Smartphone Based Detection of Retinal Abnormalities

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***Abstract*— Diabetic retinopathy (DR) is a common complication of diabetes mellitus that can lead to vision loss if not detected and treated early. Traditional diagnosis using fundus cameras is limited by cost and size. This work investigates the suitability of smartphone-based portable systems for DR screening and introduces automated DR detection algorithms using deep learning frameworks. The proposed method is integrated into a web app and a mobile-based classification smartphone application, providing an online automated system for diagnosing DR. This research contributes to the advancement of smartphone-based DR screening, enhancing healthcare access and reducing the global burden of DR.**

Keywords*— Diabetic Retinopathy, Bens Graham Preprocessing, Fine Tuning, MobileNetV2, Retinal and Non-Retinal, Automatic DR Detection, Non-Referable and Referable, Smartphone application.

I. Introduction

With the increase in population, there has been a rise in the use of technology, particularly smartphones. Smartphones have become easily accessible and are used for various purposes. In the field of medicine, smartphones have gained significance for providing healthcare services, including appointments and consultations. Artificial Intelligence (AI) has also seen a significant increase in adoption across different industries, including medicine. AI algorithms can provide machines with human-like thinking capabilities, making them valuable for tasks that require human intelligence.

Eyes are crucial organs that provide vision to living organisms. Like any other organ, they can develop diseases. Timely detection of eye diseases is essential to prevent permanent damage and vision loss. The retina, a specialized and sensitive tissue in the eye, plays a crucial role in sight. Understanding the structure of the retina is vital for diagnosing and treating retinal diseases such as diabetic retinopathy, macular degeneration, and retinal detachment. This research work highlights the potential of smartphone-based systems in enhancing early detection and intervention for diabetic retinopathy.

II. Background

A. The Structure of Retina

The retina is a specialized and sensitive tissue located on the inner surface of the eye, responsible for detecting light and enabling vision. It consists of three layers, each with its own specific functions. The outermost layer is the photoreceptor layer, which contains two types of cells: rods and cones. Rods are sensitive to low-light environments and motion, while cones are responsible for color vision and work best in bright light conditions.

The bipolar cell layer receives information from the photoreceptor layer and transmits it to the ganglion cell layer, which is the third and final layer of the retina. Ganglion cells are specialized cells that relay signals from the retina to the brain through the optic nerve.

The macula, depicted as a red circular structure, is responsible for focusing light that enters the eye through the cornea and lens, providing detailed central vision. The rest of the retina provides peripheral vision. The fovea, located at the center of the macula, is the most critical part of the retina for visual acuity.

The optic disk, seen as a white area, is also known as the optic nerve head. It is where the optic nerve exits the eye, facilitating the transmission of visual data to the brain as electrical impulses. However, the optic disk does not contain rods or cones, creating a blind spot in the visual field.

Understanding the anatomy of the retina is crucial for developing diagnostic and treatment strategies for retinal diseases such as diabetic retinopathy, macular degeneration, and retinal detachment. Vision experts and eye doctors need to have a thorough grasp of the retina's structure to carry out efficient research and ensure effective execution of their studies. Damage or disruption to any of the retinal layers can lead to vision loss or other visual impairments.

Therefore, acquiring an in-depth understanding of this vital component of the eye is imperative for field experts to comprehend the processing of visual information by the eye and the potential effects of retinal diseases on vision.

B. Diabetic Retinopathy

Diabetic Retinopathy (DR) is a significant disease that occurs when diabetes affects the eyes. It damages the blood vessels in the retina, the light-sensitive tissue at the back of the eye. If left undetected, DR can lead to vision loss. Diabetes is a chronic metabolic condition characterized by elevated blood glucose levels due to reduced insulin function. There are two primary types of diabetes: Type 1, caused by the immune system attacking insulin-producing cells, and Type 2, associated with insulin resistance or insufficient production.

Diabetic retinopathy is a common complication of diabetes that damages the blood vessels responsible for light sensing in the retina. It can lead to leakage or blockage of these vessels, potentially causing vision loss or even blindness if untreated. Glaucoma and cataracts are also eye problems associated with diabetes.

Recent data from the International Diabetes Federation (IDF) reveals a high prevalence of diabetes in Pakistan, with one out of every four adults affected. The global number of diagnosed diabetes cases has risen from 108 million in 1980 to 463 million in 2019. The IDF projects a further increase, reaching 578 million by 2030 and 700 million by 2045 [1].

Approximately one-third of people with diabetes have some degree of retinopathy. A systematic review based on IDF Atlas 2019 data estimated that around 103 million adults worldwide suffered from diabetic retinopathy in 2020, with the number expected to rise to approximately 160 million by 2045 [2]. The signs of diabetic retinopathy can vary in severity, initially showing no apparent indications and maintaining normal vision. However, as the condition progresses, symptoms may include blurred or distorted vision, floaters, difficulty seeing at night, and eventual vision loss.

C. Types of Diabetic Retinopathy

Diabetic retinopathy is traditionally diagnosed by ophthalmologists through the examination of retinal images. The diagnosis involves observing the retina for various irregularities, including unusual blood vessels, inflammation, fat build-up, retinal detachment, and abnormalities in the optic nerve. Ophthalmologists also conduct vision tests during the diagnosis to assess the growth of blood vessels and the presence of scar tissues.

The disease severity scale for diabetic retinopathy consists of five stages. The first stage, "No DR" indicates no damage to the retina caused by diabetes mellitus is stated as “non-Referable”. The second stage, "Mild DR" is characterized by a small number of microaneurysms. The third stage, "Moderate DR" is identified by the occurrence of cotton wool spots and several microaneurysms. The fourth stage, "Severe DR" exhibits microvascular abnormalities and cotton wool spots. The final stage, "Proliferative DR," is characterized by the emergence of new retinal blood vessels, retinal detachment, and vitreous hemorrhages. The stages from two to five are stated as “Referable”.

In 2020, a retrospective study conducted during a medical camp in Muzaffargarh, Multan, Punjab, involved screening 1150 individuals. Among the screened individuals, 522 (45%) were diagnosed with diabetes, with a higher prevalence observed in males (59.77%) compared to females (40.22%). Among the 522 individuals with diabetes, 54.21% were tested for diabetes for the first time. Further investigation revealed that 124 patients already had diabetic retinopathy, while 398 individuals were newly diagnosed with diabetic retinopathy [3].

The approach to treating diabetic retinopathy depends on the severity of the condition. During the early stages, monitoring blood sugar and pressure, along with regular eye check-ups, may be sufficient. However, for more severe cases, interventions such as laser therapy or surgical procedures may be necessary to prevent the progression of abnormal blood vessels and damage to the retina.

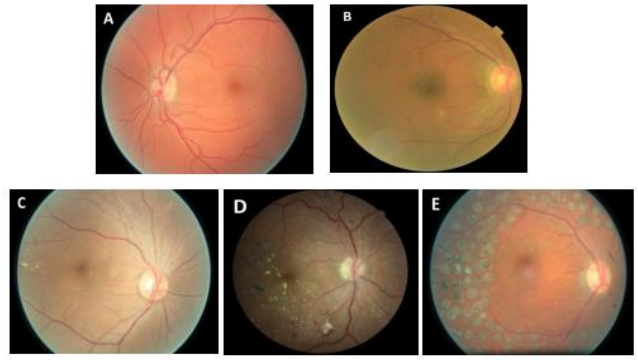

Figure 1: Referable vs Non-Referable; (A) No DR/Non-Referable;

D. Diabetic Retinopathy Detection

The diagnosis of diabetic retinopathy typically involves the use of expensive fundus imaging devices and the expertise of trained professionals in healthcare centers. Various imaging techniques, such as optical coherent tomography and colorful fundus photography, are employed for diagnosis of diabetic retinopathy [4]. However, these techniques come with high costs and require skilled professionals for their operation. Additionally, an ophthalmologist is necessary to evaluate and diagnose the captured fundus image. This poses challenges for individuals with diabetes residing in remote areas or at home, as they face difficulties in accessing early diagnosis and treatment due to the expensive equipment and the shortage of ophthalmologists and medical facilities, limiting their access to proper eye care.

E. Automatic Diabetic Retinopathy Detection

This research proposes a comprehensive method and approach for addressing the challenges in diagnosing and treating diabetic retinopathy (DR) using smartphones. It explores the utilization of deep learning algorithms to develop an automatic DR detection system for retinal images captured on smartphones. By integrating this system into a mobile-based classification application, individuals with diabetes can conveniently screen and detect DR without the need for expensive equipment or expert assistance. The study aims to improve healthcare access by providing a cost-effective and accessible method for identifying and classifying DR, particularly in remote areas. It emphasizes the significance of performance metrics, such as precision, recall, F1-score, and accuracy, for evaluating the effectiveness of the model. Although the proposed solution has limitations, including image quality constraints and reliance on smartphone-based imaging, future work suggests enhancing the deep learning models with larger datasets and advanced architectures, as well as incorporating telemedicine capabilities for remote consultations. Overall, this research highlights the potential of smartphone-based systems in enhancing early detection and intervention for diabetic retinopathy.

III. RELATED WORKS

The work comprises techniques for preparing datasets, pre-processing, and why pre-processing is crucial for improving data visualization and accuracy during model training. The work also includes using deep learning models for classification purposes. The transfer learning method is useful for classifying new data that has not been seen before. The proposed work employs deep learning models to classify diabetic retinopathy from fundus images. The first stage identifies whether the image is a retinal image, the second stage classifies it as referable or non-referable. The work also includes the integration of the two models into the smartphone and web application and the challenges involved.

In Network 1, the dataset consists of two classes: "non-retinal" (real world images) and "retinal" (images of the retina). The training dataset consists of 2800 images from the "non-retinal" class (labeled as 0) and 2800 images from the "retinal" class (labeled as 1). To ensure class balance, the dataset is carefully balanced.

In Network 2, we used EyePacs and DDR dataset for training and validation purpose respectively. The EyePacs fundus images dataset presents researchers with a valuable resource for devising and testing algorithms for the screening and diagnosis of diabetic retinopathy. The dataset is a compilation of retinal images, which was made accessible from a fundus images classification competition on Kaggle [5].

EyePacs dataset comprises 35,126 fundus images, there are five stages labeled from zero to four [3], the first stage is "No DR" it contains 25812 fundus images, the second stage is "Mild DR" it contains 2442 fundus images, the third stage is "Moderate DR" it contains 5291 fundus images, the fourth stage is "Severe DR" it contains 873 fundus images, the final stage is "Proliferative DR" it contains 708 fundus images.

DDR dataset is assembled by Tao Li et. al. It is the second largest dataset. The dataset is a compilation of retinal images, it was made accessible from a fundus images classification competition on Kaggle [5]. The dataset was obtained from health facilities that use telemedicine technology and fundus photography cameras to screen for diabetic retinopathy. Due to the uneven distribution of labels in the dataset, image augmentation is necessary while applying deep learning algorithms for DR classification. The fundus images dataset presents researchers with a valuable resource for devising and testing algorithms for the screening and diagnosis of diabetic retinopathy.

In Network 2, the training process utilizes the EyePacs dataset for training and the DDR dataset for validation. In the initial training phase, the training dataset includes 9000 images for each class: "non-referable" (labeled as 0) and "referable" (labeled as 1). To ensure class balance, the dataset is meticulously balanced. The validation and testing stages are performed on the DDR dataset, which consists of 2500 images in each class.

In the second training phase of Network 2, the training dataset is updated to the DDR dataset, while keeping the classes and labels unchanged. The training set comprises 3700 images per class, ensuring a balanced distribution across classes. To assess the model's performance, the DDR dataset is employed for testing and validation, consisting of 2500 images per class.

A. *Image Preprocessing*

The retinal images dataset [5] may pose a challenge for implementing classification algorithms or can lead to low contrast images that can affect the training of deep learning models due to the noise present in the images. This noise can impede the model's ability to extract the necessary features for effective diabetic retinopathy classification. To overcome this challenge, the selected fundus images underwent pre-processing using image pre-processing techniques. Preprocessing techniques considered for the project are described further below:

1) Contrast Limited Histogram Equalization (CLAHE)

One of the pre-processing techniques considered was Contrast Limited Adaptive Histogram Equalization (CLAHE), which is commonly used in image processing. It improves the contrast of the image and can also remove noise from images. CLAHE overcomes this challenge by equalizing the image histogram locally in small regions, rather than the entire image. In CLAHE, the image is divided into tiles, and the histogram equalization process is applied to each tile separately to prevent overamplification of noise in areas with little contrast and to prevent saturation in areas with high contrast.

2) Naturalness Preserved Enhancement Algorithm (NPEA)

We used a second pre-processing technique to address the issue of images captured in non-uniform illumination conditions. Such images often suffer from reduced contrast and less visible details due to uneven illumination distribution in the scene. To enhance the quality of these images, various image enhancement algorithms have been proposed. In this project, we presented a naturalness preserved enhancement algorithm (NPEA) that effectively enhances the visibility of details while maintaining the naturalness of the images. The NPEA algorithm consists of three key steps: correcting uneven lighting, improving contrast, and preserving naturalness [6].

3) Bens Graham Preprocessing Technique

The provided preprocessing technique, developed by Ben Graham, was used in a Kaggle competition for the detection of diabetic retinopathy. Its purpose is to prepare retinal images by enhancing relevant features, removing noise, and normalizing the images for effective classification. The technique involves cropping dark regions, converting images to a specific size, and applying an image enhancement process using Gaussian blur and linear combination [7]. These steps collectively improve the quality and suitability of the images for subsequent diabetic retinopathy classification tasks.

Figure displays the outcome of applying image pre-processing techniques to sample fundus images.

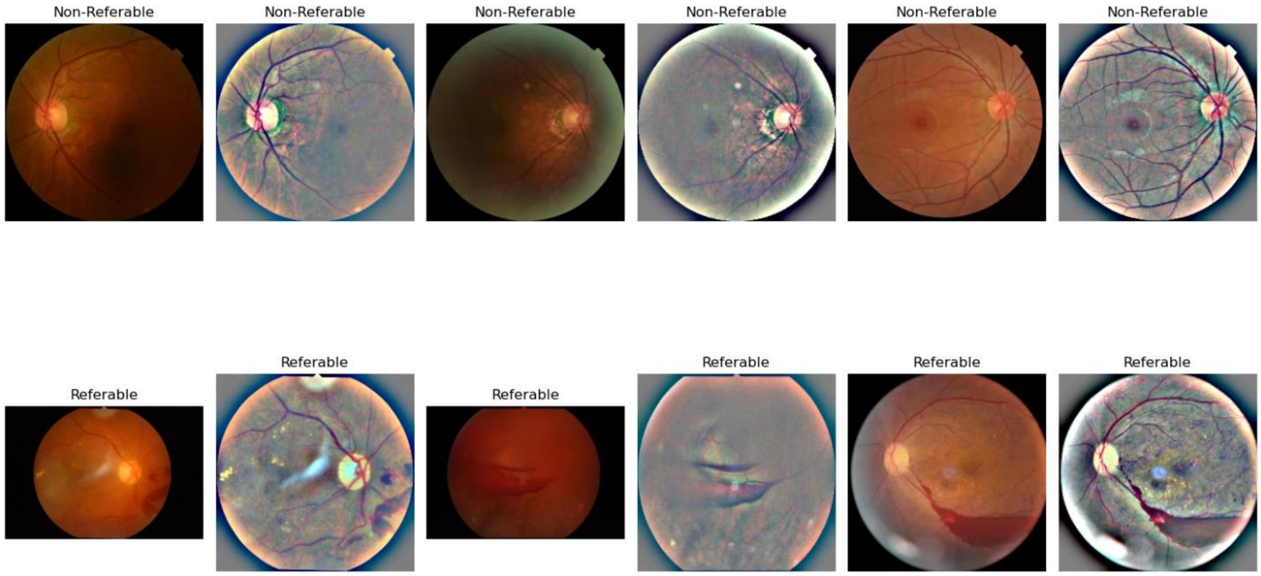

Figure 2: Images Before and After Applying Ben Graham's Preprocessing

We selected Bens Graham Preprocessing Technique over the Naturalness Preserved Enhancement Algorithm (NPEA) and CLAHE due to its superior efficiency during the preprocessing phase. This technique offers more precise and accurate detection of diabetic retinopathy.

B. Deep Learning

The retinal images were trained on MobilentV2, a lightweight and compact convolutional neural network architecture. This choice was made for easy deployment on resource-constrained devices like smartphones. However, the retinal images dataset [5] can present challenges for classification algorithms, including low contrast and noise that can impact the training of deep learning models. This noise can hinder the model's feature extraction for effective diabetic retinopathy classification. To address this challenge, the selected fundus images underwent preprocessing using various techniques, which are further described below.

IV. System Architecture

This section provides a detailed overview of the various stages involved in the development of the system, including image acquisition, image preprocessing, and classification. The system architecture is designed to effectively process and analyze diabetic retinal images.

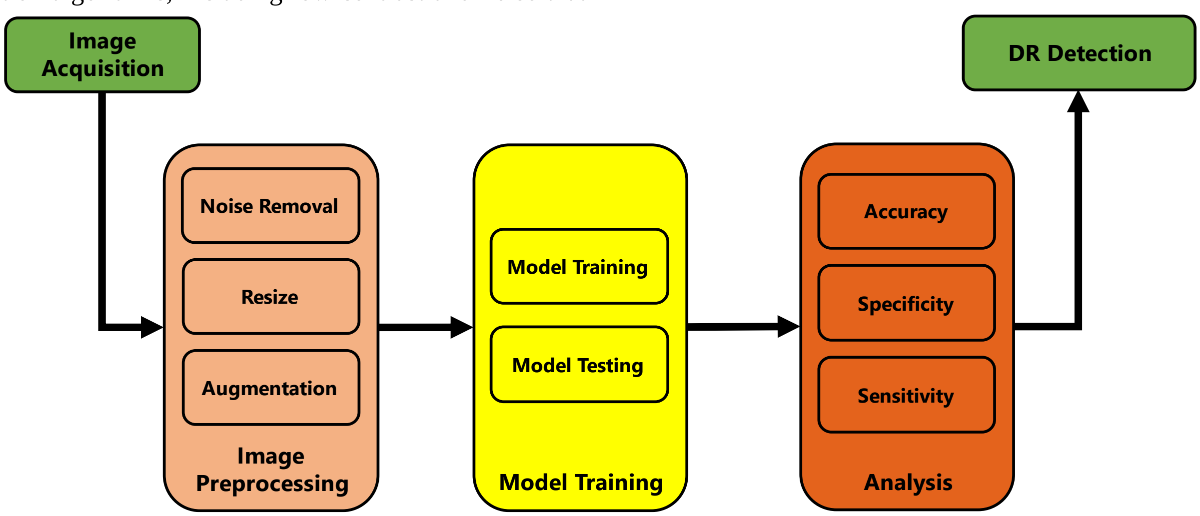

Figure 3: System Architecture

1) Image Acquisition and Preprocessing

The initial step involves obtaining retinal images from either a smartphone camera or an existing gallery. This convenient process allows individuals to easily capture their retinas during routine health check-ups or examinations, serving as the input for subsequent stages in the diabetic retinopathy detection system.

In the first phase, retinal images are acquired either through a mobile phone or by selecting them from the image gallery. Once the images are obtained, several adjustments are applied to improve their quality and extract significant features for classification. Bens Preprocessing Technique is employed to resize the images, reduce noise, and enhance contrast. The main objective is to enhance the visibility and sharpness of retinal structures, enabling precise analysis during the classification process.

Subsequently, these images undergo essential preprocessing steps, which include removing noise, resizing the images, and employing augmentation techniques.

After the completion of the preprocessing phase, the subsequent step involved intensive model training. The training process involved utilizing the preprocessed images and incorporating unseen data to enhance the model's capabilities. Following the training, rigorous testing was conducted to evaluate the model's performance.

In the third phase, the final model's performance was thoroughly examined using evaluation criteria and metrics such as accuracy, precision, and recall. This evaluation helped determine the model's proficiency in diagnosing and classifying diabetic retinopathy. Once integrated into the app, the finalized model was prepared to provide precise grading of diabetic retinopathy based on the provided retinal images.

The detection of diabetic retinopathy involves following proposed system network.

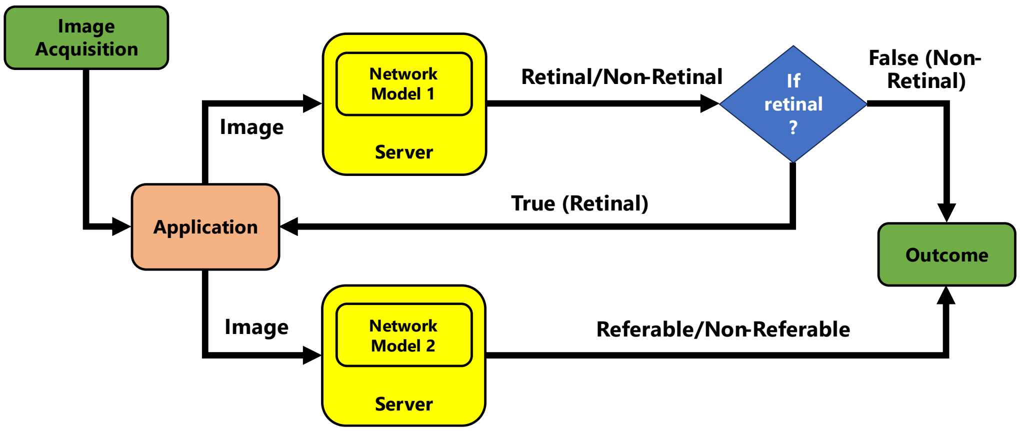

Figure 4: Flow Chart

1. Network 1 Retinal Image Identification:

Before entering the disease classification phase, the system first determines whether an image is retinal or non-retinal. This step is crucial because non-retinal images hold no value for the classification process. By identifying and filtering out non-retinal images, this step prevents users from wasting their time in the classification phase with irrelevant data.

- Simple ANN Training

The model is trained using a specific artificial neural network (ANN) architecture, utilizing both "non-retinal" and "retinal" images. The "retinal" images are carefully balanced with their respective labels to ensure class balance. Following training, the model's performance is evaluated using a test dataset consisting of 2400 images per class. Inference on single images is conducted to assess real-time prediction suitability. While the simple ANN architecture performs well on certain images, it encounters difficulties with images containing complex features.

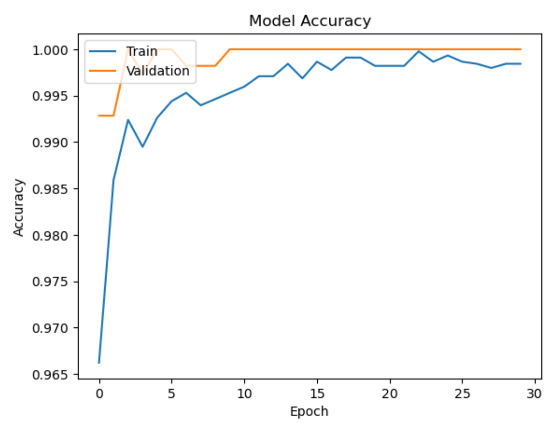

Figure 5: Graphs of Accuracy of ANN

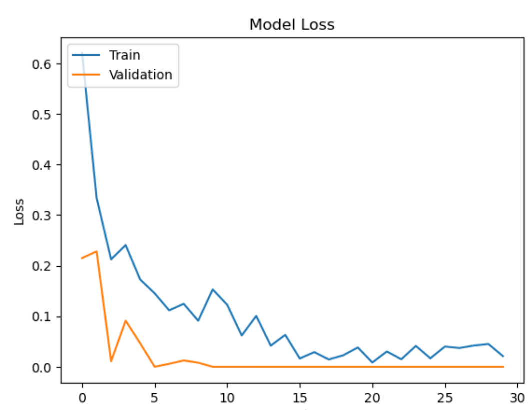

Figure 6: Graph of Loss of ANN

Table 1: Classification Report of ANN

	Precision	Recall	F1-Score	Support
Non-Retinal Image	1.0	1.0	1.0	2340
Retinal image	1.0	1.0	1.0	2405
Accuracy			1.0	4745

Table 2: Classification Report of MobileNetv2

	Precision	Recall	F1-Score	Support
Non-Retinal Image	1.0	1.0	1.0	2340
Retinal image	1.0	1.0	1.0	2405
Accuracy			1.0	4745

- MobileNetV2 Training

MobileNetV2, a lightweight deep learning model architecture designed for smartphone applications, is selected as the base model to enhance the performance of the existing simple ANN architecture. The sequential model is built by incorporating MobileNetV2 as the base and adding the previous simple ANN architecture on top. To preserve the learned features of MobileNetV2, the base model's layers are frozen during training. Only the additional layers from the simple ANN architecture are trained, using the same learning parameters as the initial training. Inference is conducted on both simple and complex feature images using the saved model. The MobileNetV2-based model demonstrates superior performance compared to the simple ANN architecture during real-time inference. As a result, MobileNetV2 is chosen over the simple ANN architecture for deployment in the mobile and web app to facilitate classification tasks.

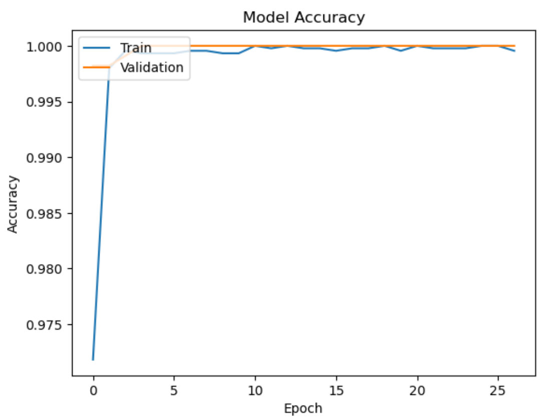

Figure 7: Graphs of Accuracy of MobileNetv2

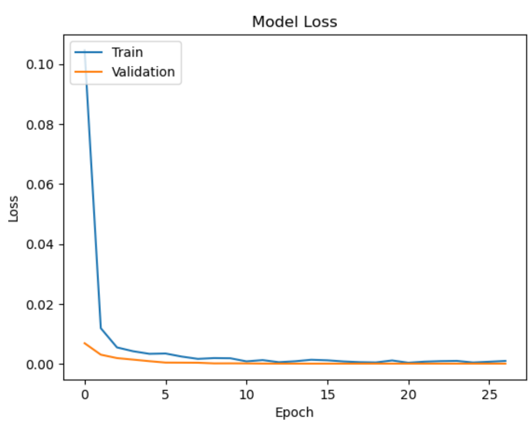

Figure 8: Graphs of Loss of MobileNetv2

2. Network 2 Disease Classification:

Once the retinal image has been identified, the subsequent step involves the classification process for disease detection. The image is classified as either "Referable" indicating the presence of a disease, or "Non-Referable" indicating that the person is free from any disease and does not require a visit to a specialist. The detailed discussion on the training networks is presented in the following section.

- Bens Graham Preprocessing and Training with MobileNetV2

The Bens Graham preprocessing technique is utilized to enhance retinal images for effective classification. It involves cropping dark regions, resizing images, and applying image enhancement techniques such as Gaussian blur and linear combination.

MobileNetV2, pretrained on the ImageNet dataset, offers a diverse collection of images. Through transfer learning, it acquires broad image characteristics relevant to DR classification, reducing the need for extensive training with limited DR-specific datasets and accelerating model convergence. MobileNetV2 stands out for its lightweight and efficient design, featuring simplified architecture with depth-wise separable convolutions that minimize computational complexity and memory requirements. This enables resource-limited devices to perform real-time classification for detecting DR without relying on external servers or internet connectivity, ensuring independence and accessibility. Additionally, a five-layer ANN architecture is added atop MobileNetV2 for classification, trained using the EyePacs dataset. The model's performance is evaluated using the DDR dataset, which consists of balanced classes with 2500 images each. Single image inference was done to assess the model's suitability for real-time predictions. While MobileNetV2 performs well on some images, it struggles with those containing complex features on the unseen dataset during the first phase of training.

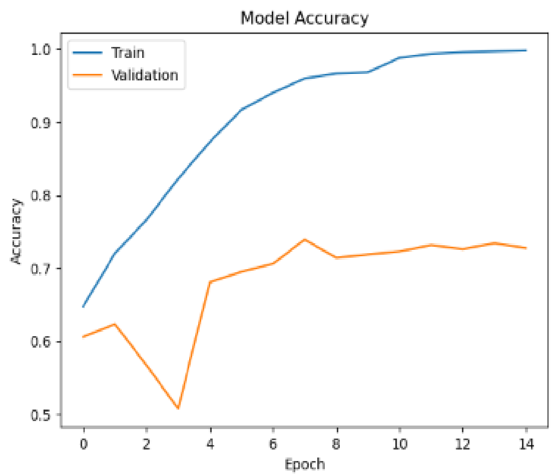

Figure 9: Graphs of Accuracy of Network 2 before Fine-tuning

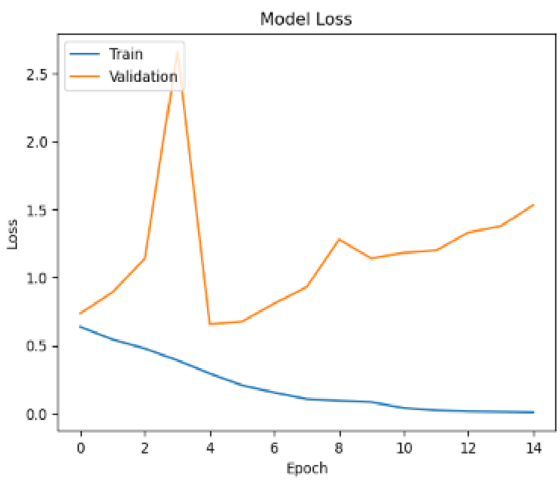

Figure 10: Graph of Loss of Network 2 before Fine-tuning

Table 3: Classification Report of Network 2 before Fine-tuning

	Precision	Recall	F1-Score	Support
Non-Referable	0.7569	0.5329	0.6254	2507
Referable	0.6393	0.8287	0.7218	2505
Accuracy			0.6807	5012

- Fine Tuning with Bens Graham Preprocessing and Transfer Learning

Due to the model's limitations in handling complex features in the first training, a second training phase is conducted. The previously saved MobileNetV2 model from the first training phase is loaded to leverage its knowledge on the new DDR dataset maintaining class balance with 3700 images for each class. By fine-tuning the MobileNetV2 model, incorporating the previous ANN architecture and applying Bens Graham preprocessing the trainable layers of MobileNetV2 are set to "True" to learn complex features from the new dataset, while the learning parameters remain the same as in the first training phase. Inference is conducted using the fine-tuned MobileNetV2 model on both simple and complex feature images, demonstrating improved performance during real-time inference. The model's performance is evaluated using the DDR dataset for testing and validation. The fine-tuned MobileNetV2 model is selected for deployment in the mobile and web app for classification purposes.

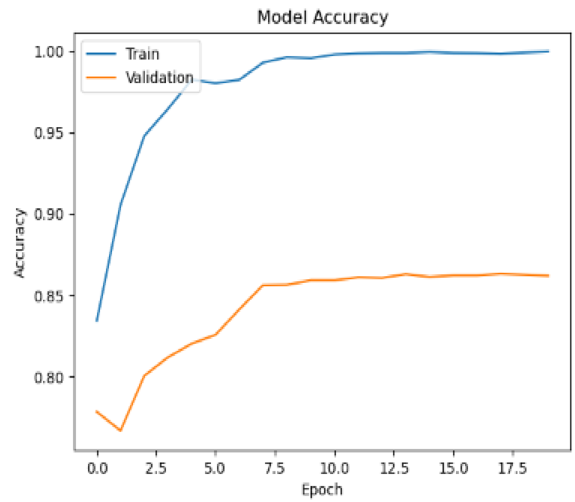

Figure 11: Graphs of Accuracy of Network 2 after Fine-tuning

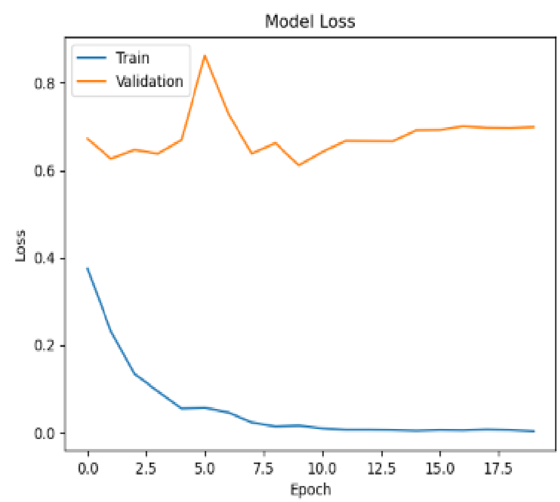

Figure 12: Graphs of Loss of Network 2 after Fine-tuning

Table 4: Classification Report of Network 2 after Fine-tuning

	Precision	Recall	F1-Score	Support
Non-Referable	0.8304	0.9026	0.8650	2507
Referable	0.8933	0.8155	0.8526	2505
Accuracy			0.8591	5012

V. Implementation

A. Model Deployment by Flask

Flask, a lightweight and popular Python web framework, serves as the foundation for developing web applications and APIs. In our project, Flask plays a crucial role in creating a seamless integration of trained models and handling classification requests from the web app. Acting as a bridge between the front-end interface and the back-end model deployment, the Flask API enables smooth communication and inference processes. Specifically, Flask is utilized to develop the API responsible for establishing a connection between the web app interface and the deployed models. Within the Flask application, we define routes and functions to effectively handle incoming requests. When a user selects an image for classification, the web app initiates a request to the Flask API. Flask receives and processes the request, extracting essential data such as the image file or URL. Leveraging the power of the deployed models, Flask performs inference on the received image data. These trained models meticulously process the image and generate classification results. The Flask API plays a pivotal role in deploying the models on the server, facilitating the seamless transfer of images for processing, and returning the classification results to the user.

B. *Developing the Flutter App*

The integration of the proposed method into a mobile-based classification smartphone application involves designing an intuitive and user-friendly interface using the Flutter framework. The Flutter framework allows for the development of cross-platform applications, ensuring compatibility with both Android and iOS devices. Flutter provides an image picker package to access gallery or camera.

C. *Developing the Web App*

The next step is to deploy trained models and integrate them into a web app. Using the React framework, an intuitive and user-friendly interface is designed for real-time inference on retinal and non-retinal images. A server is set up to host the models and handle user requests for image classification. The interface provides immediate feedback on classification results, indicating whether the image is non-retinal or requires further classification as referable or non-referable.

1) Classification Output Display

The selected image is passed through the server-based model to determine if it belongs to the retinal or non-retinal category, filtering out irrelevant images. The app interface displays the classification output to the user. A second model detects the presence of diabetic retinopathy, providing crucial information for timely intervention and treatment. The integrated smartphone and web applications offer an automatic system for DR diagnosis, enabling convenient screening without expensive equipment or expert assistance. This remote access to healthcare resources reduces the burden of DR and facilitates early intervention.

VI. Conclusion

In conclusion, this work addresses the challenges faced by individuals with diabetes in accessing early diagnosis and treatment for diabetic retinopathy (DR). The use of a smartphone-based system for detecting DR during routine health screenings is proposed as a solution to overcome the limitations of costly imaging devices and scarcity of healthcare centers. The work investigates the development of automatic DR detection algorithms using deep learning frameworks, resulting in a smartphone and web application integration for convenient diagnosis. By providing remote access to healthcare resources, this approach alleviates the burden of DR and facilitates early intervention. The contribution of this work lies in its cost-effective and accessible method for identifying and classifying DR, particularly benefiting individuals in remote areas or lacking specialized healthcare access. Performance metrics such as precision, recall, F1-score, and accuracy were used to evaluate the classification models, providing insights into their effectiveness. Future work involves enhancing deep learning models with larger datasets and advanced architectures, incorporating more precise severity classifications, and integrating telemedicine capabilities for remote consultations. However, limitations exist, including the impact of image quality and artifacts on detection accuracy, as well as the potential biases in training data and the need for continuous updates with new data. Additionally, the deployment of models on servers may be hindered during periods of high traffic or server load.

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