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

Muthukumarana M.W.A.N.C

IT20227890

B. Sc. (Hons) Degree in Information Technology Specialized in Software Engineering

Department of Computer Science and Software Engineering

Sri Lanka Institute of Information Technology
Sri Lanka

September 2023

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

Muthukumarana M.W.A.N.C

IT20227890

Dissertation submitted in partial fulfillment of the requirements for the Special Honours Degree of Bachelor of Science in Information Technology Specializing in Software Engineering

Department of Computer Science and Software Engineering

Sri Lanka Institute of Information Technology
Sri Lanka

September 2023

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.

Name	Student ID	Signature
Muthukumarana M.W.A.N.C	IT20227890	

The above candidate is carrying out research for the undergraduate Dissertation under my supervision

Signature of the supervisor Date

……………………………… ………………………..

(Mrs. Devanshi Ganegoda)

Signature of the co-supervisor Date

……………………………… ………………………..

(Mr. Jeewaka Perera)

ABSTRACT

Age-related macular degeneration (AMD) is a severe eye condition that can lead to significant loss of vision in people fifty or older. Optical coherence tomography (OCT) is an effective imaging modality for diagnosing AMD. However, manual analysis of OCT images can be time-consuming, leading to a need for automated methods for AMD detection.

This study proposes a deep learning algorithm for the automated detection of AMD from OCT images. Our approach combines two existing models and includes preprocessing techniques to enhance the image quality. The deep learning algorithm was trained and validated on a diverse dataset of OCT images, including both normal and AMD cases.

We will also develop an application that allows clinicians to upload and scan OCT images for AMD detection, integrating the trained model for real-time analysis. The application's performance was evaluated in a clinical setting involving ophthalmologists and patients. Our outcomes show that the proposed algorithm achieved high accuracy and sensitivity in classifying OCT images as normal or AMD. The application was user-friendly, efficient, and secure and received positive feedback from clinicians and patients.

Overall, this research provides a promising method for the automated detection of AMD using OCT imaging, which can enhance the efficiency and accuracy of diagnosis and treatment for this debilitating disease.

ACKNOWLEDGEMENT

I sincerely appreciate my supervisor, Mrs. Devanshi Ganegoda, for her invaluable guidance, unwavering support, and insightful mentorship throughout this research journey. Her expertise and dedication have played a pivotal role in shaping this project. I am also grateful to Mr. Jeewaka Perera, my co-supervisor, for his valuable contributions and assistance, which have greatly enriched the quality of this research. I want to acknowledge the contributions of all those who directly or indirectly supported this project, including my team members, family, and friends. Your encouragement and assistance have been instrumental in bringing this research to fruition.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

Abbreviation	Description
AMD	Age-related macular degeneration
OCT	Optical coherence tomography
DL	Deep Learning

Table 1: List of abbreviations

1. INTRODUCTION

1.1 General Introduction

Eye diseases have become a significant global public health concern due to their high prevalence and impact on people's quality of life. Age-related macular degeneration (AMD) and diabetic retinopathy are numerous debilitating eye diseases. Diabetic retinopathy is a factor of diabetes that impacts the retina and causes blindness. At the same time, AMD is a progressive degeneration of the macula, which is liable for central vision.

Age-related macular degeneration is an eye disease impacting the macula, a tiny area at the retina's centre liable for sharp, central vision. Age-related macular degeneration is the major reason for vision loss in individuals over 50 in developed countries. Early detection and intervention are critical to delay the progression of AMD and can prevent vision loss. OCT imaging is a non-invasive, high-resolution imaging approach that can provide detailed retina images, including macula.

Early detection and timely treatment of these conditions are essential to prevent irreversible damage to the eyes and preserve vision. However, traditional diagnosis and monitoring methods are time-consuming, expensive, and often require highly skilled ophthalmologists. Therefore, there is an acute need for more efficient and accurate tools to detect and annotate eye diseases, especially in low-resource settings where access to specialist care is limited.

Machine learning has emerged as an excellent approach to addressing these challenges by enabling automated analysis and interpretation of retinal images. Recently, machine-learning algorithms have been used to detect and annotate diabetic retinopathy and age-related macular degeneration. These algorithms have demonstrated high accuracy and speed, making them suitable for large-scale screening programs and clinical settings.

In this research, I will develop and evaluate a deep-learning algorithm integrated into a mobile application, that can accurately classify OCT images as usual or showing signs of Age-related macular degeneration. Specifically, we will investigate using deep-learning based algorithms like convolutional neural networks (CNN) to analyze retinal images and automatically identify symptoms of these diseases.

1.2 Background literature

Eye diseases, particularly diabetic retinopathy and age-related macular degeneration are the significant causes of blindness worldwide. Treatment and Early detection of these diseases are vital for preventing vision loss and improving the quality of life of affected individuals. In recent years, medical imaging technology and machine learning have provided new opportunities for efficient and accurate screening and diagnosis of eye diseases. This literature survey aims to provide an overview of the current knowledge on machine learning for detecting and annotating eye diseases using retinal images, explicitly focusing on classifying OCT images as usual or showing signs of age-related macular degeneration.

The literature survey identified several machine-learning approaches for detecting and annotating eye diseases using retinal images. Specifically, deep-learning models like convolutional neural networks (CNN) have shown optimistic results for classifying OCT images as usual or showing signs of age-related macular degeneration. Those models are trained on large datasets of annotated OCT images and can accurately detect subtle changes in the retinal layers that indicate the existence of age-related macular degeneration.

In recent studies, detecting and classifying ocular diseases using deep learning algorithms, such as age-related macular degeneration, has shown great potential. Lee et al. (2018) [1] found that deep-learning models were highly influential in classifying normal and AMD OCT images. The study used a fine-tuned VGG16 convolutional neural network [2] as the deep-learning model to achieve an accuracy of 86.64% with a sensitivity of 83.64% and a specificity of 92.54%.

In a study presented in 2020, Srivastava et al [3] focused on the role of the choroid [4] in automated age-related macular degeneration detection from OCT images. The study investigated choroid layer impact on the accuracy of deep learning models and found that incorporating the choroid layer improved the performance of the model in detecting AMD. The study proposed ResNet50 as the deep learning model to achieve an accuracy of 95.82% with a sensitivity of 95.45%, a specificity of 95.91%, and an AUC of 0.9942.

Moreover, Govindaiah et al. (2018) [5] proposed a new method for automated screening of AMD using ensemble deep neural networks. They developed a multi-stage screening algorithm that uses multiple CNNs [2], [6], [7] to detect and classify AMD in OCT images. Their proposed method achieved high accuracy and sensitivity in detecting AMD and outperformed other state-of-the-art techniques. Their study suggests that a multi-stage approach to AMD detection can improve the accuracy and reliability of clinical diagnosis.

1.3 Research Gap

Age-related macular degeneration (AMD) is an adequate public health concern. Early detection and treatment of AMD are critical to preserving visual function and preventing vision loss, as late-stage AMD is irreversible and leads to permanent vision impairment. Optical coherence tomography (OCT) [8] has appeared as a non-invasive, reliable, and widely used imaging technique for diagnosing and monitoring AMD. Various research approaches have been attempted using machine learning to build systems to detect and identify eye diseases.

However, existing approaches [9], [10] for analyzing OCT images for AMD detection are computationally intensive, requiring high-end computing resources, and are therefore not feasible for use in clinical settings or resource-limited areas.

Our proposed study aims to develop a novel approach to detect AMD using OCT images by combining two existing models. The novelty of this approach is to create a lightweight model that reduces computational requirements while maintaining high accuracy, making it feasible to develop a mobile app for AMD detection in clinical settings and resource-limited areas. By developing a more efficient and accurate model for AMD detection using OCT images, this study aims to improve the feasibility and accessibility of AMD screening, diagnosis, and management, leading to earlier detection and improved patient outcomes.

2. RESEARCH PROBLEM

Age-related macular degeneration (AMD) impacts millions worldwide, particularly those over fifty. AMD is an adequate reason for vision loss and blindness, potentially severely impacting patients' quality of life. Currently, the diagnosis of AMD involves a manual examination of retinal images by trained specialists, which is expensive and time-consuming.

Optical coherence tomography imaging has appeared as a promising tool for AMD detection, offering high-resolution and non-invasive visualization of retinal structures. OCT imaging produces cross-sectional retina images that can reveal abnormalities and changes in the macular region characteristic of AMD. However, accurate interpretation of OCT images remains challenging due to the complexity and variability of retinal features and limitations in current analysis methods.

The current methods for OCT image analysis involve manual measurement of retinal thickness and identification of characteristic features such as drusen, pigment changes, and neovascularization. These methods are time-consuming, leading to delayed or incorrect diagnoses. Furthermore, manual OCT image analysis is limited by the subjective nature of the research and the need for extensive training to develop the necessary expertise.

Therefore, the research problem for this component is to develop automated image analysis algorithms to improve the accuracy and efficiency of AMD detection using OCT images. The algorithms should address technical challenges such as image segmentation, feature extraction, and algorithm reliability to ensure robust and consistent performance. This research aims to develop a tool that can assist optical specialists in accurately and efficiently diagnosing AMD, leading to improved patient outcomes and reduced healthcare costs

3. RESEARCH OBJECTIVES

3.1. Main Objectives

This study's main objective is to develop and validate a machine-learning algorithm that can accurately detect AMD using OCT images. Moreover, using an extensive dataset of OCT images, the algorithm will be trained and utilize advanced deep-learning techniques to learn distinctive features indicative of AMD. The goal is to achieve high accuracy in detecting AMD while minimizing false positive and false negative rates. The algorithm will be evaluated using a separate test dataset to measure its sensitivity, specificity, precision, and accuracy performance. The aim is to provide a reliable and automated tool for early detection and diagnosis of AMD, which can assist ophthalmologists in making clinical decisions and improve patient outcomes.

3.2. Sub Objectives

- To collect a dataset of OCT images for training the machine learning model.
- Preprocess and clean OCT images to ensure high-quality input data.
- Develop a machine learning model for accurate detection of AMD using deep learning.
- Optimize the machine learning model for fast and accurate AMD detection with minimal computational resources.

4. METHODOLOGY

4.1 Methodology

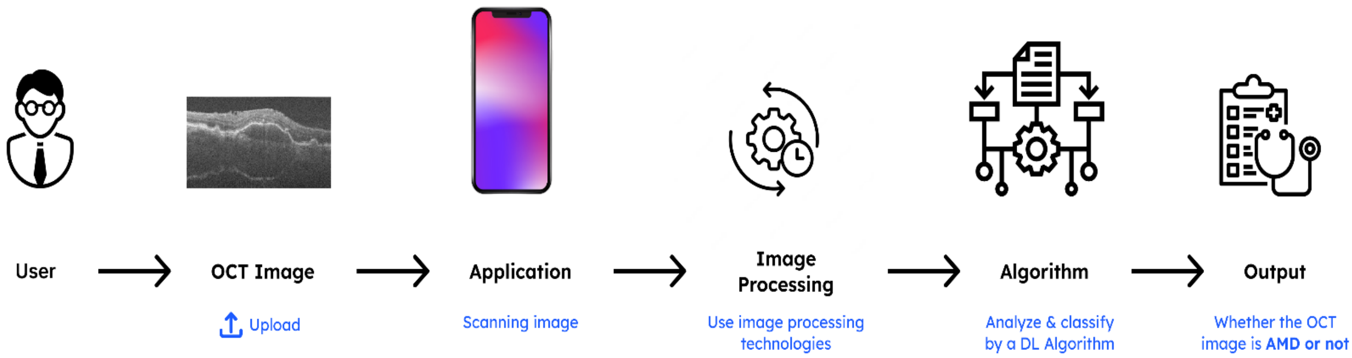

Figure 1: system overview diagram

- **User Interaction**: The process begins with the user interacting with the mobile application. The user's primary action is to upload Optical Coherence Tomography (OCT) images.

- **Data Transmission**: Once the user uploads an OCT image, the application takes charge of transmitting this image data to the backend servers for further analysis.

- **Backend Processing**: The application's backend is critical in processing the received image data. Utilizing image processing technologies, it prepares the image for analysis. This step involves various pre-processing techniques to optimize the image for subsequent analysis.

- **Deep Learning Algorithm**: The heart of the analysis lies in applying a Deep Learning (DL) algorithm. This algorithm has been designed and trained to differentiate between AMD (age-related macular degeneration) and standard OCT images. It meticulously examines the image, leveraging its learned knowledge to determine accurately.

- **Result Communication**: Once the DL algorithm completes its analysis, it generates a result indicating whether the uploaded OCT image exhibits signs of AMD or is classified as usual. This result is then communicated back to the user through the application interface.

4.1.1 Problem Statement

This research component addresses the critical challenge of age-related macular degeneration (AMD) detection in Optical Coherence Tomography (OCT) images. AMD is a prevalent and potentially sight-threatening eye condition that demands early diagnosis and intervention. Our research focuses on developing a robust algorithm for accurately detecting AMD, enabling timely medical intervention to mitigate its progression and impact.

4.2.1 Data Collection and Preprocessing

The foundation of this research was laid by acquiring a diverse and extensive dataset of OCT images sourced from Kaggle. This dataset boasted over 15,000 images, carefully curated to maintain a balance of 7,660 AMD images and 7,650 normal OCT images. This meticulous curation ensured a representative distribution of both classes, mitigating potential class imbalance issues that could compromise the model's performance. A series of essential preprocessing steps were meticulously applied to prepare the dataset for training. Firstly, all images were uniformly resized to a common resolution of 224x224 pixels, aligning them for subsequent analysis.

Furthermore, images were transformed into grayscale, simplifying the dataset while retaining crucial diagnostic information pertinent to AMD detection. Lastly, pixel values underwent normalization, scaling to the standardized range of [0, 1]. This normalization ensured data consistency and uniformity, paving the way for effective model training. The dataset was divided into three subsets: training, validation, and testing. A pivotal consideration during this division was the equal distribution of AMD and normal images in each subset. This class-balanced approach was instrumental in facilitating the model's ability to learn effectively from both classes, circumventing biases that could arise from uneven class representation.

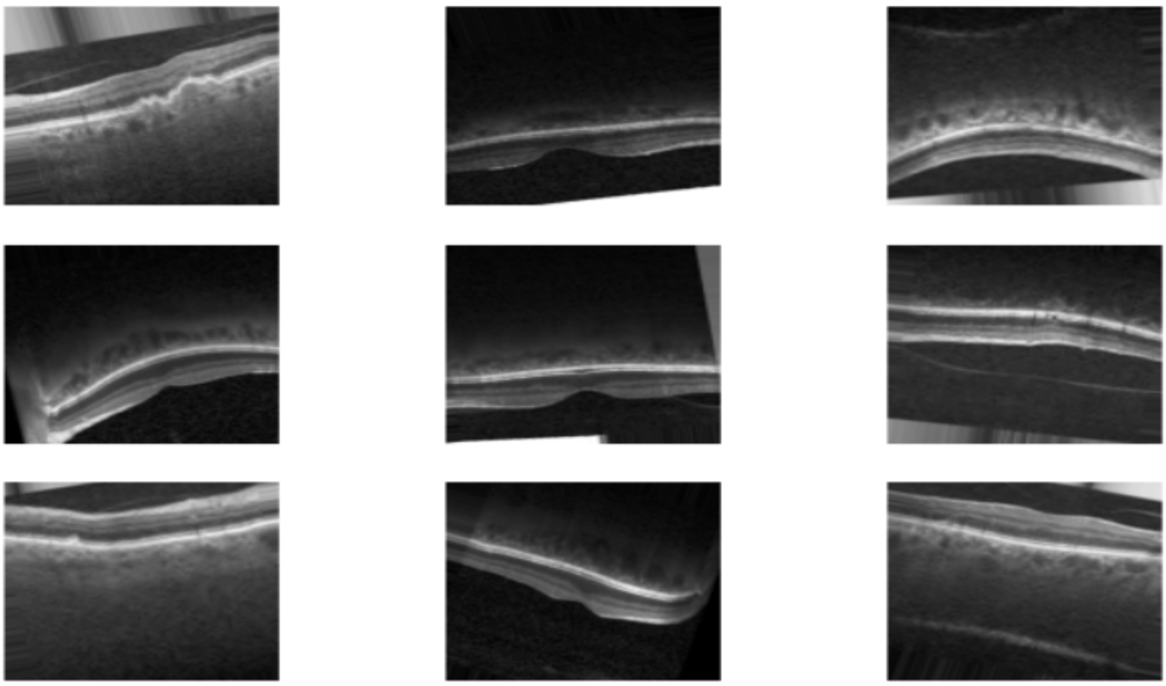

Figure 2: OCT Images After Image Preprocessing

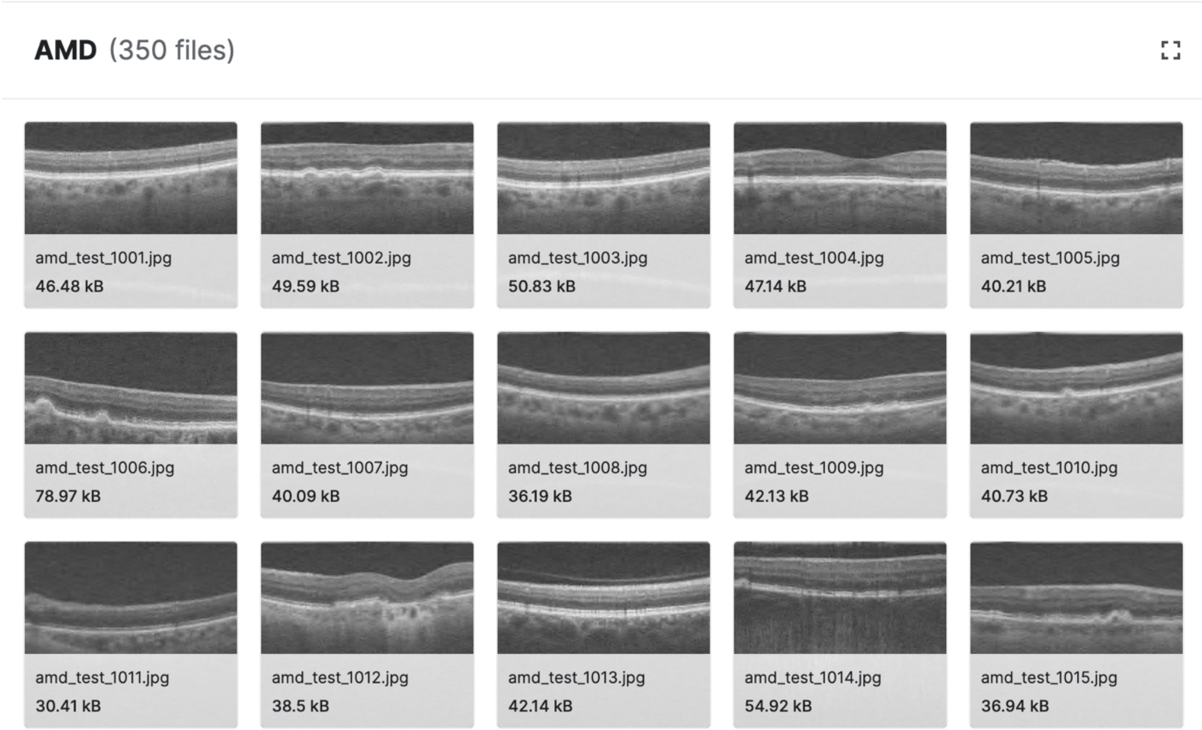

Figure 3: AMD OCT Images

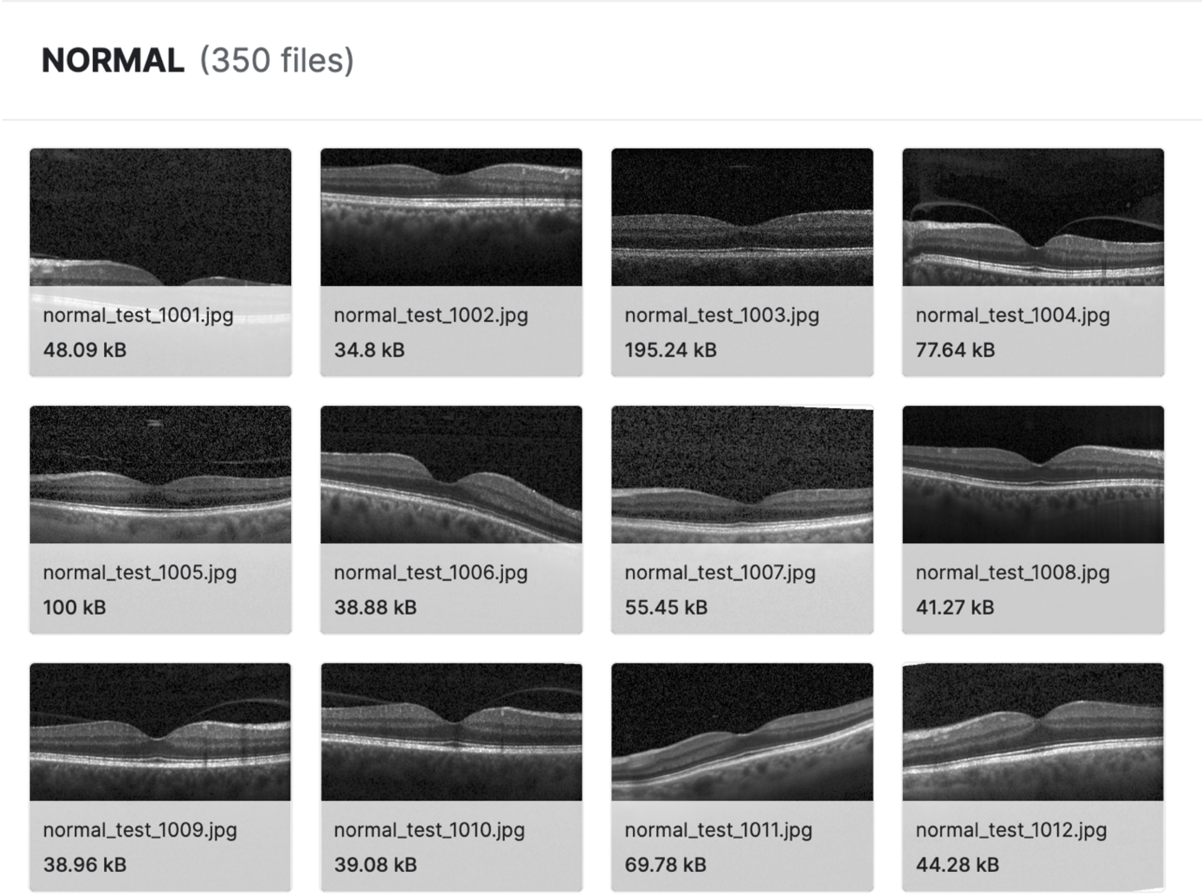

Figure 4: Normal OCT Images

4.2.2 Data Augmentation

A suite of data augmentation techniques was systematically employed to enhance the model's generalization capabilities and robustness. The cornerstone of this augmentation process was Keras ImageDataGenerator. It orchestrated a symphony of transformations, including random rotations, horizontal and vertical shifts, zooming, and horizontal flipping. This augmentation approach endowed the model with adaptability and resilience to diverse clinical scenarios by simulating variations typically encountered in real-world OCT images.

```
from keras.preprocessing.image import ImageDataGenerator

# Create an ImageDataGenerator instance for data augmentation
datagen = ImageDataGenerator(
    rotation_range=20,
    width_shift_range=0.1,
    height_shift_range=0.1,
    zoom_range=0.1,
    horizontal_flip=True,
    vertical_flip=True,
    fill_mode='nearest'
)

# Fit the ImageDataGenerator to the training data
datagen.fit(X_train.reshape(-1, 224, 224, 1))

# Define batch size
batch_size = 32

# Create a new generator for augmented training data
train_generator = datagen.flow(X_train.reshape(-1, 224, 224, 1), y_train, batch_size=batch_size)

# Create a new generator for augmented validation data
val_generator = datagen.flow(X_val.reshape(-1, 224, 224, 1), y_val, batch_size=batch_size)

# Create a new generator for test data (no data augmentation)
test_generator = ImageDataGenerator().flow(X_test.reshape(-1, 224, 224, 1), y_test, batch_size=batch_size)

# Print the shape of the augmented data and labels
print('Augmented training data shape:', train_generator[0][0].shape)
print('Augmented training labels shape:', train_generator[0][1].shape)
print('Augmented validation data shape:', val_generator[0][0].shape)
print('Augmented validation labels shape:', val_generator[0][1].shape)
print('Test data shape:', test_generator[0][0].shape)
print('Test labels shape:', test_generator[0][1].shape)
```

Figure 5: Data Augmentation

4.2.3 Model Training

The pivotal success of this AMD detection algorithm hinges significantly on the meticulous design of the model architecture. This architectural framework serves as the bedrock upon which this deep learning system operates, emphasizing the immense potential of Convolutional Neural Networks (CNNs). Its primary objective is to facilitate precise image classification, an indispensable requirement in medical image analysis.

4.2.3.1 CNN Architecture

At the very core of this model's architecture resides the Convolutional Neural Network (CNN). CNNs are revered in image analysis for their unmatched performance in tasks involving image classification. What sets them apart is their innate capability to extract complex hierarchical features from images autonomously. This inherent ability harmoniously aligns with this overarching goal – to discern and identify subtle and nuanced indicators of age-related macular degeneration (AMD) within optical coherence tomography (OCT) images.

```
from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout

# Define the model architecture
model = Sequential()
model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(224, 224, 1)))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(128, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(1, activation='sigmoid'))

# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

model.summary()
```

Figure 6: Model Architecture

4.2.3.2 Layer Configuration

This model's architectural configuration is a meticulously devised arrangement of layers endowed with a specific and indispensable role in feature extraction and abstraction. This comprehensive configuration encompasses:

- **Convolutional Layers:** As the foundation for feature extraction, these layers resemble filters that sweep across the input image. This model incorporates a meticulously designed convolutional layer, thoughtfully complemented by max-pooling layers. This architectural hierarchy is pivotal in capturing features across a spectrum of spatial scales, ranging from the finest-grained details to more comprehensive patterns inherent in the OCT images.

- **Activation Functions (ReLU):** We judiciously introduce Rectified Linear Unit (ReLU) activation functions within each of these convolutional layers. This choice is pivotal, as these non-linear activation functions substantially augment this model's capacity to identify and interpret complex patterns within the images. Their presence significantly contributes to the model's ability to differentiate between AMD-affected and normal OCT images.

4.2.3.3 Flattening and Fully Connected Layers

Beyond the initial feature extraction stages, this model seamlessly transitions into fully connected layers, where abstract, high-level features are meticulously distilled. This pivotal phase encompasses:

- **Fully Connected Layers:** As the central hubs for capturing abstract, high-level features within the data, these layers are enriched with ReLU activation functions. Their role is pivotal in identifying the nuanced distinctions that delineate AMD-affected OCT images from their normal counterparts. At this stage, the architecture's depth and complexity empower the model to discern intricate patterns essential for accurate classification.

- **Dropout Layer:** A critical protective mechanism against overfitting, a dropout layer with a dropout rate of 0.5 is thoughtfully introduced. Overfitting occurs when the model becomes excessively specialized in recognizing patterns within the training data, impairing its ability to generalize to unseen data. By selectively deactivating connections during the training process, the dropout layer ensures that the model fosters generalization, avoiding an overreliance on specific patterns in the training dataset.

4.2.3.4 Final Classification Layer

The zenith of this model architecture culminates in the final classification layer, which encompasses:

- **Sigmoid Activation Function:** We strategically leverage a sigmoid activation function in this ultimate layer. This deliberate choice equips this model with exceptional prowess in binary classification tasks, making it eminently suitable for discerning the presence of AMD within OCT images. The sigmoid function provides a probability-based assessment, offering a nuanced and highly accurate evaluation of AMD's presence in the input OCT image.

This model architecture stands as a testament to meticulous design and thoughtful layering. It draws its strength from the profound capabilities of CNNs, further enriched by the introduction of non-linear activation functions and fortified by protective measures against overfitting. This architectural marvel emerges as a robust and precise AMD detection algorithm proficient in deciphering intricate patterns within OCT images. Providing healthcare professionals with a powerful tool for early and accurate AMD diagnosis makes a substantial contribution to the relentless advancement of medical imaging technology.

4.2 Commercialization aspects of the product

This mobile application is strategically designed to cater to various healthcare stakeholders, including healthcare institutions, clinics, hospitals, and ophthalmologists. Healthcare institutions can integrate our solution to enhance their AMD detection and patient care capabilities. At the same time, specialized and general clinics can benefit by aiding ophthalmologists and healthcare professionals in diagnosing and monitoring AMD. Hospitals can seamlessly incorporate our application into their comprehensive eye care services, providing patients with a convenient and effective means of AMD assessment.

Additionally, ophthalmologists can significantly improve their diagnostic accuracy and patient care by integrating our mobile app into their practice. Our mobile application distinguishes itself through a compelling, Unique Selling Proposition (USP) that addresses critical needs in AMD detection. One of our key USPs lies in our app's ability to provide fast and highly accurate AMD detection. Leveraging advanced deep learning technologies and a meticulously crafted algorithm, our app excels in speed and precision.

4.3 Testing & implementation

4.3.1 Implementation

"Eye Care", our innovative application, is dedicated to the early detection and classification of age-related macular degeneration (AMD) and diabetic retinopathy (DR), along with the precise grading of disease severity.

Figure 7: Frontend, Backend and Database Technologies

4.3.1.1 Frontend Development

To create a seamless and user-friendly interface for our application, we focused on frontend development using React Native combined with Expo. This choice was strategic, as it offered several advantages. React Native, being a cross-platform framework, allowed us to develop a single codebase that could run on both iOS and Android devices. This saved development time and expanded our app's accessibility to a broader audience, making it available on multiple platforms without needing separate codebases.

Expo, a set of tools built around React Native, further enhanced our frontend development process. It provided a simplified workflow for tasks like building and deploying the app, making it easier for our development team to iterate and deliver updates efficiently. This combination of React Native and Expo ensured that our frontend was not only visually appealing but also highly accessible and user-friendly.

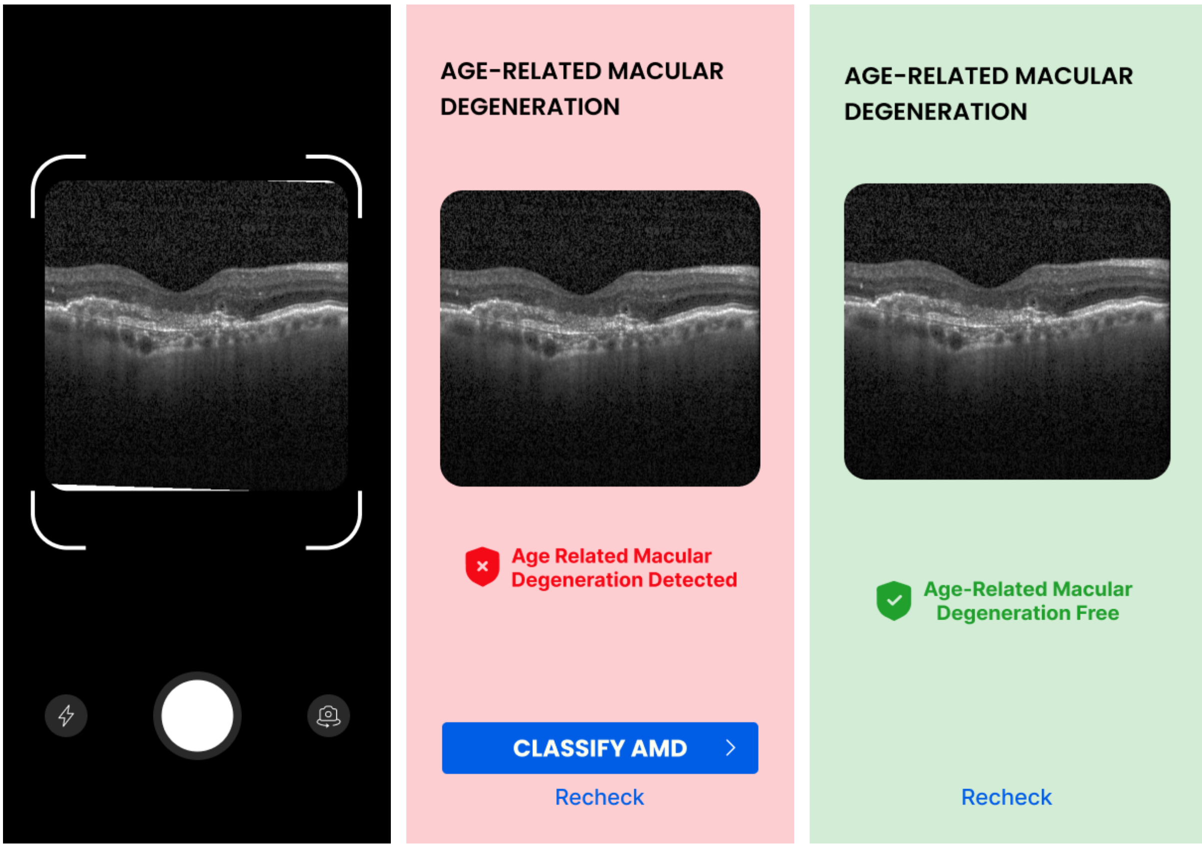

Figure 8 : Mobile Application User Interfaces

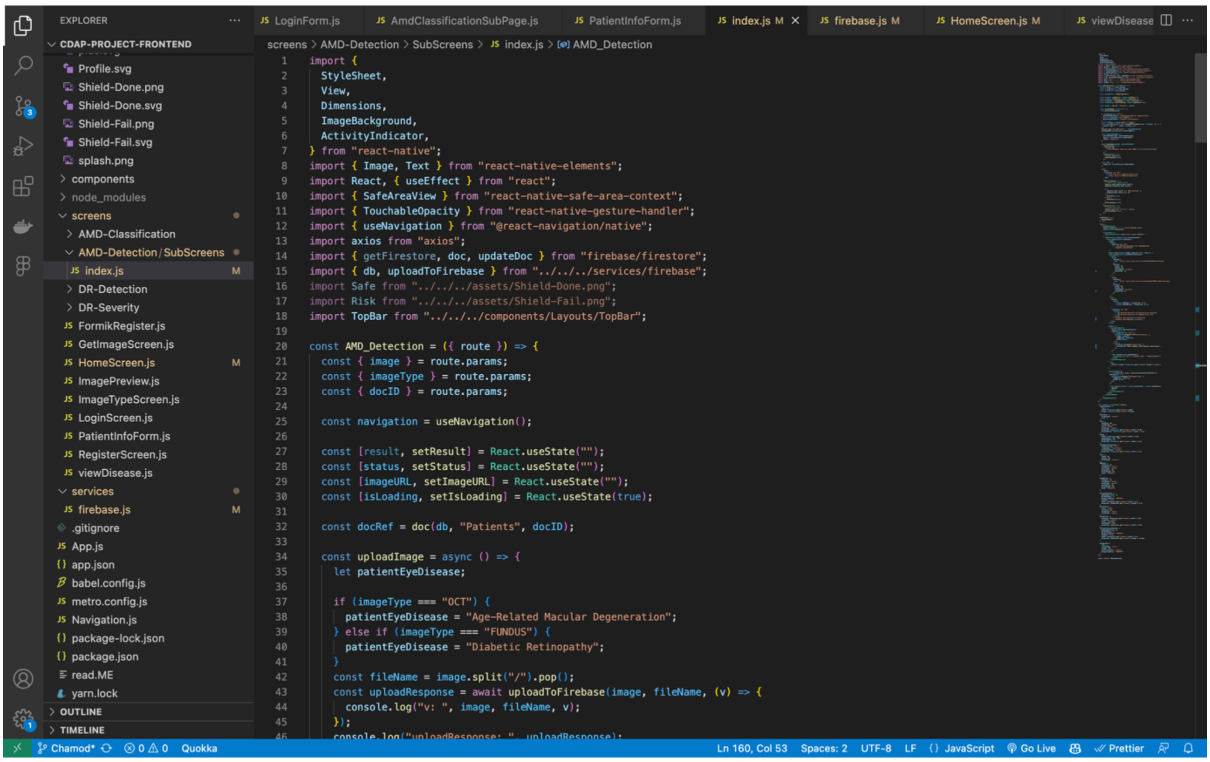

Figure 9 : Sample Frontend code

4.3.1.2 Backend Development

The backbone of our application, "Eye Care," relies on a robust backend infrastructure. For this purpose, we leveraged Python with Flask as the cornerstone of our backend development efforts. Python's versatility and extensive ecosystem of libraries made it an excellent choice for building the backend of our healthcare application.

Flask, a lightweight and flexible web framework for Python, was pivotal in developing our backend system. It allowed us to create a responsive and efficient backend that could handle the core functionalities of "Eye Care" seamlessly. Flask's simplicity and scalability made it a reliable choice for our project, ensuring our application could deliver fast and reliable responses to user requests.

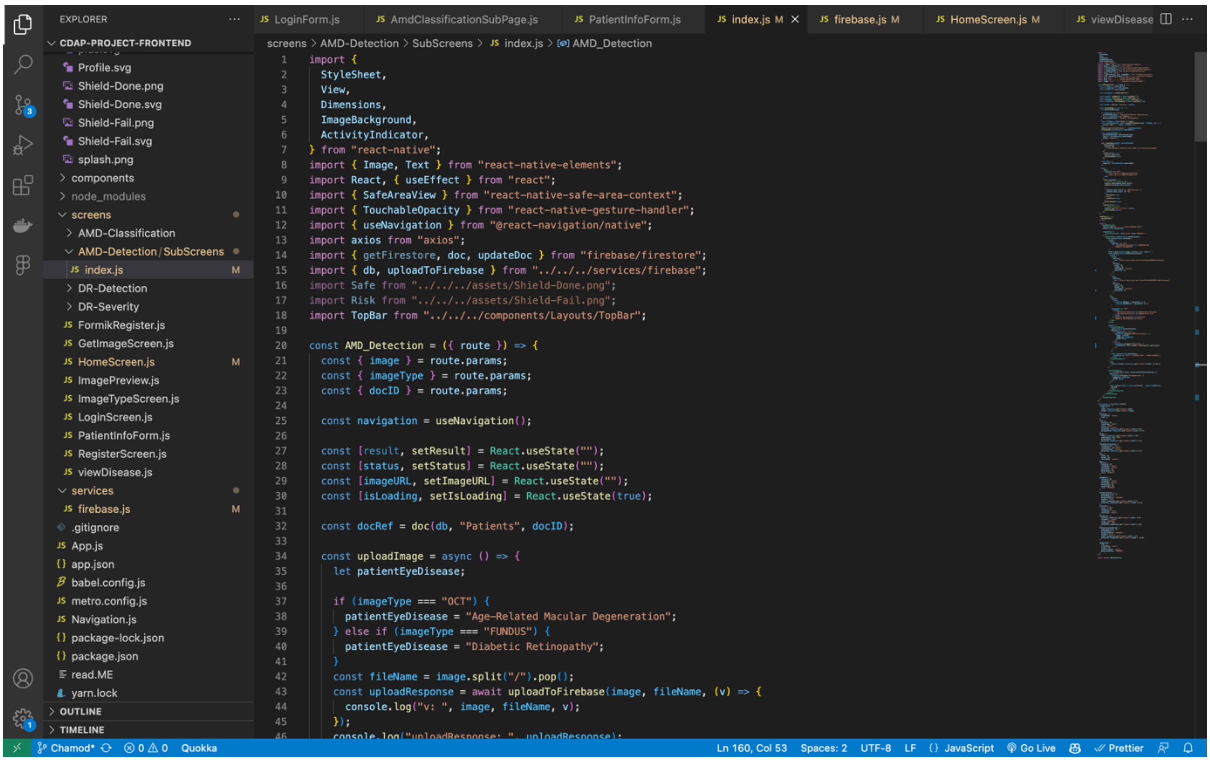

Figure 10: Sample Backend Code

4.3.1.3 Database

Managing and securely storing the vast amount of data generated during AMD (Age-related Macular Degeneration) and DR (Diabetic Retinopathy) detection and classification was critical to our application. We turned to Firebase, a trusted and scalable database solution, to address this. Firebase ensured data integrity and accessibility for both our users and healthcare professionals. It offered robust security features, ensuring that sensitive medical data was protected—Additionally, Firebase's real-time database capabilities allowed for timely updates and access to critical information.

4.3.1.4 Deployment Strategy

Our application's deployment strategy centers on Google Cloud, a robust and scalable cloud infrastructure. Hosting the backend servers on Google Cloud ensures reliability, scalability, and optimal performance. This cloud-based deployment empowers our application to deliver timely and accurate results, even under heavy loads. Furthermore, in implementing and training our machine learning models, such as those for AMD and DR detection, we leveraged Google Colab as the ideal environment. Google Colab's abundant GPU resources and memory capacity allowed us to fine-tune and optimize our models for precise and efficient disease detection. This integration of Google Colab with Google Cloud further streamlined the deployment and maintenance of our machine learning components, ensuring the highest level of performance and accuracy in our application.

4.3.2 Testing

To ensure the accuracy and reliability of our AMD detection algorithms, rigorous testing and validation procedures were implemented. We utilized a diverse dataset of OCT images, including AMD-affected and normal images, to evaluate our system's performance. The testing dataset was designed to mimic real-world scenarios, allowing us to assess the system's ability to accurately identify and classify diseases under various conditions.

Additionally, we conducted extensive validation testing to ensure that our application's frontend and backend components functioned seamlessly together. User testing and feedback collection were also integral to refining the user experience and ensuring the application's ease of use and reliability in real-world healthcare settings

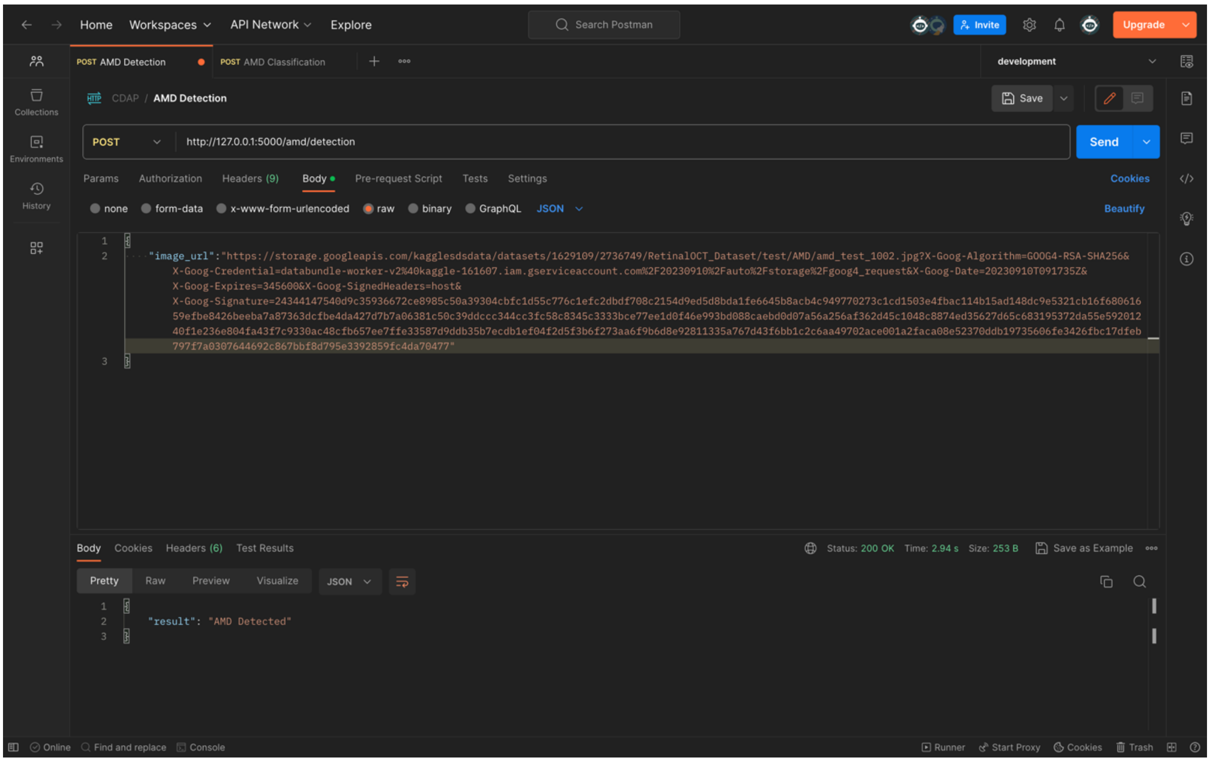

Figure 11: API Testing

5. RESULTS AND DISCUSSIONS

5.1 Results

Our study yields promising results in AMD and DR detection and severity grading. To evaluate the effectiveness of our system, we employed key performance metrics, including accuracy and loss.

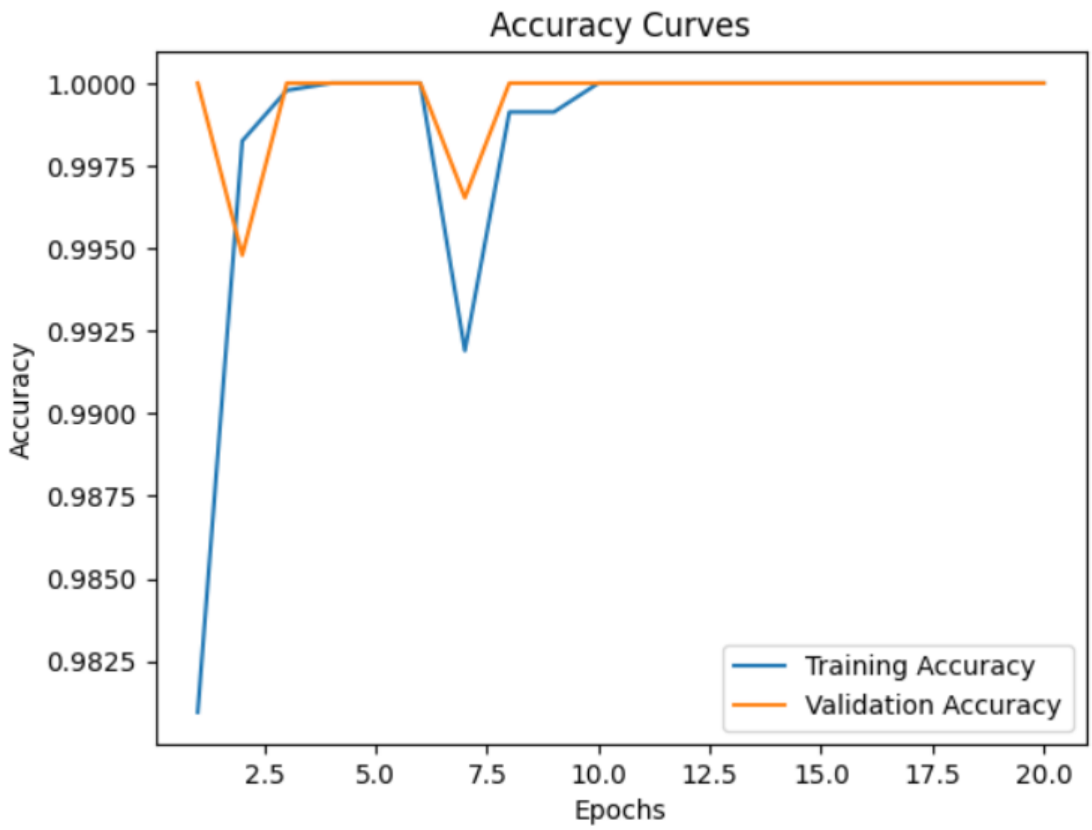

Figure 12: Model Accuracy

The accuracy curves, as depicted in Figure 12, illustrate the training and validation accuracy trends over epochs. These curves showcase the convergence of our model, indicating effective learning from the training data while maintaining generalization on unseen validation data.

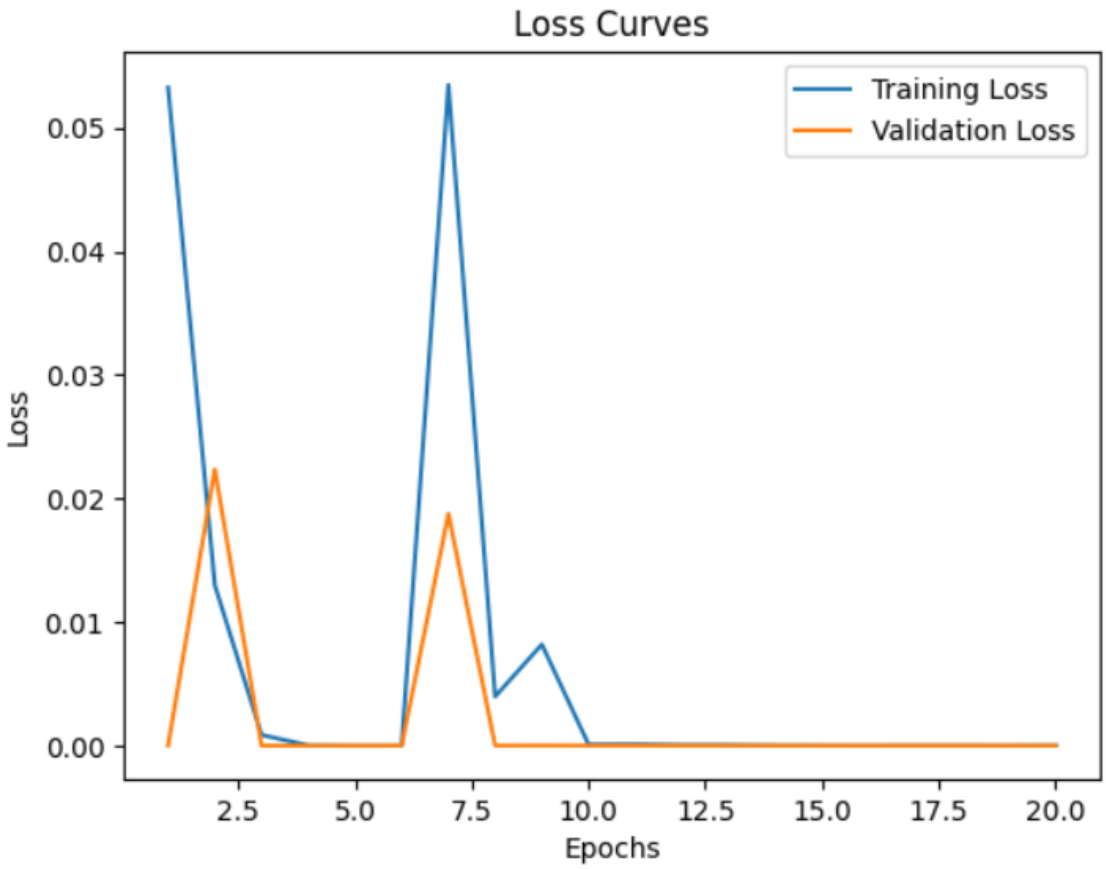

Figure 13: Model Loss

Figure 13 presents the corresponding loss curves, showcasing the model's optimization progress. These curves help assess potential overfitting or underfitting and provide insights into the system's reliability.

Our observations reveal that our model demonstrates a stable convergence, learning effectively without overfitting or underfitting. The validation accuracy aligns well with the training accuracy, indicating robust generalization. The loss curves correspond to the accuracy trends, showcasing a consistent optimization process.

These results hold significant implications for early AMD and DR detection and severity grading. Our system exhibits the potential to assist healthcare professionals in accurate disease assessment. We envision its application in routine clinical practice, contributing to timely interventions and improved patient care. While our study presents promising outcomes, we acknowledge the need for further validation and real-world testing. Future research should focus on refining the model, addressing specific challenges, and expanding its usability in the field of ophthalmology.

5.2 Discussion

This study yields promising results in AMD (age-related macular degeneration) detection, signifying a significant advancement in ophthalmology and medical image analysis. This section delves into a deeper exploration of our findings and their implications.

5.2.1 Early Disease Detection

One of the key takeaways from our research is our system's ability to detect AMD early. Early diagnosis is critical in effectively managing these sight-threatening diseases. By accurately identifying the presence of these conditions in their nascent stages, our system empowers healthcare professionals to initiate timely interventions, potentially slowing disease progression and improving patient outcomes.

5.2.2 Model Robustness

Our observations reveal that our model demonstrates a stable convergence, learning effectively without overfitting or underfitting. This robustness is crucial, ensuring the model's predictions remain reliable and accurate even when presented with unseen data. The validation accuracy aligns well with the training accuracy, indicating that our system maintains its performance across different datasets, an essential feature in real-world clinical scenarios.

5.2.3 Clinical Applicability

Our research opens doors to practical clinical applications. The potential of our system to assist healthcare professionals in accurate disease assessment means it can serve as a valuable tool in routine clinical practice. Ophthalmologists, optometrists, and other eye care specialists can integrate our technology into their diagnostic workflows. This enhances the efficiency of disease diagnosis and aids in the standardization of diagnostic processes, leading to better patient care and reducing the burden on healthcare systems.

5.2.4 Future Directions

While our study presents promising outcomes, we recognize that this is just the journey's beginning. Further validation and real-world testing are essential to ascertain the true potential of our system. Future research endeavors should focus on refining the model to achieve even higher levels of accuracy, addressing specific challenges, and expanding its usability beyond the scope of this study. Collaborations with healthcare institutions and practitioners are pivotal in ensuring the technology's seamless integration into clinical practice.

6. REQUIREMENTS

6.1 Functional Requirements

- **Image Upload**: The system must allow users, including healthcare professionals and patients, to upload Optical Coherence Tomography (OCT) images easily. This functionality should support various image formats and ensure seamless and secure data transfer.

- **AMD Detection**: A core functional requirement is accurately detecting and classifying age-related macular degeneration (AMD) in the uploaded OCT images. The system should employ advanced deep learning algorithms to analyze images, identify disease presence, and categorize them into the appropriate disease types and stages.

- **User Authentication**: To ensure data privacy and security, user authentication is essential. Users should create accounts or log in securely before accessing the application's features. This requirement helps maintain confidentiality and traceability of data access.

- **Data Storage**: The system should securely store all uploaded image data, analysis results, and user-related information. An efficient and reliable database management system ensures data integrity and easy retrieval.

- **User Feedback**: Users should be able to provide feedback and report issues within the application. This feedback mechanism fosters user engagement and continuous improvement, enhancing the user experience.

- **Real-time Updates**: The system must support real-time updates and notifications for users. For example, when analysis results are ready, users should receive timely notifications, ensuring they can respond swiftly to the findings.

6.2 Nonfunctional Requirements

- **Performance**: The system should prioritize high performance, delivering fast and responsive image analysis. Quick results are critical for timely decision-making and interventions, especially in healthcare settings.

- **Security**: Robust security measures are paramount to safeguard sensitive medical data and user information. This includes data encryption, secure user authentication, and access control to ensure privacy and compliance with data protection regulations.

- **Scalability**: The system should be designed to scale effortlessly as the user base and data volume grow. Scalability ensures that the application can accommodate increasing demand without compromising performance.

- **Usability**: The user interface must be intuitive, user-friendly, and accessible to healthcare professionals and patients. An intuitive design reduces the learning curve and enhances user satisfaction.

- **Reliability**: The system should consistently deliver accurate results without downtime. Reliability is critical in healthcare applications, where interruptions or inaccuracies can have serious consequences.

- **Privacy**: Strict privacy controls are essential to protect sensitive medical information. Compliance with data protection regulations, such as HIPAA, GDPR, or relevant local laws, should be ensured to maintain the highest level of data privacy.

- **Accessibility**: The application should be accessible on both iOS and Android platforms, ensuring that it reaches the broadest possible audience of users, regardless of their device preferences.

6.3 User Requirements

- **Ease of Use**: Users, including healthcare professionals and patients, expect an application that is easy to navigate and use. The user interface should be designed with simplicity and clarity to facilitate seamless interactions.

- **Timeliness**: Healthcare professionals rely on prompt results for timely interventions. Therefore, the system must deliver analysis results rapidly, allowing for quick decision-making and patient care.

- **Accuracy**: Accurate disease detection and severity grading are paramount. Users expect a high level of accuracy in the system's analysis, as this directly influences patient treatment and outcomes.

- **Data Security**: Both users and patients demand robust data security measures to protect sensitive medical information. Assurance of data security and privacy is a fundamental user requirement.

- **Feedback Mechanism**: Users should have a means to provide feedback and report issues within the application. This feature not only engages users but also helps promptly address any usability or functionality concerns.

6.4 System Requirements

- **Frontend**: The application's front end is built using React Native with Expo for cross-platform compatibility. React Native enables the development of a single codebase that can run on both iOS and Android devices, saving development time and resources.

- **Backend**: Python with Flask serves as the backend, providing the necessary processing and logic for the application. Flask's lightweight and flexible web framework makes it suitable for handling complex tasks efficiently.

- **Database**: Firebase is employed for secure data storage and retrieval. Its real-time database capabilities allow for timely updates and access to critical information, ensuring that data is always current.

- **Deployment**: Google Cloud hosts the backend servers, ensuring scalability and optimal performance. This cloud-based deployment strategy guarantees the application can handle heavy loads and maintain responsiveness.

- **Machine Learning**: In implementing and training machine learning models for AMD and DR detection, such as those based on deep learning algorithms, Google Colab is used. Google Colab provides ample GPU resources and memory capacity, facilitating the fine-tuning and optimization of models for precise disease detection.

7. CONCLUSION

The culmination of this research signifies a groundbreaking leap forward in the realm of ophthalmology through the development of a state-of-the-art mobile application. This meticulously crafted application stands as a dedicated platform, meticulously engineered to serve as a dedicated platform for the early detection and precise classification of age-related macular degeneration (AMD), and it exhibits a remarkable ability to pinpoint affected areas within Optical Coherence Tomography (OCT) images.

The central focus of these technological innovations revolves around addressing the pressing challenges that AMD presents in the context of eye health. This mobile application emerges as a formidable instrument for the timely and precise diagnosis of AMD, harnessing the cutting-edge prowess of advanced image analysis techniques and sophisticated deep learning algorithms.

However, the significance of this research extends beyond mere diagnosis. It is driven by an unwavering commitment to elevate awareness surrounding the debilitating conditions of AMD By facilitating early detection and offering a precise severity grading, it bestows healthcare professionals with invaluable insights crucial for tailoring treatment plans. This research strives to make a substantial contribution to the field of ophthalmology, with a specific emphasis on enhancing the care provided to AMD patients.

Moreover, the mobile application at the heart of this research does not merely streamline the diagnostic process; it substantially elevates patient care by contributing to improved patient outcomes, enhancing the management of disease progression, and raising the overall quality of care administered. In essence, it transforms the landscape of ophthalmological practice.

Furthermore, these pioneering technological advancements open a gateway to future possibilities and developments in the field. The horizon promises ongoing refinements and expansion of our technology to address a broader spectrum of AMD scenarios. These ambitious endeavors harmoniously align with our overarching mission: to provide cutting-edge solutions to medical professionals and elevate the standard of healthcare delivery in the dynamic domain of ophthalmology. Endless possibilities mark the journey ahead as we strive to improve the lives of countless individuals affected by these debilitating eye conditions.

8. REFERENCE LIST

[1] C. S. Lee, D. M. Baughman, and A. Y. Lee, “Deep Learning Is Effective for Classifying Normal versus Age-Related Macular Degeneration OCT Images,” *Ophthalmol Retina*, vol. 1, no. 4, pp. 322–327, Jul. 2017, doi: 10.1016/j.oret.2016.12.009.

[2] K. Simonyan and A. Zisserman, “Very Deep Convolutional Networks for Large-Scale Image Recognition,” Sep. 2014.

[3] R. Srivastava, E. P. Ong, and B.-H. Lee, *Role of the Choroid in Automated Age-related Macular Degeneration Detection from Optical Coherence Tomography Images; Role of the Choroid in Automated Age-related Macular Degeneration Detection from Optical Coherence Tomography Images*. 2020. doi: 10.0/Linux-x86_64.

[4] M. Farazdaghi and K. Ebrahimi, “Role of the choroid in age-related macular degeneration: A current review,” *J Ophthalmic Vis Res*, vol. 14, no. 1, p. 78, 2019, doi: 10.4103/jovr.jovr_125_18.

[5] A. Govindaiah, R. T. Smith, and A. Bhuiyan, “A New and Improved Method for Automated Screening of Age-Related Macular Degeneration Using Ensemble Deep Neural Networks,” in *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, IEEE, Jul. 2018, pp. 702–705. doi: 10.1109/EMBC.2018.8512379.

[6] C. Szegedy, S. Ioffe, V. Vanhoucke, and A. Alemi, “Inception-v4, Inception-ResNet and the Impact of Residual Connections on Learning,” *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 31, no. 1, Feb. 2017, doi: 10.1609/aaai.v31i1.11231.

[7] F. Chollet, “Xception: Deep Learning with Depthwise Separable Convolutions,” in *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, IEEE, Jul. 2017, pp. 1800–1807. doi: 10.1109/CVPR.2017.195.

[8] D. Huang *et al.*, “Optical Coherence Tomography,” *Science (1979)*, vol. 254, no. 5035, pp. 1178–1181, Nov. 1991, doi: 10.1126/science.1957169.

[9] R. R. Slavescu, Universitatea Tehnică din Cluj-Napoca. Computer Science Department, IEEE Romania Section, and Institute of Electrical and Electronics Engineers, *Proceedings, 2018 IEEE 14th International Conference on Intelligent Computer Communication and Processing (ICCP) : Cluj-Napoca, Romania, September 6-8, 2018*.

[10] C. H. Lin *et al.*, “Denoising Performance Evaluation of Automated Age-Related Macular Degeneration Detection on Optical Coherence Tomography Images,” *IEEE Sens J*, vol. 21, no. 1, pp. 790–801, Jan. 2021, doi: 10.1109/JSEN.2020.3014254.

Dataset - https://www.kaggle.com/datasets/obulisainaren/retinal-oct-c8