



**Faculty of Computer Science and Information Technology**

**Improved Multiclass Classification of Eye Diseases using a Feature-Augmented Enhanced Deep Learning Approach**

**Alvin Choo Ming Siang**

**Master of Science  
2026**

# Improved Multiclass Classification of Eye Diseases using a Feature-Augmented Enhanced Deep Learning Approach

Alvin Choo Ming Siang

A thesis submitted

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

(Visual Image Processing)

Faculty of Computer Science and Information Technology

UNIVERSITI MALAYSIA SARAWAK

2026

## DECLARATION

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



.....

Signature

Name: Alvin Choo Ming Siang

Matric No.: 23020166

Faculty of Computer Science and Information Technology

Universiti Malaysia Sarawak

Date: 30.09.2025

## ACKNOWLEDGEMENT

First and foremost, I would like to express my deepest appreciation to my research supervisor, Associate Professor Dr Stephanie Chua Hui Li, for her continuous guidance, encouragement, motivation, and insightful feedback that she has shared with me throughout the course of this research. I am equally thankful to my co-supervisors, Professor Dr Dayang Nurfatimah Awang Iskandar and Professor Dr Lim Lik Thai, for their valuable support, constructive suggestions, and academic mentorship, which have been instrumental in shaping the direction and quality of this thesis.

I would also like to sincerely deliver my appreciation to Ministry of Higher Education, Malaysia (MOHE), for funding this research under the Fundamental Research Grant [FRGS/1/2023/ICT02/UNIMAS/02/1]. Besides, I would like to thank Universiti Malaysia Sarawak (UNIMAS), the Centre for Graduate Studies, and Faculty of Computer Science and Information Technology, for providing the facilities, resources, and academic environment necessary to carry out this work.

Last but not least, I am forever grateful to my beloved family, especially my parents and friends for their unwavering support, patience and encouragement throughout this journey. Their belief in me has been a constant source of strength and motivation in completing this research.

## ABSTRACT

Vision impairment is a global health issue often caused by conditions such as cataracts, diabetic retinopathy, and glaucoma. Early detection is critical to prevent irreversible vision loss. Retinal fundus imaging plays a central role in diagnosis, and deep learning offers promising automation for disease detection. However, multiclass eye disease classification remains challenging due to limited annotated datasets, overlapping clinical features and intra-class heterogeneity. This research proposes an enhanced deep learning pipeline for classifying retinal fundus images into four classes: cataracts, diabetic retinopathy, glaucoma, and normal. A dataset, named CDGN, was constructed by integrating and standardizing images from eight publicly available sources, offering improved diversity, resolution, and patient demographics to enhance model robustness and generalizability. Image enhancement was applied to make disease-specific features more pronounced, while attention mechanisms improved focus on relevant regions, and ensemble learning further boosted performance across heterogeneous data. Multiple convolutional neural network (CNN) architectures were explored through transfer learning. An ablation study quantified the individual contributions of image enhancement, attention, and ensemble learning. Experimental results demonstrate progressive improvements in accuracy, recall, precision, F1-score and AUC across enhancement stages, with the ensemble model achieving the highest performance. These findings indicate that the feature-enhanced deep learning pipeline effectively addresses challenges in multiclass eye disease classification, supporting clinical decision-making and advancing automated diagnostic systems in ophthalmology.

**Keywords:** Multiclass eye disease classification, retinal fundus images, convolutional neural networks, attention mechanism, ensemble learning

***Penambahbaikan Pengelasan Berbilang Kelas Penyakit Mata Menggunakan Pendekatan Pembelajaran Mendalam yang Dipertingkatkan melalui Pengayaan Ciri***

***ABSTRAK***

*Kecacatan penglihatan merupakan isu kesihatan global yang sering disebabkan oleh keadaan seperti katarak, retinopati diabetik, dan glaukoma. Pengesanan awal adalah penting bagi mengelakkan kehilangan penglihatan yang tidak boleh dipulihkan. Imejan fundus retina memainkan peranan penting dalam diagnosis, dan pembelajaran mendalam menunjukkan potensi dalam pengesanan penyakit secara automatik. Walau bagaimanapun, klasifikasi penyakit mata pelbagai kelas masih mencabar disebabkan oleh set data beranotasi yang terhad, ciri klinikal yang serupa atau bertindih, serta heterogeniti dalam kelas. Kajian ini mencadangkan satu rangka kerja pembelajaran mendalam yang dipertingkatkan bagi mengklasifikasikan imej fundus retina kepada empat kelas: katarak, retinopati diabetik, glaukoma, dan normal. Satu set data baharu yang dinamakan CDGN telah dibina dengan menggabungkan dan menyeragamkan imej daripada laman sumber awam yang tersedia, memberikan kepelbagaian, resolusi, dan demografi pesakit yang lebih baik untuk meningkatkan ketahanan dan keupayaan generalisasi model. Penambahbaikan imej telah digunakan untuk menonjolkan ciri-ciri penyakit yang spesifik, manakala mekanisme perhatian meningkatkan fokus pada kawasan imej yang relevan, dan pembelajaran ensemble seterusnya meningkatkan prestasi data yang heterogen. Pelbagai seni bina rangkaian neural konvolusi (CNN) telah diterokai melalui pemindahan pembelajaran. Kajian ablasi dijalankan untuk menilai sumbangan individu penambahbaikan imej, mekanisme perhatian, dan pembelajaran ensemble. Keputusan eksperimen menunjukkan peningkatan progresif dalam ketepatan, kepekaan (recall), ketepatan ramalan (precision), skor F1 dan AUC pada setiap peringkat penambahbaikan,*

*dengan model ensemble mencatatkan prestasi tertinggi. Hasil kajian ini menyerlahkan keberkesanan rangka kerja pembelajaran mendalam yang dipertingkatkan dengan ciri tambahan dalam menangani cabaran klasifikasi pelbagai kelas penyakit mata, menyokong proses menjana keputusan klinikal dan memacu pembangunan sistem diagnostik automatik dalam bidang oftalmologi.*

***Kata kunci:*** *Pengelasan berbilang kelas penyakit mata, imej fundus retina, rangkaian neural konvolusi (CNN), mekanisme perhatian, pembelajaran ensemble*

## TABLE OF CONTENTS

	<b>Page</b>
<b>DECLARATION</b>	i
<b>ACKNOWLEDGEMENT</b>	ii
<b>ABSTRACT</b>	iii
<i><b>ABSTRAK</b></i>	iv
<b>TABLE OF CONTENTS</b>	vi
<b>LIST OF TABLES</b>	xii
<b>LIST OF FIGURES</b>	xiv
<b>LIST OF ABBREVIATIONS</b>	xix
<b>CHAPTER 1: INTRODUCTION</b>	1
1.1 Background	1
1.2 Motivation	3
1.3 Problem Statement	4
1.4 Research Questions	7
1.5 Research Objectives	7
1.6 Research Scope	8
1.7 Expected Outcomes	9
1.8 Significance of Research	9

1.9	Thesis Outline	11
1.10	Chapter Summary	12
<b>CHAPTER 2: LITERATURE REVIEW</b>		<b>13</b>
2.1	Overview	13
2.2	Anatomy of the Eye and Its Related Diseases	13
2.2.1	Cataracts	15
2.2.2	Diabetic Retinopathy	16
2.2.3	Glaucoma	18
2.3	Conventional Diagnostic Methods for Eye Diseases	20
2.3.1	Retinal Fundus Imaging	23
2.4	Machine Learning	24
2.4.1	Deep Learning	27
2.4.2	Convolutional Neural Network	30
2.5	Review of Related Work	52
2.5.1	Binary Classification of Eye Diseases	53
2.5.2	Multiclass Classification of Eye Diseases	59
2.6	Publicly Available Retinal Fundus Image Datasets	72
2.6.1	Eye Disease Retinal Images Dataset	73
2.6.2	Ocular Disease Intelligence Recognition (ODIR-5K) Dataset	73
2.6.3	Retinal Fundus Multi-Disease Image Dataset (RFMiD)	74

2.6.4	Glaucoma Fundus Imaging Dataset	75
2.6.5	PAPILA Dataset	76
2.6.6	DRISHTI-GS Dataset	76
2.6.7	Eye Disease Diagnosis and Fundus Synthesis (EDDFS) Dataset	77
2.6.8	1000 Fundus Images with 39 Categories Dataset	77
2.7	Comparative Analysis of Related Work	78
2.8	Chapter Summary	94
	<b>CHAPTER 3: METHODOLOGY</b>	95
3.1	Overview	95
3.2	Research Methodology	95
3.3	Execution Environment	97
3.4	Data Collection	97
3.4.1	Dataset Selection and Integration	99
3.5	Data Preprocessing	105
3.6	Image Enhancement	106
3.7	Model Training	110
3.7.1	Transfer Learning	110
3.7.2	Attention Mechanism	116
3.7.3	Ensemble Learning	119
3.8	Modal Evaluation	121

3.8.1	Confusion Matrix and Derived Metrics	121
3.8.2	Area Under the Receiver Operating Characteristic Curve (AUC-ROC)	124
3.9	Chapter Summary	126
<b>CHAPTER 4: RESULTS AND DISCUSSION</b>		127
4.1	Overview	127
4.2	Experimental Setup	127
4.2.1	Dataset Description	128
4.2.2	Image Preprocessing and Enhancement	128
4.2.3	Model Architectures	128
4.2.4	Training Configuration	129
4.2.5	Evaluation Metrics	129
4.3	Model Performance on Original CDGN Dataset (Baseline)	129
4.3.1	VGG16	130
4.3.2	Inception-v3	134
4.3.3	ResNet50	138
4.3.4	DenseNet121	142
4.3.5	EfficientNet-B0	146
4.3.6	Summary and Discussion	150
4.4	Model Performance on Feature-Enhanced CDGN Dataset	152
4.4.1	VGG16	152

4.4.2	Inception-v3	156
4.4.3	ResNet50	160
4.4.4	DenseNet121	164
4.4.5	EfficientNet-B0	168
4.4.6	Summary and Discussion	172
4.5	Attention-Based Model Performance on Feature-Enhanced CDGN Dataset	174
4.5.1	Attention-Based VGG16	174
4.5.2	Attention-Based Inception-v3	178
4.5.3	Attention-Based ResNet50	182
4.5.4	Attention-Based DenseNet121	186
4.5.5	Attention-Based EfficientNet-B0	191
4.5.6	Summary and Discussion	195
4.6	Ensemble Model Performance on Feature-Enhanced CDGN Dataset	198
4.7	Comparative Evaluation of Model Configurations	203
4.7.1	Macro-Performance Summary	204
4.7.2	The Impact of Attention Mechanisms (Ablation Study)	205
4.7.3	Class-Specific Discriminative Analysis	206
4.8	Chapter Summary	208
	<b>CHAPTER 5: CONCLUSION AND RECOMMENDATIONS</b>	210
5.1	Overview	210

5.2	Contribution	210
5.3	Limitations	212
5.4	Recommendations and Future Works	213
5.5	Conclusion	215
	<b>REFERENCES</b>	216

## LIST OF TABLES

	<b>Page</b>	
Table 2.1	Commonly Used Activation Functions in Deep Learning	35
Table 2.2	Summary of Reviewed Studies on Eye Disease Classification Using CNNs	81
Table 3.1	Hardware and Software Specifications	98
Table 3.2	Summary of Publicly Available Datasets Prior to Filtering	100
Table 3.3	Final Distribution of Retinal Fundus Images by Class in CDGN Dataset	103
Table 3.4	Overview of Selected CNN Architectures	111
Table 3.5	Model Size and Number of Parameters (Trainable and Non-Trainable) for Each Selected Pre-trained CNN Models	112
Table 3.6	Training Hyperparameter used for all Pre-trained CNN Models	114
Table 3.7	Confusion Matrix for Binary Classification	122
Table 3.8	Confusion Matrix for Multiclass Classification (Class $C_k$ ) (Krüger, 2016)	122
Table 4.1	Classification Metrics of VGG16	132
Table 4.2	Classification Metrics of Inception-v3	136
Table 4.3	Classification Metrics of ResNet50	140
Table 4.4	Classification Metrics of DenseNet121	145
Table 4.5	Classification Metrics of EfficientNet-B0	149
Table 4.6	Performance Metrics of Baseline CNN Models on Original CDGN Dataset	151
Table 4.7	Classification Metrics of VGG16 on Feature-Enhanced CDGN Dataset	154
Table 4.8	Classification Metrics of Inception-v3 on Feature-Enhanced CDGN Dataset.	158
Table 4.9	Classification Metrics of ResNet50 on Feature-Enhanced CDGN Dataset	162

Table 4.10	Classification Metrics of DenseNet121 on Feature-Enhanced CDGN Dataset	166
Table 4.11	Classification Metrics of EfficientNet-B0 on Feature-Enhanced CDGN Dataset	170
Table 4.12	Performance Metrics of CNN Models on Feature-Enhanced CDGN Dataset	173
Table 4.13	Classification Metrics of Attention-Based VGG16 on Feature-Enhanced CDGN Dataset	176
Table 4.14	Classification Metrics of Attention-Based Inception-v3 on Feature-Enhanced CDGN Dataset	180
Table 4.15	Classification Metrics of Attention-Based ResNet50 on Feature-Enhanced CDGN Dataset	185
Table 4.16	Classification Metrics of Attention-Based DenseNet121 on Feature-Enhanced CDGN Dataset	189
Table 4.17	Classification Metrics of Attention-Based EfficientNet-B0 on Feature-Enhanced CDGN Dataset	193
Table 4.18	Performance Metrics of Attention-Based CNN Models on Feature-Enhanced CDGN Dataset	195
Table 4.19	Classification Metrics of Ensemble Model on Feature-Enhanced CDGN Dataset	200
Table 4.20	Comparative Performance Metrics of Best-Performing Models from Each Experimental Configuration	204
Table 4.21	Class-Specific AUC Performance Comparison (Non-Attention vs. Attention-based)	207

## LIST OF FIGURES

	<b>Page</b>
Figure 2.1 Basic structure of eye (Galloway & Amoaku, 1999)	14
Figure 2.2 Clouding of the lens in a cataractous right eye (Khazaeni, 2023b)	16
Figure 2.3 Stages of diabetic retinopathy: (a) Mild non-proliferative, (b) Moderate non-proliferative, (c) Severe non-proliferative, (d) Proliferative (Qummar et al., 2019).	18
Figure 2.4 Snellen Chart (Turbert, 2022)	21
Figure 2.5 Slit-lamp examination (Porter, 2018)	22
Figure 2.6 Hand-held ophthalmoscope with labelled parts (Al-Zubaidy, 2020)	22
Figure 2.7 Labelled retinal fundus image showing the optic disc, optic cup, macula, fovea, and retinal blood vessels (Al-Zubaidy, 2020)	23
Figure 2.8 Illustration showing the hierarchical relationship between artificial intelligence, machine learning, and deep learning (Sarker, 2021).	29
Figure 2.9 Block diagram of deep neural network (Choudhary & Kesswani, 2020).	29
Figure 2.10 Common architecture of CNN for image classification (Taye, 2023)	31
Figure 2.11 Illustration of the convolution operation (Purwono et al., 2023)	33
Figure 2.12 Illustration of max-pooling for dimension reduction (Purwono et al., 2023)	34
Figure 2.13 AlexNet architecture (Han et al., 2017)	38
Figure 2.14 VGG16 architecture (Purwono et al., 2023)	39
Figure 2.15 Naïve version of the Inception module (Szegedy, Liu, et al., 2015)	41
Figure 2.16 Dimension reduction in Inception module (Szegedy, Liu, et al., 2015)	41
Figure 2.17 GoogLeNet architecture (Szegedy, Liu, et al., 2015)	43
Figure 2.18 Spatial factorization in Inception modules: (a) Original Inception module in Inception-v1, (b) Inception module with factorised convolutions (Szegedy, Vanhoucke, et al., 2015).	44
Figure 2.19 Illustration of skip connection (He et al., 2016)	45

Figure 2.20	Comparison of the architectures of VGG19, Plain ResNet34 and ResNet34 with residual blocks (He et al., 2016).	47
Figure 2.21	Direct connection in DenseNet, each layer takes all preceeding feature maps as input (Huang et al., 2017).	48
Figure 2.22	Transition layers between two dense blocks in DenseNet (Huang et al., 2017)	48
Figure 2.23	Illustration of conventional scaling and proposed compound scaling (Tan & Le, 2019)	51
Figure 2.24	Comparison of EfficientNets and other existings CNNs on ImageNet Top-1 Accuracy and Parameters Count (Tan & Le, 2019)	52
Figure 3.1	Research flowchart illustrating the sequential stages of the proposed methodology	96
Figure 3.2	Examples of poor image quality	102
Figure 3.3	Examples of incomplete central image where optic disc is not photographically visible	102
Figure 3.4	Examples of image offset: (a) Fundus region offset, (b) offset with background distortion	103
Figure 3.5	Cataracts	104
Figure 3.6	Diabetic retinopathy	104
Figure 3.7	Glaucoma	104
Figure 3.8	Normal	104
Figure 3.9	Image enhancement process	109
Figure 3.10	Comparison of original and enhanced retinal fundus images across four classes: (a) displays the original images from the CDGN dataset, (b) shows the corresponding enhanced images.	109
Figure 3.11	Architecture of the CNN model used in this research: a pre-trained base model, followed by custom fully connected layers and a final softmax output layer.	113
Figure 3.12	Architecture of CNN model with an integrated spatial attention module. The attention block, highlighted in red, is positioned between the base model and the custom classification head.	118

Figure 3.13	Overview of soft voting ensemble mechanism where the class probabilities predicted by five attention-based CNN models are averaged to generate the final prediction.	121
Figure 4.1	Training and validation accuracy and loss plots of VGG16	130
Figure 4.2	Confusion matrix of VGG16	131
Figure 4.3	ROC curves and corresponding AUC scores for each class of VGG16	133
Figure 4.4	Training and validation accuracy and loss plots of Inception-v3	134
Figure 4.5	Confusion matrix of Inception-v3	135
Figure 4.6	ROC curves and corresponding AUC scores for each class of Inception-v3	137
Figure 4.7	Training and validation accuracy and loss plots of ResNet50	138
Figure 4.8	Confusion matrix of ResNet50	139
Figure 4.9	ROC curves and corresponding AUC scores for each class of ResNet50	141
Figure 4.10	Training and validation accuracy and loss plots of DenseNet121	143
Figure 4.11	Confusion matrix of DenseNet121	144
Figure 4.12	ROC curves and corresponding AUC scores for each class of DenseNet121	145
Figure 4.13	Training and validation accuracy and loss plots of EfficientNet-B0	147
Figure 4.14	Confusion matrix of EfficientNet-B0	148
Figure 4.15	ROC curves and corresponding AUC scores for each class of EfficientNet-B0	149
Figure 4.16	Training and validation accuracy and loss plots of VGG16 on feature-enhanced CDGN dataset	153
Figure 4.17	Confusion matrix of VGG16	153
Figure 4.18	ROC curves and corresponding AUC scores for each class in feature-enhanced CDGN dataset of VGG16	155
Figure 4.19	Training and validation accuracy and loss plots of Inception-v3 on feature-enhanced CGDN dataset	156
Figure 4.20	Confusion matrix of Inception-v3	157

Figure 4.21	ROC curves and corresponding AUC scores for each class in feature-enhanced CDGN dataset of Inception-v3	159
Figure 4.22	Training and validation accuracy and loss plots of ResNet50 on feature-enhanced CDGN dataset	160
Figure 4.23	Confusion matrix of ResNet50	161
Figure 4.24	ROC curves and corresponding AUC scores for each class in feature-enhanced CDGN dataset of ResNet50	163
Figure 4.25	Training and validation accuracy and loss plots of DenseNet121 on feature-enhanced CDGN dataset	164
Figure 4.26	Confusion matrix of DenseNet121	165
Figure 4.27	ROC curves and corresponding AUC scores for each class in feature-enhanced CDGN dataset of DenseNet121	167
Figure 4.28	Training and validation accuracy and loss plots of EfficientNet-B0 on feature-enhanced CDGN dataset	168
Figure 4.29	Confusion matrix of EfficientNet-B0	169
Figure 4.30	ROC curves and corresponding AUC scores for each class in feature-enhanced CDGN dataset of EfficientNet-B0	171
Figure 4.31	Training and validation accuracy and loss plots of attention-based VGG16 on feature-enhanced CDGN dataset	174
Figure 4.32	Confusion matrix of attention-based VGG16	175
Figure 4.33	ROC curves and corresponding AUC scores for each class in feature-enhanced CDGN dataset of attention-based VGG16	177
Figure 4.34	Training and validation accuracy and loss plots of attention-based Inception-v3 on feature-enhanced CDGN dataset	179
Figure 4.35	Confusion matrix of attention-based Inception-v3	179
Figure 4.36	ROC curves and corresponding AUC scores for each class in enhanced CDGN dataset of attention-based Inception-v3	181
Figure 4.37	Training and validation accuracy and loss plots of attention-based ResNet50 on feature-enhanced CDGN dataset	183
Figure 4.38	Confusion matrix of attention-based ResNet50	184
Figure 4.39	ROC curves and corresponding AUC scores for each class in feature-enhanced CDGN dataset of attention-based ResNet50	185

Figure 4.40	Training and validation accuracy and loss plots of attention-based DenseNet121 on feature-enhanced CDGN dataset	187
Figure 4.41	Confusion matrix of attention-based DenseNet121	188
Figure 4.42	ROC curves and corresponding AUC scores for each class in feature-enhanced CDGN dataset of attention-based DenseNet121	190
Figure 4.43	Training and validation accuracy and loss plots of attention-based EfficientNet-B0 on feature-enhanced CDGN dataset	191
Figure 4.44	Confusion matrix of attention-based EfficientNet-B0	192
Figure 4.45	ROC curves and corresponding AUC scores for each class in feature-enhanced CDGN dataset of attention-based EfficientNet-B0	194
Figure 4.46	Confusion matrix of ensemble model	199
Figure 4.47	ROC curves and corresponding AUC scores for each class in feature-enhanced CDGN dataset of ensemble model	201
Figure 4.48	Comparison of Performance (Accuracy) of Non-Attention Model versus Its Attention Counterpart on Feature-Enhanced Dataset	206

## LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ANN	Artificial Neural Network
AUC-ROC	Area Under the Receiver Operating Characteristic Curve
CDR	Cup-to-Disk Ratio
CLAHE	Contrast Limited Adaptive Histogram Equalization
CNN	Convolution Neural Network
COCO	Common Objects in Context
DenseNet	Densely Connected Convolutional Network
DR	Diabetic Retinopathy
FLOPS	Floating-Point Operation Per Second
FN	False Negative
FP	False Positive
ILSVRC	ImageNet Large-Scale Visual Recognition Challenges
ISNT	Inferior, Superior, Nasal, Temporal
LSTM	Long Short-Term Memory
NLP	Natural Language Processing
NRR	Neuroretinal Rim
ODIR-5K	Ocular Disease Intelligence Recognition
ONH	Optic Nerve Head
PCA	Principal Component Analysis
ReLU	Rectified Linear Unit
ResNet	Residual Network
RFMiD	Retinal Fundus Multi-Disease Image Dataset

RGB	Red, Green, Blue
RNN	Recurrent Neural Network
ROC	Receiver Operating Characteristic
SMOTE	Synthetic Minority Oversampling Technique
SNN	Simulated Neural Network
SVM	Support Vector Machine
TN	True Negative
TP	True Positive
VGG	Visual Geometry Group
WHO	World Health Organization

# CHAPTER 1

## INTRODUCTION

### 1.1 Background

Vision is one of the most important and dominant senses among the five human senses. It is essentially needed in every aspect of life, giving individuals the ability to see and engage with their surroundings through their eyes. Vision plays an indispensable role in daily activities, such as guiding movement, helping people avoid obstacles, recognising objects, and coordinating actions with remarkable precision. Beyond these fundamental functions, vision opens a world of limitless possibilities. It allows individuals to connect with others on a deeper level, fostering empathy and understanding through subtle cues like facial expressions and body language.

For some individuals, however, this essential sense is either partially or completely diminished, resulting in a condition known as visual impairment. Visual impairment is the term used to describe any eye condition affects the visual system and its function (World Health Organization [WHO], 2023). It can have lifelong adverse effects, making it challenging for individuals to learn, walk, read, and carry out daily activities without vision. Visual impairment covers a range of conditions that affect the visual system, with a spectrum of severity, ranging from mild visual disturbances that can be corrected with spectacles or contact lenses to complete blindness.

According to the World Report on Vision, the first report by World Health Organization (WHO) on global vision health, it is estimated that at least 2.2 billion people worldwide are suffering from some form of visual impairment, and that in at least 1 billion—

nearly half—could have been avoided or are still unresolved (WHO, 2019). Additionally, the report estimates that at least 650 million people globally are living with moderate to severe vision loss. The report identified age-related macular degeneration, cataracts, diabetic retinopathy, glaucoma, and refractive errors as among the leading causes of visual impairment and blindness (WHO, 2019).

Age-related macular degeneration is brought on by the macula's deterioration with aging and is prevalent among individuals aged 50 years and above (Muchuchuti & Viriri, 2023). According to WHO (2019), cataracts is caused by clouding in the eye lens that is due to excess blood sugar, which can happen at any age but are more prevalent in older people. Diabetic retinopathy is complication of uncontrolled, long-term high blood glucose levels, which harms the retina's blood vessels. These blood vessels may become swell, leak, or blocked, leading to vision loss due to swelling in the central part of the retinal. Glaucoma, on the other hand, is an eye disease led by higher-than-normal intraocular pressure which progressively damages the optic nerve (WHO, 2023). Refractive errors are vision disorders that caused by irregularities in the eye's shape or the curvature of the cornea, which interfere with eye's ability to concentrate on objects at varying distances. These errors can be corrected using eyeglasses, contact lenses, or refractive surgical procedures.

In 2020, among 206 million adults aged 50 years and older with moderate to severe vision impairment, the predominant causes included cataract (78.8 million), diabetic retinopathy (2.9 million), glaucoma (4.1 million), refractive errors (86.1 million), and age-related macular degeneration (6.2 million). For the estimated 33.6 million blind adults in the same age group, the primary causes of blindness were cataracts (15.2 million), diabetic retinopathy (0.9 million), glaucoma (3.6 million), refractive errors (2.3 million), and age-