

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

23-162

Final Report

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

Department of Computer Science and Software Engineering

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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.

| Name | Student ID | Signature |
|-------------------|------------|---|
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The above candidates are carrying out research for the undergraduate Dissertation under my supervision.

Signature of the supervisor

Date

.....

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(Ms. Devanshi Ganegoda)

Signature of the co-supervisor

Date

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(Mr. Jeewaka Perera)

ABSTRACT

Preventing irreversible vision loss and improving patient outcomes depend on the early detection and accurate diagnosis of eye diseases. Machine learning has recently become a promising tool for examining retinal images to find conditions and assist in diagnosis.

This paper presents a novel method for classifying retinal images that show signs of diabetic retinopathy through a mobile application. To increase the correctness and dependability of the existing approaches, the proposed method optimizes its parameters and adds new functionalities. The study trains and validates the algorithm's performance using a significant dataset of labeled retinal images.

The difficulty of resource-intensive continuous monitoring of DR is also covered in the report. To lessen the strain on healthcare systems and enhance patient outcomes, the study explores the potential of healthcare and mobile health technologies for remote screening and monitoring of DR.

Overall, this research provides a more effective and reliable deep-learning-based mobile application to detect diabetic retinopathy at early stages. The suggested approach will significantly impact how well people with diabetes live their lives and how much of a financial burden diabetic retinopathy is on healthcare systems. It can also act as a base for creating scalable solutions for continuous DR monitoring.

ACKNOWLEDGEMENT

I would like to express my heartfelt thanks to my supervisor, Mrs. Devanshi Ganegoda, for her unwavering support and guidance throughout my undergraduate research endeavors. Her assistance has been instrumental in my successful completion of each project. I would like to express my heartfelt appreciation to Mr. Jeewaka Perera, the co-supervisor of this research project, along with my supervisor, for their constant availability and assistance. Lastly, I would like to extend my sincere appreciation to all those who have contributed to this project, both in a direct and indirect manner, including my fellow team members, as well as my beloved family and friends.

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..... | 15 |
| 1.4. Research Problem..... | 16 |
| 1.5. Research Objectives..... | 17 |
| 1.5.1. Main Objectives..... | 17 |
| 1.5.2. Sub Objectives..... | 17 |
| 2. METHODOLOGY..... | 20 |
| 2.1. Requirement Gathering and Analysis..... | 20 |
| 2.2. Feasibility study..... | 21 |
| 2.3. Materials and methods..... | 22 |
| 2.3.1. Image Preprocessing..... | 24 |
| 2.3.2. Model Architecture..... | 24 |
| 2.4. Commercialization aspects of the product..... | 26 |
| 2.4.1. Target Market Segmentation..... | 26 |
| 3. TESTING & IMPLEMENTATION..... | 30 |
| 3.1. Testing Methodology..... | 30 |
| 3.1.1. Unit Testing..... | 30 |

| | |
|----------------------------------|----|
| 3.1.2. Integration Testing..... | 30 |
| 3.2. Implementation Details..... | 31 |
| 4. REQUIREMENTS..... | 34 |
| 5. CONCLUSION..... | 36 |
| REFERENCE LIST..... | 37 |

LIST OF FIGURES

| | |
|--|----|
| Figure 1: System Overview Diagram | 16 |
| Figure 2: APTOS 2019 BD | 18 |
| Figure 3 : UIs of the mobile application | 30 |

LIST OF TABLES

Table 1: Results of former research

11

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

The human eye is a key organ in processing visual information by detecting and interpreting light stimuli. In addition to being vital, this sensory organ is also delicate and needs gentle handling. It is likely to be impacted by a wide range of diseases and disorders, causing irreversible damage to the eye. Thus, early diagnosis is crucial in coping with these diseases, preventing their progression and preserving the patient's vision. Eye conditions like Diabetic Retinopathy (DR) and Age-related Macular Degeneration (AMD) are prevalent conditions that lead to significant vision loss and, in some cases, visual impairments. However, the focus of this report will be on a modified approach to detect signs of DR with higher accuracy in retinal fundus images using machine learning.

Diabetic retinopathy is one of the most dangerous complications of diabetes. Also, the fourth foremost cause of blindness and the fifth most common cause of visual impairment worldwide[1]. The condition occurs when the blood vessels in the retina are damaged because of increasing levels of sugar in the bloodstream. It may eventually result in vision loss, if poorly controlled. A survey carried out by the World Health Organization found that 4.2 million people around the earth have diabetic retinopathy as a main cause of their visual impairment. Type 1 or type 2 diabetes patients are at risk of getting diabetic retinopathy, and the risk rises with duration of diabetic diagnosis and deficient blood glucose control.

Manual inspection of retinal fundus images to recognize diabetic retinopathy by eye specialists is a complex and time-consuming process that demands high training and experience. Also, since the manual inspection process depends on the availability of resources, it can be restricted to certain geographical areas as well as entities with more financial capabilities. In particular, as third-world countries like Sri Lanka have limited public healthcare services, manual inspection processes can increase the workload on specialists, and prevent them from focusing on severe cases.

To overcome the challenges in the process of manual inspection, several research studies have been carried out to automate the process of diabetic retinopathy detection using various approaches. In recent years, the field of medical imaging has seen auspicious developments in the use of machine learning (ML), especially in automating the process of detection and diagnosis of eye diseases such as diabetic retinopathy. Therefore, it is vital to develop algorithms that are more precise and credible for accurately detecting early indicators of diabetic retinopathy.

The proposed study aims to develop a novel method for classifying retinal images that show signs of diabetic retinopathy. We hope to achieve a more accurate and reliable method for detecting early signs of diabetic retinopathy by incorporating additional functionalities and optimizing the existing model's parameters.

This section discusses the key points of the literature survey related to diabetic retinopathy, current detection algorithms, research conducted on the area, research gaps in the conducted research by analyzing them, and the main research problem that is being addressed by developing the proposed system.

1.2. Literature Survey

Diabetic retinopathy is a significant cause of blindness globally, affecting millions of people. Therefore, early detection and diagnosis are crucial for preventing further deterioration of vision. Over the past few years, the application of machine learning models has demonstrated significant potential in the accurate identification and diagnosis of diabetic retinopathy using retinal images. In this literature survey, we will review the most relevant research studies on the development of novel methods for classifying retinal images that show signs of diabetic retinopathy.

In the year 2019, S M Asiful Huda, Ishrat Jahan Ila, Shahrier Sarder, Md. Shamsujjoha, Md. Nawab Yousuf Ali proposed improved machine learning & feature-importance algorithms for the detection of Diabetic Retinopathy [2]. Decision Tree, Logistic Regression, & SVM are used in their proposed system. A dataset containing nearly 15945 retinal fundus images along with 66 features associated were collected for developing the model. The model achieved a precision of 97% and a recall of 92%, which shows a notable contrast to existing results, 72% and 63% outcome.[3]–[5].

Akanksha Soni et al. (2021) in their paper “A Novel Approach for the Early Recognition of Diabetic Retinopathy using Machine Learning” developed a multi-task deep learning model that uses k-mean clustering, Support Vector Machine (SVM) and random Forest classification algorithm to recognize diabetic retinopathy using retinal images [6]. The model achieves a recognition rate of 96.2% which is a competent & stable outcome compared to SVM.

Qomariah D U N et al. in the year 2019 presented a deep learning approach to extracting features & classification using SVM & CNN [7]. The proposed approach is tested 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 study to gain the feature vector for classification. The result of the experiment shows 95.83% & 95.24% as the highest accuracy values for bases 12 & 13 respectively.

Mahendran Gandhi and Dr R. Dhanasekara in their research paper “Diagnosis of Diabetic Retinopathy Using Morphological Process and SVM Classifier” published in

the year 2013 used the SVM classifier along with Morphological processes to assess the severity of diabetic retinopathy [8]. This paper presents an accuracy of 96.67% in classifying the severity of DR.

The table below depicts some of the percentages of sensitivity, specificity and accuracy acquired using different approaches.

| 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, iterative 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

1.3. Research Gap

Even though various research has been conducted in this field and a few technologies have been implemented, improvements in the outcomes are crucial since the research is based on the medical industry. However, the existing research has some limitations in terms of accuracy, sensitivity, specificity, false-positive rates and so on. Additionally, some research was conducted using complex feature engineering methods, which is time-consuming and does not generalize well to new datasets. Furthermore, methods that can give priority to Diabetic Retinopathy early detection are needed.

The need for more reliable and scalable methods that can deal with variations in image quality, such as low resolution, noise, and artifacts, is another research gap. Several approaches are currently used to produce high-quality images, which may not be accessible in practical situations. As a result, methods are required that can handle noisy or poor-quality images without reducing accuracy.

An accurate and trustworthy tool is required for detecting early signs of DR can significantly improve patient outcomes by enabling early detection and lowering the risk of blindness. The proposed system can also aid healthcare providers in resource optimization and increased DR screening program effectiveness. The workload of healthcare professionals can also be reduced, freeing them up to concentrate on other important tasks. As a result, incorporating the developed tool into the medical field may offer significant practical benefits, including better patient outcomes, lower healthcare costs, and more efficient use of available resources. Additionally, the incorporation of such a tool can help to standardize DR screening, ensuring that patients get consistent, high-quality care regardless of where they live or how many resources are available to them.

1.4. Research Problem

Even though there have been various attempts to automate the process of diabetic retinopathy detection using machine learning, a more accurate and reliable method for early recognition of diabetic retinopathy is still required to enable early diagnosis and treatment. To increase the accuracy and reliability of automated detection and diagnosis of the condition, the research aims to produce a novel approach for classifying retinal images that exhibit symptoms of diabetic retinopathy. The method will include additional functionalities and optimize the existing model's parameters to improve its outcomes.

The significance of the proposed study is that it can offer a more effective and reliable method of identifying early indicators of diabetic retinopathy. Automated diagnosing using machine learning can help in achieving this goal by reducing the risk of severe vision loss and blindness through early detection and intervention.

For early detection, continuous monitoring of diabetic retinopathy is essential, particularly in patients who have a high risk of the condition progressing. However, this requires a significant investment of time, workforce, and resources. It is difficult to implement continuous monitoring of DR in all diabetic patients due to the constrained resources of the current healthcare system. As a result, many DR cases go undiagnosed, which causes severe vision loss and eventual blindness.

1.5. Research Objectives

The aim of the proposed research is to implement a novel machine learning algorithm to detect the symptoms of Diabetic Retinopathy using retinal images in order to improve the accuracy of outcomes for better diagnosis.

1.5.1. Main Objectives

The motive of this component is to improve the diagnosis process and optimize the outcomes to aid both ophthalmologists and patients. Since the DR diagnose process requires continuous monitoring, this approach will reduce the resource usage and expertise workload at a high level. Therefore, the main aim of the research study is to overcome the drawbacks of recent research and come up with an accurate and effective approach.

1.5.2. Sub Objectives

In addition to the main objectives, there are some specific objectives related to the implementation.

- Preprocess retinal fundus image

This step involves preparing the retinal fundus images for analysis. It includes tasks like resizing the images to a consistent resolution, normalizing pixel values, enhancing image quality through techniques like contrast adjustment and noise reduction, and augmenting the dataset by applying random transformations. These preprocessing steps ensure that the input data is in a suitable format for the subsequent analysis.

- Noise Removal and standardization of the image

In this stage, noise present in the retinal fundus images is reduced or eliminated to enhance the quality of the images. Additionally, the images are standardized by applying

techniques to make them consistent in terms of size, brightness, and contrast. This standardization is crucial for accurate and reliable feature extraction and analysis.

- Extract features of the retina to identify the signs

Feature extraction involves identifying and isolating relevant characteristics or patterns in the retinal images that are indicative of signs related to diabetic retinopathy. These features can include blood vessel patterns, lesions, or other distinctive structures within the retina. Extracting these features is a critical step in diagnosing the condition accurately.

- Analyze the features

Once the features are extracted from the retinal images, they are analyzed to identify specific signs or abnormalities associated with diabetic retinopathy. This analysis may involve statistical measurements, pattern recognition, or other algorithms to interpret the extracted information and draw meaningful conclusions.

- Prepare datasets of retinal fundus images

This step involves organizing the retinal fundus images into suitable datasets for training, validation, and testing. Careful dataset preparation ensures that the model can learn from a diverse range of images while also having separate data for evaluation to assess its performance accurately.

- Select a model architecture (CNN)

A Convolutional Neural Network (CNN) architecture is chosen as the foundation for the deep learning model. CNNs are particularly well-suited for image analysis tasks like diabetic retinopathy detection due to their ability to learn hierarchical features from images.

- Train the model

Training the model involves feeding it with the prepared retinal fundus image datasets. The model's parameters are iteratively adjusted using optimization algorithms to

minimize the loss function. During this process, the model learns to recognize the features and patterns associated with diabetic retinopathy.

- Evaluate the performance of the model

The trained model is evaluated using separate datasets that were not used during training. This evaluation assesses the model's ability to accurately identify diabetic retinopathy symptoms. Various performance metrics, such as accuracy, precision, recall, and F1-score, are used to measure the model's effectiveness.

- Analyze the accuracy metric

The accuracy metric provides an overall measure of the model's correctness in predicting diabetic retinopathy. Analyzing this metric involves understanding how well the model's predictions align with the ground truth labels. It is essential to ensure that the model is both sensitive (able to detect true positives) and specific (minimizes false positives) to make reliable diagnoses.

2. METHODOLOGY

2.1. Requirement Gathering and Analysis

To ensure the successful development of a mobile research app for diabetic retinopathy detection, 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 diabetic retinopathy 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 diabetic retinopathy 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 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 diabetic retinopathy, 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 sub component shouldn't have any mistakes or failures. The component must be more dependable, high-performing, and cost-effective. Resources and requirements for the component are not very expensive.

2.2.3. Scheduling Feasibility

Each task must be completed on time, with higher accuracy results, and the proposed component 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

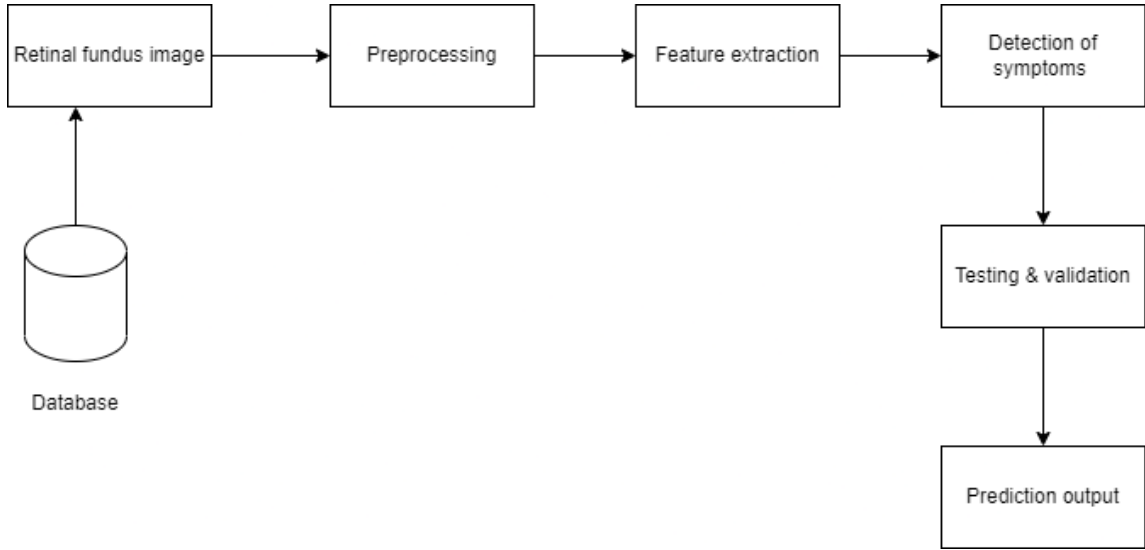


Figure 1: System Overview Diagram

The system allows registered users to take or upload retinal images. The images are delivered to a backend server run by Amazon Web Services (AWS), where the flask server is installed. The EfficientNet model in the flask server processes these images to identify DR. The system will use a unique model to determine the severity of DR if it exists. Using a customized model, the system will simultaneously determine if an OCT image has been diagnosed as having AMD. If so, the VGG16 model is used by the system to classify the AMD according to severity. The system will then give users medical advice and prevention advice based on that information. Additionally, users of the system can monitor the disease's progression while the patient is receiving treatment. Additionally, the system will utilize the prognosis of symptoms to predict future risk.

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

This research initiative focuses on a meticulous and comprehensive approach to data collection and preprocessing, which is paramount for the successful execution of our study. The acquisition of our retinal fundus image dataset involved a rigorous process, as we sourced it from the Asia Pacific Tele-Ophthalmology Society 2019 Blind Detection (APTOS 2019 BD) repository, a treasure trove of 3662 high-resolution fundus images. These images have been thoughtfully classified into five distinct categories, each representing various stages of Diabetic Retinopathy (DR), ranging from 'no DR' to 'proliferative DR'. To facilitate the optimal performance of our deep learning model, we took great care in organizing the dataset into three distinct subsets: the training set, the validation set, and the test set.

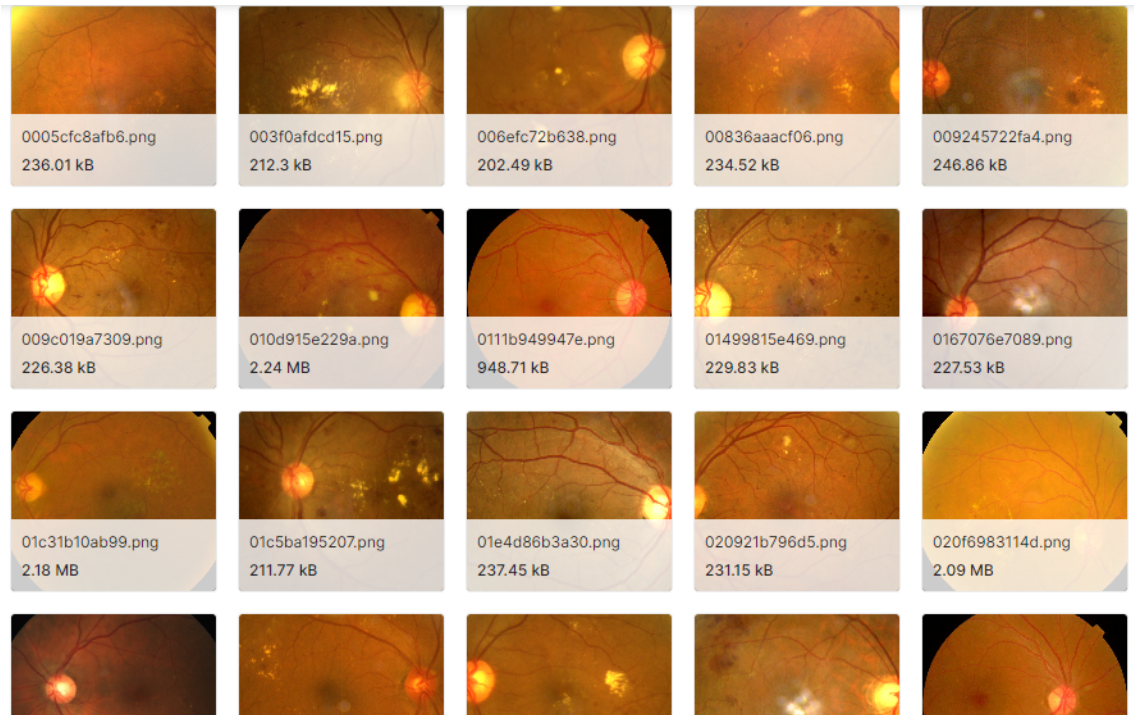


Figure 2: APTOS 2019 BD

2.3.1. Image Preprocessing

The preprocessing stage, a critical precursor to model training, encompasses several pivotal components. Firstly, we enforced uniformity in image dimensions by resizing all images to a consistent 224x224 pixel resolution. Secondly, we normalized pixel values to fall within the range of 0 to 1, a crucial step that aids gradient-based optimization during model training. In our pursuit of enhancing image quality, we implemented an array of advanced techniques, including contrast enhancement, noise reduction, and histogram equalization. Additionally, we embraced the concept of data augmentation, an indispensable strategy that broadened the diversity of our training dataset without necessitating the acquisition of new data. This augmentation involved random rotations, flips, and translations. Collectively, these measures ensured that our dataset was meticulously prepared for model training, characterized by minimal noise and standardized attributes.

2.3.2. Model Architecture

In the realm of model architecture, our approach is anchored in the TensorFlow and Keras frameworks, serving as the cornerstone of our deep learning model. At the heart of our model lies EfficientNetB3, a pre-trained Convolutional Neural Network (CNN). Harnessing the power of pre-trained weights empowers our model to efficiently extract high-level features from retinal fundus images. It's worth noting that we consciously omitted the top classification layers of EfficientNet, originally designed for the ImageNet dataset. This strategic choice strikes a balance between computational efficiency and model performance, aligning seamlessly with our objective of rendering the model suitable for mobile applications.

To bolster the model's capability to capture intricate features from retinal fundus images, we introduced additional layers atop the EfficientNetB3 base model. Batch

normalization was judiciously applied to standardize activation values, thus promoting convergence during training. A bottleneck Dense layer, comprising 256 units, was seamlessly integrated to extract crucial features from the output of the base model. In our pursuit of mitigating overfitting and encouraging the acquisition of more robust representations, we incorporated regularization techniques, including L1 and L2 regularization. A Dropout layer, featuring a dropout rate of 0.45, was strategically positioned to further safeguard against overfitting during training. The culmination of these architectural modifications resides in the output layer, which culminates in a Dense layer housing a softmax activation function. This layer is entrusted with generating predictions pertaining to Diabetic Retinopathy detection.

The training and optimization phase represents an iterative journey where the model is exposed to the preprocessed retinal fundus images. This phase is marked by the fine-tuning of parameters in a quest to minimize the loss function. Leveraging a learning rate of 0.001, we employed the Adamax optimizer, renowned for its effectiveness in updating model weights and biases. The model underwent rigorous training, with parameter adjustments aimed at achieving precise and accurate detection of Diabetic Retinopathy symptoms. Notably, regularization techniques played a pivotal role in enhancing the model's performance, contributing to its overall robustness.

In the concluding stages of our research, model evaluation was conducted with meticulous care. The trained model was subjected to distinct validation and test datasets, with meticulous precautions taken to ensure that there was no overlap with the training data, thereby ensuring unbiased assessments. Our evaluation metrics extended beyond mere accuracy, encompassing precision, recall, and F1-score, thus providing a comprehensive evaluation of the model's diagnostic accuracy. Precision was rigorously assessed by comparing the model's predictions with the ground truth labels, further affirming the robustness of our diagnostic framework.

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. Test cases included various

scenarios, such as correct predictions, incorrect predictions, and handling of unexpected errors.

3.2. Implementation Details

3.2.1. 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.

3.2.2. EfficientNet Model

The EfficientNet model, a state-of-the-art deep learning architecture for image classification, was used for diabetic retinopathy predictions. The model was fine-tuned on a dataset of retinal images with labels indicating the severity of diabetic retinopathy. The trained model weights were stored and loaded within the Flask application.

3.2.3. 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. Results and Performance

3.3.1. Accuracy of Diabetic Retinopathy Detection

The performance of the system was evaluated based on the accuracy of diabetic retinopathy detection. The model's predictions were compared to ground truth labels from a validation dataset. Evaluation metrics such as accuracy, precision, recall, and F1-score were calculated.

3.3.2. Scalability and Responsiveness

The Flask application hosted on GCP demonstrated excellent scalability and responsiveness. Load testing was conducted to assess its ability to handle multiple concurrent requests, and the system showed consistent response times even under high load.

3.3.3. 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.

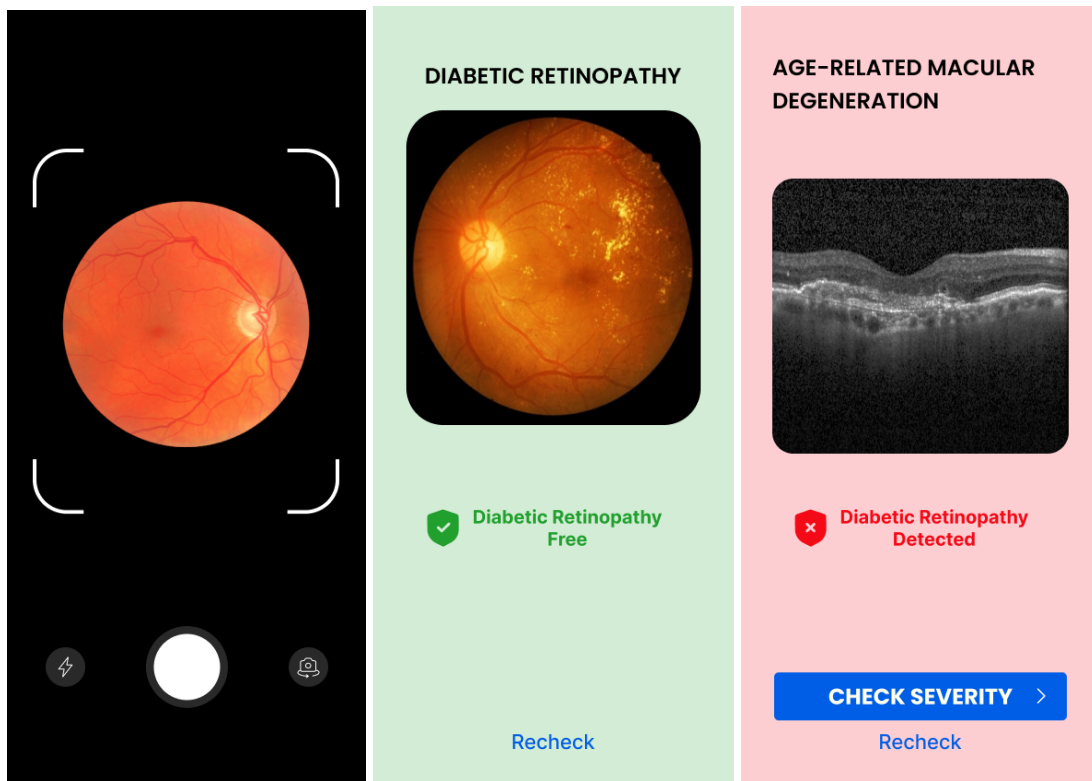


Figure 3: UIs of the Application

4. REQUIREMENTS

4.1. Functional Requirements

In your research on detecting diabetic retinopathy using retinal images through a mobile application, several functional requirements need to be addressed. Firstly, the mobile application should allow users to upload retinal images conveniently, either through the device's camera or by selecting images from the device's gallery. The application should provide real-time predictions based on the EfficientNet model, accurately classifying the severity of diabetic retinopathy in the uploaded images. Furthermore, the application should offer a user-friendly interface that displays the prediction results clearly, providing insights into the likelihood and severity of diabetic retinopathy. It is essential to implement a feedback mechanism to gather user input and improve the model's accuracy over time. Additionally, the application should enable users to save or share prediction results for future reference or consultation with medical professionals.

4.2. Non-functional Requirements

- Performance

The application should exhibit high performance by processing and generating predictions for retinal images quickly. It should be able to handle a significant number of concurrent users without significant latency, ensuring a seamless user experience.

- Scalability

The system must be scalable to accommodate increasing user loads, especially during peak usage times. It should seamlessly scale resources on the Google Cloud Platform to maintain optimal performance.

- Data Security

Robust data security measures must be in place to protect sensitive medical information contained in retinal images. This includes encryption of data in transit and at rest, access controls, and compliance with relevant data protection regulations (e.g., HIPAA or GDPR).

- Availability and Reliability

The application should maintain high availability, with minimal downtime for maintenance or updates. It should be reliable and able to recover gracefully from failures to ensure uninterrupted access for users.

- Usability

The user interface should be intuitive and user-friendly, ensuring that users can easily navigate the application and understand prediction results. It should consider accessibility features to accommodate users with disabilities.

- Accuracy and Model Performance

The prediction model's accuracy and performance should meet or exceed clinical standards. Continuous model evaluation and refinement should be performed to ensure that predictions are clinically meaningful and reliable for healthcare professionals.

- Privacy and Compliance

The application must comply with relevant privacy regulations and standards, including obtaining proper consent for data collection and usage. It should also provide transparent privacy policies and mechanisms for users to manage their data.

- Response Time

The application should provide real-time predictions, and response times for predictions should be within an acceptable range to avoid user frustration and support timely decision-making.

- Error Handling

Robust error-handling mechanisms should be in place to gracefully handle errors and exceptions, providing informative messages to users and logging errors for debugging and analysis.

- Cross-Platform Compatibility

The mobile application should be compatible with a range of devices and operating systems to ensure broad accessibility for users with varying technology preferences.

- Network Resilience

The application should be designed to function efficiently even in low-bandwidth or intermittent network conditions, ensuring accessibility in remote or resource-constrained environments.

- Documentation and Training

Comprehensive documentation for users and administrators should be available, along with any necessary training materials to ensure effective usage and management of the application.

- Scalable Storage

Adequate storage solutions should be implemented to store user data securely and efficiently, with provisions for scaling as the data volume grows.

- Monitoring and Analytics

Implement monitoring tools and analytics to track application usage, performance, and user interactions. This data can be used for continuous improvement and research purposes.

5. CONCLUSION

In conclusion, this research has presented a novel and promising approach to address the critical issue of early detection and accurate diagnosis of diabetic retinopathy (DR). The significance of this research lies in its potential to revolutionize the way we detect and manage DR, ultimately improving patient outcomes and reducing the burden on healthcare systems.

Our proposed method harnesses the power of machine learning and mobile health technologies to create a deep-learning-based mobile application for DR detection. By optimizing parameters, adding new functionalities, and leveraging a substantial dataset of labeled retinal images, we have strived to enhance the accuracy and reliability of DR diagnosis.

Furthermore, this study recognizes the challenges posed by resource-intensive continuous monitoring of DR, which can strain healthcare systems and limit access to specialized care in certain regions. To address this, we explored the potential of remote screening and monitoring through healthcare and mobile health technologies. This innovative approach has the potential to provide timely interventions and reduce the progression of DR, ultimately preserving patients' vision and quality of life.

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