

**MACHINE LEARNING APPROACH TO DETECT &
ANNOTATE EYE DISEASES USING RETINAL IMAGES**

Project ID - 23-162

Final Report

B. Sc. (Hons) Degree in Information Technology

(Specialization in Software Engineering)

Department of Computer Science and Software Engineering

Sri Lanka Institute of Information Technology

Sri Lanka

September 2023

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DECLARATION

I declare that this is my own work and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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ABSTRACT

This research addresses the escalating global health concerns of Diabetic Retinopathy (DR) and Age-Related Macular Degeneration (AMD), widespread causes of visual impairment and blindness. The investigation pivots around developing advanced diagnostic tools through image processing and machine learning techniques, with a focus on their applicability in resource-limited settings in many regions of the globe. This research aims to develop deep learning models that accurately detect and categorize the severity of DR using retinal fundus images. These models offer the potential to facilitate early detection and enhance the effectiveness of treatments by improving diagnosis efficiency. Simultaneously, work is being carried out on automated diagnostic tools that utilize Optical Coherence Tomography (OCT) images of the retina for identifying and classifying AMD's severity.

Current methodologies are time-consuming and prone to observer variations, thus necessitating a more precise and automatic diagnostic approach. By the end of this research, a cross-platform mobile application is proposed, integrating the developed deep learning technology. This application is designed for detection and classification of DR and AMD from retinal images at the early stages, with the aim of revolutionizing the current clinical processes. It is anticipated that this research will expedite the diagnostic procedure, thereby contributing to the reduction of the global burden of blindness and visual impairment.

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TABLE OF CONTENTS

DECLARATION.....	3
ABSTRACT.....	4
ACKNOWLEDGEMENT.....	5
LIST OF FIGURES.....	8
LIST OF TABLES.....	9
LIST OF ABBREVIATIONS/ACRONYMS.....	10
1. INTRODUCTION.....	11
1.1. General Introduction.....	11
1.2. Literature Survey.....	13
1.3. Research Gap.....	17
1.4. Research Problem.....	19
1.5. Research Objectives.....	20
1.5.1. Main Objectives.....	20
1.5.2. Sub Objectives.....	21
2. METHODOLOGY.....	24
2.1. Requirement Gathering and Analysis.....	24
2.2. Feasibility study.....	25
2.3. Materials and methods.....	26
2.3.1. Methodology for Detect Symptoms of Diabetic Retinopathy using Retinal Fundus Images.....	28
2.3.2. Methodology for Grade Severity of Diabetic Retinopathy using Retinal Fundus Images.....	29
2.3.3. Methodology for Detect Symptoms of Age-related Macular Degeneration	

using Retinal OCT Images.....	30
2.4. Commercialization aspects of the product.....	35
2.4.1. Target Market Segmentation.....	35
3. TESTING & IMPLEMENTATION.....	39
3.1. Testing Methodology.....	39
3.1.1. Unit Testing.....	39
3.1.2. Integration Testing.....	39
3.2. Product Release.....	40
3.3. Implementation Details.....	42
4. CONCLUSION.....	48
REFERENCE LIST.....	49

LIST OF FIGURES

Figure 1: System Overview Diagram	26
Figure 2: User Flow Diagram	42
Figure 3 : UIs of the Application	44

LIST OF TABLES

Table 1: Results of former research	14
Table 2: Model performance metrics for the complete system	45

LIST OF ABBREVIATIONS/ACRONYMS

AMD	Age-related Macular Degeneration
CNN	Convolutional Neural Networks
DR	Diabetic Retinopathy
HOG	Histogram of Oriented Gradients
RF	Random Forest

1. INTRODUCTION

1.1. General Introduction

Visual impairment and blindness are life-altering conditions affecting millions globally. Two predominant causes are Diabetic Retinopathy (DR) and Age-Related Macular Degeneration (AMD), constituting significant health problems, especially in regions like Sri Lanka. This research aims to tackle these eye diseases through advanced image processing and machine learning techniques, bridging the gap between high-tech healthcare and practical clinical applications.

Diabetes causes many intriguing complications, including diabetic retinopathy, which affects the eye's retina and is the fourth most prevalent reason for visual impairment and blindness. According to past research, one-third of Sri Lankan adults with self-reported diabetes have retinopathy. Despite the high prevalence, resources and expertise for screening and treating DR remain insufficient in the region, highlighting the urgent need for service expansion and mid-level HR training. More importantly, there is a call for advanced techniques to facilitate early detection and continuous monitoring of DR, ultimately reducing the disease's impact.

One of the primary components of this research focuses on developing deep learning models to detect DR using retinal fundus images. Additionally, our work involves classifying the severity of DR based on the same images. These models will increase the odds of early detection and effective treatment, enabling a more efficient and accurate diagnosis.

Age-Related Macular Degeneration, another debilitating eye condition, causes progressive vision loss, impacting millions worldwide. OCT image is a vital in detecting and monitoring AMD. Despite its utility, the current manual process for AMD detection from OCT images is time-consuming and suffers from observer variations, potentially leading to misdiagnosis or delayed diagnosis.

This research also aims to develop automated diagnostic tools for detecting symptoms of AMD using retinal OCT images and classifying AMD's severity. By providing an

automatic and accurate diagnostic approach, it can be helped to address the significant challenge to early detection and treatment of AMD. Current AMD classification methods, mostly developed for web applications, rely on multiple OCT images, making it challenging to distinguish between dry and wet AMD in the same patient's eye. By developing an efficient and precise method for diagnosing and classifying AMD, it can significantly enhance the clinical process.

In conclusion, this research proposes a cross-platform mobile application integrating deep learning technology for the detection and classification of DR and AMD using retinal images. The developed tools will streamline and expedite the diagnostic process, bringing us one step closer to reducing the burden of blindness and visual impairment globally.

1.2. Literature Survey

Several research papers proposed utilizing an approach based on deep learning and image processing in detecting and classifying Diabetic Retinopathy and Age-Related Macular Degeneration. In these studies, the imaging modalities for DR and AMD consisted of fundus and OCT images, respectively.

A. Detect Symptoms of Diabetic Retinopathy using Retinal Fundus Images

Akanksha Soni and Dr. Avinash Rai, "A Novel Approach for the Early Recognition of Diabetic Retinopathy using Machine Learning" proposed a deep learning approach using classification algorithms: SVM, k-mean clustering, and Random Forest [1]. A histogram equalization procedure and the k-means clustering algorithm has been used to pre-process the ocular image and segment it into the usual and unusual areas. Support VectorMachines (SVM) and Random Forest algorithms are then used to classify the image segments. The dataset used in the study consisted of 89 color images, including 84 images with mild non-proliferative signs of DR and five images without any DR symptoms. The model achieved 94.38% and 96.62% recognition rates for SVM and Random Forest classifiers, respectively.

Qomariah D U N et al., "Classification of Diabetic Retinopathy and Normal Retinal Images using CNN and SVM" 2019 presented a deep learning approach to feature extraction and classification using SVM CNN [2]. The pro- posed system is evaluated on 77 retinal images from Messidor's base 12 and 70 retinal images from base 13 databases. Alexnet, VggNet, InceptionNet, GoogleNet, DenseNet, and Resnet were used in this approach to gain the feature vector for classification. An SVM classifier is used to determine the best hyperplane for segmenting the extracted feature vectors into healthy and DR diagnosis classes. The experiment results show 95.83% & 95.24% as the highest accuracy values for base 12 & 13, respectively.

M Asiful Huda et al. in their research "An Improved Approach for Detection of Diabetic Retinopathy Using Feature Importance and Machine Learning Algorithms" proposed improved machine learning & feature importance algorithms in detecting Diabetic Retinopathy [3]. Decision Tree, Logistic Regression, & SVM is utilized in their

proposed system to improve the overall performance and accuracy of Diabetic Retinopathy detection. The model achieved a precision of 97% & a recall of 92%, which shows a notable contrast concerning existing results, 72% and 63% outcome.

Method	Sensitivity (%)	Specificity (%)	Accuracy (%)
FCM clustering and SVM [9]	97.5	97.8	97.7
Feature fusion from Inception-v3, ResNet-50, and VGGNet-19 models [10]	-	-	98.91
DCNN Feature + SVM [11]	-	-	86.1
Adaptive histogram equalization, Gabor, Top-hat, 1iterative thresholding approach [12]	96.7	91.4	94.1
Custom convolutional neural network [13]	90	87	-
R-sGAN technique [14]	79.01	97.95	-
Handcraft feature, CNN and Random Forest classifier [15]	97.2	-	93.4
CNN architecture [16]	-	93.65	83.68

Table 1: Results of former research

Narayana et al. proposed an algorithm in detecting Diabetic Retinopathy using Convolutional Neural Network with the VGG-16 model. The model was trained using the EyePACS dataset, which contains 35,126 pictures from both the left and right eyes [4]. The system used normalization, center-ing, and cropping to 512 x 512 pixels to preprocess the retinal images. The research addresses the class imbalances in the dataset through data augmentation techniques. In this study, CNN architecture incorporates the VGG-16 model with trainable convolutional layers in Block-5 and an optimized dense layer to grade the severity of Diabetic Retinopathy. The study achieved an Average Class Accuracy (ACA) of 74%, sensitivity of 80%, and specificity of 65%, with an area under the curve (AUC) of 0.80.

A research study conducted by Jyostna proposed an optimized model for predicting the severity level of Diabetic Retinopathy [5]. In this research, pre-trained model features

were extracted. The researchers use activation filter values from convolution blocks 3, 4, and 5 of the VGG-16 model to acquire feature representation. Different pooling methods and fusion techniques were designed to represent retinal images. The proposed model is trained using a dataset from the Kaggle APTOS 2019 contest. The proposed method achieved an accuracy of 84.31% and an AUC of 97. The outcomes outperformed existing models, particularly for severe and proliferate stage DR images.

In their study, “Deep Learning Is Effective for Classifying Normal versus Age-Related Macular Degeneration OCT Images,” Lee et al. in 2018 investigated the effectiveness of deep-learning models for distinguish normal or Age-related Macular Degeneration symptoms using OCT images [6]. The researchers use an optimized VGG16 convolutional neural network as the deep learning model. The model was adapted to suit the specific requirements of the classification task at hand. The results demonstrated promising performance, with a ROC curve achieving 93.83% and an accuracy of 88.98%. These results indicate the effectiveness of the proposed deep-learning model for accurately distinguishing normal and AMD OCT images.

Srivastava et al. proposed an automated system for detecting AMD using OCT images [7]. The objective of their research aimed to enhance the deep learning model’s performance by integrating the choroid layer. The ResNet1 model achieved an accuracy of 96.78%, and ResNet2 achieved accuracy of 95.82% in detecting AMD using OCT images.

Ali Serener et al. have proposed an automated approach using deep learning Convolutional Neural Networks for classifying dry and wet Age-related Macular Degeneration [8]. The study employed pre-trained AlexNet and ResNet models. The ImageNet dataset, which contains 8000 OCT pictures of four classes—healthy, dry AMD, wet AMD, and diabetic macular edema—is used to train the algorithm. The ResNet model achieves an area under the Receiver Operating Characteristic curve of 94% and 63% for dry AMD and wet AMD, respectively.

Govindaiah et al., in their study, proposed a novel deep learning framework for automated screening to identify individuals susceptible of developing AMD [9]. The proposed system utilizes Age-Related Eye Disease Study (AREDS) dataset, composed

of 150000 images graded by expert graders and ophthalmologists. Inception-ResNet-V2 and Xception deep neural networks were used to screen AMD. The images were split into four categories in the second experiment: no AMD, early AMD, intermediate AMD, and advanced AMD. Over

95.3% of accuracy is achieved for the first experiment, and the second experiment demonstrates an accuracy of 86%.

Sertkaya et al., in their study, use various CNN models, LeNet, AlexNet, and Vgg16 architectures for the diagnosis of Neovascularization, Diabetic Macular Edema, Drusen, and healthy eye conditions using OCT images [10]. The study shows successful results, especially with Vgg16 and AlexNet architectures in classifying AMD stages. The dropout layer structure in the AlexNet model minimized the training loss. The classification rate for the VGG-16 architecture was 93.11%.

1.3. Research Gap

While many studies have explored various deep learning architectures such as CNNs like VGG-16 and ResNet, there is a need to investigate the potential benefits of integrating multiple architectures within a single model. An optimal fusion of architectures could potentially enhance the accuracy and robustness of disease detection. Research should focus on developing hybrid models that leverage the strengths of different CNN architectures.

Current research has primarily been centered around offline processing of medical images. The development of a mobile application for DR and AMD detection requires real-time image processing capabilities, considering factors like low latency and resource-efficient algorithms. Research should delve into optimizing deep learning models for mobile deployment to ensure accessibility and usability for healthcare practitioners and patients.

Many studies mentioned in the literature review used relatively small datasets. To build a reliable and clinically applicable mobile application, researchers must address the challenge of limited data availability. Collecting and curating large, diverse datasets that encompass a wide range of disease stages and demographics is essential for training robust deep learning models.

Developing a mobile application for medical diagnosis necessitates seamless integration into the clinical workflow. Research should explore the development of standardized data exchange formats and communication protocols to facilitate the exchange of patient data between the mobile application and electronic health record systems. Additionally, adherence to regulatory and ethical guidelines is crucial.

Transfer learning techniques, where models are pre-trained on large datasets and fine-tuned for specific tasks, have shown promise in the literature. Future research should investigate the most effective strategies for transferring knowledge from general image datasets to the domain of retinal images to improve the efficiency of model training and enhance diagnostic accuracy.

Deep learning models often lack transparency, which can be a significant barrier to their clinical adoption. Research should focus on developing methods for explaining the decisions made by these models, providing clinicians with insights into why a particular diagnosis was reached. Explainable AI techniques are crucial for building trust in automated medical diagnosis systems.

A mobile application should be designed to run on various mobile operating systems, ensuring accessibility to a broad user base. Research should address the challenges of developing cross-platform applications that are user-friendly, responsive, and consistent across different devices and operating systems.

1.4. Research Problem

Design and implement a mobile application that leverages state-of-the-art deep learning techniques for the accurate and early detection and classification of Diabetic Retinopathy and Age-Related Macular Degeneration from retinal fundus images and OCT images. Address the following challenges: limited dataset size, cross-dataset generalization, model interpretability, real-time application, and early detection. The application should provide reliable and clinically actionable results to assist healthcare professionals in diagnosing and managing these sight-threatening conditions efficiently.

This research problem encompasses the need to develop a practical and user-friendly mobile application that can operate in real-time, utilize interpretable deep learning models, adapt to various datasets and populations, and facilitate the early detection and classification of DR and AMD. Addressing this problem will contribute to improved eye healthcare by making early diagnosis more accessible and accurate.

1.5. Research Objectives

The research objectives for the proposed study, aimed at developing a mobile application for the accurate detection and classification of Diabetic Retinopathy (DR) and Age-Related Macular Degeneration (AMD) using deep learning algorithms in order to improve the accuracy of outcomes for better diagnosis.

1.5.1. Main Objectives

The main research objective of this study is to develop a mobile application that leverages state-of-the-art deep learning techniques for the accurate and early detection and classification of Diabetic Retinopathy (DR) and Age-Related Macular Degeneration (AMD) from retinal fundus images and OCT images. This research addresses several critical challenges, including the limited size of available datasets, the need for cross-dataset generalization, model interpretability, real-time application capability, and early detection. The primary aim is to create an application that provides reliable and clinically actionable results, empowering healthcare professionals to diagnose and manage these sight-threatening conditions more efficiently. By tackling these challenges and objectives, this research seeks to contribute significantly to the field of eye healthcare, enhancing accessibility and accuracy in the early diagnosis of DR and AMD, ultimately improving patient outcomes and care quality.

1.5.2. Sub Objectives

In addition to the main objectives, there are some specific objectives related to the implementation. These sub-objectives collectively contribute to the overarching goal of developing a mobile application that effectively addresses the challenges of early detection and classification of Diabetic Retinopathy and Age-Related Macular Degeneration while ensuring usability, security, and clinical relevance in real-world healthcare settings.

- Dataset Augmentation

Develop methods to augment limited retinal fundus and OCT image datasets to overcome data scarcity, ensuring the deep learning models have sufficient samples for training and validation.

- Cross-Dataset Generalization

Create a framework for robust model generalization across different datasets and populations, ensuring the application's effectiveness in diverse clinical settings.

- Interpretable Deep Learning Models

Design and implement deep learning models with interpretability features, allowing healthcare professionals to understand how the model makes predictions, increasing trust and aiding in decision-making.

- Real-time Processing

Optimize the mobile application for real-time image processing, ensuring quick and seamless analysis of retinal images, which is crucial for timely diagnosis and intervention.

- Early Detection Algorithms

Develop algorithms that specialize in early detection of DR and AMD, enabling the application to identify these conditions in their nascent stages, when interventions are most effective.

- User Interface and Experience (UI/UX)

Create an intuitive and user-friendly interface for healthcare professionals to interact with the application, ensuring ease of use and efficient integration into their workflow.

- Clinical Validation

Conduct rigorous validation studies in clinical settings to assess the accuracy and clinical relevance of the application's diagnoses, ensuring its reliability as a diagnostic tool.

- Security and Privacy

Implement robust security measures to protect patient data and ensure compliance with healthcare privacy regulations, safeguarding patient information within the application.

- Scalability

Design the application with scalability in mind, allowing for future expansion and updates to accommodate evolving clinical requirements and advances in technology.

- Feedback Integration

Develop mechanisms for healthcare professionals to provide feedback on application performance, facilitating continuous improvement and refinement of the diagnostic capabilities.

2. METHODOLOGY

2.1. Requirement Gathering and Analysis

To ensure the successful development of a mobile research app for Diabetic Retinopathy and Age-related Macular Degeneration detection and classification, a comprehensive requirement gathering process was conducted in collaboration with Prof. M. Maduwanthi Dissanayake, an experienced ophthalmologist and a professor at University of Colombo with expertise in eye disease diagnosis. The primary objective of this requirement gathering process was to align the app's features and functionalities with the specific needs and expectations of medical professionals and patients involved in eye care.

By gathering these requirements in collaboration with Prof. Maduwanthi, we develop a mobile app that meets the specific needs of medical professionals and patients in the field of diabetic retinopathy and age-related macular degeneration diagnosis while adhering to industry regulations and standards. This collaborative approach ensures that the app will contribute significantly to the early detection and management of eye diseases, ultimately improving patient outcomes and healthcare delivery.

2.2. Feasibility study

2.2.1. Technical Feasibility

Members in the research project should have a working knowledge of mobile app development, software architectures, and frameworks.

2.2.2. Economic Feasibility

The mobile application shouldn't have any mistakes or failures. The sub components must be more dependable, high-performing, and cost-effective. Resources and requirements for the components are not very expensive.

2.2.3. Scheduling Feasibility

Each task must be completed on time, with higher accuracy results, and the proposed application must be finished within the provided time frame.

2.2.4. Operational Feasibility

A member should be in charge of each stage of the software life cycle, with the requirement analysis phase receiving special consideration. All outlined user requirements should be satisfied by the finished product.

2.3. Materials and methods

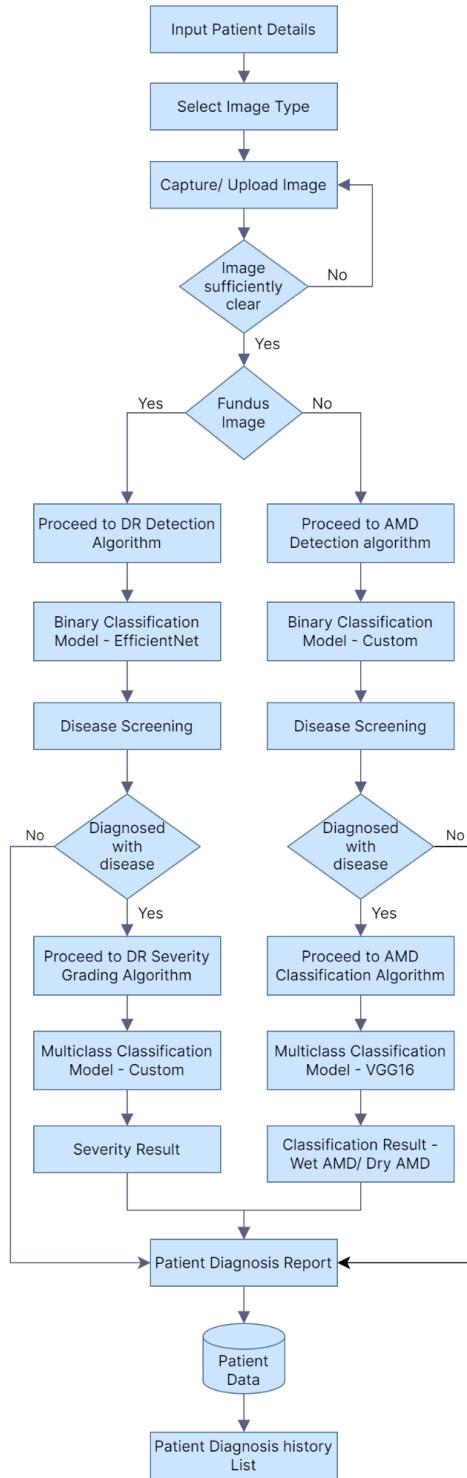


Figure 1: System Overview Diagram

The implemented system provides the capability for registered users to both capture and upload retinal images. The images are transmitted to a backend server hosted on Amazon Web Services (AWS), where the flask server is deployed. The flask server utilizes the EfficientNet model to perform image processing tasks aimed at identifying Diabetic Retinopathy (DR). The severity of diabetic retinopathy (DR), if present, will be determined by the system utilizing a distinctive model. Utilizing a bespoke model, the system will concurrently ascertain whether an optical coherence tomography (OCT) image has been diagnosed with age-related macular degeneration (AMD). The system utilizes the VGG16 model for the purpose of classifying AMD based on its severity. The system will subsequently provide users with medical advice and preventive recommendations, drawing upon the information provided. Furthermore, it is worth noting that individuals utilizing the system have the capability to closely observe the advancement of the disease during the course of the patient's treatment. Moreover, the system will employ the analysis of symptom prognosis to anticipate potential future risks.

The overall system was divided into four main components.

1. Detect Symptoms of Diabetic Retinopathy using Retinal Fundus Images
2. Grade Severity of Diabetic Retinopathy using Retinal Fundus Images
3. Detect Symptoms of Age-related Macular Degeneration using Retinal OCT Images
4. Classification of Age-related Macular Degeneration using Retinal OCT Images

2.3.1. Methodology for Detect Symptoms of Diabetic Retinopathy using Retinal Fundus Images

Preprocessing, a vital step preceding model training, involves several crucial aspects. Firstly, we standardized the dimensions of all images to a uniform 224x224 pixel resolution. Secondly, we normalized pixel values to a range between 0 and 1. This normalization aids gradient-based optimization during model training. To enhance image quality, we applied a series of advanced techniques including contrast enhancement, noise reduction, and histogram equalization. Furthermore, data augmentation, an indispensable strategy for diversifying our training dataset without acquiring new data, involved random rotations, flips, and translations. These steps collectively ensured that our dataset was well-prepared for model training, with minimized noise and standardized attributes.

In the domain of model architecture, our approach incorporates TensorFlow and Keras frameworks, forming the backbone of our deep learning model. The foundation of our model lies in EfficientNetB3, a pre-trained Convolutional Neural Network (CNN). Leveraging pre-trained weights empowers the model to effectively extract high-level features from retinal fundus images. Notably, we opted to exclude the top classification layers of EfficientNet, which are originally designed for the ImageNet dataset. This choice strikes a balance between computational efficiency and performance, aligning with our goal of making the model suitable for mobile applications.

To bolster the model's capacity to learn intricate features from retinal fundus images, we introduced additional layers on top of the EfficientNetB3 base model. Batch normalization was applied to normalize activation values, enhancing convergence during training. A bottleneck Dense layer, featuring 256 units, was introduced to extract essential features from the base model's output. To combat overfitting and encourage the model to learn more robust representations, we integrated regularization techniques, including L1 and L2 regularization. A Dropout layer with a 0.45 dropout rate was employed to further prevent overfitting during training. The output layer, culminating in a Dense layer with a softmax activation function, is responsible for generating predictions related to Diabetic Retinopathy detection.

In the training and optimization phase, we exposed the model to the preprocessed retinal fundus images. This phase is characterized by iterative parameter adjustments aimed at minimizing the loss function. With a learning rate of 0.001, we employed the Adamax optimizer, a choice known for effectively updating model weights and biases. The model underwent rigorous training, fine-tuning its parameters to achieve accurate detection of Diabetic Retinopathy symptoms. Regularization techniques played a pivotal role in enhancing model performance.

Finally, model evaluation was conducted meticulously. We subjected the trained model to separate validation and test datasets, meticulously avoiding any overlap with the training data to ensure unbiased assessments. Our evaluation metrics encompassed not only accuracy but also precision, recall, and F1-score, providing a holistic evaluation of the model's diagnostic accuracy. Precision was assessed by comparing the model's predictions with ground truth labels, ensuring robustness in our diagnosis.

2.3.2. Methodology for Grade Severity of Diabetic Retinopathy using Retinal Fundus Images

For this research study, the retinal fundus image dataset was sourced from the Asia Pacific Tele-Ophthalmology Society 2019 Blind Detection (APROS 2019 BD). The dataset was divided into training and validation sets, with 80% for training and 20% for validation. The division was determined using TensorFlow's ImageDataGenerator class. The images were resized to a standard resolution of 48x48 pixels, maintaining grayscale color mode to retain essential features and reduce computational complexity.

The research developed a deep learning model using TensorFlow and Keras, focusing on image processing tasks. The model's architecture includes two convolutional layers, each with a kernel size of 3x3, for feature extraction. MaxPooling layers are introduced to downscale the representation and reduce dimensions, making the model more efficient. Dropout layers are used for regularization, reducing overfitting by randomly turning off a fraction of neurons during each training update. The flattened layer transforms the 2D matrix output into a 1D array or vector, crucial for the dense layer.

The final layer is the dense layer, fully connected, designed with five units corresponding to one of the five severity classes of diabetic retinopathy. A softmax activation function is applied to give it a probability distribution over the five classes, with the class with the highest probability being considered the model's prediction.

The model was compiled using the Adam optimizer, known for its high performance, small requirements, and suitability for problems with large amounts of data and parameters. Given the nature of the various classes of matter, a categorical cross-entropy loss function. The model was then trained on the preprocessed dataset for five epochs. The model parameters were adjusted iteratively to minimize the loss function, optimizing the model's capability to accurately detect symptoms of diabetic retinopathy from the retinal fundus images. It was then evaluated using a separate validation set, and the model's performance was assessed.

2.3.3. Methodology for Detect Symptoms of Age-related Macular Degeneration using Retinal OCT Images

The dataset, obtained from Kaggle, consisted of 15,900 OCT images, with 7,950 images classified as AMD and 7,950 as healthy. The images were resized into 224x224 pixels, then made grayscale, and had their pixel values normalized to a range of 0 to 1 to preprocess the data. We obtained a balanced representation by choosing 2,300 samples per class for the training set, 300 samples per class for the validation

set, and 500 samples per class for the test set. Mentioned samples came from the related class directories and were chosen at random. To enhance model generalization, we utilized the ImageDataGenerator from the Keras library for data augmentation. This involved applying rotation, shifts, zooming, and flipping to the training data. The ImageDataGenerator was fitted to the training data, enabling real-time augmentation during model training. During the training process, we used a batch size of 32. We generated augmented training and validation data using the fitted ImageDataGenerator, and for the test data, no augmentation was applied.

A convolutional neural network (CNN) was used to detect AMD symptoms in retinal OCT images. The CNN architecture consisted of multiple layers: three 2D convolutional layers with increasing filter sizes (32, 64, and 128), each followed by max-pooling layers to reduce spatial dimensions. The feature maps were flattened and fed into a fully connected layer with 128 neurons and ReLU activation. A dropout layer with a dropout rate of 0.5 was employed to prevent overfitting. The output layer had a single neuron with sigmoid activation for binary classification. The model was compiled with the Adam optimizer and binary cross-entropy loss, and accuracy was used as the evaluation metric. This model design aimed to effectively capture relevant patterns and features in retinal OCT images to detect AMD symptoms accurately.

We used a deep learning approach to train a convolutional neural network (CNN) on a preprocessed and augmented retinal OCT image dataset. The dataset was divided into training and validation sets, with an 80:20 ratio. The model was trained for 20 epochs using the Adam optimizer and specified batch size. We monitored the model's performance using training and validation loss and metrics like accuracy. The training process involved adjusting the model's architecture and hyperparameters to optimize performance. By iteratively refining the model, we aimed to create an accurate and reliable system for detecting AMD symptoms from retinal OCT images.

2.3.4. Methodology for Classification of Age-related Macular Degeneration using Retinal OCT Images

Data gathering, preprocessing, model development, model evaluation, ethical considerations, and statistical analysis will be the main parts of the research project. Several sources, including open-access databases and exclusive ophthalmology practices, will be used to gather a sizable dataset of OCT images. The dataset will contain wet and dry AMD cases along with healthy controls. To ensure accuracy, the labels will be applied to the images following the categories they belong to.

We have employed a thorough and multidimensional data collection approach to produce a complete and varied dataset for classifying age-related macular degeneration

(AMD) using Optical Coherence Tomography (OCT) images. This project draws from several public and private sources, including ophthalmology clinics, to construct a comprehensive and representative dataset.

Our dataset includes information from various sources, ensuring that healthy controls and AMD patients are adequately represented. We have drawn on widely used datasets that have significantly contributed to medical image analysis research to achieve this. Additionally, through partnerships with private ophthalmology practices, we can access an extensive collection of clinical OCT images in actual medical settings. Combining these sources adds a wide variety of examples to the dataset, enriching it.

Dry AMD, Wet AMD, and Normal retina are the three separate groups into which the cases are painstakingly divided in the dataset. Each classification is essential to capturing the complete range of AMD pathology. While Wet AMD refers to the mature stage involving choroidal neovascularisation, Dry AMD defines the early set of AMD characterized by the buildup of drusen. The model can distinguish between sick and healthy circumstances using the Normal retina category as a crucial benchmark.

The process of constructing a robust classification model for AMD is supported by thorough data preprocessing and augmentation techniques. The aforementioned crucial stages guarantee the excellence and variety of our dataset and establish the foundation upon which a resilient and flexible model is built.

A significant problem in categorizing medical images is a class imbalance, which exists by nature in our dataset. We use the concept of class weight computation to solve this problem. During model training, this method balances out the AMD categories of Dry AMD, Wet AMD, and Normal retina. By inversely scaling the class frequencies, we give underrepresented classes more weight, ensuring that our model considers each category equally.

Our dataset's rigorous curation is its main strength. We rely on various sources, such as open-source data sets and private ophthalmology practices, to create a comprehensive database of AMD patients and healthy controls. This thorough approach guarantees that our dataset accurately represents the range of AMD disorders and healthy retinas. We

methodically compile the paths to specific photographs inside each category to keep our dataset organized and intact.

By augmenting, we fortify our model against overfitting and improve its generalization performance. Using the Keras ImageDataGenerator, we expand the training dataset using various methods.

A DL model will be produced from a single OCT image to differentiate between wet and dry AMD. To learn and extract useful features from the OCT images, the model will be trained using a combination of convolutional neural networks (CNNs) and recurrent neural networks (RNNs). The proposed model's architecture will be optimized using various hyperparameter tuning techniques to achieve maximum performance. It will be contrasted with other recognized diagnostic methods to assess the efficacy and accuracy of the developed model.

A crucial stage in our research is assessing the suggested AMD classification model. Evaluating the model's performance and utility in the real world goes beyond merely training it. To do this, we'll use a broad range of evaluation indicators that provide an in-depth understanding of the model's capabilities. These measurements include sensitivity, specificity, accuracy, and the F1 score. Specificity defines a model's power to accurately identify true negatives, whereas sensitivity measures how well it can recognize actual positive cases. Precision measures prediction accuracy by looking at the percentage of accurate positive forecasts among all optimistic

predictions. The F1 score, a well-balanced combination of precision and recall, offers a comprehensive picture of the model's performance.

A dedicated test dataset will systematically evaluate the model's generalizability in addition to these criteria. This dataset tests the model's ability to apply training data to new samples. It lets us test the model's robustness and clinical efficacy outside training. The model's performance will also be benchmarked against known diagnostic procedures to ensure it meets or exceeds criteria.

The main objective of model evaluation is to assess our suggested deep learning approach's efficacy in detecting and classifying wet and dry AMD early. This stage

offers empirical proof supporting the model's clinical applicability and capability to improve diagnostic procedures.

2.4. Commercialization aspects of the product

In the pursuit of advancing our mobile application, we have not only engineered a robust and innovative tool, but also established a solid foundation for a prosperous commercialization strategy. The application we have developed, with the intention of tackling a prominent market demand, possesses the capability to deliver substantial benefits to both its users and potential investors. Presented here is our comprehensive strategy to effectively commercialize this groundbreaking innovation.

2.4.1. Target Market Segmentation

The initial step in our research endeavor entails the identification and segmentation of our intended target audience. In light of the inherent characteristics of our application, it is imperative to acquire a comprehensive comprehension of the demographics, behaviors, and preferences exhibited by prospective users. Our research will primarily concentrate on healthcare professionals, patients who are currently managing the specific medical condition that our application aims to address, and pertinent stakeholders within the medical domain.

2.4.2. Pricing Model

The pricing model is a crucial aspect of any business strategy as it directly impacts the profitability and competitiveness of the company. In order to develop an effective pricing model, extensive research and analysis must

The formulation of a meticulously crafted pricing model is of paramount importance in ensuring our triumph in the realm of commerce. Our proposed business model entails the implementation of a tiered subscription plan, wherein users will be granted access to a rudimentary version of our product at no cost. Additionally, we will offer a premium version equipped with enhanced features, which will be made available to users who opt for a monthly or annual subscription. The pricing structure of our app will be designed

to maintain competitiveness in the market, while also accurately reflecting the value it provides to users.

2.4.3. Marketing and Promotion

The topic of marketing and promotion is of great significance in the field of business and commerce. It involves various strategies and techniques that organizations employ to create awareness, generate interest, and ultimately drive sales for their products or services. Marketing

The significance of effective marketing cannot be overstated as it serves as the fundamental pillar of any endeavor aimed at commercialization. Our proposed approach involves the implementation of a comprehensive and diverse marketing strategy, which will incorporate various tactics such as digital advertising, social media campaigns, content marketing, and collaborations with esteemed healthcare organizations. In order to enhance the adoption rates, it will be crucial to implement a strategy of focused outreach towards medical professionals and clinics.

2.4.4. User Engagement and Retention

The topic of user engagement and retention is of utmost importance in the field of research. It is crucial to understand the factors that contribute to user engagement and retention in order to design effective strategies for enhancing user experiences and ensuring their continued participation. User engagement refers to the level

Ensuring the continuous engagement of users is of utmost importance for achieving sustained success in the long run. Continuous updates, iterative feature improvements, and a highly responsive customer support team are crucial factors in maintaining user satisfaction. The integration of gamification elements and the establishment of a

community-building framework within the application have the potential to cultivate a profound sense of belonging among its users.

The topic of data security and compliance is of utmost importance in today's digital age. As an undergraduate researcher, I am intrigued by the complexities and challenges associated with ensuring the confidentiality, integrity, and availability of data, while also adhering to various regulatory and legal requirements

In light of the intricate and confidential nature of healthcare data, our utmost focus will be directed towards ensuring robust data security measures and strict adherence to healthcare regulations. In order to establish a sense of trust among our users and ensure compliance with legal obligations, we will undertake the acquisition of essential certifications and conduct thorough audits.

In addition to the acquisition of user subscriptions, our research will delve into the exploration of alternative avenues for monetization. One potential avenue for generating significant revenue could involve the licensing of our cutting-edge technology to esteemed healthcare institutions, esteemed research organizations, or reputable insurance companies. Moreover, the establishment of strategic alliances with pharmaceutical companies to foster research collaborations or gain access to valuable data insights has the potential to generate a significant source of revenue.

The process of user feedback and iteration plays a crucial role in the development and improvement of various systems and products. By actively seeking and incorporating user feedback, researchers can gain valuable insights into the strengths and weaknesses of their designs. User feedback serves as a valuable source of information

The central focus of our commercialization strategy lies in the pursuit of continuous improvement, which is driven by the valuable feedback provided by our users. The implementation of user feedback channels will be instrumental in facilitating user engagement and fostering a collaborative environment. By leveraging these channels, we will be able to gather valuable insights and perspectives from users, which will serve as a catalyst for the ongoing refinement and improvement of the application. The

utilization of an iterative approach in the development of this application serves to maintain its relevance and competitiveness in the market.

In light of our current endeavor to commercialize our mobile application, we are motivated by the conviction that our innovative solution has the potential to significantly influence the healthcare sector. Through the implementation of a meticulously devised strategy, an unwavering focus on the requirements of our users, and an unwavering dedication to excellence, our objective is to not solely attain commercial prosperity, but also to enhance the well-being of individuals who depend on our application. In collaboration, our efforts aim to enhance the accessibility, efficiency, and effectiveness of healthcare.

3. TESTING & IMPLEMENTATION

The system consists of a Flask-based backend deployed on Google Cloud Platform (GCP), utilizing an EfficientNet model for retinal image predictions. This section provides an overview of the testing methods employed to ensure the system's functionality and details the implementation of the Flask backend, the EfficientNet model, and the deployment on Google Cloud Platform. Additionally, it highlights the performance and user interface aspects of the mobile application.

3.1. Testing Methodology

3.1.1. Unit Testing

Unit testing was conducted to ensure the functionality of individual components of the system, including the Flask API, the EfficientNet model, and any other critical backend modules. Python's unittest library was employed to create and run unit tests, assessing the correctness of the API endpoints and the accuracy of predictions.

3.1.2. Integration Testing

Integration testing focused on evaluating how the different components of the system interacted with each other. This included testing the communication between the mobile application and the Flask API, as well as the integration of the Flask application with the EfficientNet model.

3.1.3. End-to-End Testing

End-to-end testing aimed to assess the complete functionality of the system. It involved sending retinal images from the mobile application to the Flask API hosted on GCP, receiving predictions, and displaying the results to the user.

3.2. Product Release

The product release plan for our mobile application designed for diabetic retinopathy detection is a critical milestone in our research journey. Following extensive development, rigorous testing, and collaboration with healthcare professionals and experts in the field, we are excited to outline our strategy for bringing this innovative solution to the market.

In the initial phase, we will conduct alpha testing with a select group of ophthalmologists and medical practitioners to assess the application's functionality and identify any major issues or bugs. This phase will help us refine the core features and address critical concerns.

Building on the feedback from the alpha testing phase, we will launch a beta version of the application to a wider group of users, including both medical professionals and patients. This phase will focus on fine-tuning the user experience, optimizing performance, and gathering additional feedback for improvement.

Ensuring compliance with relevant healthcare regulations and data privacy standards is paramount. During this phase, we will work closely with regulatory authorities to obtain necessary approvals and certifications, ensuring that our application meets the highest standards of security and reliability.

Following successful testing and regulatory compliance, we will release the mobile application to the broader market. This will involve a comprehensive marketing and outreach campaign to raise awareness among healthcare providers, patients, and relevant stakeholders.

Post-launch, our commitment to improvement and innovation remains unwavering. We will actively monitor user feedback, conduct regular updates, and explore opportunities for enhancements, new features, and expanded functionalities to keep our application at the forefront of diabetic retinopathy diagnosis and care.

Throughout this product release plan, our overarching goal is to contribute significantly to the early detection and management of diabetic retinopathy, thereby improving patient outcomes and healthcare delivery. We are dedicated to ensuring that our mobile application remains a valuable and reliable tool for medical professionals and patients in this critical domain.

3.3. Implementation Details

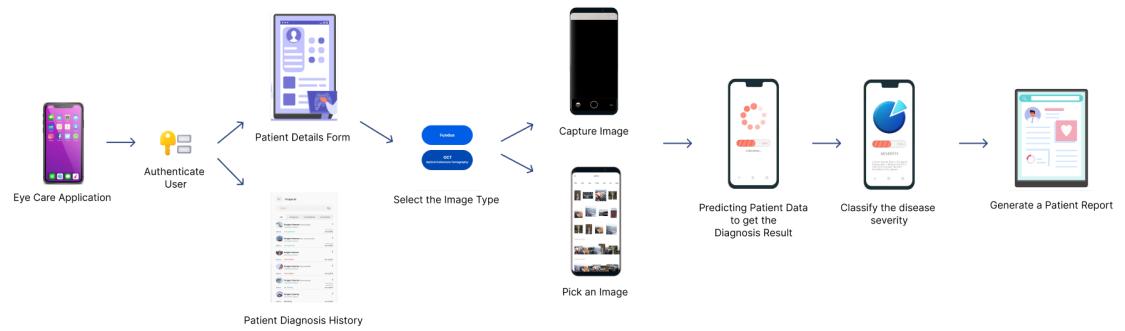


Figure 2: User Flow Diagram

3.3.1. Flask Backend

The Flask backend was developed to handle incoming image uploads from the mobile application, preprocess the images, and pass them to the EfficientNet model for prediction. The backend also incorporated error handling, authentication, and logging for robust performance. It exposed the following endpoints:

POST /predict: Accepts image uploads, preprocesses them, and returns the predicted diabetic retinopathy grade.

3.3.2. React Native Frontend

A crucial component of our implementation plan is the frontend development of our "EyeCare" mobile application. We have used React Native, a well-known and incredibly flexible framework, to provide cross-platform interoperability and seamless user experiences. With React Native, we can create a single codebase that works flawlessly

on both the iOS and Android platforms, increasing development productivity and lowering maintenance costs.

The use of Expo, a well-liked and developer-friendly toolkit, improves our frontend development procedure even more. Expo simplifies the development process by giving users the tools they need to complete tasks like developing, testing, and deploying the application. Through this connectivity, we can bring new features and updates to our users more quickly and easily.

3.3.3. Google Cloud Platform

The Flask application was deployed on Google Cloud Platform (GCP) for scalability, reliability, and ease of management. Google App Engine was chosen as the hosting environment due to its simplicity and scalability features. The application was containerized using Docker and deployed on the App Engine Flexible Environment.

3.3.4. User Interface and Mobile Application

A user-friendly mobile application was developed to facilitate the easy upload of retinal images for diabetic retinopathy prediction. The application was designed to provide users with clear and informative results, including the predicted grade of diabetic retinopathy and guidance on the next steps.

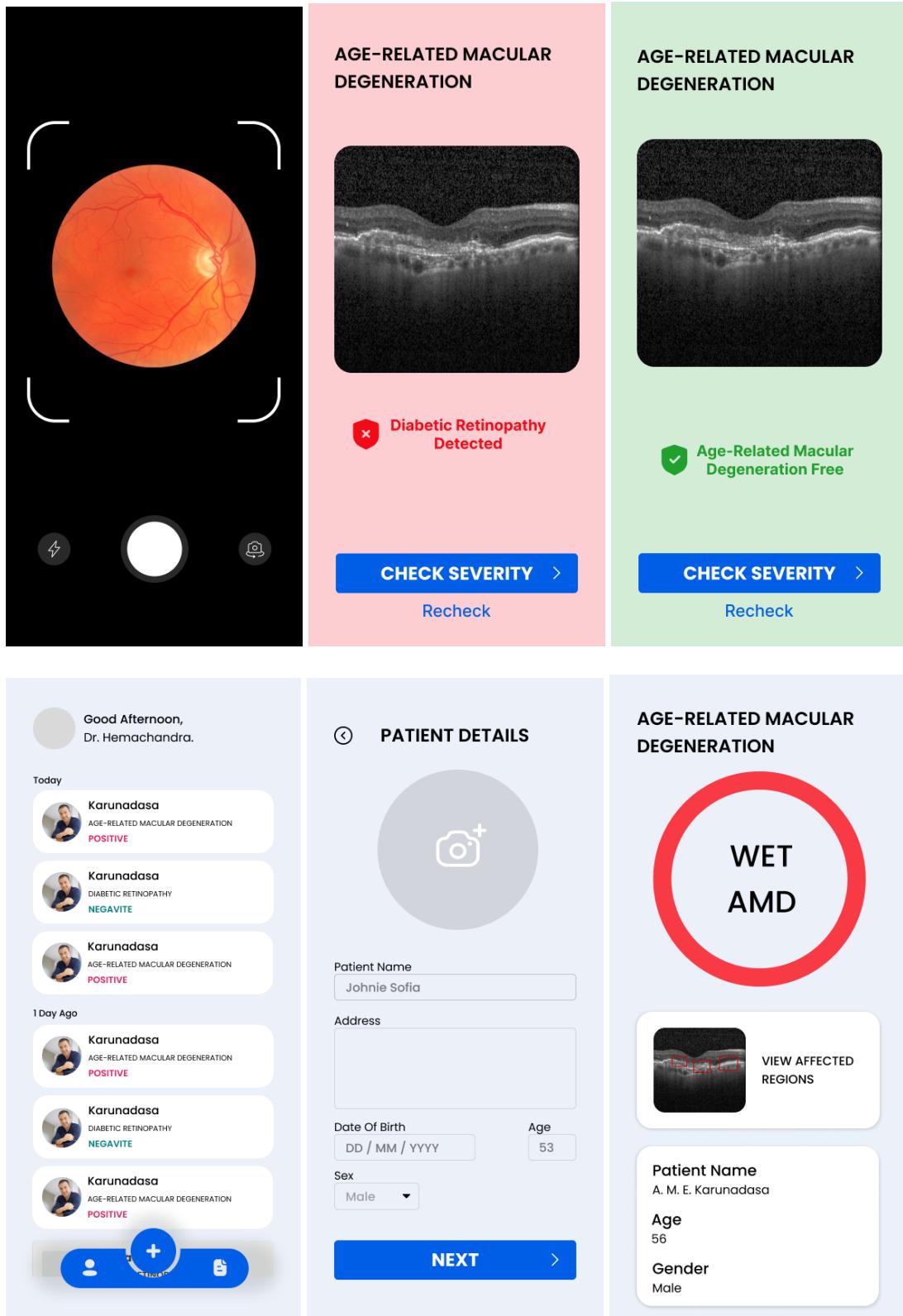


Figure 3: UIs of the Application

3.4. Results and Performance

Component of the System	Accuracy	Loss
Detect DR	97.4%	4.52%
Grade Severity of DR	71.06%	7.76%
Detect AMD	99.1%	1.61%
Classification of AMD	95.42%	8.05%

Table 2: Model performance metrics for the complete system

3.4.1. Detect Symptoms of Diabetic Retinopathy using Retinal Fundus Images

The EfficientNet model was used in classifying Diabetic Retinopathy from retinal fundus images. This model was selected because of its proven success in image classification tasks. EfficientNet models have demonstrated outstanding performance with relatively fewer parameters, making them suitable for studies where computational resources are limited.

The model structure consisted of multiple convolutional layers, leveraging the efficient architecture to learn hierarchical features from retinal fundus images. It also incorporated various pooling and regularization layers, ensuring the model's robustness and generalization capabilities.

After training the EfficientNetB3 model on our dataset, we achieved an accuracy of approximately 97.4%. This indicates the effectiveness of the proposed model in accurately diagnosing Diabetic Retinopathy using retinal fundus images.

3.4.2. Grade Severity of Diabetic Retinopathy using Retinal Fundus Images

A custom model was developed to grade the severity of Diabetic Retinopathy since the need for fine-grained classification.

The custom model architecture included two convolutional layers, each followed by a max pooling layer to downsample the spatial dimensions. A dropout layer was incorporated to prevent overfitting, and a flattened layer was used to reshape the data for feeding into the subsequent dense layer for classification.

Upon training the custom model on a labelled dataset of retinal fundus images, the model achieved an accuracy of approximately 71% in grading the severity of Diabetic Retinopathy, showcasing its ability to accurately classify the different stages of the disease based on retinal fundus images

3.4.3. Detect Symptoms of Age-related Macular Degeneration using Retinal OCT Images

A custom model was developed and designed to detect AMD symptoms using retinal OCT images. The custom model for OCT images comprised three 2D convolutional layers with increasing filter sizes (32, 64, and 128) to capture different levels of details. Max-pooling layers were added after each convolutional layer to reduce the spatial dimensions while preserving the most essential features.

During training on a labelled dataset of retinal OCT images, the custom model achieved an accuracy of approximately 99%. This demonstrates the effectiveness of the CNN architecture in capturing relevant patterns and features for the accurate detection of AMD symptoms.

3.4.4. Classification of Age-related Macular Degeneration using Retinal OCT Images

The proposed model employed the VGG16 model to classify Age-related Macular Degeneration using retinal OCT images. VGG16 is a widely adopted architecture with a

deep stack of convolutional layers, making it suitable for capturing intricate features from complex images.

The modified architecture removed the fully connected layers of VGG16 and introduced a novel classification layer structure. It included a flattening layer, a fully connected layer with 256 units and ReLU activation, and a dropout layer with a rate of 0.5 for regularization. The output layer consisted of three units activated by the softmax function for multi-class classification.

After training VGG16 on the OCT image dataset, we obtained an accuracy of approximately 95.42%. This showcases the efficacy of the VGG16-based architecture for accurate classification of AMD based on retinal OCT images.

4. CONCLUSION

In summary, this research introduces innovative approaches for both diabetic retinopathy and age-related macular degeneration detection. The DR study leverages machine learning and mobile health technologies to create a deep-learning-based mobile application, aiming to enhance DR diagnosis accuracy and reduce healthcare system burdens. Additionally, it explores remote screening and monitoring to preserve vision and improve patient outcomes.

The AMD research focuses on early detection and classification using a robust dataset, achieving an outstanding accuracy rate. These advancements have the potential to transform AMD diagnosis, leading to improved patient treatment, disease progression control, and better outcomes. Future developments aim to broaden the scope of AMD situations and integrate these technologies into clinical practice, ultimately raising the standard of ophthalmological healthcare delivery.

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