | 92          |

|             |                                                                          |     |
|-------------|--------------------------------------------------------------------------|-----|
| Figure 4.6  | Cropped FTB images                                                       | 93  |
| Figure 4.7  | Blister region detection process                                         | 94  |
| Figure 4.8  | Sample output images with the colour ranges used for characterising DPTB | 98  |
| Figure 4.9  | Sample output images with the colour ranges used for characterising FTB  | 99  |
| Figure 4.10 | Sample output images with the colour ranges used for characterising SPTB | 99  |
| Figure 4.11 | Misclassified images                                                     | 107 |
| Figure 4.12 | Common FTB                                                               | 107 |

# **CHAPTER 1**

## **INTRODUCTION**

### **1.1 Overview**

Burn incidents occur very commonly and suddenly without any prior notification to anyone, at anywhere and at any time. Burn incidents happen differently from one region to another region. According to Badea, Vertan, Florea, Florea, and Badoiu (2016), burn incidents have caused about 330,000 deaths per year and it is the fourth leading cause of death globally. The clinical information of any burn incidents was unable to be clearly transmitted remotely to a burn unit through communication via phone, therefore, the use of digital images to convey these clinical information was the most effective.

Digital images play a very important role in the medical field. In the past, a burn image is very crucial for the diagnosis of a patient as the selection for the type of emergency treatment, place and the method to evacuate the patient is based on the burn image (Roa, Gómez-Cía, Acha, & Serrano, 1999). The information in the image is transmitted from a remote location via phone to the burns unit with a burn specialist when the burn specialist is not present in one location. This leads to the patient sometimes not receiving the appropriate treatment as the clinical information transferred were not sufficient to describe the burn characteristics and the transferring via phone also lack efficiency (Roa et al., 1999). Since 1980's, communications via digital technology has become increasingly important and later digital images emerged as part of human communication. Due to the use of digital image requiring a relatively higher cost, the applications that utilised or involved digital images were very limited. The representation of digital image with a huge quantity of data had become the main challenge for many

applications. Besides that, the storage and transmission cost for the digital images had deterred the development of many applications although the device for capture and visualisation were available (Roa et al., 1999). The advance from visual examination to an automated system allows a more accurate evaluation and diagnosis of skin burn depths.

According to Roa et al. (1999), any automated systems that were developed for the evaluation or diagnosis of burns should fulfil certain criteria. The criteria are as follows:

- (i) It should be affordable in terms of operation and purchasing;
- (ii) It should preserve the burn characteristics;
- (iii) It should not cause any psychological impact to patients when their clinical state information is being acquired;
- (iv) The quality of the information should be retained when transferred.

An automated system can be developed with the help of image processing as the techniques in image processing are objective and reproducible (Acha, Serrano, & Roa, 2001).

Image processing is getting more popular nowadays with the advances in technology as well as the use of Computer Aided Diagnosis (CAD) systems in the medical field. The colour skin images in the earlier research fields were only limited to two applications, which were the assessment of the healing of ulcers (Arnqvist, Hellgren, & Vincent, 1988) or skin lesions (Herbin et al., 1993) and the diagnosis of pigmented skin lesions (Fiorini et al., 1997). With the emergence of image mining, more applications can be developed making use of colour images from the medical field. Image mining is said to be an extension of data mining in the image processing field (Sudhir, 2011). The image mining approach will be further discussed in Chapter 2 of this thesis.

## 1.2 Human Skin Structure and Burn Injury

Human skin is made up of three layers as shown in Figure 1.1, which are: (i) the epidermis, which is the outermost layer of the skin, (ii) the dermis, lay underneath the epidermis layer and (iii) the subcutaneous layer, which is the inner layer of the skin, constitutes of fat and connective tissue. The dermis layer is further divided into two sub-layers, which are papillary layer (superficial) and reticular layer (deep) (“Boundless Anatomy and Physiology in Structure of the Skin: Dermis,” 2016). Generally, burns are classified into: (i) Superficial burn, which involves only the epidermis, (ii) Partial thickness burn, which is further divided into (a) superficial partial thickness burn, involving the entire epidermis and the upper layer of the dermis (papillary layer) and (b) deep partial thickness burn, affecting the entire epidermis and most of the dermis and (iii) Full thickness burn, in which all the layers of the skin are destroyed and some may extend into muscle and bone (Koutoukidis, Stainton, & Hughson, 2012).

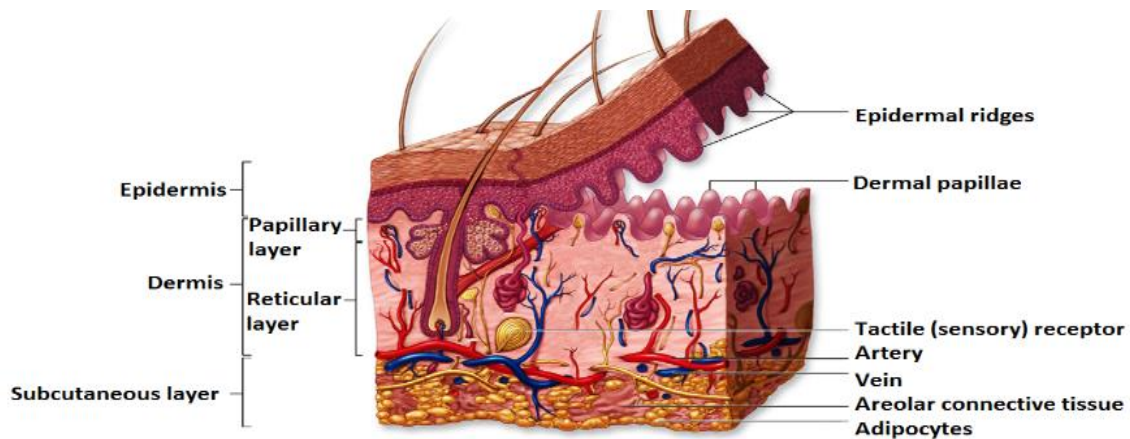


**Figure 1.1:** Human skin structure (Mescher, 2016)

Singer (2000) described the appearance of superficial burn, superficial partial thickness burn, deep partial thickness burn and full thickness burn as follows. The appearance of superficial burn has erythema that turns pale to pressure and it presents with

pain. This type of burn will take about three to six days for healing and leave no scar. Superficial burn is normally caused by ultraviolet exposure and mild scald.

Superficial partial thickness burn can has blisters forming on the surface and this burn is very painful. This burn will appears moist and erythematous once the blisters rupture. This burn will turn pale after applying some pressure. This type of burn takes two to three weeks for healing with minimal scarring. Superficial partial thickness burn is caused by scald, flash burns or contact with hot objects in short duration.

Deep partial thickness burn appears white with erythematous areas, dry, waxy, less elastic and the paleness is reduced after applying some pressure on it. This burn takes about three to six weeks to heal and often leaves scar and causes joint contractures. Deep partial thickness burn is caused by flame, scalds or hot grease.

Full thickness burn appears white, charred and tan. This burn appears to have a leathery texture due to the loss of elasticity of the skin. The wound is anaesthetic and hence is not painful. This type of burn cannot heal spontaneously and thus require an excision, followed by skin grafting. Full thickness burn is caused by electrocution, chemicals, flame and exposure to heat sources at temperatures greater than 55 °C in a longer duration.

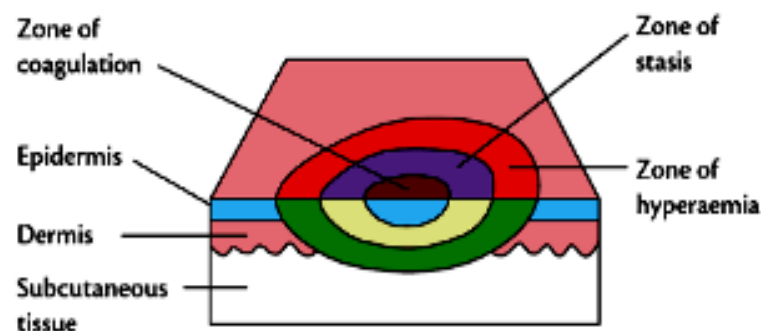


**Figure 1.2:** Jackson's burn model (Thomas, Reed, & Wyatt, 2016)

According to Jackson (1953), burn wound consists of three zones as shown in Figure 1.2. The “zone of coagulation” is the centre of the burn wound and it results from the direct thermal injury at the time the skin surface is exposed to the heat source. The “zone of stasis” surrounding the “zone of coagulation” is the zone where the inflammation response is prominent and the blood flow is reduced due to the vascular reactivity. The blood flow reduction may cause the burn wound to extend and deepen for the first 24 to 48 hours after injury. The “zone of hyperaemia” is the outermost area that surrounds the burn wound and where the vasodilation and increase in blood flow occurs.

Classification of burn types depends on the location, the depth and extent of the injury (Singer, 2000). Burns on the hand and feet need admission and excision due to its complexity and the significant functions played by these areas, in terms of movement and ability to work. Dead and coagulated skin caused by full thickness burn may lead to weakening of vascular or respiratory system in human body. Apart from that, burns on the limbs, neck and chest require special attention (Singer, 2000). According to Suvarna, Sivakumar, and Niranjana (2013), the most serious burn depth normally occur at the centre of the burn area. The progress of the burn wound needs to be observed over several weeks until the burn is either in the healing process or it extends to be clearly full thickness burn. This observation is said to be the most accurate way to determine the burn depth (Afromowitz, Liew, & Heimbach, 1987). However, if an appropriate treatment is provided within the first few days after the injury, it will be a great advantage for the burn wound to heal especially for full thickness burn, when the burn wound size is small to medium (Afromowitz et al., 1987). Despite many evaluations or tests conducted to examine the seriousness of a burn injury, the burn specialists’ evaluation is still the most reliable ones (Suvarna, Sivakumar, & Niranjana, 2013).

The superficial burn is not included in the scope of this thesis as this type of burn can heal spontaneously and do not normally require consultation with a burn specialist. In clinical practice, there are normally three types of burn being considered. They are superficial partial thickness burn (SPTB), deep partial thickness burn (DPTB) and full thickness burn (FTB).

### **1.3 Histological tools for clinical assessment of burn depths**

The skin is known to be transparent to short wavelength infra-red light in 1920's (Heimbach, Afromowitz, Engrav, Marvin, & Perry, 1984). Thus, infra-red light was used to diagnose the burn depth in 1960's by studying the heat radiation from the burn (Lawson, Wlodek, & Webster, 1961). Besides this, there were other methods such as radioactive isotopes (Bennett & Dingman, 1957), vital dyes (Randolph, Leape, & Gross, 1964), optical reflectance technique (Afromowitz et al., 1987), multispectral imaging (Afromowitz, Callis, Heimbach, Desoto, & Norton, 1988), ultraviolet imaging (Barsley, West, & Fair, 1990) and Laser Doppler (Niazi et al., 1993) used in determining the burn depths. Each of these techniques have their own limitations. For example, thermography is sensitive to the temperature of the patient and environment, has difficulty in calibration and the reading is varied due to the evaporative cooling of the wound and the presence of exudate on the wound surface (Heimbach et al., 1984). Laser Doppler is sensitive to positioning, patient's temperature, environmental temperature, as well as the reading is varied due to the resuscitation stage and the general circulation of the patient (Heimbach et al., 1984). The analysis time for using thermography is too slow for clinical decision making.

## 1.4 Motivation

The method currently used in determining and evaluating the burn depths is the visual examination carried out by an experienced burn specialist. According to Heimbach et al. (1984), the accuracy of experienced burn specialists in evaluating the burn depths is 64% to 76% whereas for inexperienced doctors, the accuracy is around 50%. This was due to the reason that burns like deep partial thickness burn, full thickness burn or even intermediate burn can share the same clinical features that are generally used in evaluating the burn depths (Heimbach et al., 1984). Although there are many methods in determining the depth of the burn injury automatically, the reliability of these methods is very inconsistent. The burn specialist evaluation still remains the standard in differentiating the burn depths (Singer, 2000). In addition, a correct evaluation of the burn depths can reduce the risk of false-positive and false negative evaluations. The false-positive evaluation refers to a patient undergoing surgery for a burn that can heal spontaneously whereas for false-negative evaluation, the patient may experience contracture and formation of hypertrophic scar (Jaskille, Shupp, Jordan, & Jeng, 2009).

The best automated burn depths classification system in terms of feature extraction should capture the knowledge of the burn specialist in evaluating the burn depths. This can be incorporated in image mining. Image mining is important as human faces difficulties to learn and understand the underlying patterns from a collection of images. Two images may appear the same in colour, but they are different in their underlying patterns. An experienced burn specialist may sometimes be confused with the depth of burn through visual examination. Thus, the motivation is to capture the knowledge of the burn specialist that can characterise each burn depth to be incorporated in an image mining approach to distinguish between the classes of burn depths.

## 1.5 Research Problems

Currently, none of the existing research works focused on extracting features that specifically characterise each burn depth. Many of the existing research works were concerned with extracting global features from the skin burn images, which were normally the common colour features for images (Serrano, Boloix-Tortosa, Gómez-Cía, & Acha, 2015; Tran, Le, Le, & Nguyen, 2015). The most recent works for skin burn images were not focused on the classification of skin burn depths, rather, they classified images into burned skin and healthy skin (Despo et al., 2017; Sabeena & Raj Kumar, 2017). The current state-of-the-art in skin burn depths classification is performed by using deep learned convolutional neural network (CNN) (Badea et al., 2016; Tran, Le, & Nguyen, 2016) and fully convolutional network (FCN) (Despo et al., 2017), which automatically extracts the relevant features from the input images without users knowing the extracted features. However, because deep learning was used, the features extracted were unknown and further analysis could not be performed. Therefore, this research focuses on extracting features that are representative of the characteristics of each skin burn depth.

Besides that, burn specialists may not always be available at the accident site or at the clinics or hospitals especially in more remote locations. In addition, the accuracy of diagnosis by experienced burn specialists through visual examination are only between 64% and 76% whereas those inexperienced doctors are less accurate in evaluating the burn depths. Moreover, current technologies such as Laser Doppler is very sensitive to the patient and environment temperature and the reading is varied as described in Section 1.3. In addition, it is a very high cost machine and majority of clinics and hospitals cannot afford it. Therefore, a tool for evaluation of burn depths is essential to assist and augment the diagnosis of both experienced and inexperienced doctors.

## 1.6 Research Objectives

The research question based on the research problems is: *How to characterise each skin burn depth?* This question further give rise to the following subsidiary questions:

- (i) *How to represent each skin burn depth using image features?*
- (ii) *What are the best features that can classify the skin burn depths effectively?*
- (iii) *How to evaluate the performance of the features?*

The main objectives of this research, which are derived from the research questions are to:

- (i) extract image features that characterise the skin burn depths for classification of skin burn images.
- (ii) determine features that can effectively classify the skin burn depths.
- (iii) compare the performance of the features used in this research work with the features used in previous research works.

## 1.7 Expected Contributions

The main contributions of this research are:

- (i) A process to extract image features that characterise the burn depths for the classification of skin burn images. Colour and texture features are important in classification of skin burn depths. Previous research works were mostly extracting global features to classify the skin burn depths. The global features are extracted by considering the entire pixels of an image, which was straight forward in the extraction. According to Chan, Xiong, Liu, and Purnomo (2001), global features are weak to represent images that contain variety of objects or regions, in which each of the images have their own image attributes. Although global features are straight forward and fast to extract, they cannot describe an image content

specifically especially for images that contain variations and are domain specific. Thus, a process is proposed to extract features that can characterise the skin burn depths.

- (ii) A set of image features that are representative of the characteristics of the three burn depths. Global features as extracted by previous research works were used to represent an entire image. If there was a mixed burn depth appearance in an image, this implies that a generalised pixel value of the entire image was taken into consideration. This generalisation may not be able to represent the characteristic of each burn depth. Global features are assumed to be used with images that contain only a single object as global features are sensitive to clutter (Lisin, Mattar, Blaschko, Learned-Miller, & Benfield, 2005). Thus, in this thesis, global features are assumed to work well with homogeneous skin burn images but not for heterogeneous burn images. Homogeneous skin burn image refers to an image that consist of only one burn depth colour whereas heterogeneous burn image refers to an image that consist of multiple burn depths colour. The skin burn dataset consists of both homogeneous and heterogeneous skin burn images. In a preliminary experiment, it was discovered that using the global features were not sufficient. There were images, specifically, SPTB images that contained blisters. Therefore, blister features were extracted. Blister features refer to features that characterise the appearance of blister.

## **1.8 Structure of Thesis**

The rest of the thesis is organised as follows. Chapter 2 presents a number of previous research works in the classification of skin burn images. Chapter 3 presents the methodology used, the proposed feature extraction process and the features extracted for

the classification of skin burn depths. Chapter 4 discusses the classification results of the proposed feature extraction process and the comparison between the features extracted and the different sets of features used in the past literatures. Chapter 5 summarises the research and suggests some future works.

## **1.9 Summary**

This chapter presented the overview of human skin structure and burn injury, histological tools used for clinical assessment of burn depths, motivation, research problems, research objectives and expected contributions in this research. The literature review is discussed next in Chapter 2.

## **CHAPTER 2**

### **LITERATURE REVIEW**

#### **2.1 Introduction**

In this chapter, the related literatures are reviewed. These cover image mining and its processes, including image acquisition, image pre-processing, image feature extraction, image classification and results interpretation and evaluation.

#### **2.2 Image Mining**

Image mining plays a crucial role in today's technological advanced world as the demand for extracting useful information from images is increasing. The increasing of demands, in turn, is corresponded to the increasing in the need of image data such as digital photographs, medical images, satellite images, business images and so on for various purposes. Hence, this phenomena leads to image mining becoming one of the important research areas to continue finding a better way to represent images so that data mining techniques can be easily applied on those images (Karthikeyan & Manikandaprabhu, 2013).

Image mining is a technique that is often used to discover hidden yet significant knowledge or patterns which are not clearly visible from an image (Sudhir, 2011). According to Khodaskar & Ladhake (2014), image mining is defined as follows. Image mining extract the implicit knowledge, image data relationship, or patterns that are not explicitly seen in the images. Image mining is different from computer vision in which image mining extracts patterns from a collection of images whereas computer vision is the understanding and/or extraction of specific features from a single image. Image mining is an interdisciplinary field with a combination of techniques such as computer vision, image

processing, image retrieval, data mining, machine learning, database and artificial intelligence (Sudhir, 2011).

The definition of image mining given by Kaur and Kaur (2014) is as follows. Image mining is said to be the extension of data mining that focus on knowledge discovery on images. Although there are some overlapping between image mining and content-based image retrieval as both handles a collection of images, there exists a difference between both of them whereby image mining goes beyond the issue of retrieving relevant images, which is to discover the significant patterns from the collection of images. There is also some confusion or misinterpretation that exist between image mining and data mining, in which image mining is said to be just applying data mining techniques on images. This statement was denied by them. According to them, there were differences between relational database and image database. The differences are as follows: (i) The data value in relational database is semantical whereas the data value in image database is less significant unless the context supports it. For example, student identification number of 36562 in a relational database is understandable, but in an image database, a grey intensity value of 78 appears brighter than a grey intensity value of 28 if their context pixels values are all darker, (ii) Spatial information is important for the analysis of image contents as the position is dependent but in relational database, spatial information is not required as the position is independent and (iii) Image characteristics require multiple interpretation for the same patterns whereas the data value in relational database requires only unique interpretation.

The need for image mining in today's digital world is due to the advances in image acquisition and storage technology, which has led to the growth of large and detailed image databases (Khodaskar & Ladhake, 2014).

There were various techniques and applications developed in the earlier research that used the image mining approach including natural scene recognition, remote sensing, weather forecasting, image segmentation and so on (Gajjar & Chauhan, 2012). According to Nagthane (2013), such domains expands to a variety of fields such as medical diagnosis, agriculture, industries and even in education. There are some real-world application that uses image mining approach such as monsoon and rainfall prediction, satellite image mining for weather forecasting and textile image retrieval (Tripathi & Jangir, 2016).

According to Sudhir (2011), the primary purpose of image mining is to result in discovering a significant pattern without any prior information of the image content. Thus, this leads to various patterns being discovered, which can be classification patterns, description patterns, correlation patterns, temporal patterns or spatial patterns. Image mining is still an emerging and challenging field as it extends the structured data from data mining to unstructured data in images (Shukla & Vala, 2016). The following sub-section describe the general image mining process.

### 2.2.1 Image Mining Process

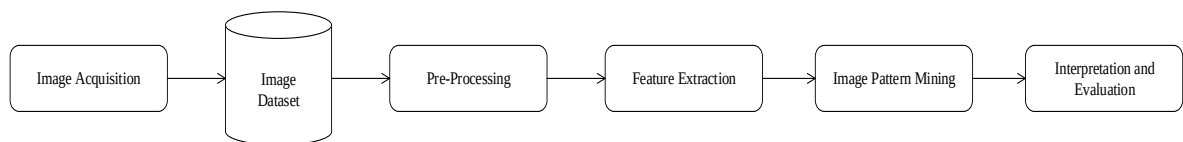


**Figure 2.1:** Image mining process (Shukla & Vala, 2016)

According to Shukla and Vala (2016), the image mining process include refining image databases, pre-processing of images to increase the image quality, feature extraction to extract features that are representative of the image, image pattern mining to discover the image patterns and the final interpretation and evaluation of the resulting image pattern

to discover the final knowledge, which is applied to its uses. The general image mining process is shown in Figure 2.1. The image pattern mining techniques include object recognition, image retrieval, image indexing, image classification and image clustering (Shukla & Vala, 2016). This thesis focuses on image classification in the image pattern mining process and this will be discussed in paragraphs to follow and Chapter 3.

In the image acquisition stage, images can be collected from various sources, such as from the Internet, digital cameras, the hospital image repository and so on. The techniques and protocols used in collecting images can vary from one work to another. Digital camera has become one of the main sources in acquiring skin burn images. The digital camera is chosen because according to Serrano, Roa, and Acha (1998), digital camera is easy to use, the equipment needed is minimal, specifically; only the computer and camera are needed in the process. Image acquisition can be carried out by any non-expert personnel easily. Hence, using the digital camera is a good option as an affordable image acquisition method. A number of subtasks may be conducted as part of the image acquisition stage, in which the most common ones include searching for the available image sources, estimate the total number of images required for each burn depth that will be studied, protocols required for standardisation and techniques required in collecting images.

In the pre-processing stage, various techniques can be used to pre-process the images. Image pre-processing is very subjective as the techniques used for one image may not be suitable for the other images (Nagthane, 2013). One of the most common techniques used by previous research works in the classification of skin burn depths was image segmentation. Image segmentation, according to Sabeena and Raj Kumar (2017), is a process in which the input image is partitioned into non-overlapping regions, which are

homogeneous regions, referring to each region and heterogeneous region, referring to the union of any two adjacent regions. There were many different segmentation algorithms or approaches that had been done through extensive research all this while but the accuracy of each algorithm or approach was still difficult to assess (Sabeena & Raj Kumar, 2017). Image segmentation can be carried out, either automatically or manually, based on the requirements of the application (Kaur & Kaur, 2014).

A good segmentation is able to identify objects individually, leading to a successful solution for an imaging problem whereas a poor segmentation will eventually lead to failure (Nagthane, 2013). However, according to Acha, Serrano, Acha, and Roa (2003), general-purpose segmentation algorithms are less capable in separating the burnt skin from the healthy skin because of the slight difference between them. None of the segmentation algorithms available can be used as a standard because most of these segmentation algorithms are developed specifically for specific applications. The subtasks in image pre-processing stage can be divided into segmentation-based approach and segmentation-free approach. Segmentation-based approach means that the burn wound needs to be segmented from the skin region before feature extraction whereas a segmentation-free approach means that features are directly extracted from the burn image. The most common tasks for segmentation-based approach are user selection, image conversion, image thresholding, remove unnecessary noise from the image and object clustering, whereas for segmentation-free approach, the common tasks include image conversion, image cropping, image resizing and contrast enhancement.

According to Kaur and Kaur (2014), in the feature extraction stage, the common image attributes such as colour, edges, shape and texture were used to extract features for mining, either globally or locally from the images. According to Nagthane (2013), feature

extraction referred to the extraction of the basic elements that could represent an image while omitting those that were insignificant to the mining result. Sometimes, to get a better mining result, it would be essential to merge multiple features to form a multidimensional feature vector.

Generally, there are two types of approaches often used by many object recognition system for classification, which are either using global or local features (Lisin et al., 2005). Local feature is referring to multiple interest points that are computed in image patches and it is mostly used to represent texture (Lisin et al., 2005). Local feature are robust to occlusion and clutter. To the best of our knowledge, there is no other work extracting local features from the skin burn images. All of the previous research works for skin burn depths classification were extracting global features by computing the statistical moments such as mean of hue, standard deviation of chroma and so on. Their approaches revolved around finding the features in terms of colour and texture as Acha and Serrano (2000) stated that colour and texture were the characteristics observed by the experts in order to differentiate the burn depths and to give a diagnosis (Acha, Serrano, & Acha, 2002; Acha et al., 2003; Acha, Serrano, Acha, & Roa, 2005; Acha, Serrano, Palencia, & Murillo, 2004; Serrano, Acha, Gómez-Cía, Acha, & Roa, 2005).

There are two different methods for feature extraction, which are structural method and statistical method. Structural method refers to the method that looks for features that have contour such as edges and shapes, whereas statistical method refers to the method that focuses on the relationship between pixels and the statistical moments (Krig, 2016). These two methods are commonly used in texture analysis, whereas for colour analysis, statistical method is more commonly used in finding the statistical moments. Statistical methods can be classified into first order (one pixel), second order (two pixel) and higher order (three or

more pixels) statistics (Vardhan & Rao, 2014). The first order statistics is different from the second and higher orders statistics because single pixel does not need to consider the relationship between pixels at specific locations. The Grey-Level Co-occurrence Matrix (GLCM) (Haralick, Shanmugan, & Dinstein, 1973) is one of the well-known second order statistics for texture analysis.

The most common types of feature used are colour and texture features. Colour feature is the basic feature that is able to be visually seen by human for recognition of objects or regions in an image. Colour feature is widely being extracted in feature extraction due to the reason that the human eye is more sensitive to the colour compared to the grey intensity of an image. Most of the previous research works extracted colour features from the burn images globally, by considering the pixels from a whole image. Texture of colour is also another colour feature. The texture of colour feature refers to skewness and kurtosis of the colour of an image. Texture feature in an image refers to the visual properties or pattern of an object or region in an image such as smoothness, roughness, coarseness and so on. The texture feature is able to provide information on the spatial arrangement of intensities or selected object or region in an image.

Several techniques can be used for image pattern mining. The most common techniques used, specifically in the classification of skin burn depths, was image classification. In the image classification stage, the extracted features from a collection of pre-labelled images are used with machine learning to discover the significant patterns, which are later used to predict the class of new images. Image classification, according to Shukla and Vala (2016), is a collection of pre-labelled images that are given as an input to the machine learning algorithms, which in turn are used to label new unlabelled images in the supervised classification environment. Generally, classification is divided into two



Previous research works for the classification of skin burn depths include global classification (Acha & Serrano, 2000), cross validation (Acha et al., 2005; Serrano, Acha, Gómez-Cía, et al., 2005; Wantanajittikul, Auephanwiriyaikul, Theera-Umpon, & Koanantakool, 2012), blind test (Wantanajittikul et al., 2012), binary classification (Sabeena & Raj Kumar, 2017; Wantanajittikul et al., 2012) and multiclass classification (Suvarna, Sivakumar, Kumar, & Niranjana, 2013; Suvarna, Sivakumar, & Niranjana, 2013). Global classification according to the literature, referred to the images assigned to each possible group of burn and later the colour and texture features were joined using the AND operator. Cross validation referred to partitioning the images in the training set into training and validation set, in which the average of the results of these partitions was taken as the final output (Brownlee, 2018). Blind test referred to the trained model used to test the images in the testing set, which were different from the training set (Wantanajittikul et al., 2012). Binary classification referred to the classification in which one class was taken against the other class, in which there existed two classes (Hackeling, 2014). Multiclass classification referred to the classification in which one class was taken to against the other classes, in which there existed more than two classes (Hackeling, 2014).

The most common classification algorithms used were Fuzzy-ARTMAP neural network (Acha et al., 2002, 2005; Serrano, Acha, Gómez-Cía, et al., 2005), Support Vector Machine (SVM) (Serrano et al., 2015; Suvarna, Sivakumar, & Niranjana, 2013; Wantanajittikul et al., 2012) and K-Nearest Neighbour (KNN) (Acha, Serrano, Fondon, & Gomez-Cia, 2013; Suvarna, Sivakumar, & Niranjana, 2013; Wantanajittikul et al., 2012). Other classification algorithms such as Linde-Buzo-Grey (LBG) vector quantisation algorithm (Acha et al., 2001; Acha & Serrano, 2000), Bayes (Wantanajittikul et al., 2012), one-class support vector machine (OC-SVM) (Tran et al., 2015), template matching

method (Suvarna, Sivakumar, Kumar, et al., 2013; Suvarna, Sivakumar, & Niranjana, 2013) and Artificial Neural Network (ANN) (Suvarna, Sivakumar, Kumar, et al., 2013) were also used in the literature to classify the skin burn depths images.

Before obtaining the final knowledge, the significant patterns obtained need to be evaluated and interpreted to discover the required knowledge (Tripathi & Jangir, 2016). The most common measure used by the literature to evaluate the performance of the classification was the accuracy measure (Acha et al., 2005; Tran et al., 2015; Wantanajittikul et al., 2012). Other measures such as sensitivity, specificity (Acha et al., 2013; Serrano et al., 2015), positive predictive value and negative predictive value (Acha et al., 2013) were also used by the literatures. In this thesis, the measures used to evaluate the performance of the classifier were accuracy, precision, recall and F<sub>1</sub>-measure, which were calculated based on the confusion matrix shown in Table 2.1. The formulas for accuracy, precision, recall and F<sub>1</sub>-measure are shown in Formulas 2.1, 2.2, 2.3 and 2.4.

**Table 2.1:** Confusion matrix

|              |      | Prediction Class |     |      |
|--------------|------|------------------|-----|------|
|              |      | DPTB             | FTB | SPTB |
| Actual Class | DPTB | TP               | FN  | FN   |
|              | FTB  | FP               | TN  | FN   |
|              | SPTB | FP               | FN  | TN   |

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100\% \quad (2.1)$$

$$Precision = \frac{TP}{TP+FP} \times 100\% \quad (2.2)$$

$$Recall = \frac{TP}{TP+FN} \times 100\% \quad (2.3)$$

$$F_1\text{-measure} = \frac{2 \star \text{Precision} \star \text{Recall}}{\text{Precision} + \text{Recall}} \quad (2.4)$$

where, TP = True Positive, TN = True Negative, FP = False Positive, FN = False Negative

The true positive (TP) refers to positive images that are correctly predicted as positive, true negative (TN) refers to negative images that are correctly predicted as negative, false positive (FP) refers to negative images that are incorrectly predicted as positive and false negative (FN) refers to positive images that are incorrectly predicted as negative.

In some existing research works, the image pre-processing was conducted under image segmentation as shown in Figure 2.3 (Acha et al., 2003), while some researchers separated both processes into individual modules as shown in Figure 2.4 (Deshpande & Amruta, 2016). There were some works that directly went through feature extraction stage from the pre-processing stage, where cropped burn wound images were used in the work, as shown in Figure 2.5 (Suvarna, Sivakumar, Kumar, et al., 2013).

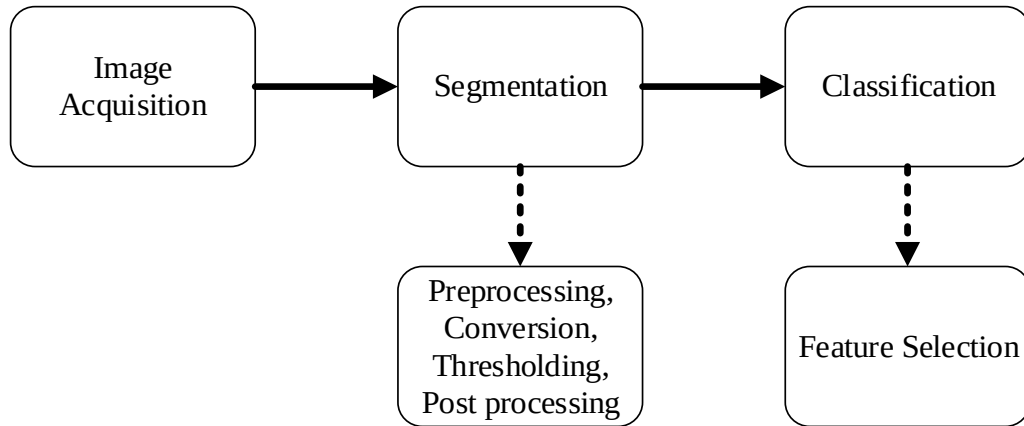


**Figure 2.3:** Image mining process used in the classification of skin burn depths images (Acha et al., 2003)

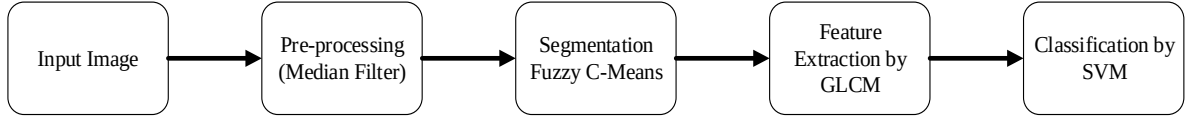


**Figure 2.4:** Image mining process used in the classification of skin cancer and skin allergy (Deshpande & Amruta, 2016)

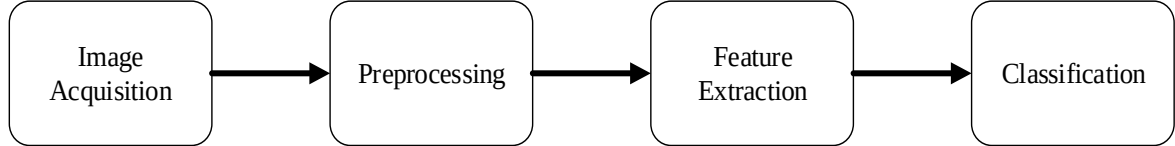


**Figure 2.5:** Image mining process used in the classification of skin burn depths images (Suvana, Sivakumar, Kumar, et al., 2013)

### 2.3 Colour Model

Different people perceive colour differently. This different perception may be influenced by numerous physiological factors such as age and eye fatigue, experiential and environmental factors as well as human personal preferences. CIE  $L^*a^*b^*$  and CIE  $L^*u^*v^*$  colour representations are both perceptually uniform colour spaces (Petrou & Petrou, 2010). According to Baldevbhai and Anand (2012), perceptually uniform colour is defined as a change of the same amount of colour value should produce a change of the same visual importance. Both of these colour spaces are used as reference for device independent models. Device independent refers to the colour constancy across all devices and represents the true colours as perceived by the human eye (Baldevbhai & Anand, 2012). Both colour spaces are defined in terms of XYZ colour system and the reference white point ( $X_n, Y_n, Z_n$ ).

The reference white is normally chosen based on the conditions under which the image was captured (Petrou & Petrou, 2010). In this thesis, the standard illuminant,  $D_{65}$  was used, which is discussed in Section 3.4.

### 2.3.1 CIE 1976 L\*a\*b\* Colour Space

In 1930s, the colour scientists had formed a scientific body, which was the Commission Internationale d'Eclairage (CIE) or International Commission on Light. The standard observer, the L\*a\*b\* colour space and Delta E measurements were the three core definitions provided by the CIE (Martin, 2015). The standard observer represents the average person with normal colour perception, which describes the colour via numbers (Mokrzycki & Tatol, 2011). The L\*a\*b\* colour space and Delta E measurements are important for colour management. L\*a\*b\* colour space is also known as CIE 1976, CIELAB, or the informal abbreviation such as Lab (Baldevbhai & Anand, 2012). L\*a\*b\* is the most complete colour space specified by CIE (Baldevbhai & Anand, 2012). The L\*a\*b\* colour space consists of three axes, which are L\*: represents darkness to lightness, a\*: represents greenness to redness and b\*: represents blueness to yellowness. The L\* axis has values ranging from 0 (darkness) to 100 (lightness), the a\* axis has values ranging from -128 (greenness) to +127 (redness) and the b\* axis has values ranging from -128 (blueness) to +127 (yellowness) (Martin, 2015). The L\*a\*b\* colour space is divided into two parts, which are achromatic and chromatic. Achromatic is represented by the L\* axis, which means it does not consist of colour whereas chromatic is represented by the a\* and b\* axes, relating to colour characters and types of light (Martin, 2015). Based on Figure 2.6, the colours toward the centre of the colour space, along the L\* axis are more neutral and grey. The extremes of the a\* and b\* axes are the most saturated colours, in which they have the large negative and positive numbers. The L\*a\*b\* is defined as follows, in which Formula 2.5 shows the formula of L\*, Formula 2.6 shows the formula of a\*, Formula 2.7 shows the formula of b\* and Formula 2.8 shows the formula of function  $f$  used in Formulas 2.6 and 2.7 (Petrou & Petrou, 2010).

$$L^* = \begin{cases} 116 \left( \frac{Y}{Y_n} \right)^{\frac{1}{3}} - 16, & \text{if } \frac{Y}{Y_n} > 0.008856 \\ 903.3 \frac{Y}{Y_n}, & \text{if } \frac{Y}{Y_n} \leq 0.008856 \end{cases} \quad (2.5)$$

$$a^* = 500 \left[ f \left( \frac{X}{X_n} \right) - f \left( \frac{Y}{Y_n} \right) \right] \quad (2.6)$$

$$b^* = 200 \left[ f \left( \frac{Y}{Y_n} \right) - f \left( \frac{Z}{Z_n} \right) \right] \quad (2.7)$$

where,

$$f(x) = \begin{cases} x^{\frac{1}{3}}, & \text{if } x > 0.008856 \\ 7.787x + \frac{4}{29}, & \text{if } x \leq 0.008856 \end{cases} \quad (2.8)$$

Delta E ( $\Delta E$ ), is the difference between two colours, which can be between a sample's colour and a standard colour. Deltas  $L^*$  ( $\Delta L^*$ ),  $a^*$  ( $\Delta a^*$ ) and  $b^*$  ( $\Delta b^*$ ) can be positive or negative, but  $\Delta E$  is always positive. Formula 2.9 shows the formula for delta E ( $\Delta E$ ) of  $L^*a^*b^*$ , Formula 2.10 shows the formula of delta  $L^*$  ( $\Delta L^*$ ), Formula 2.11 shows the formula of delta  $a^*$  ( $\Delta a^*$ ) and Formula 2.12 shows the formula of delta  $b^*$  ( $\Delta b^*$ ) (Sharma, 2004).

$$\Delta E = \sqrt{\Delta L^{*2} + \Delta a^{*2} + \Delta b^{*2}} \quad (2.9)$$

where,

$$\Delta L^* = L^* \text{ sample} - L^* \text{ standard} \quad (2.10)$$

$$\Delta a^* = a^* \text{ sample} - a^* \text{ standard} \quad (2.11)$$

$$\Delta b^* = b^* \text{ sample} - b^* \text{ standard} \quad (2.12)$$

Generally, the  $\Delta E$  value can range from 0 to 100 as shown in Table 2.2. In this thesis,  $\Delta E$  is used between the selected colour range and a pixel in the image and is described in Sub-section 3.4.3.

**Table 2.2:** General Delta E value (Schuessler, n.d.)

| Delta E, $\Delta E$ | Perception                             |
|---------------------|----------------------------------------|
| $\leq 1.0$          | Not perceivable with human eye         |
| 1 - 2               | Perceivable through close observation  |
| 2 - 10              | Perceivable at a glance                |
| 11 - 49             | Colours are more similar than opposite |
| 100                 | Colours are totally not the same       |

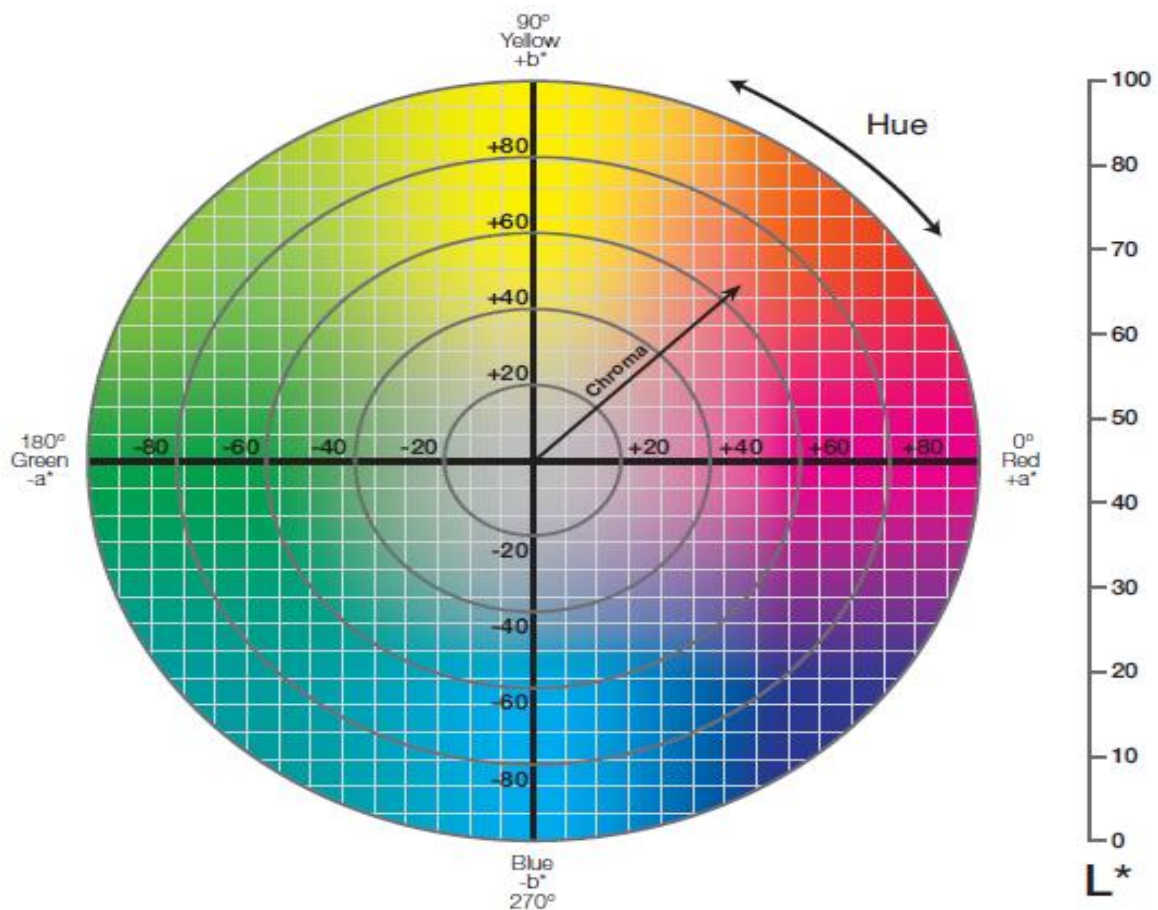


**Figure 2.6:** CIE L\*a\*b\* colour chart (“A Guide to Understanding Color,” 2016)

Every colour, specifically in Munsell colour system, has three attributes, which are hue, value and chroma. Hue refers to 100 equal divisions around a colour circle. The colour circle is formed by the five principal hues and the five intermediate hues. The five principal hues refers to red, yellow, green, blue and purple whereas the five intermediate hues refers to yellow-red, green-yellow, blue-green, purple-blue and red-purple. Each of these hues is further divide into 10 sub-hues, forming a 100 equal divisions (“A Guide to Understanding Color,” 2016). Value, also known as brightness or lightness, refers to the brightness scale divided into scale of “value” from black (0) to white (10). Chroma, also known as saturation, refers to the intensity or saturation of a particular hue (“A Guide to Understanding Color,” 2016). Chroma also refers to the distance between a chromatic colour and the neutral (grey) colour with the same value. According to Jha (2010), the colour values can transform from one colour system to another colour system through mathematical functions. Formulas 2.13, 2.14 and 2.15 shows the transformation of colour values from CIE  $L^*a^*b^*$  colour system to Munsell colour system. The hue, value and chroma for  $L^*a^*b^*$  are given in Formulas 2.13, 2.14 and 2.15 respectively (Jha, 2010).

$$hue(h^0) = \tan^{-1} \frac{b^*}{a^*} \quad (2.13)$$

$$value(v) = L^* \quad (2.14)$$

$$chroma(C^*) = \sqrt{a^{*2} + b^{*2}} \quad (2.15)$$

## 2.4 Texture Analysis Function

Texture analysis function used standard statistical measures to filter an image. Texture analysis tends to describe the spatial variation in pixel intensities, in terms of roughness, smoothness, silkiness or bumpiness of a region (*MathWorks Documentation*,

2018). This means that the roughness or bumpiness are used to describe the variations of grey intensity values. The statistics of texture analysis provide the information about the local variability of the intensity values of pixels. Standard deviation filter provides the degree of variability of pixel in a particular region by calculating the standard deviation of all the values in the neighbourhood. Entropy filter calculate the entropy of the neighbourhood (Gonzalez, Woods, & Eddins, 2009). Both standard deviation filter and entropy filter work in such a way that the neighbourhood around the pixel of interest is defined and the statistic for that neighbourhood is calculated. The value is later used as the value of the pixel of interest for the image. By default, standard deviation filter function uses 3-by-3 neighbourhood whereas entropy filter function uses 9-by-9 neighbourhood to compute the standard deviation and entropy value of the neighbourhood around the pixel of interest respectively (*MathWorks Documentation*, 2018). Brighter pixels in the output image correspond to its neighbourhood having larger standard deviations and higher entropy values.

## **2.5 Grey-Level Co-Occurrence Matrix (GLCM)**

GLCM is founded by Haralick et al. (1973). GLCM considers the spatial relationship of pixels. The GLCM function computes how often a pair of pixel with a specific value and in a specified spatial relationship occurs in an image. This function produces a matrix called the GLCM. Later, the statistical measures are extracted from this matrix. The difference between the GLCM function and the texture analysis function is that the texture analysis function is unable to provide information about the shape, which is the spatial relationship of pixels in the image.

There are four statistics properties that can be extracted from the GLCM. They are contrast, correlation, energy and homogeneity. Contrast measures the local variations,

correlation measures the joint probability occurrence of the specified pixel pairs, energy measures the uniformity in the matrix and homogeneity measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal (*MathWorks Documentation*, 2018).

## 2.6 Pattern Search Algorithm

Pattern search is one of the direct search method algorithms. Direct search solves optimisation problems from a set of points around the current point without requiring any information of the higher derivatives. Pattern search uses the polling method to find the local minimum of an objective function. The objective function is a function that requires optimisation. The pattern search algorithm works as follows (*MathWorks Documentation*, 2018):

- (i) The search starts from an initial point, generates a pattern of the points, which is generally plus and minus the coordinate directions, times the mesh size. This pattern is centred on the current point, which is taken from the initial point. The pattern is a set of vectors  $\{v_i\}$ , defined by the number of independent variables in the objective function,  $N$  and the positive basis set. Maximal basis, with  $2N$  vectors and the minimal basis, with  $N + 1$  vectors are the two commonly used positive basis sets (Kolda, Lewis, & Torczon, 2006). For example, when there are three independent variables, the default for  $2N$  positive basis consists of these pattern vectors:

$$v_1 = [1 \ 0 \ 0], v_2 = [0 \ 1 \ 0], v_3 = [0 \ 0 \ 1], v_4 = [-1 \ 0 \ 0], v_5 = [0 \ -1 \ 0], v_6 = [0 \ 0 \ -1]$$

The default for  $N+1$  positive basis consists of these pattern vectors:

$$v_1 = [1 \ 0 \ 0], v_2 = [0 \ 1 \ 0], v_3 = [0 \ 0 \ 1], v_4 = [-1 \ -1 \ -1]$$

The patterns from these collection of vectors are fixed-direction vectors and are used in generalised pattern search (GPS) algorithm. The mesh is a set of points that is formed by:

- a. Multiplying each pattern vector  $v_i$  by a scalar  $\Delta^m$ , which is the mesh size, to generate a set of vectors  $\{d_i\}$ .
- b. The current point, which is the best objective function value found in the previous step is added to the  $\{d_i\}$ .

For example, if the current point is [2.2 4.7] and the pattern consists of the vectors:

$v_1 = [1 \ 0]$ ,  $v_2 = [0 \ 1]$ ,  $v_3 = [-1 \ 0]$ ,  $v_4 = [0 \ -1]$ , then the current mesh size  $\Delta^m$  is 4. The pattern vectors are then multiplied by 4 and added to the current point as follows:

$$[2.2 \ 4.7] + 4*[1 \ 0] = [6.2 \ 4.7]$$

$$[2.2 \ 4.7] + 4*[0 \ 1] = [2.2 \ 8.7]$$

$$[2.2 \ 4.7] + 4*[-1 \ 0] = [-1.8 \ 4.7]$$

$$[2.2 \ 4.7] + 4*[0 \ -1] = [2.2 \ 0.7]$$

- (ii) The objective function is evaluated at every point in the pattern.
- (iii) The poll is successful if the minimum objective in the pattern is lower than the current point's value and the following will happen:
  - a. The minimum point becomes the current point.
  - b. The mesh size is doubled.
  - c. The algorithm proceeds to step (i).
- (iv) If the poll is unsuccessful, the following will happen:
  - a. The mesh size is halved.
  - b. The iterations will stop if the mesh size is below a threshold. Otherwise, the current point will maintain and the algorithm proceeds to step (i).

The mesh size is by default equals to 1 at the first iteration and the mesh points are computed by adding the pattern vectors to the initial points  $x_0$ .

## **2.7 Related Works**

Acha and Serrano (2000) collected 80 burn images, with 16 images representing each of the five burn appearances studied. The five burn appearances were superficial dermal burn with red colour, superficial dermal burn with blisters, deep dermal burn, full thickness burn with white-creamy colour and full thickness burn with brown colour. They proposed the classification of burn images by using colour and texture features. Segmentation-free approach was used in which they converted the burn images into  $L^*a^*b^*$  colour space for feature extraction. The colour centroid of each burn image was clustered by using vector quantiser algorithm into its respective class. The chrominance components (V1 and V2) of CIE  $L^*a^*b^*$  colour space were used in the clustering. The texture features, which were kurtosis (normalised fourth order moment) and skewness (normalised third order moment), were used to reduce the misclassification of burn images. The kurtosis and skewness were used to measure the burn which had wet and bright colours, indicated by high and positive kurtosis and skewness. Negative skewness was also used to indicate the deepest burn wound with dark spots. Linde-Buzo-Grey (LBG) vector quantisation algorithm was used for classification as the quantiser was able to minimise the overall mean-square classification. The quantiser was first trained with training images. After that, the centroid was fixed and the quantiser was used for classification. The images were assigned to each possible group of burn and later the colour and texture features were joined using the AND operator, in which the approach used was known as global classification. They stated that using the kurtosis and skewness features were not sufficient to classify the burn depths, but after they used kurtosis and skewness with colour, they

obtained better results with an average accuracy of 88.75%. Based on their work, the deep dermal burn had the most misclassified images, as this burn had dotted surface. They proposed to solve this using texture parameter by using region growing algorithm in the future.

The Linde-Buzo-Grey (LBG) vector quantisation algorithm was also used by Acha et al. (2001). However, the images were assigned and grouped based on the burn colour only. Acha et al.'s (2001) work only focused on burns that marked the requirements for skin graft, which were superficial dermal and deep dermal burns and 96 images of different burn depths were collected. The images were acquired by following the image acquisition protocol, which was: (i) the camera and the burn's distance should be 15 to 60 cm, (ii) the flash should always be on when an image is being taken to ensure a uniform illumination on the wound, (iii) the background should be homogeneous, like dark blue or green in colour and (iv) the position of the camera should be parallel to the surface of the wound. This acquisition protocol was first developed in 1999 by Roa et al. (1999). Acha et al. (2001) had proposed a segmentation algorithm that was based on greyscale multiresolution, because of the need to visualise the image globally at different resolution levels. This multiresolution algorithm was founded on mathematical stack approach (Koenderink, 1984). This approach worked by identifying the extrema in a stack of images in which the higher image was the slightly blurred version than its previous one. They transformed the colour image to HSI coordinates for segmentation. Their results showed that the burn wound was correctly segmented in all cases. After that, they divided the segmented image into 9 x 9 squares and then extracted the average of the chrominance coordinate (V1, V2) of CIE L\*a\*b from each square. The result was presented in the form of percentage of

squares in one burn depth over the total number of squares in the burn wound. Based on the results, there were two misclassification on mixed burn wounds images.

The same image acquisition protocol was used in the authors' other works (Acha et al., 2002, 2004). This acquisition protocol was improved along their extended works and to adapt to their research work's objectives. An improved version of the acquisition protocol, which comprised of: (i) the distance between the camera and the patient should be about 40 – 50 cm in order to ensure that the texture can be distinguished and the burn can be visualised globally, (ii) the background should be green or blue sheet, (iii) the camera flash must be on, (iv) the camera should be placed parallel to the burn and (v) the camera's parameter should be set to: ISO speed 100, exposure time 1/200s and aperture (f-stop) 20 (Serrano et al., 2015). In another work, an additional acquisition protocol such as the image should include healthy skin when possible had also been considered (Acha et al., 2003, 2005, 2013; Serrano, Acha, Gómez-Cía, et al., 2005).

Five burn appearances were also studied by Acha et al. (2002, 2003, 2005, 2004), however, with slightly different burn appearances from Acha and Serrano (2000)'s work. The five burn appearances studied were superficial dermal with blisters, superficial dermal with bright red colour, deep dermal, full thickness with beige-yellow colour and full thickness with dark brown colour. Acha et al. (2005) used the digital camera for image acquisition. The digital camera was also widely used in other works as an image acquisition tool (Acha et al., 2002, 2003, 2004, 2001; Acha & Serrano, 2000; Roa et al., 1999; Serrano, Acha, Gómez-Cía, et al., 2005; Serrano et al., 1998). Acha et al. (2005) proposed solutions to the influence of different sources of illumination on colour and the camera calibration issues that they had identified when using a digital photographic camera. For the illumination influence issue, Acha et al. (2005) concluded that the xenon flash

illumination was able to dominate the illumination after their experiments. For the issue of camera calibration, Acha et al. (2005) proposed a calibration method, which is a matrix transformation between the RGB and CIE XYZ based on the Macbeth ColourChecker DC chart.

Acha et al. (2005) proposed a manual segmentation algorithm based on the Euclidean distance of CIE  $L^*u^*v^*$  colour space. This segmentation algorithm was also used in the authors' other works (Acha et al., 2002, 2003; Serrano, Acha, Gómez-Cía, et al., 2005) but instead of automatic thresholding, manual thresholding was used in the work of Acha et al. (2002), in which the lightness coordinate was not considered. According to Acha et al. (2005),  $L^*u^*v^*$  and  $L^*a^*b^*$  colour representation systems are known as uniform systems. The reason is because the Euclidean distance between the measured colours in these spaces are almost similar to human perception of colour differences. Although these two colour spaces are slightly different from each other in terms of their formulation, both of the colour spaces are equally good in providing a very good estimate of the colour difference between two colour vectors. Acha et al. (2005) chose the  $L^*u^*v^*$  colour space to be used in their work because  $a^*$  and  $b^*$  components were independent from luminance and the colour perception was known to be strongly influenced by the luminance. The segmentation algorithm proposed was divided into three stages: (i) User selection and pre-processing stage, (ii) Conversion to single channel image stage and (iii) Thresholding and post processing stage. The pre-processing of the images and the crop region by user were done by using anisotropic diffusion filter in order to homogenise the regions while preserving the borders or edges, which was performed by separating the diffusion of chromatic (hue and chroma) and achromatic (lightness  $L^*$  component) information (Lucchese & Mitra, 2001). The segmented image was applied with median

filtering to remove noises from the images or pixels that did not belong to the burn. Their results showed that the burn wound was correctly segmented in all cases. The reason the researchers needed the help of user in selecting the colour of the burn was because they had studied and noted that the healthy skin, blisters in superficial dermal burn and the full thickness burn with brown colour appearance had strong overlapping features among one another. Thus, it is very difficult to build a completely automatic system. Besides this reason, they also found that the healthy skin had large variability, even within the same human race (Acha et al., 2002, 2003).

Serrano, Acha, and Acha (2003) studied the colour image segmentation algorithm for burn wound images that was based on colour and texture information. This work was an improvement compared to the previous manual thresholding segmentation algorithm (Acha et al., 2002). This work improved the manual thresholding conducted in the last step of the former work to automatic thresholding in achieving the segmented image as well as including lightness and texture information in the single channel conversion step. Based on the results they obtained, the proposed segmentation algorithm did not work well if the images were not acquired by following the image acquisition protocol, or had different burn depths or if the user selected a small area of the burn. They reported that the segmentation work well with most of the images, but for the failed images, the manual thresholding was used instead. They also reported that the new proposed algorithm worked well for beige or brown colour full thickness burn.

The drawback for segmentation algorithm that required the help of the user to select the colour to be segmented was that the segmentation of the burn wound based on the colour selected by the user may affect the burn degree classification results. For example, if the burn wound consisted of mix burns (i.e. SPTB and DPTB), with two

colours of different degrees of burn depth in one burn wound, the user might select the colour to be segmented which belonged to SPTB, despite the burn wound being actually DPTB. Besides that, the classification only classified one type of burn depth at a time based on the burn area that was selected by the user. For example, in a mixed burn depth of SPTB and DPTB, if the user selected the SPTB, then the network will classify the burn as SPTB and vice versa.

The descriptors or features extracted from the CIE  $L^*u^*v^*$  colour space as well as hue and chroma by Acha et al. (2005), with consideration of the pixels only in the burn area were: mean of lightness ( $L^*$ ), mean of hue ( $h$ ), mean of chroma ( $c$ ), standard deviation of lightness ( $\sigma_L$ ), standard deviation of hue ( $\sigma_h$ ), standard deviation of chroma ( $\sigma_c$ ), mean of  $u^*$ , mean of  $v^*$ , standard deviation of  $u^*$  ( $\sigma_u$ ), standard deviation of  $v^*$  ( $\sigma_v$ ), skewness of lightness ( $s_L$ ), kurtosis of lightness ( $k_L$ ), skewness of  $u^*$  ( $s_u$ ), kurtosis of  $u^*$  ( $k_u$ ), skewness of  $v^*$  ( $s_v$ ) and kurtosis of  $v^*$  ( $k_v$ ). Hue and chroma were said to be closely related to the way the human perceived chromaticity (Acha et al., 2005). These features were then analysed using the Sequential Forward Selection (SFS) method and the Sequential Backward Selection (SBS) method in Fuzzy-ARTMAP neural network in terms of their discrimination power. The five burn appearances studied were used to train the network (Acha et al., 2002, 2003, 2005, 2004). The performance of the feature selection was evaluated using fivefold cross validation (XVAL) (Ganster et al., 2001). The features selected using the SBS method were used in the work because this set of features produced the smaller average error when compared to using the SFS method. The optimum set of features after the SBS method was: lightness, hue, standard deviation of the hue component,  $u^*$  chrominance component, standard deviation of the  $v^*$  component and skewness of lightness. The same descriptors, feature selection process and optimum set of

features were also used in the authors' other works (Acha et al., 2002, 2003, 2004; Serrano, Acha, Gómez-Cía, et al., 2005). In Acha et al. (2004)'s work, both the SFS and SBS methods yielded the same minimum classification error, which was 0.7% by using the Support Vector Machine (SVM) but the SFS method had the least number of features used for classification, which were mean of lightness, mean of hue, mean of saturation, standard deviation of saturation, mean of  $u^*$ , standard deviation of  $u^*$  and skewness of lightness.

In Acha et al. (2005)'s work, the Fuzzy-ARTMAP neural network algorithm was used for classification. This network was based on the Adaptive Resonance Theory developed by Carpenter, Grossberg, Markuzon, Reynolds, and Rosen (1992). The number of neurons used in the hidden layer were fixed during training for testing purposes. The six selected features by the SBS method were used as an input to the network and the network classified the segmented burn region into one of the five burn appearances. The same classifier was also used in the authors' other works (Acha et al., 2002, 2003, 2004; Serrano, Acha, Gómez-Cía, et al., 2005). However, in Acha et al. (2004)'s work, the researchers applied a 5-fold cross validation to split their image dataset into training and validation sets, which were later used in SVM for classification. The results in term of classification error obtained from SVM were used to compare with the results obtained from the Fuzzy-ARTMAP neural network. The same set of features were used as an input to the SVM. The SFS and SBS method were also applied to SVM with different kernels, which were Gaussian Variance and Polynomial Order (Acha et al., 2004).

The output of Acha et al. (2002)'s work was to calculate the percentage of the surface area of each burn depth over total surface area of the burned area. According to Acha et al. (2002), a non-burn specialist doctor or medical personnel may differentiate a burned skin from the healthy skin based on their experience but they might face problem in

classifying the burn into their respective burn depths. Based on the results, the average accuracy achieved was 88.89% in the classification of burn images into three burn depths.

An average accuracy of 82.26% was achieved by Acha et al. (2003). Based on the results obtained, all the misclassified superficial dermal burns were classified by the network as deep dermal burns whereas all the misclassified deep dermal burns were classified by the network as superficial dermal burns (Acha et al., 2003). According to Acha et al. (2003), it was common for the misclassification as in real cases, the doctors would also make these kind of mistakes, as there were some burns that appear as intermediate depth, which were neither clearly superficial dermal nor deep dermal burn. A minimum classification error of 0.7% was achieved by Acha et al. (2004) with 1 variance Gaussian kernel of SVM whereas Fuzzy-ARTMAP neural network yielded a classification error of 1.6%. The results showed that overall, the SVM performed better than Fuzzy-ARTMAP neural network. The five out of the six features selected by the Fuzzy-ARTMAP was also selected by the SVM.

An average accuracy of 82.26% was achieved by Acha et al. (2005). The results showed that all the misclassified superficial dermal burns were classified by the network as deep dermal burns whereas all the misclassified deep dermal burns were classified by the network as superficial dermal burns. 80% of the misclassified full thickness burn were classified by the network as superficial dermal burn and 20% of the misclassified full thickness burn were classified as deep dermal burn (Acha et al., 2005). The same results in terms of misclassification of superficial dermal and deep dermal burn were obtained in the other work as well (Serrano, Acha, Gómez-Cía, et al., 2005) but with the different result for misclassification of full thickness burn, in which 100% of the full thickness burn were

misclassified as superficial dermal burn by the network. The average accuracy achieved by Serrano, Acha, Gómez-Cía, et al. (2005) was 88.6%.

Acha et al. (2013) and Serrano et al. (2015) had implemented image acquisition protocol as discussed during their image acquisition. They also used camera calibration algorithm, which was colourimetric camera characterisation algorithm (Sáez, Acha, & Serrano, 2009; Serrano, Acha, & Sangwine, 2005) that was applied on the burn images in order to tackle the problem of the different RGB values of an image acquired, in uncontrolled illumination conditions. In other words, the RGB values of an image was dependent on the illumination where the image was captured. The algorithm converted the RGB values under unknown illuminant to RGB values under D50 illuminant. The algorithm was expected to produce the colour for display to be the same as the ones captured using the camera (Acha et al., 2013). However, both of these works were focused on expressing the physical characteristics of burn depths in a mathematical way by conducting a subjective experiment in finding new features to classify the burn depths. Subjective experiment refers to an experiment that subjectively describe the physical characteristics of burn that consciously or unconsciously observed and were difficult to translate into physical measure by the specialist. In their work, classifiers were used to verify the ability of the new features that were identified from the experiment in the classification of burn depths. The work was first started by Fondón, Acha, Serrano, and Sosa (2006), which used the multidimensional scaling (MDS) and hierarchical clustering (HCA) in interpreting the new features for burn depths. MDS was used to find the most significant burn similarity in terms of dimension whereas HCA was used to interpret how the dimensions had been combined when the burn images were compared. Amount of pink, texture of the colour and the freshness of the burn were concluded as the characteristics

observed by specialist when evaluating a burn depth. In the extended works of Acha et al. (2013) and Serrano et al. (2015), the ability of the mathematical features in the classification of the burn depths that were obtained by conducting a psychophysical experiment and a multidimensional scaling (MDS) analysis was studied. The intention was to determine the physical characteristics of the burn depth that were normally employed by the burn specialists and later on, translate these physical features into mathematical equations. A dataset that consisted of 20 images for training set and 74 images for testing set were used by Acha et al. (2013) and Serrano et al. (2015). However, in Fondón et al. (2006)'s work, 20 images were used as the training set and there was no testing set. All the burn images were captured using Canon EOS 300D in the first-aid room and followed the image acquisition protocol. The procedure consisted of three main steps: which were psychophysical experiment, multidimensional scaling and interpretation of the coordinates. This procedure was first used in the work of Fondón et al. (2006).

Three coordinates were identified in their works, which were: (i) Dimension 1, labelled as amount of pink in the image, (ii) Dimension 2, labelled as texture of the colour and (iii) Dimension 3, considered as related to "colourfulness". Fondón et al. (2006) related Dimension 1 to hue and saturation of the image, Dimension 2 to the amount of centroid obtained by using k-means techniques and Dunn coefficient (Maulik & Bandyopadhyay, 2002) and the characteristics chosen for Dimension 3 were mean of B, mean of lightness, mean of V and skewness of V. In the extended works, eight features were obtained after translation to mathematical features, which were: chroma ( $C_{a^*b^*}^*$ ), outliers ( $O_{RGB}$ ), hue (h), variance of hue ( $V_{h^*}$ ), skewness of  $a^*$  ( $sk_{a^*}$ ), skewness of  $b^*$  ( $sk_{b^*}$ ), quartile skewness ( $SK_{0.25}$ ) and kurtosis of  $a^*$  ( $k_{a^*}$ ) (Acha et al., 2013; Serrano et al., 2015). To avoid overfitting, feature selection was carried out, to obtain the most discriminant

descriptors with the lowest classification error. In Acha et al. (2013)' work, correlation coefficient and p-value were calculated to verify whether the identified features were correlated to their dimensions. The classification by SVM was performed using sequential forward selection (SFS) and sequential backward selection (SBS) for feature selection. Three features out of eight features, with lower classification error were selected. They were chroma ( $C_{a^*b^*}^*$ ), variance of hue ( $V_{h^*}$ ) and skewness of  $b^*$  ( $sk_{b^*}$ ). In the work of Serrano et al. (2015), SFS and SBS methods were also used to identify features that were capable of classifying the burns into two categories, which were burns that needed grafts and burns that did not need grafts. The eight features then underwent feature selection using SFS and SBS. SVM was used to implement SFS and SBS. The selected features were chroma ( $C_{a^*b^*}^*$ ), hue ( $h$ ), kurtosis of  $a^*$  ( $k_{a^*}$ ) and skewness of  $b^*$  ( $sk_{b^*}$ ).

Acha et al. (2013) used KNN, principal component analysis (PCA) and SVM to classify the burn images into three burn depths (superficial dermal, deep dermal and full thickness) and two types of burns (burn that needed grafts and burns that did not need grafts). The SVM, with a radial basis function (RBF) kernel, was used to study the discriminant power of the eight selected features identified in the psychophysical experiment and MDS analysis. The measures that were used for evaluation were accuracy, sensitivity (S), specificity (E), positive predictive value (PPV) and negative predictive value (NPV). An accuracy of 66.2% was obtained by Acha et al. (2013) when KNN classified the burn images into three burn depths and 83.8% was obtained when classifying the burn images into two types of burns. In their context, burn that needed grafts referred to deep dermal and full thickness burns, whereas burn that did not need grafts referred to superficial dermal burns. Based on their results using KNN, deep dermal burns images were the most misclassified images. An accuracy of 51.4% was obtained when KNN, after

applying PCA, classified the burn into three burn depths and 71.6% when classifying the burn into two types. The results showed that the features obtained via MDS was better than the features obtained from PCA. The SVM yielded an accuracy of 75.7% when classifying the images into three burn depths and 82.4% when classifying into two burn types. The results of SVM showed that the eight selected features had higher discriminant power for classification as compared to the three selected features. Serrano et al. (2015) used the SVM classifier to classify images to either a burn that needed grafts or did not need grafts. The four selected features were used as input to the SVM for classification. Serrano et al. (2015) achieved 79.73%, 0.97 and 0.60 for accuracy, sensitivity and specificity respectively using the SVM classifier.

Wantanajittikul et al. (2012) and Tran et al. (2015) collected their burn images from the hospital. Wantanajittikul et al. (2012) formed their image dataset using 34 sub-images from the five images collected by selecting the different burn areas and were validated by the burn experts. They proposed a new segmentation algorithm to separate the skin region from the background and then in turn, separate the wound region from the healthy skin. The algorithm first converted the entire RGB image to the Cr-space. Fuzzy C-means (FCM) clustering was used to separate the skin region from the background. After that, in order to emphasise the burn wound region, the skin region from the RGB colour space was converted to the  $L^*u^*v^*$  colour space. FCM clustering was used again to separate the wound region from the healthy skin. Finally, the segmented wound region was post-processed to eliminate noise by using the opening and closing mathematical morphology. The results showed that the algorithm worked well for the segmentation of burn images. The features selected in their work were: mean of h-space, standard deviation of h-space, the contrast and the homogeneity. The h-space was formed from RGB colour space, in

which  $h\text{-space} = 256 - (256 \times (G/R))$ . They used SVM, Bayes and KNN classifiers to make a comparison of the results obtained in identifying the degree of burn. There were two types of experiments conducted, which were cross validation experiment and blind test experiment. Cross validation experiment was performed on training set in which later the trained model was used on the testing set in the blind test experiment. A binary classification was performed by using SVM. The SVM was trained and tested with 4-fold cross validation in the cross validation experiment. An accuracy of 89.29% was achieved using a 4-fold cross validation on the validation set and an accuracy of 75.33% was achieved when testing on an unseen testing set. The results showed that SVM performed better than Bayes and KNN.

Tran et al. (2015) conducted their experiments on a burn image dataset that consisted of a total of 396 images for degree II, III and IV burns, with 180, 192 and 24 images respectively. The images for degree IV were very little due to the high level of burn that caused the patients to succumb to their injuries. They pre-processed their burn images by standardising the image size with the rate of 4:3 and by removing the non-burned regions from the images. They proposed the feature extraction of burn images using multi-colour channels, which were red, green, blue and grey. They suggested to use the fast feature extraction based on multi-colour channels because real-time processing speed was a requirement. The multi-colour channels would be in binary format to increase the performance of machine learning. They proposed to use one-class support vector machine (OC-SVM) for the burn image classification due to the unbalanced number of burn images in the dataset. A 2-fold cross validation was used to divide their image dataset. The criteria they used to evaluate the classification rate were precision, false acceptance rate (FAR) and false reject rate (FRR). The results obtained from using OC-SVM were compared with the

results from the traditional SVM, using the same kernels, which were Gauss and Polynomial. The results achieved showed that OC-SVM achieved higher accuracy than the traditional SVM when using the Gauss and Polynomial kernels, with accuracies of 73.23% and 77.78% respectively.

Suvarna, Sivakumar and Niranjana (2013) and Suvarna, Sivakumar, Kumar, et al. (2013) collected the burn image dataset from the Internet, hospital and scanned from biomedical books. The burn images were captured using digital camera, as well as the cameras found in basic mobile phones or laptop web-cam. The burn images were captured under various lighting conditions, thus, the images they collected were presented with noise such as poor illumination, insufficient dynamic range and incorrect settings of lens aperture. The dataset consisted of 120 images, each burn grades, which represented superficial burn, partial thickness burn and full thickness burn respectively, had 40 images and had been labelled by a plastic surgeon. Suvarna, Sivakumar and Niranjana (2013) and Suvarna, Sivakumar, Kumar, et al. (2013) pre-processed their burn images by resizing it to 90 x 90 pixels. The resized burn images were converted from RGB to L\*a\*b\* colour space. The reason they resized the burn images was to obtain a uniform size of images in their burn dataset, as the burn images they collected were taken from different cameras, which produced different sizes of burn images in terms of number of pixels. The burn images were standardised to jpeg format. Contrast enhancement was performed on the luminous component of the L\*a\*b\* colour space. Suvarna, Sivakumar and Niranjana (2013) selected the V1 chrominance of the L\*a\*b\* colour space for feature extraction. The images were further divided into 9 x 9 blocks. Mean and (2, 1)<sup>th</sup> coefficient of Discrete Cosine Transform (DCT) function were the features that were chosen to train the classifiers. In another work, the same features were extracted, but instead of V1 chrominance, both the

V1 and V2 chrominance of the L\*a\*b\* colour space were selected for feature extraction (Suvarna, Sivakumar, Kumar, et al., 2013).

Suvarna, Sivakumar and Niranjana (2013) used template matching method, KNN classifier and SVM for the classification of skin burn images. In the template matching method, a 2-fold cross validation was used to split the image dataset into training and testing set. In the KNN method, a 3-fold cross validation was used on the image dataset to perform multiclass classification. By using SVM with quadratic kernel function, a 3-fold cross validation on the image dataset and binary classification approach were used to perform multiclass classification. Multi classification was performed by taking one class against the other classes. In another work, Suvarna, Sivakumar, Kumar, et al. (2013) used template matching, KNN classifier and Artificial Neural Network (ANN) for the classification of skin burn images. A 2-fold cross validation was used to split the image dataset for the template matching method. A 3-fold cross validation on the image dataset was used by KNN classifier to perform multiclass classification. The ANN used in the work was trained using the Back Propagation algorithm. The performance of each of these techniques were compared.

An accuracy of 66%, 75% and 90% were obtained by Suvarna, Sivakumar and Niranjana (2013) using template matching method, KNN and SVM respectively. The results by Suvarna, Sivakumar, Kumar, et al. (2013) showed that the ANN technique had yielded the best results, which were more than 90% of accuracy for each burn depth respectively. The accuracy yielded for superficial burn was 95%, partial thickness burn was 97.5% and full thickness burn was 95%. According to the researchers, the drawbacks of template matching method was that when the sample size was increasing, the time taken for

computing would also increase as well as the probability of misclassification would increase when no exact matches were found.

Previous research works also covered other types of medical images such as skin lesions. Sumithra, Suhil and Guru (2015) proposed an automatic segmentation and classification approach for skin lesions. A dataset of 726 samples from 141 images was used, comprising of five different disease classes. The studied skin disease classes were melanoma, bullae, seborrheic keratosis, shingles and squamous cell. The skin lesion images were first pre-processed to remove noises, followed by segmentation to extract the lesion areas. The colour and texture features were then extracted from the extracted lesion areas. For the colour feature, they extracted the statistical colour moments which comprised of mean, standard deviation, variation and skewness. These four statistical colour moments were extracted using the individual channels of six colour spaces, which were RGB, HSV, YCbCr, NTSc, CIE  $L^*u^*v^*$  and CIE  $L^*a^*b^*$ . RGB histogram features were extracted with every image represented by histogram of size 4096. For texture feature, the 14 features proposed by Haralick et al. (1973) were extracted. The texture features were computed for each of the four orientation ( $\{0^\circ, 45^\circ, 90^\circ, 135^\circ\}$ ) and feature vector was formed by taking the average of each individual orientation. The classification was performed by using SVM and KNN. The performance was evaluated using accuracy, precision, recall and  $F_1$ -measure. They obtained an  $F_1$ -measure value of 46.71% using SVM and 34% using KNN. 61% of  $F_1$ -measure was achieved by using the fusion of SVM and KNN.

Tran, Le and Nguyen (2016) proposed a customized CNN, named as Burn Convolutional Neural Network (B-CNN) to identify the degree of burn from the skin burn images. The images were pre-processed using Local Binary Pattern operator. After the

images were pre-processed, the images were input to the CNN model. The CNN was trained with both burn images and their degrees label. The scores of the predicted burn images was obtained and B-CNN model was created based on the probability distribution of the degree of skin burn from the training data. The best learning rate for B-CNN was from 0.57 to 0.6.

Badea et al. (2016) proposed two main approaches for the distinguishing of burn wounds from the healthy skin. Their approaches were identifying relevant features that were able to differentiate between healthy skin and the burn wound and perform feature selection by using intelligent classifiers. An extensive database was used in their work, in which the images had been collected over several months in hospital with a mixed colour-thermal camera. The burn wound, as well as healed wound in the images have been manually marked using infrared based on the burn depths. Their approach was to identify the rectangular patches correspond to burns. Deep learning convolutional neural networks (CNN) was used to separate the normal skin region and burn region, which took a single patch and output the skin type. Their result showed that there were misclassification of healthy skin as burn, in which the burns were actually in the healing state.

Sabeena and Raj Kumar (2017) proposed a new automated skin lesion segmentation via image-wise supervised learning (ISL) and multiscale superpixel. The image-wise supervised learning approach initialised seeds via probabilistic map in order to separate the burn wound from the background image. They used grey level co-occurrence matrix (GLCM) to extract the second order statistical texture features for motion estimation of images in order to differentiate the burn region from normal skin region. According to them, the statistics in the statistical texture analysis were classified into first-order, second-order and higher-order statistics based on the grey level intensity distribution

at specified positions relative to each other in the image. First order statistical measures such as mean, variance, skewness and kurtosis were calculated from the intensity value of an image without considering the relationship between the pixel of interest and its neighbour (Rao, Sastry, Mallika, Tiong, & Mahalakshmi, 2013). Second order statistical measure, in contrast to the first order, considered the spatial relationship between the pixel and its neighbouring pixels (Rao et al., 2013). Third and higher order statistical measure considered three or more pixels' relationships. The third and higher order measures were seldom used due to the duration of its calculation and complexity of its interpretation. The four extracted texture features for the second order statistical measures were contrast, correlation, energy and homogeneity. Sabeena and Raj Kumar (2017) also used SVM to perform binary classification but their experiment was to classify between burn region and normal skin.

Despo et al. (2017) proposed to use deep learning algorithm to study the segmentation and classification of skin burn depths. In their work, they had created the largest dataset of segmented and labelled skin burn images. Besides that, they had shown that with a minimal training, they were able to classify the burned skin from the healthy skin in an image. Their system was based on fully convolutional network and was able to predict the burn severity given an RGB input image and output the different burn depths and the spatial outline of the burn. They obtained 749 images from medical centre and 180 images from the Internet. They only used 656 images, which consisted of 1351 masked burn in their work. The results showed that the system was able to differentiate burned skin and healthy skin. However, the system was only good at predicting the partial thickness burns due to the imbalanced number of images for the different burn depths. In addition,

they showed that there was a large potential to improve the accuracy for segmentation and classification of different burn depths by making some adjustments to the data and model.

Carcagnì, Cuna and Distantè (2018) proposed to use CNN approach for the multiclass classification of skin lesion diseases using dermatoscopy images. The CNN was based on the DenseNet architecture, which had 61 layers. The network was pre-trained on IMAGENET dataset. The images in the dataset did not require any pre-processing. The samples of the starting dataset was increased for the purpose of training the network during the fine-tuning process due to the complexity of the network and the requirement to train the number of parameters. During the training phase, the image dataset was divided into training set and validation set. 80% of the images were used for training and 20% were used for validation. An accuracy of 89.2% was achieved during the validation phase.

## **2.8 Burn Depth Characteristics**

Different burn specialist may describe the burn colour and its appearance differently for the same type of burn depths. Table 2.3 shows the different characteristics of burn depths described in different works, in terms of colour, appearance and pinprick test.

**Table 2.3:** Burn depths characteristics defined in different previous research works

|                      |                                           | Type of Burn                                       |                                          |                                 |
|----------------------|-------------------------------------------|----------------------------------------------------|------------------------------------------|---------------------------------|
|                      |                                           | Superficial<br>Partial<br>Thickness<br>Burn (SPTB) | Deep Partial<br>Thickness<br>Burn (DPTB) | Full<br>Thickness<br>Burn (FTB) |
| <b>Colour</b>        | (Acha & Serrano, 2000)                    | Bright red                                         | Red-whitish                              | Creamy-white or dark brown      |
|                      | (Acha et al., 2002, 2003, 2005)           | Bright red                                         | Pink-whitish                             | Beige-yellow or dark brown      |
|                      | (Suvarna, Sivakumar, & Niranjana, 2013)   | Bright red                                         | Cream coloured                           | Grey or white                   |
|                      | (Acha et al., 2013; Serrano et al., 2015) | Reddish                                            | Pink-Whitish                             | Beige-yellow or dark brown      |
| <b>Appearance</b>    | (Acha & Serrano, 2000)                    | Wet and bright, with blister (brown colour)        | With dark spot                           | -                               |
|                      | (Acha et al., 2002, 2003, 2005)           | Wet and bright, with blister (brown colour)        | With dotted                              | -                               |
|                      | (Suvarna, Sivakumar, & Niranjana, 2013)   | With blisters                                      | With broken blisters                     | Without blisters                |
|                      | (Acha et al., 2013; Serrano et al., 2015) | Wet                                                | Wet or waxy dry                          | Dry                             |
| <b>Pinprick Test</b> | (Suvarna, Sivakumar, & Niranjana, 2013)   | Sensitive to pain                                  | Dullness to pain                         | No sensation                    |

Based on Table 2.3, it can generally be concluded that SPTB is mostly reddish in colour, has a wet and bright appearance, with brown blisters and is sensitive to pain. DPTB's colour ranges from pinkish to whitish, has a waxy dry appearance, has dark spots, with broken blisters and is not as painful as in SPTB. FTB, in turn, as described by

different previous research works, has a larger range of colour, ranging from greyish-white, beige-yellow to dark brown. FTB has a dry appearance without blisters and is not painful.

## 2.9 Literature Analysis

Table 2.4 shows a summary of the previous works and Table 2.5 shows a summary of colour and texture features extracted by previous works.

**Table 2.4:** Summary of previous works

| <b>Previous Research Works</b> | <b>Features for Burn Depth</b> | <b>Focus</b>                                                                                                                   | <b>Burn Depth Considered</b>                                                       |
|--------------------------------|--------------------------------|--------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------|
| (Carcagnì et al., 2018)        | CNN Feature Extraction         | Focused on classification of skin lesions.                                                                                     | Skin lesions                                                                       |
| (Despo et al., 2017)           | Fully Convolutional Network    | Focused on segmentation and classification of burned and non-burned skin.                                                      | Superficial, superficial partial thickness, deep partial thickness, full thickness |
| (Sabeena & Raj Kumar, 2017)    | Texture - GLCM                 | Segmented the burn region from normal skin region. Focused on classifying the image dataset into burned or non-burned classes. | Not mentioned                                                                      |
| (Badea et al., 2016)           | CNN Feature Extraction         | Focused on classifying the images into healthy skin region and burn wound region.                                              | Degree I, II, III                                                                  |
| (Tran et al., 2016)            | CNN Feature Extraction         | Focused on identify the degree of burn images.                                                                                 | Degree I, II, III, IV                                                              |
| (Sumithra et al., 2015)        | Colour and Texture             | Focused on segmentation and classification of skin lesions.                                                                    | Skin lesions                                                                       |
| (Tran et al., 2015)            | Colour                         | Focused on the classification of burn images into three degrees of burns.                                                      | Degree II, III, IV                                                                 |

**Table 2.4** continued

|                                                                                  |                           |                                                                                                                                                                                                                                                                                                       |                                                                       |
|----------------------------------------------------------------------------------|---------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------|
| (Acha et al., 2013; Serrano et al., 2015)                                        | Colour and Colour Texture | Both works focused on finding new features for the classification of burn images. The burn images were classified into burn that needed grafts and those that did not need grafts (Acha et al., 2013; Serrano et al., 2015) and also classifying the burn into three burn depths (Acha et al., 2013). | Superficial dermal, deep dermal and full thickness                    |
| (Suvarna, Sivakumar, Kumar, et al., 2013; Suvarna, Sivakumar, & Niranjana, 2013) | Colour                    | Focused on the classification of burn images into three degrees of burns.                                                                                                                                                                                                                             | Superficial dermal, partial thickness, full thickness                 |
| (Wantanajittikul et al., 2012)                                                   | Colour and Texture        | Focused on segmentation and classification of burn images.                                                                                                                                                                                                                                            | Superficial partial thickness, deep partial thickness, full thickness |
| (Fondón et al., 2006)                                                            | Colour and Colour Texture | Focused on identifying new features.                                                                                                                                                                                                                                                                  | Superficial dermal, deep dermal and full thickness                    |
| (Acha et al., 2004)                                                              | Colour and Colour Texture | Focused on classification of burn images.                                                                                                                                                                                                                                                             | Superficial dermal burn, deep dermal burn, full thickness burn        |
| (Acha et al., 2002, 2003, 2005; Serrano, Acha, Gómez-Cía, et al., 2005)          | Colour and Colour Texture | Focused on segmentation and classification of burn images, which was to separate the burn wound region from the healthy skin region and to classify the burn images to their respective burn depths.                                                                                                  | Superficial dermal burn, deep dermal burn, full thickness burn        |

**Table 2.4** continued

|                        |                           |                                                                                                 |                                                                |
|------------------------|---------------------------|-------------------------------------------------------------------------------------------------|----------------------------------------------------------------|
| (Acha et al., 2001)    | Colour                    | Focused on separating the burn skin from normal skin and the classification of the burn images. | Superficial dermal burn, deep dermal burn                      |
| (Acha & Serrano, 2000) | Colour and Colour Texture | Focused on classification of burn images into three degrees of burns.                           | Superficial dermal burn, deep dermal burn, full thickness burn |

**Table 2.5:** Summary of colour and texture features extracted by previous works

| Previous Research Works                   | Features Extracted                                                                                                                                                                                                                                                                                                                                                       |
|-------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| (Sabeena & Raj Kumar, 2017)               | Contrast, correlation, energy and homogeneity                                                                                                                                                                                                                                                                                                                            |
| (Tran et al., 2015)                       | Multi-colour channels, which were red, green, blue and grey                                                                                                                                                                                                                                                                                                              |
| (Serrano et al., 2015)                    | Chroma ( $C_{a^*b^*}^*$ ), outliers ( $O_{RGB}$ ), hue (h), variance of hue ( $V_{h^*}$ ), skewness of $a^*$ ( $sk_{a^*}$ ), skewness of $b^*$ ( $sk_{b^*}$ ), quartile skewness ( $SK_{0.25}$ ) and kurtosis of $a^*$ ( $k_{a^*}$ )<br><br>Selected features - chroma ( $C_{a^*b^*}^*$ ), hue (h), kurtosis of $a^*$ ( $k_{a^*}$ ) and skewness of $b^*$ ( $sk_{b^*}$ ) |
| (Acha et al., 2013)                       | Chroma ( $C_{a^*b^*}^*$ ), outliers ( $O_{RGB}$ ), hue (h), variance of hue ( $V_{h^*}$ ), skewness of $a^*$ ( $sk_{a^*}$ ), skewness of $b^*$ ( $sk_{b^*}$ ), quartile skewness ( $SK_{0.25}$ ) and kurtosis of $a^*$ ( $k_{a^*}$ )<br><br>Selected features - chroma ( $C_{a^*b^*}^*$ ), variance of hue ( $V_{h^*}$ ) and skewness of $b^*$ ( $sk_{b^*}$ )            |
| (Suvarna, Sivakumar, Kumar, et al., 2013) | Mean and (2, 1) <sup>th</sup> coefficient of Discrete Cosine Transform (DCT) function of V1 and V2 chrominance of the $L^*a^*b^*$                                                                                                                                                                                                                                        |
| (Suvarna, Sivakumar, & Niranjan, 2013)    | Mean and (2, 1) <sup>th</sup> coefficient of Discrete Cosine Transform (DCT) function of V1 chrominance of the $L^*a^*b^*$                                                                                                                                                                                                                                               |
| (Wantanajittikul et al., 2012)            | Mean of h-space, standard deviation of h-space, contrast and homogeneity                                                                                                                                                                                                                                                                                                 |

**Table 2.5** continued

|                                                                               |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                  |
|-------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| (Acha et al., 2002, 2003, 2005, 2004; Serrano, Acha, Gómez-Cía, et al., 2005) | Mean of lightness ( $L^*$ ), mean of hue ( $h$ ), mean of chroma ( $c$ ), standard deviation of lightness ( $\sigma_L$ ), standard deviation of hue ( $\sigma_h$ ), standard deviation of chroma ( $\sigma_c$ ), mean of $u^*$ , mean of $v^*$ , standard deviation of $u^*$ ( $\sigma_u$ ), standard deviation of $v^*$ ( $\sigma_v$ ), skewness of lightness ( $s_L$ ), kurtosis of lightness ( $k_L$ ), skewness of $u^*$ ( $s_u$ ), kurtosis of $u^*$ ( $k_u$ ), skewness of $v^*$ ( $s_v$ ) and kurtosis of $v^*$ ( $k_v$ ) |
|                                                                               | Selected features - lightness, hue, standard deviation of the hue component, $u^*$ chrominance component, standard deviation of the $v^*$ component and skewness of lightness                                                                                                                                                                                                                                                                                                                                                    |
| (Acha et al., 2001)                                                           | Average of the chrominance coordinate ( $V1$ , $V2$ ) of CIE $L^*a^*b$                                                                                                                                                                                                                                                                                                                                                                                                                                                           |
| (Acha & Serrano, 2000)                                                        | Centroid vector of chrominance components ( $V1$ and $V2$ ) of CIE $L^*a^*b^*$ , kurtosis, skewness                                                                                                                                                                                                                                                                                                                                                                                                                              |

In the medical field, skin burn injury is considered a serious illness especially when the deeper depth of skin is involved. A correct evaluation of burn wound is a crucial issue as it is required to provide a correct first treatment. If the non-experienced doctors or non-expert know the depth of the skin burn, it will be easier for them to provide the correct treatment. A wrong evaluation on DPTB and FTB can lead to prolong hospitalisation in terms of waiting for the burned area to be healthier and ready for the skin grafting procedure. On the other hand, a wrong evaluation for SPTB, can lead to unnecessary operation. Therefore, it is important that the doctors or medical personnel get the correct diagnosis of the skin burn injury.

Based on the literature review, the approach that was most commonly used for classification of skin burn depths consisted of these processes: image acquisition, image pre-processing, feature extraction, image classification and result interpretation and evaluation. Therefore, in this thesis, the image mining approach, specifically the image

classification process, which consisted of those processes was used. The image classification process is discussed in Chapter 3. Global features were extracted by most of the literature for the classification of skin burn depths. Global features as stated in Section 1.7 were weak in representing images that consisted of multiple burn depths colour. Therefore, global features would be used as supporting features for the proposed image feature in this thesis, in which global features could be used to represent the general image features of images in the dataset. In addition, some of the global features such as skewness and kurtosis could be used to represent the wetness and brightness of the burn appearance (Acha et al., 2005; Serrano et al., 2015). Global features like hue and chroma could be used to represent the amount of pink in the burn depths (Serrano et al., 2015). The deep learning approach used by the literature might not be suitable in this research due to the amount of burn images available. Deep learning requires a large amount of labelled data to learn an accurate model for the classification of skin burn images.

In this thesis, a feature extraction process was proposed to extract features that could characterise each skin burn depth. No segmentation was necessary because there were many burn images that had only the burn region. Even in Acha et al. (2005)'s work, out of 62 burn images they collected, they only segmented 35 images. According to their acquisition protocol, the healthy skin should appear together with the burnt skin in the image, but because the extent of some of the burn wound was often so large, they only had burnt skin appearing in the image.

## **2.10 Summary**

This chapter presented the features proposed in the past literature, which were mostly global features. These features were not sufficient to represent the specific characteristic of each burn depth. In Chapter 3, the methodology to extract a set of image

features that represent the characteristic of each burn depth to improve the classification results.

## CHAPTER 3

### METHODOLOGY

#### 3.1 Introduction

This chapter focuses on finding a set of features to represent the different burn depths within the image classification process. The set of features extracted can lead to the distinguishing of the different burn depths more effectively and accurately for classification. In most of the research works, the skin burn depths classification system often consists of these common steps: image acquisition, image pre-processing, burn segmentation, feature extraction, feature selection, burn classification as well as, results and evaluation. Figure 3.1 shows the image classification process that is applied in this thesis.

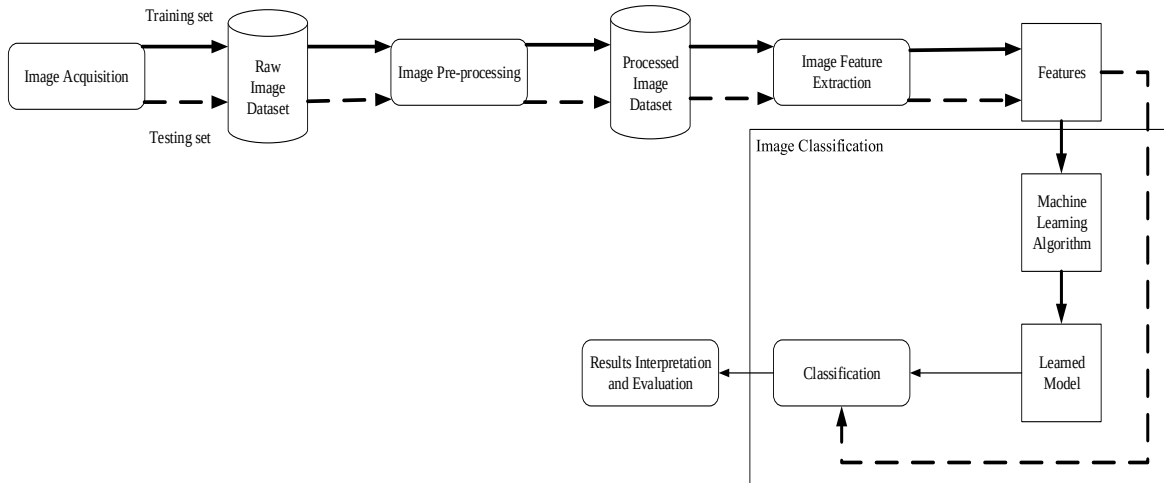


**Figure 3.1:** Proposed image classification process for skin burn depths

Based on Figure 3.1, the first process is the image acquisition process, whereby a dataset of images are collected. The images collected contained various types of image files such as Joint Photographic Experts Group (JPEG) and Portable Network Graphics

(PNG) as well as in various image sizes. Therefore, these images needed to be pre-processed for standardisation. After image pre-processing, the images underwent various transformation and image features are extracted to represent the corresponding image content (Shukla & Vala, 2016). The extracted features act as an input for the classification process. The machine learning algorithm used training images to learn a model, which would later be used to classify new testing images. The final step is to evaluate the results obtained by comparing the performance of the proposed features in this work with those features proposed by previous research works in the classification of skin burn depths images. The set of features that can represent all the three burn depths for effective classification is desired. The following sections describe the processes in the image classification process.

### **3.2 Image Acquisition**

There are no public and open-source datasets available on skin burn. The images used in this work were acquired by burn specialists, Dr Ehfa binti Bujang Safawi and Dr William Tiong from the Faculty of Medicine and Health Science, UNIMAS. There is no standardisation applied when the burn images were taken. Thus, illumination from the environment might vary when the burn images were taken. Our image dataset generally covered burn images that were captured under various illumination with the assumption that images of any level of lighting should be classified correctly with the proposed features used in this thesis. The number of collected images were 97. The images were used in both training (64 images) and test (33 images) datasets and consisted of both homogeneous and heterogeneous colour images. The collected images in the dataset is in the form of colour and it is a primary dataset. Table 3.1 shows the total images collected

for training and testing sets. Both training and testing sets were pre-labelled by burn specialist.

**Table 3.1:** Total images collected for training and testing sets

| <b>Burn Depth</b>                         | <b>Training</b> | <b>Testing</b> |
|-------------------------------------------|-----------------|----------------|
| Superficial Partial Thickness Burn (SPTB) | 24              | 10             |
| Deep Partial Thickness Burn (DPTB)        | 20              | 8              |
| Full Thickness Burn (FTB)                 | 20              | 15             |
| Total                                     | 64              | 33             |

### 3.3 Image Pre-Processing

Most of the collected burn images were cropped by the burn specialist. There were some collected burn images that were the original images. These original images were cropped and validated with the assistance of the burn specialist. There were some collected original images that came with various background apart from the burn and skin regions. For example, some of the images came with the background that had the same colour as the burn wound. Thus, the images in the dataset were cropped in such a way that the cropped images consisted of the burn wound only, with little or no skin region. For images such as the burn wound covering the whole human body parts without any skin region present, these images were cropped with more than 50% of the burn wound included. The cropped images were able to show the burn wound clearly as having the background and noise would affect the colour image processing. The images in the dataset consisted of burn wounds that had various colours, meaning the images were not limited to have only one burn depth present. There could be multiple burn depths present in a single image with

multiple colours. All the cropped images were then standardised to portable network graphic (PNG) files. This is the lossless compression format that is able to retain the image's original information upon compression. The cropped images in PNG form are used as input to the feature extraction processes.

### 3.4 Image Feature Extraction

Colour and texture both play a vital role in skin burn image classification (Serrano et al., 2015). Colour feature is an important feature because the colour information from an image is sufficient to represent a burn type. It is the main feature that the specialists use to determine a burn depth when diagnosing a burn wound. Table 3.2 shows the colour definition given by the burn specialist, Dr Ehfa binti Bujang Safawi for this research for each burn depth.

**Table 3.2:** Colour definition for each burn depth

| Type of Burn                              | Colour                                         |
|-------------------------------------------|------------------------------------------------|
| Superficial Partial Thickness Burn (SPTB) | Pinkish                                        |
| Deep Partial Thickness Burn (DPTB)        | Cream-coloured or whitish                      |
| Full Thickness Burn (FTB)                 | Brown-black or greyish-yellow or greyish-white |

Based on the colour definition given for each burn depth in Table 3.2, the colour focus in this thesis is divided into seven colours, which are defined as follows:

- (i) SPTB = {Pink, Dark Red}
- (ii) DPTB = {White}
- (iii) FTB = {Light Brown, Dark Brown, Beige-yellow, Greyish-white}

In this thesis, CIE L\*a\*b\* colour space was chosen for feature extraction. The reasons CIE L\*a\*b\* colour space was chosen to be used are as follows:

- (i) It is a perceptually uniform colour space and a device independent model when compared to other colour spaces such as RGB and HSV, which are not perceptually uniform colour spaces and are device dependent model (Bianconi, Bello, Fernández, & González, 2015).
- (ii) It was chosen over RGB colour space because RGB colour space is not suitable for colour analysis as its colour (chrominance) and intensity (luminance) information are mixed up (Shaik, Ganesan, Kalist, Sathish, & Jenitha, 2015).
- (iii) It was mostly used by the literature in the classification of skin burn depths images (Acha et al., 2013; Serrano et al., 2015; Suvarna, Sivakumar, Kumar, et al., 2013; Suvarna, Sivakumar, & Niranjana, 2013).

There are also cases where the colour information is not sufficient, to represent a certain burn depth. This is when the texture feature comes in handy and acts as a supporting feature to augment the colour information. There is also a case where the colour information of two different burn depths are almost the same in term of colour value. This usually leads to misclassification if only the colour feature was used to classify these images. The texture feature can help to separate the two almost similar colour yet coming from different burn depths. The standard illuminant, D<sub>65</sub>, as shown in Table 3.3 was used for the transformation from RGB to the CIE L\*a\*b\* colour representation.

**Table 3.3:** Reference white point,  $D_{65}$  values

| Channel | $D_{65}$ |
|---------|----------|
| $X_n$   | 95.0155  |
| $Y_n$   | 100.0000 |
| $Z_n$   | 108.8259 |

Figure 3.2 shows the overall proposed feature extraction process and the features extracted in each sub-processes. Based on Figure 3.2, the process works as follows:

- (i) Each input image from the dataset is converted from RGB colour space image to  $L^*a^*b^*$  colour space image.
- (ii) The  $L^*a^*b^*$  image is split into  $L^*$ ,  $a^*$  and  $b^*$  channels.
- (iii) The  $a^*$  and  $b^*$  channels are used by the global feature extraction process to extract global colour features. The output of the global feature extraction process are listed as follows:
  - a. Standard deviation of hue (*stdHue*)
  - b. Mean of  $a^*$  channel (*meanA*)
  - c. Mean of  $b^*$  channel (*meanB*)
  - d. Standard deviation of  $a^*$  channel (*stdA*)
  - e. Skewness of  $a^*$  channel (*skewA*)
  - f. Kurtosis of  $a^*$  channel (*kurtA*)
- (iv) The RGB input image is used by blister region detection process as shown in Figure 3.3 to segment the region that contain blister and region that did not contain blister. Later, colour and texture features are extracted from both of the segmented

regions. The extracted colour features are mean of chroma (*meanChromaBlister*) and standard deviation of hue (*stdHueBlister*) whereas the extracted texture features are listed as follows:

- a. Mean of standard deviation filter (*meanStdFiltBlister*)
  - b. Mean of entropy filter (*meanEntropyFiltBlister*)
  - c. Contrast (*contrastBlister*)
  - d. Energy (*energyBlister*)
- (v) The minimum and maximum values of L\*, a\* and b\* channels are loaded from the files saved in the average and standard deviation colour ranges calculation process and optimum weightage generation process as shown in Figure 3.4 and Figure 3.5.
- (vi) The loaded minimum and maximum of L\*, a\* and b\* channels values are used to threshold each channel of the L\*a\*b\* image to get the matching colour pixels in an image.
- (vii) The thresholded image is in binary format and is obtained for each burn depth, which are named as *BWDeep*, *BWSuperficial* and *BWFull* respectively.
- (viii) Then, it is mapped to RGB image to get the image in RGB format.
- (ix) The mean value of RGB image for each burn depth are calculated and used as colour features. The extracted colour features in terms of mean value are mean of DPTB range (*meanDeepRange*), mean of SPTB range (*meanSuperficialRange*) and mean of FTB range (*meanFullRange*).
- (x) The L\*a\*b\* image is used in the colour ranges refining process as shown in Figure 3.6. The process returned binary images, which are *deepBurnColour*, *superficialBurnColour* and *fullBurnColour*.

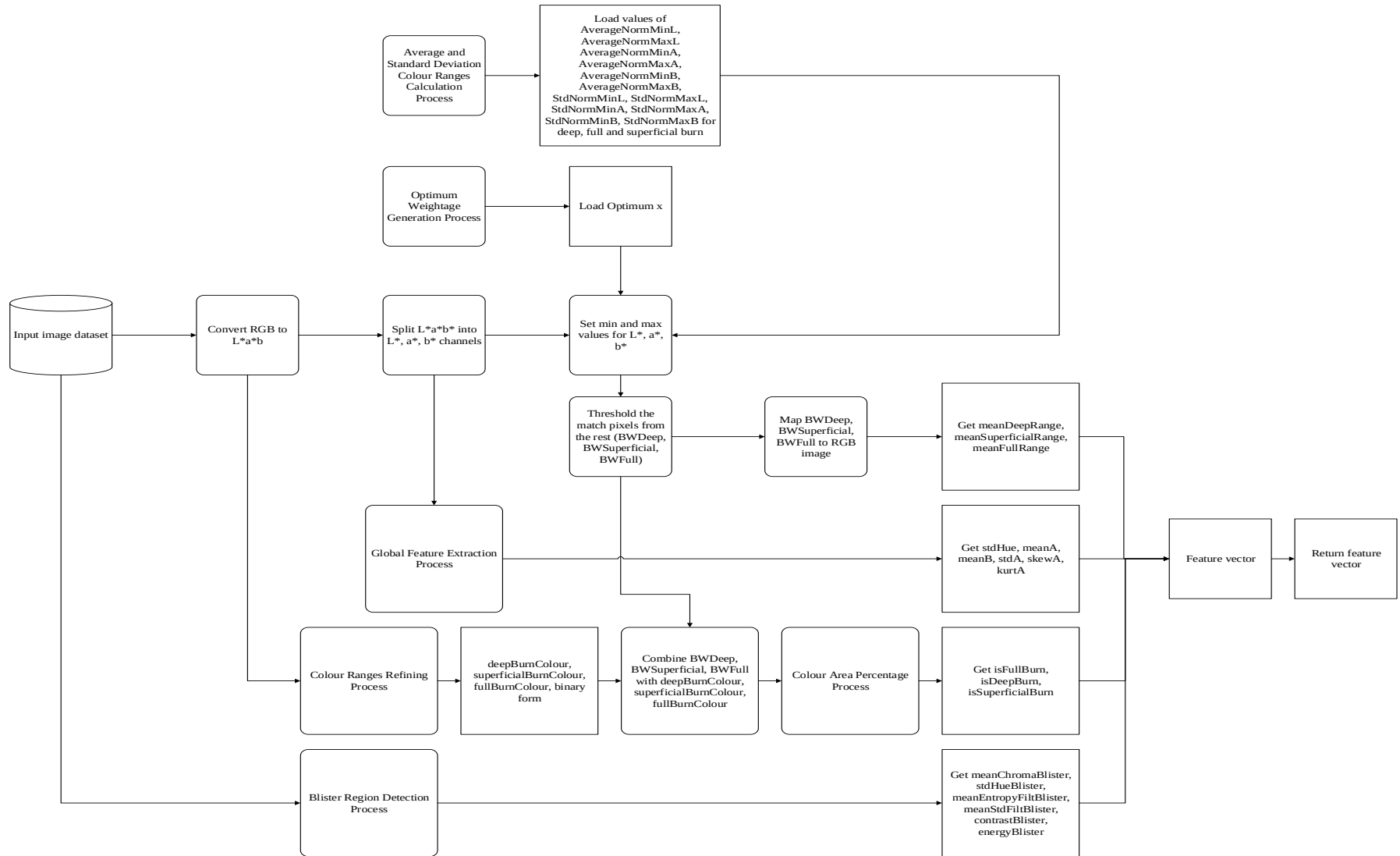


**Figure 3.2:** Proposed feature extraction process

- (xi) These binary images, *deepBurnColour*, *superficialBurnColour* and *fullBurnColour* are then combined with the thresholded binary images, *BWDeep*, *BWSuperficial* and *BWFull*. The combinations are formed using logical OR in which *deepBurnColour* is combined with *BWDeep*, *superficialBurnColour* is combined with *BWSuperficial* and *fullBurnColour* is combined with *BWFull*.
- (xii) These combined binary images are later used in colour area percentage process as shown in Figure 3.7 to calculate the percentage colour area of each of the burn depths. The colour area percentage process return colour features in terms of percentage colour area of burn, which are percentage colour area of FTB (*isFullBurn*), percentage colour area of DPTB (*isDeepBurn*) and percentage colour area of SPTB (*isSuperficialBurn*).
- (xiii) All the extracted features are stored in a feature vector, which is later used as an input to the classifier.

The following sub-sections discussed the proposed colour and texture features extracted for the classification of skin burn depths. There are three feature sets been extracted, namely Feature Set A, Feature Set B and Feature Set C. Feature Set A is the global feature set, Feature Set B is the blister feature set and Feature Set C is the image feature set.

#### **3.4.1 Feature Set A – Global Features (*stdHue*, *meanA*, *meanB*, *stdA*, *skewA*, *kurtA*)**

Global features in terms of statistical measures were extracted as Feature Set A. According to Lisin et al. (2005), global features described the image as a whole by generalising the entire image with a single vector. The global features produced very compact representation of an image but were very sensitive to clutter and occlusion in

which a good segmentation of an object from the background image was assumed to be available (Lisin et al., 2005). Global features alone may not work well with heterogeneous kind of burn images. The global features are adopted from previous research works (Acha et al., 2005, 2013; Serrano, Acha, Gómez-Cía, et al., 2005; Serrano et al., 2015). The global feature extraction process works as follows:

- (i) Each input image from the dataset is converted from RGB colour space image to  $L^*a^*b^*$  colour space image.
- (ii) The  $L^*a^*b^*$  image is split into  $L^*$ ,  $a^*$  and  $b^*$  channels.
- (iii) The standard deviation of hue is calculated. The hue formula is shown in Formula 2.13 in Sub-section 2.3.1.
- (iv) The mean of  $a^*$  and  $b^*$  channels are calculated using mean function implemented in MATLAB.
- (v) The skewness, kurtosis and standard deviation of  $a^*$  channel are calculated using the skewness, kurtosis and standard deviation functions implemented in MATLAB.

Overall, the extracted global colour features in  $L^*a^*b^*$  colour space are listed as follows:

- (i) Standard deviation of hue (*stdHue*)
- (ii) Mean of  $a^*$  channel (*meanA*)
- (iii) Mean of  $b^*$  channel (*meanB*)
- (iv) Standard deviation of  $a^*$  channel (*stdA*)
- (v) Skewness of  $a^*$  channel (*skewA*)
- (vi) Kurtosis of  $a^*$  channel (*kurtA*)

### 3.4.2 Feature Set B – Blister Features (*meanChromaBlister*, *stdHueBlister*, *meanStdFiltBlister*, *meanEntropyFiltBlister*, *contrastBlister*, *energyBlister*)

Blisters, as appeared in SPTB, are usually brownish in colour and not all SPTB has blister occurrence. Before extracting the colour features from the region that contain blister, the region needs to be detected and segmented out from an image. The proposed process for blister region detection is shown in Figure 3.3.

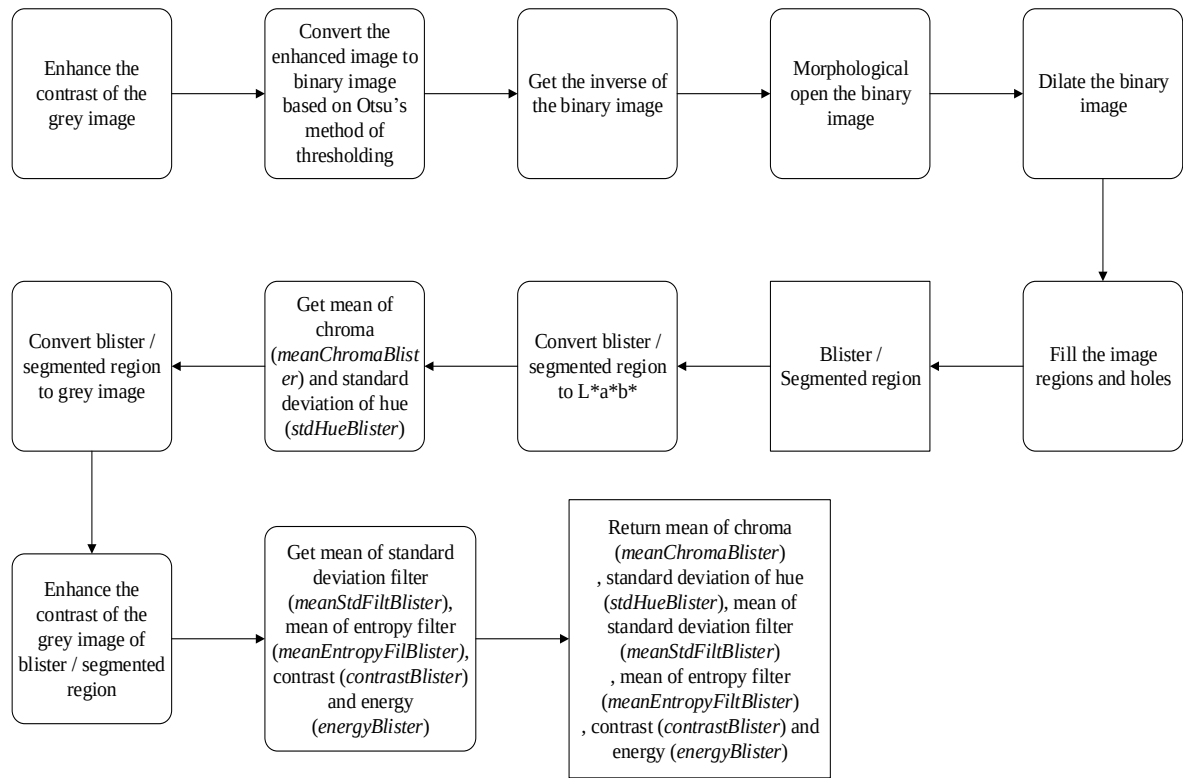


**Figure 3.3:** Blister region detection process

Based on Figure 3.3, the process works as follows:

- (i) The contrast of the grey image is enhanced.
- (ii) After that, the enhanced image is converted to binary image based on a global threshold using Otsu's method (Otsu, 1979). A threshold needs to be applied to the grey scale image in order to get the region that consist of blister. The threshold

based on Otsu's method is selected based on minimising the intraclass variance and maximising the interclass variance (Petrou & Petrou, 2010).

- (iii) After applied the Otsu's method of thresholding to the grey scale image, a binary image is formed. The inverse of the binary image is the region that contain the blister. Thus, the binary image is inverted to get the region that contains blister.
- (iv) The morphological open is an operation that is performed on the binary image by using erosion followed by dilation with the specified structuring element. The specified structuring element used is a disk-shaped structuring element, with a radius of 5. Those pixels included in the morphological computation are true pixel, whereas those pixels that not included are false pixels. In other words, in a binary image, those true pixels are in white or have the value one, while the false pixels are black or have the value zero. Morphological opening operation will enlarge the false pixels and fill in the true pixels with false pixels, mimicking an erosion process.
- (v) After that, the binary image is again dilated with disk-shaped structuring element, with a radius of 10. Dilation operation will enlarge the true pixels and fill in the false pixels with true pixels.
- (vi) Flood-fill operation is performed on the dilated binary image to fill the holes in between the white pixels.
- (vii) Finally, the blister region and non-blister region are formed.

The region that contains blister is detected based on grey intensity, in which the blister appears as darker intensity pixels after contrast enhancement. The Otsu's method thresholds the grey scale image and forms binary image with brighter intensity pixels. To get the region that contain blister, the binary image formed after the thresholding needs to

be inverted. However, not all darker intensity pixels are blisters. They are some darker intensity pixels that appear as a burn wound inside another burn wound or burn wound with low light intensity. To overcome this problem, both colour and texture features are extracted from the segmented blisters and non-blisters region. This can be further defined as: if the segmented region contain blister, both colour and texture features extracted can be used to differentiate the blister in SPTB from DPTB and FTB; else, if the segmented region do not contain blister, the colour and texture features extracted can be used to differentiate the colour and texture of SPTB from DPTB and FTB as the texture of SPTB are normally moist and wet as compared to DPTB and FTB, which are less moist or drier than SPTB.

(viii) The blister or segmented region is converted to  $L^*a^*b^*$  colour space for colour feature extraction.

(ix) The colour features that are extracted are the mean of chroma (*meanChromaBlister*) and the standard deviation of hue (*stdHueBlister*). The chroma and hue features are adopted from the previous research works (Acha et al., 2013; Serrano et al., 2015). The chroma formula is shown in Formula 2.15 in Sub-section 2.3.1.

The texture features extracted in this thesis refer to the texture of the blister and texture of SPTB. Blisters normally occur in SPTB. DPTB and FTB do not contain blister. The blisters can vary in shape and can be a single blister or a group of small blisters. Based on the process for detecting blister region as shown in Figure 3.3, the texture features are extracted from both segmented region that contain blister and region that do not contain blister.

(x) The segmented region is converted from RGB colour space to grey image.

- (xi) The contrast of the grey image of the segmented region is further enhanced before texture feature extraction.
- (xii) Mean of standard deviation filter (*meanStdFiltBlister*) and mean of entropy filter (*meanEntropyFiltBlister*) are extracted to differentiate the blister or SPTB from non-blister textures or non-SPTB texture. Standard deviation filter and entropy filter are texture analysis functions, which are described in Section 2.4.
- (xiii) Apart from using texture analysis function to extract the texture content of a region, GLCM is also used to examine the texture of the blister or SPTB. GLCM is discussed in Section 2.5. However, only contrast and energy are extracted and used in this work. Correlation and homogeneity are not used because both of the values computed are very close to each other among the three burn depths and thus, these values do not help in differentiating the burn depths. The extracted texture features from GLCM are contrast (*contrastBlister*) and energy (*energyBlister*). The GLCM features are adopted from Sabeena and Raj Kumar (2017).
- (xiv) The overall features set that are extracted to identify the texture of blister or texture of SPTB are listed as follows:
  - a. Mean of chroma (*meanChromaBlister*)
  - b. Standard deviation of hue (*stdHueBlister*)
  - c. Mean of standard deviation filter (*meanStdFiltBlister*)
  - d. Mean of entropy filter (*meanEntropyFiltBlister*)
  - e. Contrast (*contrastBlister*)
  - f. Energy (*energyBlister*)

Algorithm 1 describes the blister region detection process.

---

**Algorithm 1: Blister Region Detection Process**

---

**INPUT:** RGB image  $R$  in dataset

**OUTPUT:**  $blister\_rgb$

1. **CALL**  $rgb2gray(R)$  **RETURN**  $grey$  //Convert RGB image to grey image
  2. **CALL**  $adapthisteq(grey)$  **RETURN**  $I_{eq}$  // Enhance the contrast of the greyscale image
  3. **CALL**  $graythresh(I_{eq})$  **RETURN**  $thres\_level$
  4. **CALL**  $im2bw(I_{eq}, thres\_level)$  **RETURN**  $bw$  //Convert image to binary image with global image threshold
  5.  $bw2 \leftarrow \text{NOT } bw$
  6. **CALL**  $imopen(bw2, strel('disk', 5))$  **RETURN**  $bg1$ , where  $bg1 \in [0,1]$  // Morphological open image with disk-shaped structuring element and radius of 5
  7. **CALL**  $imdilate(bg1, strel('disk', 10))$  **RETURN**  $bg2$ , where  $bg2 \in [0,1]$  // Dilate image with disk-shaped structuring element and radius of 10
  8. **CALL**  $imfill(bg2, 'holes')$  **RETURN**  $bg3$ , where  $bg3 \in [0,1]$  // Fill image regions
  9.  $blister\_rgb \leftarrow R * bg3$
  10. **RETURN**  $blister\_rgb$
- 

### 3.4.3 Feature Set C – Image Features ( $meanDeepRange$ , $meanSuperficialRange$ , $meanFullRange$ , $isFullBurn$ , $isDeepBurn$ , $isSuperficialBurn$ )

There are several processes taken to extract image colour features. Image features are used to enhance the extracted global feature for the classification of skin burn depths images. The first process is to calculate the average and standard deviation colour ranges for each of the burn depths in the training image dataset as shown in Figure 3.4.

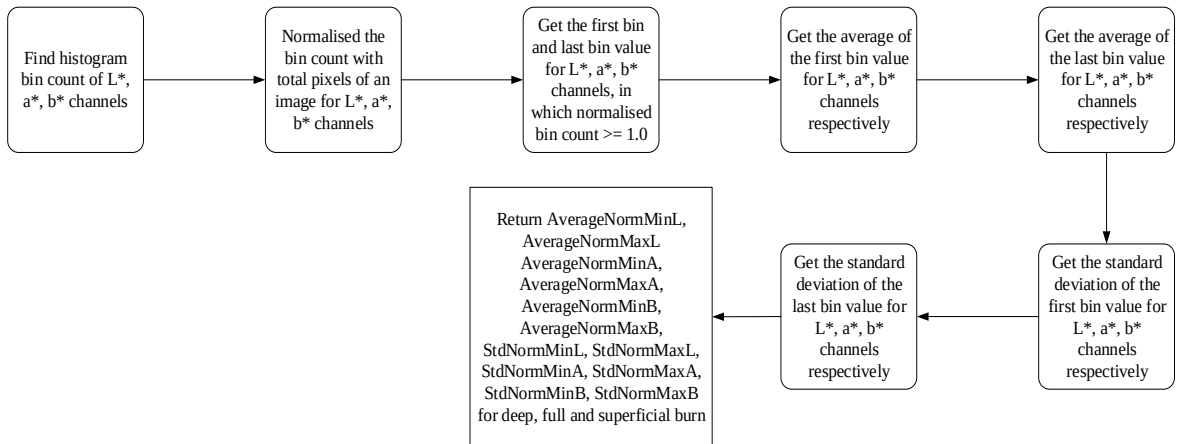


**Figure 3.4:** Average and standard deviation colour ranges calculation process

Based on Figure 3.4, the process works as follows:

- (i) The histogram count function partitions the L\*, a\* and b\* channels into bins and sorts the bins with the specified bin edges. The specified bin edges for L\* channel is 0 to 100 and for a\* and b\* channel are -26 to 100, which are set based on the observation on the CIE L\*a\*b\* colour chart as shown in Figure 2.6. The a\* and b\* channels are set to include -26 as beyond -26, the colour pixels tend to become more green and blue respectively as illustrated in Figure 2.6, in which the green and blue colours are not important in determining the burn depths. The histogram count function returns the count in each bin.
- (ii) The count in each bin are later normalised with the total pixels of an image as shown in Formula 3.1:

$$NormalisedCount = \frac{countL}{totalPixels} \times 100 \quad (3.1)$$

The normalisation is done separately for L\*, a\* and b\* channels for DPTB, FTB and SPTB.

- (iii) The normalised count with a value of more than or equal to 1.0 are considered. After that, the first bin and last bin values are obtained for each of the classes of DPTB, FTB and SPTB images, class by class.
- (iv) The average minimum and maximum of the L\*, a\* and b\* channels for DPTB, FTB and SPTB are calculated using Formulas 3.2 and 3.3 respectively (Welkowitz, Ewen, & Cohen, 2014).

$$AverageNormMin = \frac{\sum firstNormalised}{totalImages} \quad (3.2)$$

$$AverageNormMax = \frac{\sum lastNormalised}{totalImages} \quad (3.3)$$

where,  $totalImages$  = number of images in each burn depth.

- (v) The minimum and maximum standard deviation of the  $L^*$ ,  $a^*$  and  $b^*$  channels for DPTB, FTB and SPTB are calculated using Formulas 3.4 and 3.6 respectively, with Formulas 3.5 and 3.7 showing the formula used in Formulas 3.4 and 3.6 (Welkowitz et al., 2014).

$$StdNormMin = \sqrt{\frac{\sum(firstNormalised - meanfirstNormalised)^2}{totalImages - 1}} \quad (3.4)$$

where,

$$meanfirstNormalised = \frac{(\sum firstNormalised)^2}{totalImages} \quad (3.5)$$

$totalImages$  = number of images in each burn depth

$$StdNormMax = \sqrt{\frac{\sum(lastNormalised - meanlastNormalised)^2}{totalImages - 1}} \quad (3.6)$$

where,

$$meanlastNormalised = \frac{(\sum lastNormalised)^2}{totalImages} \quad (3.7)$$

$totalImages$  = number of images in each burn depth

- (vi) After the average and standard deviation colour ranges for each burn depth are obtained, they are saved into a file, which will later be loaded and used by the optimum weightage generation process and the main proposed feature extraction process.

The average and standard deviation colour ranges for each burn depth obtained from the training image dataset are referred to as follows and will be used throughout this thesis.

- (i) The average colour ranges for DPTB are divided into minimum and maximum values of  $L^*$ ,  $a^*$  and  $b^*$  channels. The minimum value of  $L^*$ ,  $a^*$  and  $b^*$  channels

are indicated by *AverageNormalisedMinLDeep*, *AverageNormalisedMinADeep* and *AverageNormalisedMinBDeep*, whereas the maximum value of  $L^*$ ,  $a^*$  and  $b^*$  channels are indicated by *AverageNormalisedMaxLDeep*, *AverageNormalisedMaxADeep* and *AverageNormalisedMaxBDeep*.

- (ii) The average colour ranges for FTB are divided into minimum and maximum values of  $L^*$ ,  $a^*$  and  $b^*$  channels. The minimum value of  $L^*$ ,  $a^*$  and  $b^*$  channels are indicated by *AverageNormalisedMinLFull*, *AverageNormalisedMinAFull* and *AverageNormalisedMinBFull*, whereas the maximum value of  $L^*$ ,  $a^*$  and  $b^*$  channels are indicated by *AverageNormalisedMaxLFull*, *AverageNormalisedMaxAFull* and *AverageNormalisedMaxBFull*.
- (iii) The average colour ranges for SPTB are divided into minimum and maximum values of  $L^*$ ,  $a^*$  and  $b^*$  channels. The minimum value of  $L^*$ ,  $a^*$  and  $b^*$  channels are indicated by *AverageNormalisedMinLSuperficial*, *AverageNormalisedMinASuperficial* and *AverageNormalisedMinBSuperficial*, whereas the maximum value of  $L^*$ ,  $a^*$  and  $b^*$  channels are indicated by *AverageNormalisedMaxLSuperficial*, *AverageNormalisedMaxASuperficial* and *AverageNormalisedMaxBSuperficial*.
- (iv) The standard deviation colour ranges for DPTB are divided into minimum and maximum values of  $L^*$ ,  $a^*$  and  $b^*$  channels. The minimum value of  $L^*$ ,  $a^*$  and  $b^*$  channels are indicated by *StdNormalisedMinLDeep*, *StdNormalisedMinADeep* and *StdNormalisedMinBDeep*, whereas the maximum value of  $L^*$ ,  $a^*$  and  $b^*$  channels are indicated by *StdNormalisedMaxLDeep*, *StdNormalisedMaxADeep* and *StdNormalisedMaxBDeep*.

- (v) The standard deviation colour ranges for FTB are divided into minimum and maximum values of  $L^*$ ,  $a^*$  and  $b^*$  channels. The minimum value of  $L^*$ ,  $a^*$  and  $b^*$  channels are indicated by *StdNormalisedMinLFull*, *StdNormalisedMinAFull* and *StdNormalisedMinBFull*, whereas the maximum value of  $L^*$ ,  $a^*$  and  $b^*$  channels are indicated by *StdNormalisedMaxLFull*, *StdNormalisedMaxAFull* and *StdNormalisedMaxBFull*.
- (vi) The standard deviation colour ranges for SPTB are divided into minimum and maximum values of  $L^*$ ,  $a^*$  and  $b^*$  channels. The minimum value of  $L^*$ ,  $a^*$  and  $b^*$  channels are indicated by *StdNormalisedMinLSuperficial*, *StdNormalisedMinASuperficial* and *StdNormalisedMinBSuperficial*, whereas the maximum value of  $L^*$ ,  $a^*$  and  $b^*$  channels are indicated by *StdNormalisedMaxLSuperficial*, *StdNormalisedMaxASuperficial* and *StdNormalisedMaxBSuperficial*.

Algorithm 2 describes the average and standard deviation colour ranges calculation process.

---

**Algorithm 2: Average and Standard Deviation Colour Ranges Calculation Process**

---

**INPUT:** RGB image  $R$  in dataset

**OUTPUT:** *AverageNormalisedMinLDeep*, *AverageNormalisedMaxLDeep*,  
*AverageNormalisedMinADeep*, *AverageNormalisedMaxADeep*,  
*AverageNormalisedMinBDeep*, *AverageNormalisedMaxBDeep*,  
*StdNormalisedMinLDeep*, *StdNormalisedMaxLDeep*, *StdNormalisedMinADeep*,  
*StdNormalisedMaxADeep*, *StdNormalisedMinBDeep*, *StdNormalisedMaxBDeep*,  
*AverageNormalisedMinLFull*, *AverageNormalisedMaxLFull*,  
*AverageNormalisedMinAFull*, *AverageNormalisedMaxAFull*,  
*AverageNormalisedMinBFull*, *AverageNormalisedMaxBFull*, *StdNormalisedMinLFull*,  
*StdNormalisedMaxLFull*, *StdNormalisedMinAFull*, *StdNormalisedMaxAFull*,  
*StdNormalisedMinBFull*, *StdNormalisedMaxBFull*, *AverageNormalisedMinLSuperficial*,  
*AverageNormalisedMaxLSuperficial*, *AverageNormalisedMinASuperficial*,  
*AverageNormalisedMaxASuperficial*, *AverageNormalisedMinBSuperficial*,  
*AverageNormalisedMaxBSuperficial*, *StdNormalisedMinLSuperficial*,  
*StdNormalisedMaxLSuperficial*, *StdNormalisedMinASuperficial*,  
*StdNormalisedMaxASuperficial*, *StdNormalisedMinBSuperficial*,  
*StdNormalisedMaxBSuperficial*

1. **SORT** the  $L_{comp}$  into bins with the bin edges specified,  $edgesL_{comp} \leftarrow 0:1:100$ , where 0 is the first bin and 100 is the last bin
-

2. **SORT** the *Acomp* into bins with the bin edges specified,  $edgesAcomp \leftarrow -26:1:100$ , where -26 is the first bin and 100 is the last bin
  3. **SORT** the *Bcomp* into bins with the bin edges specified.  $edgesBcomp \leftarrow -26:1:100$ , where -26 is the first bin and 100 is the last bin
  4.  $countL \leftarrow \mathbf{GET}$  the histogram count for *Lcomp* with  $edgesLcomp$
  5.  $countA \leftarrow \mathbf{GET}$  the histogram count for *Acomp* with  $edgesAcomp$
  6.  $countB \leftarrow \mathbf{GET}$  the histogram count for *Bcomp* with  $edgesBcomp$
  7. **IF**  $R = \text{DPTB images}$ ,
  8.  $normalisedLDeep \leftarrow (countL / totalPixels) * 100$ , where  $totalPixels \leftarrow U * V$
  9.  $normalisedADeep \leftarrow (countA / totalPixels) * 100$ , where  $totalPixels \leftarrow U * V$
  10.  $normalisedBDeep \leftarrow (countB / totalPixels) * 100$ , where  $totalPixels \leftarrow U * V$
  11. **IF**  $normalisedLDeep \geq 1.0$
  12. **GET** the first bin ( $firstNormalisedLDeep$ ) and last bin ( $lastNormalisedLDeep$ ) value of  $normalisedLDeep$  for all DPTB images in dataset
  13. **ENDIF**
  14. **IF**  $normalisedADeep \geq 1.0$
  15. **GET** the first bin ( $firstNormalisedADeep$ ) and last bin ( $lastNormalisedADeep$ ) value of  $normalisedADeep$  for all DPTB images in dataset
  16. **ENDIF**
  17. **IF**  $normalisedBDeep \geq 1.0$
  18. **GET** the first bin ( $firstNormalisedBDeep$ ) and last bin ( $lastNormalisedBDeep$ ) value of  $normalisedBDeep$  for all DPTB images in dataset
  19. **ENDIF**
  20.  $AverageNormalisedMinLDeep \leftarrow \sum firstNormalisedLDeep / totalDeepImages$ , where  $firstNormalisedLDeep \in$  all DPTB images in training dataset
  21.  $AverageNormalisedMaxLDeep \leftarrow \sum lastNormalisedLDeep / totalDeepImages$ , where  $lastNormalisedLDeep \in$  all DPTB images in training dataset
  22.  $AverageNormalisedMinADeep \leftarrow \sum firstNormalisedADeep / totalDeepImages$ , where  $firstNormalisedADeep \in$  all DPTB images in training dataset
  23.  $AverageNormalisedMaxADeep \leftarrow \sum lastNormalisedADeep / totalDeepImages$ , where  $lastNormalisedADeep \in$  all DPTB images in training dataset
  24.  $AverageNormalisedMinBDeep \leftarrow \sum firstNormalisedBDeep / totalDeepImages$ , where  $firstNormalisedBDeep \in$  all DPTB images in training dataset
  25.  $AverageNormalisedMaxBDeep \leftarrow \sum lastNormalisedBDeep / totalDeepImages$ , where  $lastNormalisedBDeep \in$  all DPTB images in training dataset
  26.  $StdNormalisedMinLDeep \leftarrow \sqrt{(\sum firstNormalisedLDeep - meanfirstNormalisedLDeep)^2 / totalDeepImages - 1}$ , where  $meanfirstNormalisedLDeep \leftarrow (\sum firstNormalisedLDeep)^2 / totalDeepImages$
  27.  $StdNormalisedMaxLDeep \leftarrow \sqrt{(\sum lastNormalisedLDeep - meanlastNormalisedLDeep)^2 / totalDeepImages - 1}$ , where  $meanlastNormalisedLDeep \leftarrow (\sum lastNormalisedLDeep)^2 / totalDeepImages$
  28.  $StdNormalisedMinADeep \leftarrow \sqrt{(\sum firstNormalisedADeep - meanfirstNormalisedADeep)^2 / totalDeepImages - 1}$ , where  $meanfirstNormalisedADeep \leftarrow (\sum firstNormalisedADeep)^2 / totalDeepImages$
  29.  $StdNormalisedMaxADeep \leftarrow \sqrt{(\sum lastNormalisedADeep - meanlastNormalisedADeep)^2 / totalDeepImages - 1}$ , where  $meanlastNormalisedADeep \leftarrow (\sum lastNormalisedADeep)^2 / totalDeepImages$
  30.  $StdNormalisedMinBDeep \leftarrow \sqrt{(\sum firstNormalisedBDeep -$
-

- $meanfirstNormalisedBDeep)^2 / totalDeepImages - 1)$ , where  
 $meanfirstNormalisedBDeep \leftarrow (\sum firstNormalisedBDeep)^2 / totalDeepImages$
31.  $StdNormalisedMaxBDeep \leftarrow \sqrt{(\sum lastNormalisedBDeep - meanlastNormalisedBDeep)^2 / totalDeepImages - 1)}$ , where  
 $meanlastNormalisedBDeep \leftarrow (\sum lastNormalisedBDeep)^2 / totalDeepImages$
32. **ENDIF**
33. Repeat step 7 to 32 for FTB images to get *AverageNormalisedMinLFull*,  
*AverageNormalisedMaxLFull*, *AverageNormalisedMinAFull*,  
*AverageNormalisedMaxAFull*, *AverageNormalisedMinBFull*,  
*AverageNormalisedMaxBFull*, *StdNormalisedMinLFull*, *StdNormalisedMaxLFull*,  
*StdNormalisedMinAFull*, *StdNormalisedMaxAFull*, *StdNormalisedMinBFull*,  
*StdNormalisedMaxBFull*
34. Repeat step 7 to 32 for SPTB images to get *AverageNormalisedMinLSuperficial*,  
*AverageNormalisedMaxLSuperficial*, *AverageNormalisedMinASuperficial*,  
*AverageNormalisedMaxASuperficial*, *AverageNormalisedMinBSuperficial*,  
*AverageNormalisedMaxBSuperficial*, *StdNormalisedMinLSuperficial*,  
*StdNormalisedMaxLSuperficial*, *StdNormalisedMinASuperficial*,  
*StdNormalisedMaxASuperficial*, *StdNormalisedMinBSuperficial*,  
*StdNormalisedMaxBSuperficial*
- 

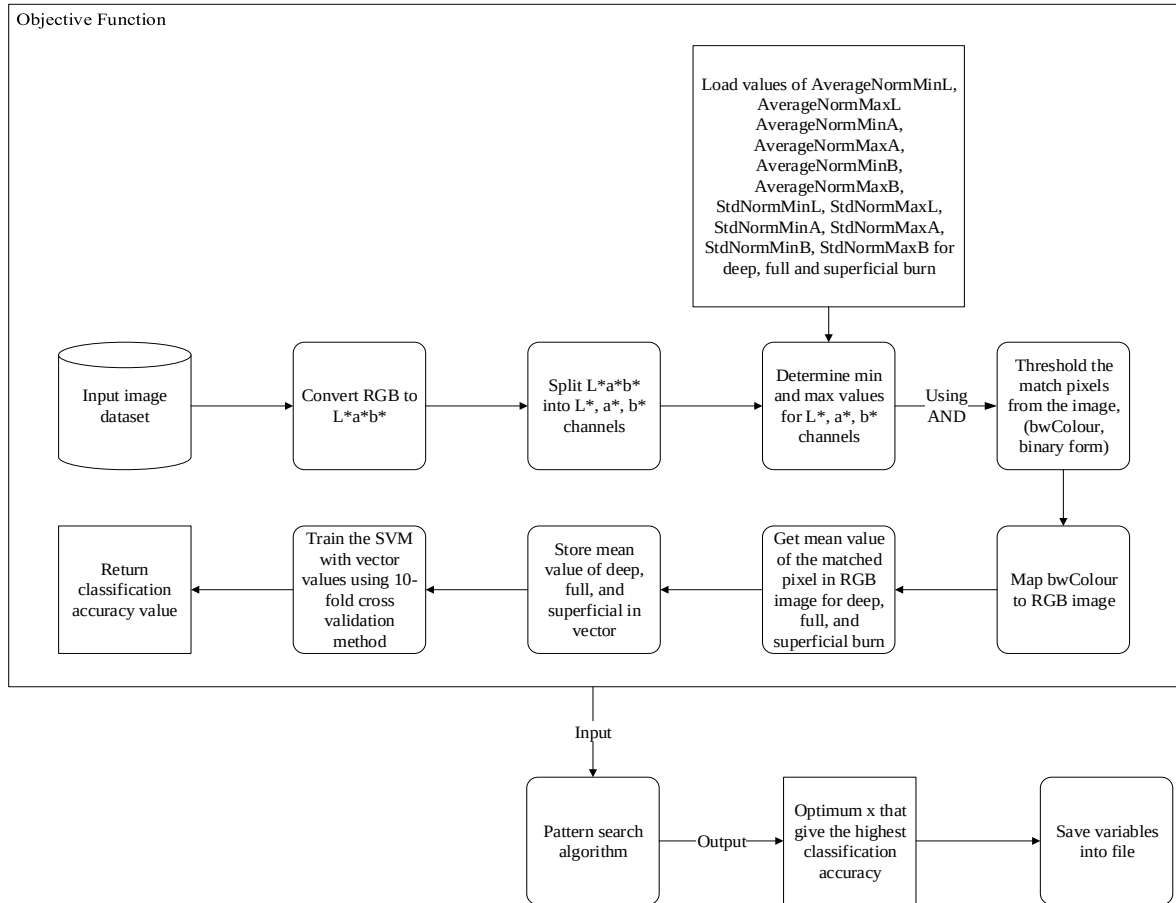


**Figure 3.5:** Optimum weightage generation process using pattern search algorithm

The second process, as shown in Figure 3.5, is using the pattern search algorithm to find the optimum weightage for the standard deviation colour ranges, which is computed from the training image dataset. The pattern search algorithm is described in Section 2.6. Using the average colour ranges from the training image dataset is not sufficient to represent some of the burn depths in terms of colour pixels. Thus, image features are proposed and extracted using this process to find the optimum weightage which determines whether or not to add or subtract standard deviation colour ranges, to or from the average colour ranges of each burn depth in training image dataset. The following example shows the formula used in determining the minimum and maximum values of L\*, a\* and b\* channels of DPTB. The average colour ranges and standard deviation colour ranges are obtained from DPTB images in the training dataset.

$$\text{channel1MinDeep} = \text{AverageNormalisedMinLDeep} - \text{var}(1) * \text{StdNormalisedMinLDeep}$$

$$\text{channel1MaxDeep} = \text{AverageNormalisedMaxLDeep} + \text{var}(2) *$$

$$\text{StdNormalisedMaxLDeep}$$

$$\text{channel2MinDeep} = \text{AverageNormalisedMinADeep} - \text{var}(3) *$$

$$\text{StdNormalisedMinADeep}$$

$$\text{channel2MaxDeep} = \text{AverageNormalisedMaxADeep} + \text{var}(4) *$$

$$\text{StdNormalisedMaxADeep}$$

$$\text{channel3MinDeep} = \text{AverageNormalisedMinBDeep} - \text{var}(5) *$$

$$\text{StdNormalisedMinBDeep}$$

$$\text{channel3MaxDeep} = \text{AverageNormalisedMaxBDeep} + \text{var}(6) *$$

$$\text{StdNormalisedMaxBDeep}$$

where,  $\text{var}(1)$ ,  $\text{var}(2)$ ,  $\text{var}(3)$ ,  $\text{var}(4)$ ,  $\text{var}(5)$  and  $\text{var}(6)$  are the variables that represent the optimum weightage that are determined by using the pattern search algorithm. There are

six variables for one burn depth, thus there are 18 variables to be determined for a total of three burn depths.

The objective function that is used as input to pattern search algorithm is shown in Figure 3.5. Based on Figure 3.5, the process works as follows:

- (i) Each input image from the dataset is first converted from RGB colour space image to  $L^*a^*b^*$  colour space image.
- (ii) The  $L^*a^*b^*$  image is then split to obtained  $L^*$ ,  $a^*$  and  $b^*$  channels.
- (iii) The variables required to determine the minimum and maximum values of  $L^*$ ,  $a^*$  and  $b^*$  channels are loaded from the process in Figure 3.4, which are the average and standard deviation colour ranges of each  $L^*$ ,  $a^*$  and  $b^*$  channels for each of the burn depths, with the 18 variables of optimum weightages for standard deviation colour ranges to be determined by the pattern search algorithm.
- (iv) The loaded minimum and maximum values of  $L^*$ ,  $a^*$  and  $b^*$  for each of the burn depths are then required to threshold each channel of the  $L^*a^*b^*$  colour space image, to obtain the colour pixels that match the colour range.
- (v) The thresholded image is in binary form, thus, it is mapped to RGB image to obtain the colour image.
- (vi) The mean value is then calculated from the matched colour pixels image for each of the burn depths, which are *meanDeepRange*, *meanSuperficialRange* and *meanFullRange*.
- (vii) Then, the mean value is stored in a feature vector.
- (viii) SVM is used to perform image classification using the 10-fold cross validation method.

(ix) Finally, the classification accuracy using the features is obtained. The accuracy obtained will be different each time when the objective function is evaluated at every iteration.

In this thesis, pattern search is used to find the maximum classification accuracy of the mean colour features (*meanDeepRange*, *meanSuperficialRange*, *meanFullRange*) that is possible to be achieved when adding the optimum weightage to the standard deviation colour ranges obtained from each burn depth in the training image dataset. The optimum standard deviation colour ranges, whose weightages are determined by the pattern search algorithm, are then added to or subtract from the average colour ranges obtained from the training data. This, in turn, determined the minimum and maximum values of  $L^*$ ,  $a^*$  and  $b^*$  for each burn depth.

Pattern search is originally used to find the minimum point of the objective function. Thus, in order to find the maximum classification accuracy in the objective function  $f(x)$ , the  $f(x)$  need to be maximised. This can be done by minimising  $-f(x)$ . In other words, maximising an objective function can be defined as  $g(x) = -f(x)$  and  $g(x)$  is then minimised. This is because the point at which the minimum of  $-f(x)$  occurs is the same as the point at which the maximum of  $f(x)$  occurs.

The optimum weightage for the standard deviation colour ranges of each burn depth, allows different optimum weightages to be computed for different training dataset used. The pattern search algorithm used is bound by constraints, which means that there are lower and upper bound limits to the components of the solution  $x$ . There are 18 variables in the objective function. The lower bounds are set to [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0] and upper bounds are set to [2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2], one lower and upper bound for each variable. The lower bounds are set to 0 to represent that there is no

need to add or subtract standard deviation from average colour ranges. The upper bounds are set to 2 to represent that two times of the standard deviation are needed to add to or subtract from the average colour range in order to increase or decrease the overall colour ranges. The upper bound is not set to 3 because this causes overlapping colour ranges. The pattern search begins at the initial point,  $x_0 = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]$ . The 10-fold cross validation method and quadratic SVM with one versus all classes approach are used to find the highest classification accuracy that can possibly be achieved.

After the optimum weightage for the standard deviation colour ranges are obtained, they are saved into a file, which is later loaded in the main function to extract colour features. The extracted colour features using these processes are mean of DPTB range (*meanDeepRange*), mean of SPTB range (*meanSuperficialRange*) and mean of FTB range (*meanFullRange*).

The third process is to refine the colour ranges obtained from the training image dataset. The colour ranges in this context refer to the minimum and maximum values of  $L^*$ ,  $a^*$  and  $b^*$  channels. This process is to discover the colour range that characterise each burn depth. Some of the colour pixels for example, the white colour pixels for DPTB are not in the colour ranges of the average and standard deviation of the DPTB training images, or the white colour pixels that are supposed to be extracted as the colour characteristic for DPTB are not being covered in the range. The same case happens in FTB, in which the beige-yellow colour pixels that are important as a colour characteristic to FTB are not being covered or included in the colour ranges of the FTB training images. Thus, the colour pixels from the training images are refined so that the colour characteristics that are important to each burn depth are covered or included. The process to do this is shown in

Figure 3.6 and was adapted from MathWorks. Based on Figure 3.6, the process works as follows:

- (i) Each input image from the dataset is converted from RGB colour space image to  $L^*a^*b^*$  colour space image.
- (ii) The  $L^*a^*b^*$  image is split into  $L^*$ ,  $a^*$  and  $b^*$  channels.
- (iii) The  $L^*$ ,  $a^*$  and  $b^*$  channel ranges need to be determined in order to threshold the required colour pixels in the images. Thus, the average and standard deviation colour ranges for each burn depth obtained from the training image dataset are refined. In addition, there are a total of seven burn colour characteristics studied in this thesis. They are white, pink, dark red, light brown, dark brown, grey white and beige-yellow.
- (iv) There are two methods that are used to refine and determine the channel ranges for each colour, which are with the help of a colour thresholder application implemented in MATLAB and using the CIE  $L^*a^*b^*$  colour chart as a guideline. The CIE  $L^*a^*b^*$  colour chart is shown in Figure 2.6.
- (v) After determining and setting the minimum and maximum values for channels  $L^*$ ,  $a^*$  and  $b^*$ , the colour ranges are used to threshold each channels of the  $L^*a^*b^*$  image, in which pixels that fall into the colour ranges are the colour pixels that represent the burn colour characteristics that are defined.
- (vi) The thresholded image is in binary format, which will be used to threshold the  $L^*$ ,  $a^*$  and  $b^*$  channels of an image to calculate the mean value.
- (vii) The mean value for each channels are then used to form standard matrices of  $L^*$  ( $L_{\text{Standard}}$ ),  $a^*$  ( $a_{\text{Standard}}$ ) and  $b^*$  ( $b_{\text{Standard}}$ ).

- (viii) The split  $L^*$  (LChannel),  $a^*$  (aChannel) and  $b^*$  (bChannel) channels of the image are used to subtract the standard of  $L^*$  (LStandard),  $a^*$  (aStandard) and  $b^*$  (bStandard) channels in order to calculate the delta L, delta A and delta B as shown in Formulas 2.10, 2.11 and 2.12.
- (ix) With the values of delta L, delta A and delta B, delta E is calculated as shown in Formula 2.9. Later, the thresholded image in binary format is again used to threshold the delta E to get selected delta E values.
- (x) Once the selected delta E values in matrix form are obtained, they are used to calculate the mean.
- (xi) The mean value is used to threshold delta E values to get the closest matching colour pixels. The same process in Figure 3.6 is repeated to obtain the colour ranges of other colours. The overlapping of colour ranges among the different burn depths has caused difficulty in classification of the different burn depths. To overcome this, the  $\Delta E$  is thresholded with its mean value. This also means that one pixel may belong to more than one class. For example, a pixel may belong to white colour and it may belong to pink colour, depending on the colour ranges for each of the colour defined.
- (xii) Finally, the seven colours obtained are grouped as follows:
  - a. *deepBurnColour* = {white}
  - b. *superficialBurnColour* = {pink, dark red}
  - c. *fullBurnColour* = {beige-yellow, grey-white, light brown, dark brown}

The process in Figure 3.6 returns *deepBurnColour*, comprising of white colour pixels for characterising DPTB images, *superficialBurnColour*, comprising of pink and dark red colour pixels for characterising SPTB and *fullBurnColour*, comprising of beige-

yellow, grey-white, light brown and dark brown colour pixels for characterising FTB. These *deepBurnColour*, *superficialBurnColour* and *fullBurnColour* are later combined with the binary images: *BWDeep*, *BWSuperficial* and *BWFull* in the main process to form binary images, which comprise of burn colour characteristics that are specified by the burn specialist. This is discussed in Section 3.4.

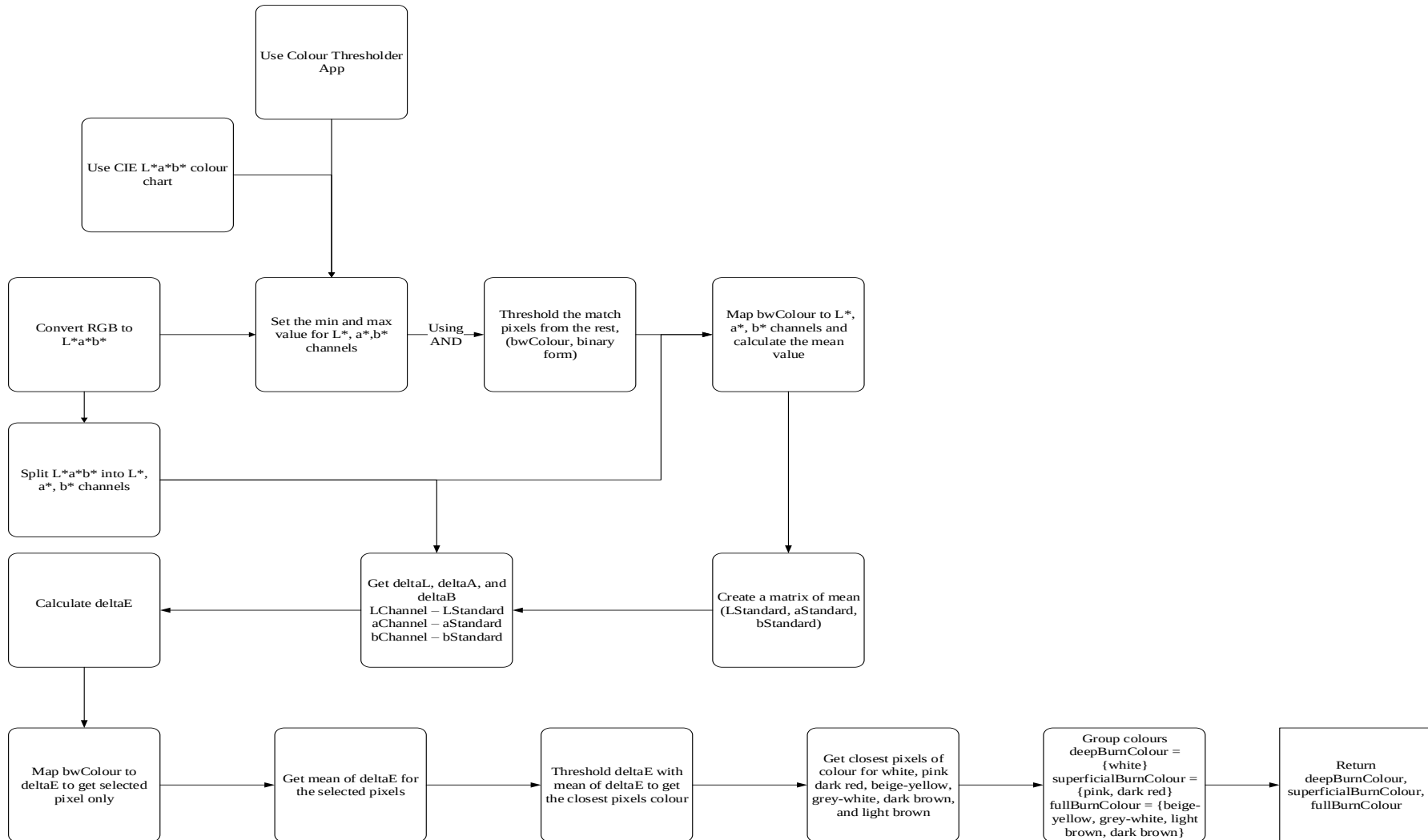


**Figure 3.6:** Colour ranges refining process

The fourth process is to find the percentage area of the colour of each burn depth in an image. The binary images used in this process are the combination of binary images: *BWDeep*, *BWSuperficial*, *BWFull* and binary images: *deepBurnColour*, *superficialBurnColour*, *fullBurnColour*. The binary images: *BWDeep*, *BWSuperficial* and *BWFull* are obtained from the average and standard deviation colour ranges calculation process and the optimum weightage generation process whereas the binary images: *deepBurnColour*, *superficialBurnColour* and *fullBurnColour* are obtained from the colour ranges refining process. The combined binary images are used in the colour area percentage process to calculate the percentage of the colour area covered by each burn depth. There are four conditions applied to find the percentage area of the burn colour, which are as follows:

**Condition 1:** Percentage colour area of FTB > Percentage colour area of DPTB AND Percentage colour area of FTB > Percentage colour area of SPTB

**Condition 2:** Percentage colour area of FTB > Percentage colour area of DPTB / 2 AND Percentage colour area of FTB > Percentage colour area of SPTB / 2

**Condition 3:** Percentage colour area of DPTB burn > Percentage colour area of SPTB

**Condition 4:** Percentage colour area of DPTB burn > Percentage colour area of SPTB burn \* 0.2

The condition is set to find FTB first because it is the most serious burn injury when compared with DPTB and SPTB. Condition 1 and condition 2 are set to find FTB colour area whereas condition 3 and condition 4 are set to find DPTB colour area. If both conditions 1 and 2 are not fulfilled, the burn is not a FTB, then the process continues to conditions 3 and 4 to check whether it is a DPTB. If both conditions 3 and 4 are again not fulfilled, the burn is then consider as SPTB. If the conditions 1 or 2 are fulfilled, *isFull*

variable will hold the percentage colour area of the FTB; else the value is zero. If the conditions 3 or 4 are fulfilled, *isDeep* variable will hold the percentage colour area of the DPTB burn; else the value is zero. If none of the conditions are fulfilled, *isSuperficial* variable will hold the percentage colour area of the SPTB; else the value is zero. This process is implemented to overcome the following issues:

- (i) Mixed burn depth appearance image consisting of multiple colours of different burn depths.
- (ii) The colours that are significant to the burn depth appear to have a smaller surface area compared to the colours that are non-significant to that particular burn depth, which occupy a larger surface area in the image.

The burn depth that appear to have a smaller surface area as compared to a larger surface area of non-significant colour of the other burn depth in the image is solved using conditions 2 and 4. A burn image is considered a FTB if the percentage colour area of the FTB is more than half of the percentage colour area of the DPTB and SPTB. For a burn image to be considered as DPTB, the percentage colour area of DPTB must exceed 20% of the percentage colour area of the SPTB. 20% is selected as the threshold based on the feedback from the burn specialist.

Figure 3.7 shows the process of colour area percentage. The features extracted are percentage colour area of FTB (*isFull*), percentage colour area of DPTB (*isDeep*) and percentage colour area of SPTB (*isSuperficial*).

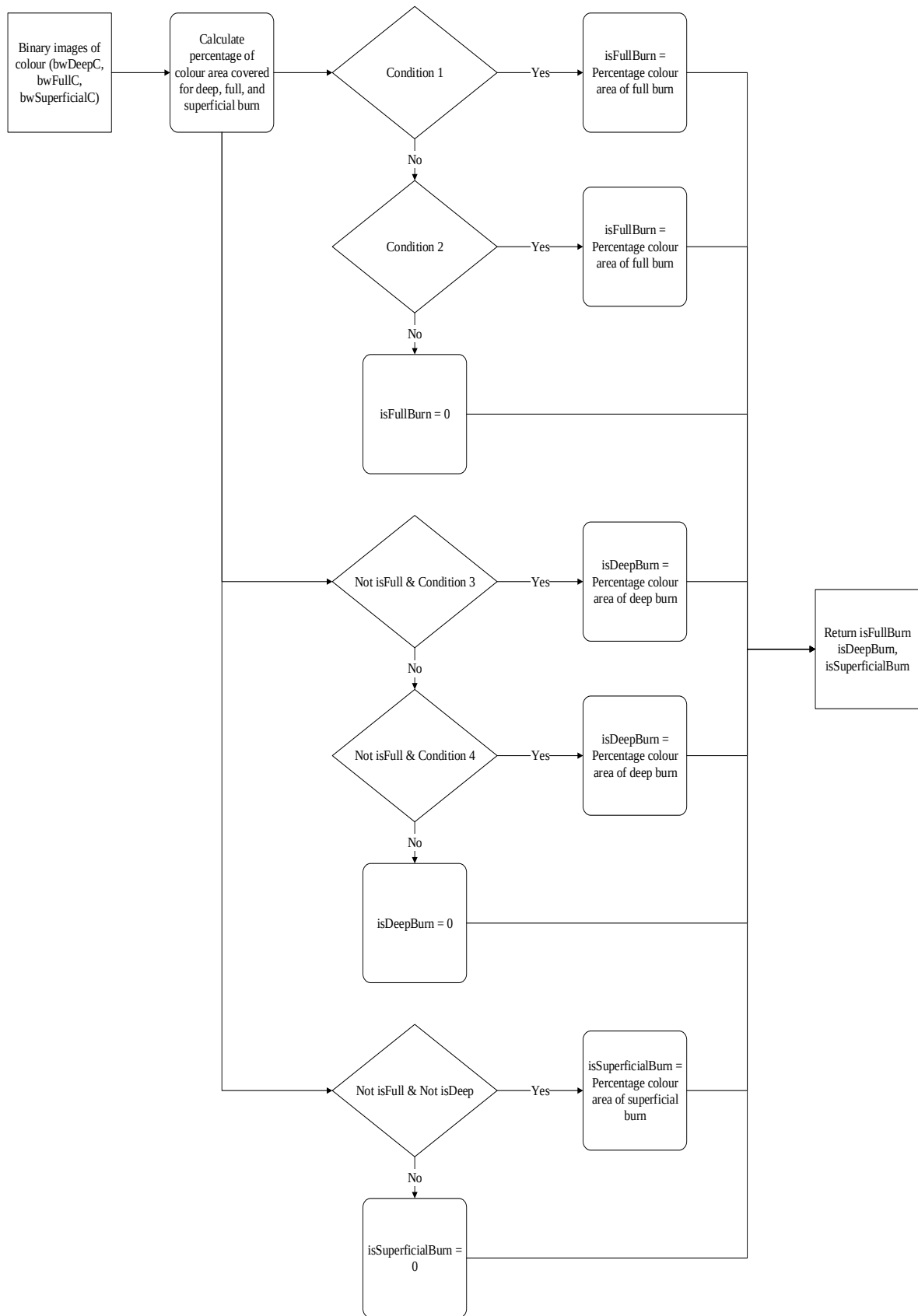


**Figure 3.7:** Colour area percentage process

Algorithm 3 describes the colour area percentage process.

---

**Algorithm 3: Colour Area Percentage Process**

---

**INPUT:**  $bwDeepC$ ,  $bwFullC$ ,  $bwSuperficialC$ ,  $numberOfPixels$ , where  $bwDeepC$ ,  $bwFullC$ ,  $bwSuperficialC \in [0\ 1]$

**OUTPUT:**  $isFullBurn$ ,  $isDeepBurn$ ,  $isSuperficialBurn$

1.  $AreaPercentageDeep \leftarrow (\sum bwDeepC / numberOfPixels) \times 100$
  2.  $AreaPercentageFull \leftarrow (\sum bwFullC / numberOfPixels) \times 100$
  3.  $AreaPercentageSuperficial \leftarrow (\sum bwSuperficialC / numberOfPixels) \times 100$
  4.  $Condition1 \leftarrow (AreaPercentageFull > AreaPercentageDeep) \ \&\& \ (AreaPercentageFull > AreaPercentageSuperficial)$
  5.  $Condition2 \leftarrow (AreaPercentageFull > AreaPercentageDeep/2) \ \&\& \ (AreaPercentageFull > AreaPercentageSuperficial/2)$
  6.  $isFull \leftarrow (Condition1 \mid Condition2)$
  7. **IF**  $(Condition1 \parallel Condition2)$
  8.      $isFullBurn \leftarrow AreaPercentageFull$
  9. **ELSE**
  10.      $isFullBurn \leftarrow 0$
  11. **ENDIF**
  12.  $Condition3 \leftarrow (AreaPercentageDeep > AreaPercentageSuperficial)$
  13.  $Condition4 \leftarrow (AreaPercentageDeep > AreaPercentageSuperficial*0.2)$
  14.  $isDeep \leftarrow (\text{not } isFull \ \&\& \ (Condition3 \mid Condition4))$
  15. **IF**  $(\text{NOT } isFull \ \&\& \ (Condition3 \parallel Condition4))$
  16.      $isDeepBurn \leftarrow AreaPercentageDeep$
  17. **ELSE**
  18.      $isDeepBurn \leftarrow 0$
  19. **ENDIF**
  20. **IF**  $(\text{not } isFull \ \&\& \ \text{not } isDeep)$
  21.      $isSuperficialBurn \leftarrow AreaPercentageSuperficial$
  22. **ELSE**
  23.      $isSuperficialBurn \leftarrow 0$
  24. **ENDIF**
  25. **RETURN**  $isFullBurn$ ,  $isDeepBurn$ ,  $isSuperficialBurn$
- 

### 3.5 Image Classification

The main purpose for classification is to learn the pattern from a given set of known image classes and based on the learned pattern, assign the most appropriate class for a new or unseen image. The supervised learning approach for classification is employed in this thesis.

Classification of the skin burn images was carried out using the multiclass classification approach. The classification algorithm used on the skin burn dataset for the comparative study in this thesis, was linear SVM with both 10-fold cross validation and supplied test set methods. Linear SVM had been shown to be one of the best classifiers in the literature (Acha et al., 2004; Suvarna, Sivakumar, & Niranjan, 2013; Wantanajittikul et al., 2012). The 10-fold cross validation method was used to validate the training image dataset. The 10-fold cross validation method takes the average of the different test partitions in the dataset. Hence, the results will be void of bias. The learnt model was then tested on the test dataset, which is the supplied test set method.

### **3.6 Results Interpretation and Evaluation**

The measures used to evaluate the performance of the Linear SVM were accuracy, precision, recall and  $F_1$ -measure. The formulas for all these four measures are discussed in Sub-section 2.2.1. The accuracy, precision, recall and  $F_1$ -measure in this thesis were calculated by taking the average of the three burn depths.

### **3.7 Summary**

This chapter presented the methodology used in this research. It covered the proposed feature extraction process. The implementation of this is next discussed in Chapter 4, together with the results obtained.

## **CHAPTER 4**

### **IMPLEMENTATION AND RESULTS DISCUSSION**

#### **4.1 Introduction**

This chapter presents the implementation of the proposed feature extraction within the image classification process. A comparison of classification measures between the set of features extracted in this thesis and the set of features extracted by previous research works is also discussed.

#### **4.2 Image Acquisition**

Figure 4.1, Figure 4.2 and Figure 4.3 show the samples burn images acquired from burn specialist. Figure 4.1 shows the samples of images for SPTB.



**Figure 4.1:** SPTB images

Figure 4.2 shows the samples of images for DPTB.



**Figure 4.2:** DPTB images

Figure 4.3 shows the samples of images for FTB.



**Figure 4.3:** FTB images

### **4.3 Image Pre-Processing**

Figure 4.4, Figure 4.5 and Figure 4.6 show the samples of cropped burn images used for feature extraction. Figure 4.4 shows the samples of cropped images for SPTB.



**Figure 4.4:** Cropped SPTB images

Figure 4.5 shows the samples of cropped images for DPTB.



**Figure 4.5:** Cropped DPTB images

Figure 4.6 shows the samples of cropped images for FTB.

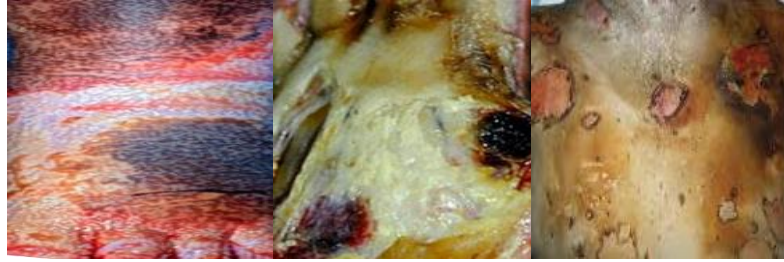


**Figure 4.6:** Cropped FTB images

#### **4.4 Image Feature Extraction**

This section discusses the output of the feature extraction processes using  $L^*a^*b^*$  colour space. The algorithm for the proposed feature extraction process is shown in Appendix A.

##### **4.4.1 Feature Set A – Global Features (*stdHue*, *meanA*, *meanB*, *stdA*, *skewA*, *kurtA*)**

The output from the global feature extraction process had already been discussed in Sub-section 3.4.1.

##### **4.4.2 Feature Set B – Blister Features (*meanChromaBlister*, *stdHueBlister*, *meanStdFiltBlister*, *meanEntropyFiltBlister*, *contrastBlister*, *energyBlister*)**

Figure 4.7 shows one of the image output of the blister region detection process. The last image shows the segmented region that consisted of blister. This segmented region would be used for colour and texture feature extraction. The output of blister region detection process had already been discussed in Sub-section 3.4.2.

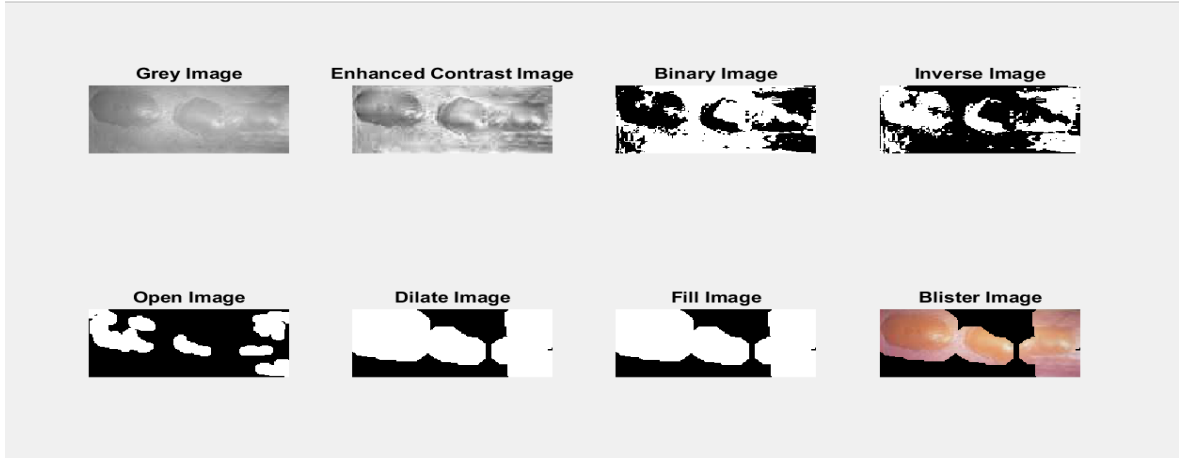


**Figure 4.7:** Blister region detection process

#### 4.4.3 Feature Set C – Image Features (*meanDeepRange*, *meanSuperficialRange*, *meanFullRange*, *isFullBurn*, *isDeepBurn*, *isSuperficialBurn*)

Table 4.1 shows the average and standard deviation colour values of the  $L^*$ ,  $a^*$  and  $b^*$  channels of the training images in the dataset for each of the burn depths.

**Table 4.1:** Average and standard deviation colour values of the  $L^*$ ,  $a^*$  and  $b^*$  channels of the training images in the dataset for each of the burn depths

| Variables             | DPTB    | SPTB    | FTB     |
|-----------------------|---------|---------|---------|
| AverageNormalisedMinL | 50.0500 | 45.0833 | 36.3000 |
| AverageNormalisedMaxL | 82.3500 | 67.7500 | 73.9000 |
| AverageNormalisedMinA | 4.1000  | 22.8750 | -2.9000 |
| AverageNormalisedMaxA | 34.1000 | 40.4167 | 15.4000 |
| AverageNormalisedMinB | 2.8000  | 11.8333 | 2.3500  |
| AverageNormalisedMaxB | 22.5500 | 29.3750 | 23.9500 |
| STDNormalisedMinL     | 9.2365  | 9.5048  | 18.4394 |
| STDNormalisedMaxL     | 8.6710  | 10.4601 | 14.8922 |
| STDNormalisedMinA     | 5.2606  | 7.3857  | 4.3878  |

**Table 4.1** continued

|                   |         |         |         |
|-------------------|---------|---------|---------|
| STDNormalisedMaxA | 14.1455 | 9.4313  | 10.0703 |
| STDNormalisedMinB | 4.4438  | 7.0505  | 6.8154  |
| STDNormalisedMaxB | 11.4500 | 10.6763 | 14.1216 |

The result of the pattern search was a set of optimum x values as shown in Table 4.2. The value zero showed that there was no standard deviation used, while the values one and two showed that there was one and two standard deviation used respectively. The pattern search algorithm computed the optimum x to achieve the highest objective function value, which was 89.0625, in terms of classification accuracy.

**Table 4.2:** Optimum x values

| Variables        | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 |
|------------------|---|---|---|---|---|---|---|---|---|----|----|----|----|----|----|----|----|----|
| <b>Optimum x</b> | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 0 | 0  | 2  | 1  | 1  | 2  | 0  | 0  | 0  | 0  |

Based on Table 4.2, each variable corresponding to the minimum and maximum of  $L^*$ ,  $a^*$  and  $b^*$  channels for each burn depth were as follows:

DPTB

$$\begin{aligned} channel1MinDeep &= AverageNormalisedMinLDeep - var(1)*StdNormalisedMinLDeep \\ channel1MaxDeep &= AverageNormalisedMaxLDeep + var(2)*StdNormalisedMaxLDeep \\ channel2MinDeep &= AverageNormalisedMinADeep - var(3)*StdNormalisedMinADeep \\ channel2MaxDeep &= AverageNormalisedMaxADeep + var(4)*StdNormalisedMaxADeep \\ channel3MinDeep &= AverageNormalisedMinBDeep - var(5)*StdNormalisedMinBDeep \\ channel3MaxDeep &= AverageNormalisedMaxBDeep + var(6)*StdNormalisedMaxBDeep \end{aligned}$$

|      |                                                                                                      |
|------|------------------------------------------------------------------------------------------------------|
| SPTB | $channel1MinSuperficial = AverageNormalisedMinLSuperficial - var(7) * StdNormalisedMinLSuperficial$  |
|      | $channel1MaxSuperficial = AverageNormalisedMaxLSuperficial + var(8) * StdNormalisedMaxLSuperficial$  |
|      | $channel2MinSuperficial = AverageNormalisedMinASuperficial - var(9) * StdNormalisedMinASuperficial$  |
|      | $channel2MaxSuperficial = AverageNormalisedMaxASuperficial + var(10) * StdNormalisedMaxASuperficial$ |
|      | $channel3MinSuperficial = AverageNormalisedMinBSuperficial - var(11) * StdNormalisedMinBSuperficial$ |
|      | $channel3MaxSuperficial = AverageNormalisedMaxBSuperficial + var(12) * StdNormalisedMaxBSuperficial$ |
| FTB  | $channel1MinFull = AverageNormalisedMinLFull - var(13) * StdNormalisedMinLFull$                      |
|      | $channel1MaxFull = AverageNormalisedMaxLFull + var(14) * StdNormalisedMaxLFull$                      |
|      | $channel2MinFull = AverageNormalisedMinAFull - var(15) * StdNormalisedMinAFull$                      |
|      | $channel2MaxFull = AverageNormalisedMaxAFull + var(16) * StdNormalisedMaxAFull$                      |
|      | $channel3MinFull = AverageNormalisedMinBFull - var(17) * StdNormalisedMinBFull$                      |
|      | $channel3MaxFull = AverageNormalisedMaxBFull + var(18) * StdNormalisedMaxBFull$                      |

Table 4.3 shows the values computed from the average and standard deviation colour ranges calculation process and the optimum weightage for the standard deviation from the optimum weightage generation process. Table 4.4 shows the value set for the seven colours in the colour ranges refining process. The values for each colour in Table 4.4 were set based on the colour thresholder application and CIE L\*a\*b\* colour chart.

**Table 4.3:** Values computed from average and standard deviation colour ranges calculation process and optimum weightage generation process

| <b>Variables</b> | <b>DPTB</b> | <b>SPTB</b> | <b>FTB</b> |
|------------------|-------------|-------------|------------|
| Minimum L*       | 50.0500     | 45.0833     | 17.8606    |
| Maximum L*       | 82.3500     | 88.6702     | 103.6844   |
| Minimum a*       | 4.1000      | 22.8750     | -2.9000    |
| Maximum a*       | 34.1000     | 40.4167     | 15.4000    |
| Minimum b*       | 2.8000      | -2.2677     | 2.3500     |
| Maximum b*       | 22.5500     | 40.0513     | 23.9500    |

The output of average and standard deviation colour ranges calculation process and optimum weightage generation process had already been discussed in Sub-section 3.4.3.

**Table 4.4:** Values in colour ranges refining process

| <b>Variables</b> | <b>White</b> | <b>Pink</b> | <b>Dark Red</b> | <b>Light Brown</b> | <b>Beige-Yellow</b> | <b>Dark Brown</b> | <b>Grey-White</b> |
|------------------|--------------|-------------|-----------------|--------------------|---------------------|-------------------|-------------------|
| Minimum L*       | 55           | 49          | 20              | 30                 | 45                  | 0                 | 35                |
| Maximum L*       | 100          | 85          | 50              | 70                 | 100                 | 50                | 80                |
| Minimum a*       | 6            | 23          | 25              | 5                  | -15                 | -5                | -7                |
| Maximum a*       | 22           | 50          | 60              | 25                 | 0                   | 20                | 5                 |
| Minimum b*       | -5           | 5           | 5               | 30                 | 16                  | -20               | -1                |
| Maximum b*       | 30           | 25          | 45              | 45                 | 55                  | 20                | 10                |

Based on Table 4.4, the seven colour were grouped into three colour groups as the output of the colour ranges refining process. The three colour groups were as follows:

- (i) *deepBurnColour* = {white}
- (ii) *superficialBurnColour* = {pink, dark red}
- (iii) *fullBurnColour* = {beige-yellow, grey-white, light brown, dark brown}

These three colour groups represented as binary images, were later combined with the binary images with the values from Table 4.3 respectively.

Figure 4.8, Figure 4.9 and Figure 4.10 show the sample output images after combining the colour ranges in Tables 4.3 and 4.4 for all the three burn depths. Figure 4.8 shows the sample output image with the colour ranges used for characterising DPTB.

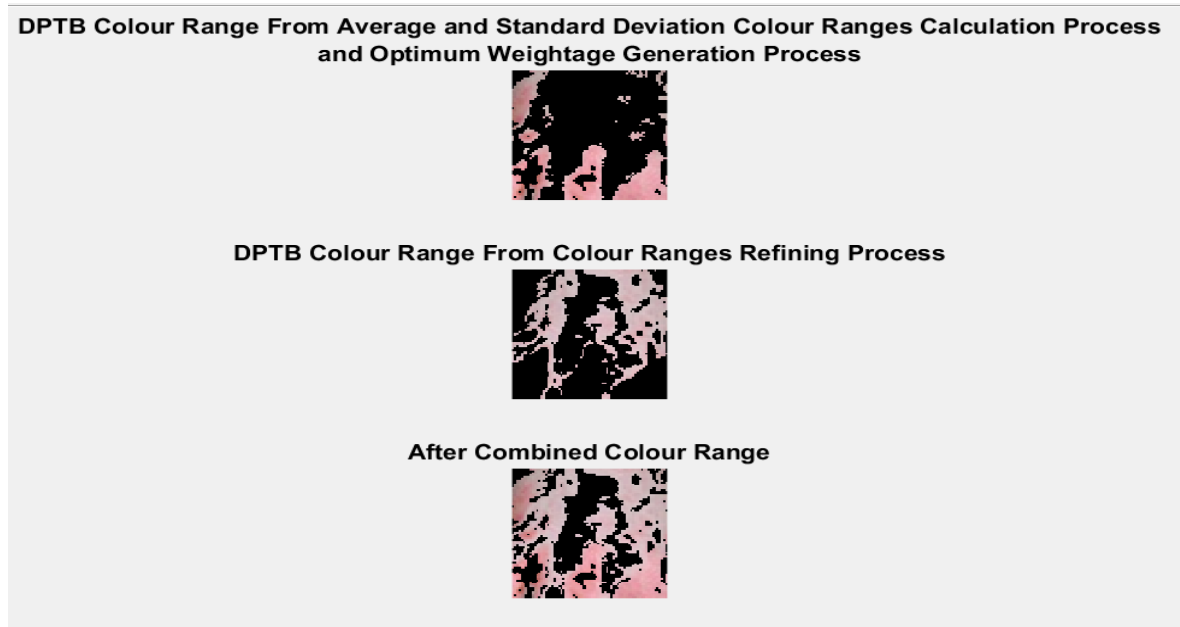


**Figure 4.8:** Sample output images with the colour ranges used for characterising DPTB

Figure 4.9 shows the sample output image with the colour ranges used for characterising FTB.



**Figure 4.9:** Sample output images with the colour ranges used for characterising FTB

Figure 4.10 shows the sample output image with the colour ranges used for characterising SPTB.

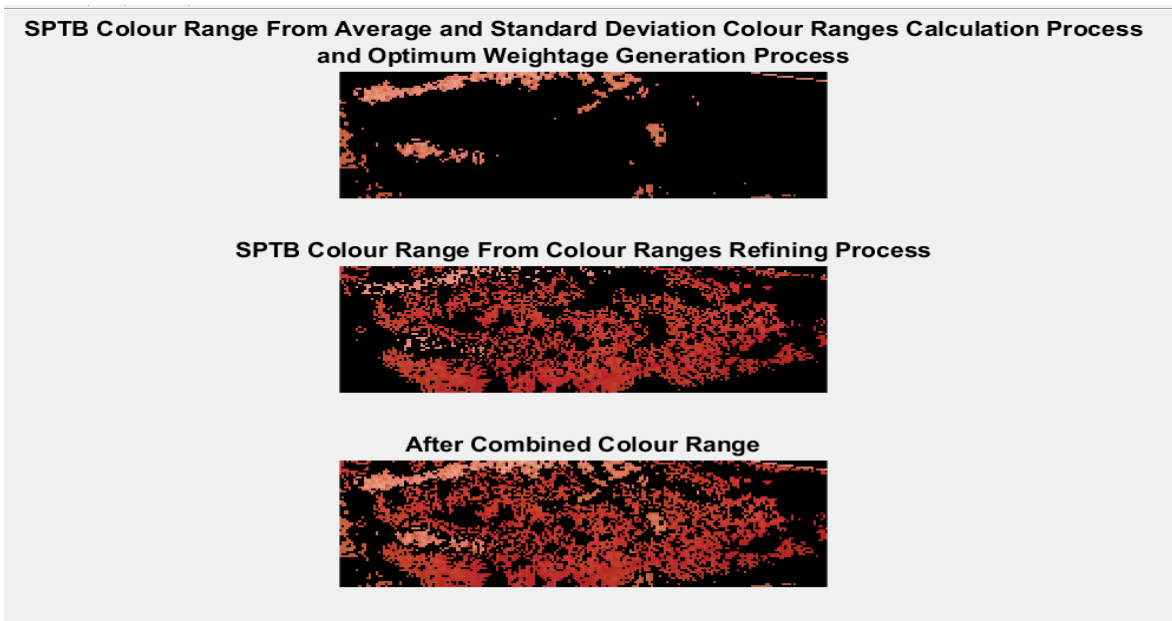


**Figure 4.10:** Sample output images with the colour ranges used for characterising SPTB

Figure 4.8, Figure 4.9 and Figure 4.10 show that after combining the colour ranges obtained from average and standard deviation colour ranges calculation process, optimum weightage generation process and colour ranges refining process, the burn colour characteristic for each burn depth as specified by the burn specialist were covered. The colour ranges before the combination were not sufficient to represent the burn depths as some of the burn colours specified by the burn specialist were not covered within the colour ranges.

The output of colour ranges refining process and colour area percentage process had already been discussed in Sub-section 3.4.3.

#### **4.5 Image Classification**

There were two methods used to classify the skin burn depths images. These methods were 10-fold cross validation and supplied test set. The 10-fold cross validation method used training image dataset, in which the training images were divided into training and testing sets. The average of the different test partitions was then computed as the result. The supplied test set method used a test image dataset, which was a different dataset from the training image dataset. The test image dataset was used to test how well the performance of the learnt model in the classification of skin burn depths images was. The testing set was pre-labelled by the burn specialist. Thus, the results obtained were validated with the labels given by the burn specialist. The features proposed by previous research works were extracted from the image dataset for a comparative study with the features in this thesis. The classification algorithm used for comparison was linear SVM. The classification performance was measured using accuracy, precision, recall and F<sub>1</sub>-measure.

Table 4.5 shows the proposed feature set combination between global, blister and image features.

**Table 4.5:** Proposed feature set combination

| Feature Set | Features                                                                                                                                                                                                                                              | Description                                          |
|-------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------|
| A           | stdHue, meanA, meanB, stdA, skewA, kurtA                                                                                                                                                                                                              | Global features.                                     |
| B           | stdHue, meanA, meanB, stdA, skewA, kurtA, meanChromaBlister, stdHueBlister, meanEntropyFiltBlister, meanStdFiltBlister, contrastBlister, energyBlister                                                                                                | Global features + Blister features.                  |
| C           | stdHue, meanA, meanB, stdA, skewA, kurtA, meanChromaBlister, stdHueBlister, meanEntropyFiltBlister, meanStdFiltBlister, contrastBlister, energyBlister, meanDeepRange, meanSuperficialRange, meanFullRange, isFullBurn, isDeepBurn, isSuperficialBurn | Global features + Blister features + Image features. |

Tables 4.6 and 4.7 shows the classification measures for the proposed feature set combination listed in Table 4.5 using 10-fold cross validation and supplied test set methods respectively.

**Table 4.6:** Classification measures for proposed feature set combination using 10-fold cross validation method

| Features set | 10-Fold Cross Validation Method |           |         |                         |
|--------------|---------------------------------|-----------|---------|-------------------------|
|              | Accuracy                        | Precision | Recall  | F <sub>1</sub> -measure |
| A            | 89.0625                         | 89.5833   | 88.6111 | 89.0946                 |
| B            | 92.1875                         | 91.9444   | 91.9444 | 91.9444                 |
| C            | 96.8750                         | 96.9697   | 96.6667 | 96.8179                 |

**Table 4.7:** Classification measures for proposed feature set combination using supplied test set method

| Features set | Supplied Test Set Method |           |         |                         |
|--------------|--------------------------|-----------|---------|-------------------------|
|              | Accuracy                 | Precision | Recall  | F <sub>1</sub> -measure |
| A            | 69.6970                  | 71.6136   | 70.5556 | 71.0806                 |
| B            | 63.6364                  | 70.8333   | 65.0000 | 67.7914                 |
| C            | 87.8788                  | 87.7451   | 85.8333 | 86.7787                 |

Based on Tables 4.6 and 4.7, the Feature Set C shows that the proposed image features improved the accuracy of the global features and blister features in the classification of skin burn depths. Thus, Feature Set C would be used in comparison with the features proposed by previous research works in the following sub-sections. The following sub-sections discussed the experiments using 10-fold cross validation and supplied test set methods respectively.

#### 4.5.1 Experiment Using 10-Fold Cross Validation Method

Table 4.8 shows the comparison in terms of classification measures between Feature Set C and the feature set proposed by the previous research works using the 10-fold cross validation method.

**Table 4.8:** Comparison of classification measures between the proposed feature set and the feature set proposed by previous research works using 10-fold cross validation method

|                                                                                             | Set ID | Feature Set                                                                                                                                                                                                                                 | Accuracy | Precision | Recall  | F <sub>1</sub> -measure |
|---------------------------------------------------------------------------------------------|--------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------|-----------|---------|-------------------------|
| <b>Global features + Blister features + Image features (Feature Set C from Section 4.5)</b> | 1      | meanDeepRange, meanSuperficialRange, meanFullRange, isFullBurn, isDeepBurn, isSuperficialBurn, stdHue, meanA, meanB, stdA, skewA, kurtA, meanChromaBlister, stdHueBlister, meanEntropyFilter, meanStdFilter, contrastBlister, energyBlister | 96.8750  | 96.9697   | 96.6667 | 96.8179                 |
| (Acha et al., 2002, 2003, 2005, 2004; Serrano, Acha, Gómez-Cía, et al., 2005)               | 2      | MeanL, MeanHue, MeanChroma, StdL, StdHue, StdChroma, MeanU, MeanV, StdU, StdV, SkewL, KurtL, SkewU, KurtU, SkewV, KurtV                                                                                                                     | 76.5625  | 77.1280   | 76.1111 | 76.6162                 |
|                                                                                             | 3      | Selected features – MeanL, MeanHue, StdHue, MeanU, StdV, SkewL                                                                                                                                                                              | 64.0625  | 65.2381   | 63.6111 | 64.4143                 |
| (Wantanajittikul et al., 2012)                                                              | 4      | Mean of h-space, standard deviation of h-space, contrast, homogeneity                                                                                                                                                                       | 45.3125  | 42.8718   | 44.4444 | 43.6440                 |

**Table 4.8** continued

|                                           |   |                                                                                                                         |         |         |         |         |
|-------------------------------------------|---|-------------------------------------------------------------------------------------------------------------------------|---------|---------|---------|---------|
| (Suvarna, Sivakumar, & Niranjana, 2013)   | 5 | Mean and (2,1) <sup>th</sup> coefficient of Discrete Cosine Transform (DCT) function of V1 chrominance of L*a*b*        | 64.0625 | 54.7174 | 62.2222 | 58.2290 |
| (Suvarna, Sivakumar, Kumar, et al., 2013) | 6 | Mean and (2,1) <sup>th</sup> coefficient of Discrete Cosine Transform (DCT) function of V1 and V2 chrominance of L*a*b* | 65.6250 | 65.8781 | 63.8889 | 64.8683 |

Based on Table 4.8, Set ID 1, which consisted of features from Feature Set C, performed the best in classification as it achieved the highest classification measures in terms of accuracy, precision, recall and F<sub>1</sub>-measure, compared to the features proposed by the previous research works. The Feature Set ID 1 achieved the highest result because it was able to capture the colour ranges for different burn depths. The worst classification performance was using features from Set ID 4.

#### 4.5.2 Experiment Using Supplied Test Set Method

Table 4.9 shows the comparison in terms of classification measures between Feature Set C and the feature set proposed by the previous research works using the supplied test set method.

**Table 4.9:** Comparison of classification measures between the proposed feature set and the feature set proposed by previous research works using supplied test set method

|                                                                                             | Set ID | Feature Set                                                                                                                                                                                                                                 | Accuracy | Precision | Recall  | F <sub>1</sub> -measure |
|---------------------------------------------------------------------------------------------|--------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------|-----------|---------|-------------------------|
| <b>Global features + Blister features + Image features (Feature Set C from Section 4.5)</b> | 1      | meanDeepRange, meanSuperficialRange, meanFullRange, isFullBurn, isDeepBurn, isSuperficialBurn, stdHue, meanA, meanB, stdA, skewA, kurtA, meanChromaBlister, stdHueBlister, meanEntropyFilter, meanStdFilter, contrastBlister, energyBlister | 87.8788  | 87.7451   | 85.8333 | 86.7787                 |
| (Acha et al., 2002, 2003, 2005, 2004; Serrano, Acha, Gómez-Cía, et al., 2005)               | 2      | MeanL, MeanHue, MeanChroma, StdL, StdHue, StdChroma, MeanU, MeanV, StdU, StdV, SkewL, KurtL, SkewU, KurtU, SkewV, KurtV                                                                                                                     | 63.6364  | 63.4921   | 61.3889 | 62.4228                 |
|                                                                                             | 3      | Selected features —<br>MeanL, MeanHue, StdHue, MeanU, StdV, SkewL                                                                                                                                                                           | 54.5455  | 53.0951   | 50.5556 | 51.7942                 |
| (Wantanajittikul et al., 2012)                                                              | 4      | Mean of h-space, standard deviation of h-space, contrast, homogeneity                                                                                                                                                                       | 45.4545  | 62.7706   | 53.0556 | 57.5056                 |

**Table 4.9** continued

|                                           |   |                                                                                                                         |         |         |         |         |
|-------------------------------------------|---|-------------------------------------------------------------------------------------------------------------------------|---------|---------|---------|---------|
| (Suvarna, Sivakumar, & Niranjana, 2013)   | 5 | Mean and (2,1) <sup>th</sup> coefficient of Discrete Cosine Transform (DCT) function of V1 chrominance of L*a*b*        | 54.5455 | 45.1389 | 47.7778 | 46.4209 |
| (Suvarna, Sivakumar, Kumar, et al., 2013) | 6 | Mean and (2,1) <sup>th</sup> coefficient of Discrete Cosine Transform (DCT) function of V1 and V2 chrominance of L*a*b* | 57.5758 | 46.2418 | 51.1111 | 48.5547 |

Based on Table 4.9, features from Set ID 1 yet again recorded the best performance in classification. Features from Set ID 4 again had the worst performance.

#### 4.6 Results Interpretation and Evaluation

On closer inspection, there are misclassification of images using the proposed features set. Figure 4.11 shows the misclassified images of the unseen test dataset when using the supplied test set method and linear SVM. The misclassified images consisted of one DPTB and three SPTB.

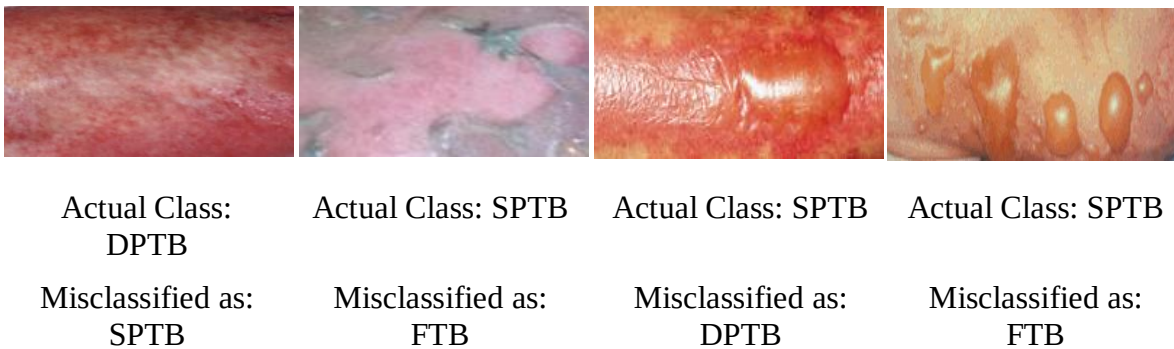


**Figure 4.11:** Misclassified images

Based on Figure 4.11, the first DPTB image was misclassified as SPTB, whereas the second and fourth SPTB images were misclassified as FTB. The third SPTB images are misclassified as DPTB. For the misclassified DPTB burn image as SPTB, the proposed feature *isDeepBurn* was able to get the percentage colour area of the DPTB. However, because the SPTB colour value was very close to the DPTB colour value, the image was misclassified. The second SPTB image had been misclassified as FTB because the surrounding death skin was not fully cleaned properly when the burn image was captured. The death skin had the same colour characteristic as the FTB, and thus it was misclassified as FTB. The third SPTB image was misclassified as DPTB because of the lighting reflection that fell on the burn wound. This led to the extraction of more DPTB colour characteristic than SPTB colour characteristic. This misclassification is also due to the reason that SPTB colour characteristic is very close to DPTB colour characteristic. The fourth SPTB image was misclassified as FTB because more FTB colour characteristic had been found than the SPTB colour characteristic. The absence of pinkish or reddish colours as the SPTB colour characteristic and the presence of light brown as the FTB colour characteristic caused the fourth image to be misclassified as FTB. In this thesis, a small image dataset was used. However, it was prepared in the way that the images of the common burn appearance for each burn depths were included. For example, Figure 4.12 shows three samples images that are from the same FTB class. The images covered a range of possible wound for a particular burn depth.



**Figure 4.12:** Common FTB  
10/

## **4.7 Summary**

This chapter presented the implementation of the proposed feature extraction process. It covered the output of the feature extraction process and the results of the classification process, as well as comparison of the results with previous research works. A summary of the proposed feature extraction process is presented in Chapter 5, together with the contributions of the research, the limitations of the research and the possible future works.

## CHAPTER 5

### CONCLUSION AND FUTURE WORKS

#### 5.1 Introduction

This chapter concludes the thesis with a summary of the proposed feature extraction process for the classification of skin burn depths, the contributions of the research, the limitations of the research and the possible future works.

#### 5.2 Summary of Research

A feature extraction process was proposed in this thesis for the classification of skin burn depths. The evaluation of the proposed features indicated that the feature extraction process used worked well in the classification, specifically, for multiclass classification. The burn depth image dataset consisted of three class labels, which were DPTB, FTB and SPTB. Both colour and texture features were extracted. There were several processes in feature extraction. These processes were global feature extraction process, blister region detection process, average and standard deviation colour ranges calculation process, optimum weightage generation process, colour ranges refining process and colour area percentage process. The first global feature set was extracted using the global feature extraction process. The first extracted global feature set consisted of the following features:

- (i) Standard deviation of hue (*stdHue*)
- (ii) Mean of a\* channel (*meanA*)
- (iii) Mean of b\* channel (*meanB*)
- (iv) Standard deviation of a\* channel (*stdA*)
- (v) Skewness of a\* channel (*skewA*)

- (vi) Kurtosis of a\* channel (*kurtA*)

The second blister feature set was extracted using the blister region detection process. The second extracted blister feature set consisted of the following features:

- (i) Mean of chroma (*meanChromaBlister*)
- (ii) Standard deviation of hue (*stdHueBlister*).
- (iii) Mean of standard deviation filter (*meanStdFiltBlister*)
- (iv) Mean of entropy filter (*meanEntropyFiltBlister*)
- (v) Contrast (*contrastBlister*)
- (vi) Energy (*energyBlister*)

The third image feature set was extracted using the average and standard deviation colour ranges calculation process, the optimum weightage generation process, the colour ranges refining process and the colour area percentage process. The third extracted image feature set consisted of the following features:

- (i) Mean of DPTB range (*meanDeepRange*)
- (ii) Mean of SPTB range (*meanSuperficialRange*)
- (iii) Mean of FTB range (*meanFullRange*)
- (iv) Percentage colour area of FTB (*isFull*)
- (v) Percentage colour area of DPTB (*isDeep*)
- (vi) Percentage colour area of SPTB (*isSuperficial*)

The reported classification measures showed that the proposed features worked well on multiclass classification and produced the best results in comparison with the features proposed by other researchers in the literature.

### 5.3 Objective Achievement and Contributions

This section described the objective achievement and contributions of the reported research corresponding to the objective and expected contributions identified in Section 1.6 and 1.7. The main objectives of this research have been achieved, which are to:

- (i) extract image features that characterise the burn depths for classification of skin burn images.
- (ii) determine features that can effectively classify the skin burn depths.
- (iii) compare the performance of the features used in this research work with the features used in previous research works.

The results showed that the extracted six image features using the proposed feature extraction process had improved the performance in the classification of skin burn depths when used with the existing global features and blister features.

The main contributions of this research are two-fold:

- (i) A process to extract image features that characterise the burn depths for the classification of skin burn images.
  - a. Colour and texture features are two important burn depths characteristics that are useful in the classification of skin burn depths.
  - b. Global features were mostly extracted by previous research works to classify the skin burn depths. However, they do not reflect the characteristics of the skin burn depths.
- (ii) A set of image features that are representative of the characteristics of the three burn depths.
  - a. A generalised pixel value of the entire image is taken into consideration when global features were used to represent an image. This implies that a

generalised pixel value was used to represent a mixed burn depth appearance in an image. Thus, this generalisation may not be able to represent the characteristic of each burn depth.

- b. Global features were assumed by Lisin et al. (2005) to be used with images that contain only a single object as global features are sensitive to clutter. Thus, global features are assumed to work well with homogeneous skin burn images but not for heterogeneous burn images. In this thesis, the skin burn dataset consists of both homogeneous and heterogeneous skin burn images.

#### 5.4 Research Work Limitations

This section discussed the research work limitations in this thesis. Table 5.1 shows the limitations of the research work in this thesis.

**Table 5.1:** Limitations of the research work in this thesis

| Limitations                                                                                             | Reasons                                                                                                                                                                                                                                                                                                                                                                       |
|---------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| A small dataset of skin burn images was used to train and test the proposed feature extraction process. | There was no open source dataset for skin burn depths available. The images used in this thesis were provided by the burn specialist, consisting of images that were captured under uncontrolled environment. Skin burn images were collected based on real cases. In many cases, the images were not recorded as there was no proper data collection and storage procedures. |

**Table 5.1** continued

---

|                                                                                                             |                                                                                                                                                                                                                     |
|-------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Difficulty in controlling the environment lighting in which the images were captured by the burn specialist | There were quite a number of burn images that had lighting reflection on the burn wound. Thus, we assumed that the classification accuracy could be improved if there is no lighting reflection on the burn images. |
|-------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|

---

## 5.5 Future Works

The potential future research works are listed in this section.

1. **Refine colour ranges for each class of burn depths.** The proposed feature extraction process in this thesis refined the colour ranges from the training image dataset with a total of seven colours, which are white, pink, dark red, brown, light brown, beige-yellow and grey-white. It would be useful if more colours were studied to refine the colour ranges from the training image dataset, for example, adding in the different shades of red for SPTB, or different shades of brown for FTB. This could improve the accuracy for each burn depth as a wider range of colours that are significant for each burn depth are covered and extracted for classification.
2. **The use of deep learning in the classification of skin burn depths.** Deep learning automatically extracts relevant features from the images and it learns how to automatically perform classification on the given raw images. The feature extraction performed by deep learning is known as automatic feature extraction, as it learns the features directly from the input images without the user knowing the relevant features extracted. Deep learning helps to simplify the classification tasks

as well as, makes predictions based on the trained model. However, deep learning requires a large amount of labelled data and high computational power.

## **5.6 Summary**

The proposed feature extraction process and the image feature set are intended to improve the skin burn depths classification accuracy. From the experiments conducted, the image features extracted using the proposed feature extraction process, had been shown to improve the classification results when used with the global and blister features. The objectives of the research are therefore fulfilled. With the proposed feature extraction process and a set of image features that are able to characterise each burn depth, it is truly hoped that this research will contribute to the medical field in assisting and augmenting the diagnosis of the inexperienced doctors and the specialist in evaluating the skin burn depths.

## REFERENCES

- A Guide to Understanding Color. (2016). Retrieved from <https://www.xrite.com/>
- Acha, B., & Serrano, C. (2000). Image Classification Based on Color and Texture Analysis. In *Proceedings of the First International Workshop on Image and Signal Processing and Analysis, 2000, IWISPA 2000*. (pp. 95–99). Institute of Electrical and Electronics Engineers (IEEE).
- Acha, B., Serrano, C., & Acha, J. I. (2002). Segmentation of Burn Images Using the L\*u\*v\* Space and Classification of Their Depths by Color and Texture Information. *Medical Imaging 2002: Image Processing*, 1508–1515.
- Acha, B., Serrano, C., Acha, J. I., & Roa, L. M. (2003). CAD Tool for Burn Diagnosis. *Information Processing in Medical Imaging*, 18, 294–305.
- Acha, B., Serrano, C., Acha, J. I., & Roa, L. M. (2005). Segmentation and Classification of Burn Images by Color and Texture Information. *Journal of Biomedical Optics*, 10(3), 34014–3401411.
- Acha, B., Serrano, C., Fondon, I., & Gomez-Cia, T. (2013). Burn Depth Analysis Using Multidimensional Scaling Applied to Psychophysical Experiment Data. *IEEE Transactions on Medical Imaging*, 32(6), 1111–1120.
- Acha, B., Serrano, C., Palencia, S., & Murillo, J. J. (2004). Classification of Burn Wounds Using Support Vector Machines. *Medical Imaging 2004: Image Processing*, 5370, 1018–1025.
- Acha, B., Serrano, C., & Roa, L. (2001). Segmentation and Classification of Burn Color Images. In *Proceedings of the 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (Vol. 3, pp. 2692–2695). Institute of Electrical and Electronics Engineers (IEEE).
- Afromowitz, M. A., Callis, J. B., Heimbach, D. M., Desoto, L. A., & Norton, M. K. (1988). Multispectral Imaging of Burn Wounds: A New Clinical Instrument for Evaluating Burn Depth. *IEEE Transactions on Biomedical Engineering*, 35(10), 842–850.

- Afromowitz, M. A., Liew, G. S. V., & Heimbach, D. M. (1987). Clinical Evaluation of Burn Injuries Using an Optical Reflectance Technique. *IEEE Transactions on Biomedical Engineering, BME-34*(2), 114–127.
- Arnqvist, J., Hellgren, J., & Vincent, J. (1988). Semiautomatic Classification of Secondary Healing Ulcers in Multispectral Images. In *Proceedings of the 9th International Conference on Pattern Recognition* (pp. 459–461). Institute of Electrical and Electronics Engineers (IEEE).
- Badea, M. S., Vertan, C., Florea, C., Florea, L., & Badoiu, S. (2016). Automatic Burn Area Identification in Color Images. In *Proceedings of the 2016 International Conference on Communications (COMM)* (pp. 65–68). Institute of Electrical and Electronics Engineers (IEEE).
- Baldevbhai, P. J., & Anand, R. S. (2012). Color Image Segmentation for Medical Images Using  $L^*a^*b^*$  Color Space. *IOSR Journal of Electronics and Communication Engineering, 1*(2), 24–45.
- Barsley, R. E., West, M. H., & Fair, J. A. (1990). Forensic Photography. Ultraviolet Imaging of Wounds on Skin. *The American Journal of Forensic Medicine and Pathology, 11*(4), 300–308.
- Bennett, J. E., & Dingman, R. O. (1957). Evaluation of Burn Depth by the Use of Radioactive Isotopes-An Experimental Study. *Plastic and Reconstructive Surgery, 20*(4), 261–272.
- Bianconi, F., Bello, R., Fernández, A., & González, E. (2015). On comparing colour spaces from a performance perspective: application to automated classification of polished natural stones. In *Proceedings of the International Conference on Image Analysis and Processing* (pp. 71–78). Cham: Springer.
- Boundless Anatomy and Physiology in Structure of the Skin: Dermis. (2016). Retrieved from <https://www.boundless.com/physiology/textbooks/boundless-anatomy-and-physiology-textbook/integumentary-system-5/the-skin-64/structure-of-the-skin-dermis-395-7489/>
- Brownlee, J. (2018). A Gentle Introduction to k-fold Cross-Validation. Retrieved from <https://machinelearningmastery.com/k-fold-cross-validation/>
- Carcagni, P., Cuna, A., & Distant, C. (2018). A Dense CNN approach for skin lesion classification.

*Computing Research Repository (CoRR)*, [abs/1807.06416](https://arxiv.org/abs/1807.06416).

- Carpenter, G. A., Grossberg, S., Markuzon, N., Reynolds, J. H., & Rosen, D. B. (1992). Fuzzy ARTMAP: A Neural Network Architecture for Incremental Supervised Learning of Analog Multidimensional Maps. *IEEE Transactions on Neural Networks*, 3(5), 698–713.
- Chan, K. L., Xiong, X., Liu, F., & Purnomo, R. (2001). Content-based Image Retrieval Using Regional Representation. In *Multi-Image Analysis* (pp. 238–250). Springer, Berlin, Heidelberg.
- Deshpande, A. S., & Amruta, G. (2016). Automated Detection of Skin Cancer and Skin Allergy. *International Journal of Advance Research in Computer Science and Management Studies*, 4(1), 248–261.
- Despo, O., Yeung, S., Jopling, J., Pridgen, B., Sheckter, C., Silberstein, S., ... Milstein, A. (2017). BURNED: Towards Efficient and Accurate Burn Prognosis Using Deep Learning.
- Fiorini, R. A., Crivellini, M., Codagnone, G., Dacquino, G. F., Libertini, M., & Morresi, A. (1997). DELM Image Processing for Skin Melanoma Early Diagnosis. In *Proceedings of the Applications of Digital Image Processing XX* (Vol. 3164, pp. 359–371). International Society for Optics and Photonics.
- Fondón, I., Acha, B., Serrano, C., & Sosa, M. (2006). New Characteristics for the Classification of Burns: Experimental Study. *International Conference Image Analysis and Recognition*. Springer Berlin Heidelberg.
- Gajjar, T. Y., & Chauhan, N. C. (2012). A Review on Image Mining Frameworks and Techniques. *International Journal of Computer Science and Information Technologies*, 3(3), 4064–4066.
- Ganster, H., Pinz, P., Rohrer, R., Wildling, E., Binder, M., & Kittler, H. (2001). Automated Melanoma Recognition. *IEEE Transactions on Medical Imaging*, 20(3), 233–239.
- Gonzalez, R. C., Woods, R. E., & Eddins, S. L. (2009). Digital Image Processing Using MATLAB. In *Digital Image Processing Using MATLAB*. New Jersey: Prentice Hall.
- Hackeling, G. (2014). *Mastering Machine Learning with scikit-learn*. Birmingham: Packt Publishing Ltd.

- Haralick, R. M., Shanmugan, K., & Dinstein, I. (1973). Textural Features for Image Classification. *IEEE Transactions on Systems, Man, and Cybernetics*, SMC-3(6), 610–621.
- Heimbach, D. M., Afromowitz, M. A., Engrav, L. H., Marvin, J. A., & Perry, B. (1984). Burn Depth Estimation - Man or Machine. *The Journal of Trauma*, 24(5), 373–378.
- Herbin, M., Bon, F. X., Venot, A., Jeanlouis, F., Dubertret, M. L. Dubertret, L., & Strauch, G. (1993). Assessment of Healing Kinetics through True Color Image Processing. *IEEE Transactions on Medical Imaging*, 12(1), 39–43.
- Jackson, D. M. (1953). The Diagnosis of the Depth of Burning. *British Journal of Surgery*, 40(164), 588–596.
- Jaskille, A. D., Shupp, J. W., Jordan, M. H., & Jeng, J. C. (2009). Critical Review of Burn Depth Assessment Techniques: Part I. Historical Review. *Journal of Burn Care and Research*, 30(6), 937–947.
- Jha, S. N. (2010). Colour Measurements and Modeling. In *Nondestructive Evaluation of Food Quality* (pp. 17–40). Springer, Berlin, Heidelberg.
- Karthikeyan, T., & Manikandaprabhu, P. (2013). Function and Information Driven Frameworks for Image Mining - A Review, 2(11), 4202–4206.
- Kaur, P., & Kaur, K. (2014). Review of Different Existing Image Mining Techniques. *International Journal of Advanced Research in Computer Science and Software Engineering*, 4(6), 518–524.
- Khodaskar, A. A., & Ladhake, S. A. (2014). Image Mining: An Overview of Current Research. In *Proceedings of the 2014 4th International Conference on Communication Systems and Network Technologies, CSNT 2014* (pp. 433–438).
- Koenderink, J. J. (1984). The Structure of Images. *Biological Cybernetics*, 50(5), 363–370.
- Kolda, T. G., Lewis, R. M., & Torczon, V. J. (2006). *A Generating Set Direct Search Augmented Lagrangian Algorithm for Optimization with a Combination of General and Linear Constraints*. United States.
- Koutoukidis, G., Stainton, K., & Hughson, J. (2012). *Tabbner's Nursing Care: Theory and*

- Practice* (6th ed.). Churchill Livingstone: Elsevier Australia.
- Krig, S. (2016). Global and Regional Features. In *Computer Vision Metrics* (pp. 75–114). Cham: Springer.
- Kumar, Y., & Sahoo, G. (2012). Analysis of Parametric & Non Parametric Classifiers for Classification Technique using WEKA. *International Journal of Information Technology and Computer Science*, 4(7), 43–49.
- Lawson, R. N., Wlodek, G. D., & Webster, D. R. (1961). Thermographic Assessment of Burns and Frostbite. *Canadian Medical Association Journal*, 84, 1129–1131.
- Lisin, D. A., Mattar, M. A., Blaschko, M. B., Learned-Miller, E. G., & Benfield, M. C. (2005). Combining Local and Global Image Features for Object Class Recognition. In *Proceedings of the 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05) - Workshops* (Vol. 3, p. 47). Institute of Electrical and Electronics Engineers (IEEE).
- Lucchese, L., & Mitra, S. K. (2001). Colour Segmentation Based on Separate Anisotropic Diffusion of Chromatic and Achromatic Channels. In *Proceedings of IEEE on Vision, Image and Signal Processing* (Vol. 148, pp. 141–150). Institute of Electrical and Electronics Engineers (IEEE).
- Martin, A. (2015). Lab Colour Space and Delta E Measurements. In *Graphic Design and Print Production Fundamentals*. British Columbia: BCcampus.
- MathWorks Documentation. (2018). The MathWorks Inc.
- Maulik, U., & Bandyopadhyay, S. (2002). Performance Evaluation of Some Clustering Algorithms and Validity Indices. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 24(12), 1650–1654.
- Mescher, A. L. (2016). *Junqueira's Basic Histology: Text and Atlas* (14th ed.). New York: McGraw-Hill Education.
- Mokrzycki, W. S., & Tatol, M. (2011). Colour Difference Delta E - A Survey. *Machine Graphics and Vision*, 20(4), 383–411.

- Nagthane, D. K. (2013). Image Mining Techniques and Applications. *International Journal of Engineering Sciences & Research Technology*, 2(7), 1873–1876.
- Niazi, Z. B. M., Essex, T. J. H., Papini, R., Scott, D., McLean, N. R., & Black, M. J. M. (1993). New Laser Doppler Scanner, A Valuable Adjunct in Burn Depth Assessment. *Burns*, 19(6), 485–489.
- Otsu, N. (1979). A Threshold Selection Method from Gray-level Histograms. *IEEE Transactions on Systems, Man, and Cybernetics*. Institute of Electrical and Electronics Engineers (IEEE).
- Petrou, M., & Petrou, C. (2010). *Image Processing: The Fundamentals* (2nd ed.). Chichester: John Wiley & Sons Ltd.
- Randolph, J. G., Leape, L. L., & Gross, R. E. (1964). The Early Surgical Treatment of Burns. I. Experimental Studies Utilizing Intravenous Vital Dye for Determining the Degree of Injury. *Surgery*, 56, 193–202.
- Rao, C. N., Sastry, S. S., Mallika, K., Tiong, H. S., & Mahalakshmi, K. B. (2013). Co-Occurrence Matrix and its Statistical Features as an Approach for Identification of Phase Transitions of Mesogens. *International Journal of Innovative Research in Science Engineering and Technology*, 2(9), 4531–4538.
- Roa, L., Gómez-Cía, T., Acha, B., & Serrano, C. (1999). Digital Imaging in Remote Diagnosis of Burns. *Burns*, 25(7), 617–623.
- Sabeena, B., & Raj Kumar, P. (2017). Diagnosis and Detection of Skin Burn Analysis Segmentation in Colour Skin Images. *International Journal of Advanced Research in Computer and Communication Engineering ISO Certified*, 6(2), 369–374.
- Sáez, A., Acha, B., & Serrano, C. (2009). Colorimetric Calibration of Images Captured under Unknown Illuminants. In *Proceedings of the 11th Congress of the International Colour Association (Aic)*. Sydney, Australia.
- Schuessler, Z. (n.d.). Delta E 101. Retrieved from <http://zschuessler.github.io/DeltaE/learn/>
- Serrano, C., Acha, B., & Acha, J. I. (2003). Segmentation of Burn Images Based on Color and Texture Information. In *Proceedings of the SPIE 5032 of Medical Imaging 2003: Image*

- Processing* (Vol. 5032, pp. 1543–1551). International Society for Optics and Photonics.
- Serrano, C., Acha, B., Gómez-Cía, T., Acha, J. I., & Roa, L. M. (2005). A Computer Assisted Diagnosis Tool for the Classification of Burns by Depth of Injury. *Burns*, 31(3), 275–281.
- Serrano, C., Acha, B., & Sangwine, S. J. (2005). Colorimetric Calibration of Images of Human Skin Captured under Hospital Conditions. In *Proceedings of the 10th Congress of the International Colour Association AIC* (pp. 773–776). Granada, Spain.
- Serrano, C., Boloix-Tortosa, R., Gómez-Cía, T., & Acha, B. (2015). Features Identification for Automatic Burn Classification. *Burns*, 41(8), 1883–1890.
- Serrano, C., Roa, L., & Acha, B. (1998). Evaluation of a Telemedicine Platform in a Burn Unit. In *Proceedings of the 1998 IEEE International Conference on Information Technology Applications in Biomedicine, ITAB '98 (Cat. No.98EX188)* (pp. 121–126). Institute of Electrical and Electronics Engineers (IEEE).
- Shaik, K. B., Ganesan, P., Kalist, V., Sathish, B. S., & Jenitha, J. M. M. (2015). Comparative study of skin color detection and segmentation in HSV and YCbCr color space. *Procedia Computer Science*, 57, 41–48.
- Sharma, A. (2004). Color By Numbers. In *Understanding Color Management* (p. 100). New York: Cengage Learning.
- Shukla, V. S., & Vala, J. (2016). A Survey on Image Mining, its Techniques and Application. *International Journal of Computer Applications*, 133(9), 975–8887.
- Singer, A. J. (2000). Thermal Burns: Rapid Assessment and Treatment. *Emergency Medicine Practice An Evidence-Based Approach To Emergency Medicine*, 2(9).
- Sudhir, R. (2011). A Survey on Image Mining Techniques: Theory and Applications. *Computer Engineering and Intelligent Systems*, 2(6), 44–52.
- Sumithra, R., Suhil, M., & Guru, D. S. (2015). Segmentation and Classification of Skin Lesions for Disease Diagnosis. *Procedia Computer Science*, 45, 76–85.
- Suvarna, M., Sivakumar, Kumar, K., & Niranjana, U. C. (2013). Diagnosis of Burn Images Using Template Matching, K-Nearest Neighbor and Artificial Neural Network. *International*

- Journal of Image Processing (IJIP)*, 7(2), 191–202.
- Suvarna, M., Sivakumar, & Niranjana, U. C. (2013). Classification Methods of Skin Burn Images. *International Journal of Computer Science and Information Technology*, 5(1), 109–118.
- Thomas, W. E. G., Reed, M. W. R., & Wyatt, M. G. (Eds.). (2016). *Oxford Textbook of Fundamentals of Surgery*. Oxford: Oxford University Press.
- Tran, H., Le, T., Le, T., & Nguyen, T. (2015). Burn Image Classification Using One-Class Support Vector Machine. In *Proceedings of the International Conference on Context-Aware Systems and Applications* (pp. 233–242). Cham: Springer International Publishing.
- Tran, H. S., Le, T. H., & Nguyen, T. T. (2016). The Degree of Skin Burns Images Recognition using Convolutional Neural Network. *Indian Journal of Science and Technology*, 9(45).
- Tripathi, A., & Jangir, H. (2016). A Study on Image Mining Methods and Techniques. *International Journal of Innovative Research in Computer and Communication Engineering*, 4(4), 7047–7053.
- Vardhan, M. H., & Rao, S. V. (2014). GLCM Architecture for Image Extraction. *International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE)*, 3(1), 75–82.
- Wantanajittikul, K., Auephanwiriyaikul, S., Theera-Umpon, N., & Koanantakool, T. (2012). Automatic Segmentation and Degree Identification in Burn Color Images. In *Proceedings of the 4th 2011 Biomedical Engineering International Conference (BMEiCON)* (pp. 169–173). Institute of Electrical and Electronics Engineers (IEEE).
- Welkowitz, J., Ewen, R. B., & Cohen, J. (2014). *Introductory Statistics for the Behavioral Sciences*. New York: Academic Press.

## APPENDIX

### Appendix A – Pseudocode for Proposed Feature Extraction Process

---

#### Proposed Feature Extraction Process

---

**INPUT:** RGB image  $R$  in dataset

**OUTPUT:** *Features*, where *Features* is a vector of *isFullBurn*, *isDeepBurn*, *isSuperficialBurn*, *meanDeepRange*, *meanSuperficialRange*, *meanFullRange*, *stdHue*, *meanA*, *meanB*, *stdA*, *skewA*, *kurtA*, *meanChromaBlister*, *stdHueBlister*, *meanEntropyFiltBlister*, *meanStdFiltBlister*, *contrastBlister*, *energyBlister*

1. **FOR** each image  $R$  in the image dataset
  2. **READ** image  $R$  in dataset
  3. **CALL** *size*( $R$ ) **RETURN** [ $U, V$ ], where  $U$  is row,  $V$  is column
  4. **CALL** *im2double*( $R$ ) **RETURN** *doubleR* //Convert integer to double
  5. **CALL** *rgb2lab*(*doubleR*) **RETURN** *labImg* //Convert RGB to  $L^*a^*b^*$
  6. **CALL** *AverageAndStandardDeviationRangesCalculationProcess* **RETURN**  
*AverageNormalisedMinLDeep*, *AverageNormalisedMaxLDeep*,  
*AverageNormalisedMinADeep*, *AverageNormalisedMaxADeep*,  
*AverageNormalisedMinBDeep*, *AverageNormalisedMaxBDeep*,  
*StdNormalisedMinLDeep*, *StdNormalisedMaxLDeep*, *StdNormalisedMinADeep*,  
*StdNormalisedMaxADeep*, *StdNormalisedMinBDeep*, *StdNormalisedMaxBDeep*,  
*AverageNormalisedMinLFull*, *AverageNormalisedMaxLFull*,  
*AverageNormalisedMinAFull*, *AverageNormalisedMaxAFull*,  
*AverageNormalisedMinBFull*, *AverageNormalisedMaxBFull*,  
*StdNormalisedMinLFull*, *StdNormalisedMaxLFull*, *StdNormalisedMinAFull*,  
*StdNormalisedMaxAFull*, *StdNormalisedMinBFull*, *StdNormalisedMaxBFull*,  
*AverageNormalisedMinLSuperficial*, *AverageNormalisedMaxLSuperficial*,  
*AverageNormalisedMinASuperficial*, *AverageNormalisedMaxASuperficial*,  
*AverageNormalisedMinBSuperficial*, *AverageNormalisedMaxBSuperficial*,  
*StdNormalisedMinLSuperficial*, *StdNormalisedMaxLSuperficial*,  
*StdNormalisedMinASuperficial*, *StdNormalisedMaxASuperficial*,  
*StdNormalisedMinBSuperficial*, *StdNormalisedMaxBSuperficial*
  7. **CALL** *OptimumWeightageGenerationProcess* **RETURN** *param1*, *param2*, *param3*,  
*param4*, *param5*, *param6*, *param7*, *param8*, *param9*, *param10*, *param11*, *param12*,  
*param13*, *param14*, *param15*, *param16*, *param17*, *param18*
  8.  $channel1MinDeep \leftarrow AverageNormalisedMinLDeep - param1 * StdNormalisedMinLDeep$
  9.  $channel1MaxDeep \leftarrow AverageNormalisedMaxLDeep + param2 * StdNormalisedMaxLDeep$
  10.  $channel2MinDeep \leftarrow AverageNormalisedMinADeep - param3 * StdNormalisedMinADeep$
  11.  $channel2MaxDeep \leftarrow AverageNormalisedMaxADeep + param4 * StdNormalisedMaxADeep$
  12.  $channel3MinDeep \leftarrow AverageNormalisedMinBDeep - param5 * StdNormalisedMinBDeep$
  13.  $channel3MaxDeep \leftarrow AverageNormalisedMaxBDeep + param6 * StdNormalisedMaxBDeep$
-

14.  $BW_{Deep} \leftarrow labImg(:,:,1) \geq channel1MinDeep \ \& \ labImg(:,:,1) \leq channel1MaxDeep \ \& \ labImg(:,:,2) \geq channel2MinDeep \ \& \ labImg(:,:,2) \leq channel2MaxDeep \ \& \ labImg(:,:,3) \geq channel3MinDeep \ \& \ labImg(:,:,3) \leq channel3MaxDeep$ , where  $BW_{Deep} \in [0 \ 1]$
  15.  $maskedRgbImageDeep \leftarrow doubleR * BW_{Deep}$
  16.  $channel1MinSuperficial \leftarrow AverageNormalisedMinLSuperficial - param7 * StdNormalisedMinLSuperficial$
  17.  $channel1MaxSuperficial \leftarrow AverageNormalisedMaxLSuperficial + param8 * StdNormalisedMaxLSuperficial$
  18.  $channel2MinSuperficial \leftarrow AverageNormalisedMinASuperficial - param9 * StdNormalisedMinASuperficial$
  19.  $channel2MaxSuperficial \leftarrow AverageNormalisedMaxASuperficial + param10 * StdNormalisedMaxASuperficial$
  20.  $channel3MinSuperficial \leftarrow AverageNormalisedMinBSuperficial - param11 * StdNormalisedMinBSuperficial$
  21.  $channel3MaxSuperficial \leftarrow AverageNormalisedMaxBSuperficial + param12 * StdNormalisedMaxBSuperficial$
  22.  $BW_{Superficial} \leftarrow labImg(:,:,1) \geq channel1MinSuperficial \ \& \ labImg(:,:,1) \leq channel1MaxSuperficial \ \& \ labImg(:,:,2) \geq channel2MinSuperficial \ \& \ labImg(:,:,2) \leq channel2MaxSuperficial \ \& \ labImg(:,:,3) \geq channel3MinSuperficial \ \& \ labImg(:,:,3) \leq channel3MaxSuperficial$ , where  $BW_{Superficial} \in [0 \ 1]$
  23.  $maskedRgbImageSuperficial \leftarrow doubleR * BW_{Superficial}$
  24.  $channel1MinFull \leftarrow AverageNormalisedMinLFull - param13 * StdNormalisedMinLFull$
  25.  $channel1MaxFull \leftarrow AverageNormalisedMaxLFull + param14 * StdNormalisedMaxLFull$
  26.  $channel2MinFull \leftarrow AverageNormalisedMinAFull - param15 * StdNormalisedMinAFull$
  27.  $channel2MaxFull \leftarrow AverageNormalisedMaxAFull + param16 * StdNormalisedMaxAFull$
  28.  $channel3MinFull \leftarrow AverageNormalisedMinBFull - param17 * StdNormalisedMinBFull$
  29.  $channel3MaxFull \leftarrow AverageNormalisedMaxBFull + param18 * StdNormalisedMaxBFull$
  30.  $BW_{Full} \leftarrow labImg(:,:,1) \geq channel1MinFull \ \& \ labImg(:,:,1) \leq channel1MaxFull \ \& \ labImg(:,:,2) \geq channel2MinFull \ \& \ labImg(:,:,2) \leq channel2MaxFull \ \& \ labImg(:,:,3) \geq channel3MinFull \ \& \ labImg(:,:,3) \leq channel3MaxFull$ , where  $BW_{Full} \in [0 \ 1]$
  31.  $maskedRgbImageFull \leftarrow doubleR * BW_{Full}$
  32. **CALL** ColourRangesRefiningProcess( $labImg$ ,  $U$ ,  $V$ ), where  $U$  is row,  $V$  is column  
**RETURN**  $deepBurnColour$ ,  $superficialBurnColour$ ,  $fullBurnColour$
  33.  $bwDeepC \leftarrow BW_{Deep} | deepBurnColour$ , where  $bwDeepC \in [0 \ 1]$
  34.  $bwFullC \leftarrow BW_{Full} | fullBurnColour$ , where  $bwFullC \in [0 \ 1]$
  35.  $bwSuperficialC \leftarrow BW_{Superficial} | superficialBurnColour$ , where  $bwSuperficialC \in [0 \ 1]$
  36. **CALL** ColourAreaPercentageCalculationProcess( $bwDeepC$ ,  $bwFullC$ ,  $bwSuperficialC$ ,  $numberOfPixels$ ), where  $numberOfPixels \leftarrow U * V$  **RETURN**  $isFullBurn$ ,  $isDeepBurn$ ,  $isSuperficialBurn$
-

```

37. CALL mean(maskedRgbImageDeep) RETURN meanDeepRange
38. CALL mean(maskedRgbImageSuperficial) RETURN meanSuperficialRange
39. CALL mean(maskedRgbImageFull) RETURN meanFullRange
40. CALL GlobalFeatureExtractionProcess(doubleR) RETURN stdHue, meanA,
    meanB, stdA, skewA, kurtA
41. CALL BlisterRegionDetectionProcess(R) RETURN meanEntropyFiltBlister,
    meanStdFiltBlister, contrastBlister, energyBlister, meanChromaBlister,
    stdHueBlister
42. Features(R, :) ← [isFullBurn, isDeepBurn, isSuperficialBurn, meanDeepRange,
    meanSuperficialRange, meanFullRange, stdHue, meanA, meanB, stdA, skewA,
    kurtA, meanChromaBlister, stdHueBlister, meanEntropyFiltBlister,
    meanStdFiltBlister, contrastBlister, energyBlister]
43. RETURN Features
44. ENDFOR

```

---