Diabetic Retinopathy Detection using Android Application

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Abstract—**Diabetes is a chronic health condition that arises due to inability to maintain a healthy glucose level in the blood. Over a period of time, due to this condition body organ of any individual may get damaged as diabetes affects primary organs like heart, blood vessels, eyes, brain, etc. The main cause of Diabetic Retinopathy is diabetes mellitus, which causes vision problems due to excess swelling of blood vessels of the retina, which further causes leakage of fluids and blood, into retina membrane. Almost 60% to 80% of diabetes patients who are suffering from chronic diabetes suffer from diabetic retinopathy. It is a leading factor for blindness in people from age 21 to 60 years. Diabetic Retinopathy can be treated in the early stage by observing abnormal growth of tissues called lesions which start from Micro-aneurysms in the non-proliferative stage of Diabetic Retinopathy. Many researchers throughout the world have proposed numerous Machine Learning models for early detection of Diabetic Retinopathy from developing into later stages, that is, to prevent blindness. In this paper, android application is developed to detect severity of Diabetic Retinopathy using deep learning techniques.**

Keywords—Android, Deep Learning, Diabetic Retinopathy, Image Processing, Retinal Images

I. INTRODUCTION

This Diabetes is a long term health condition which arises due to weak functioning of the liver, or inability of the human body, to intake the secreted insulin. This health condition has many severe effects on the human body. Excess amount of glucose in the body for a very long term may damage the organs like eyes, heart, nerves, feet, kidneys, etc. [1], and make our body weak. It also damages one of the main parts of our body, Retina, light sensitive tissue at the back of the eye, which converts light entering into the eyes to the electrical signals which the optic nerve sends to the brain, in turn creating the image that we see [2].

Anatomy of human eye consists of various nourishing cells and tissues for stable vision. Damage to the blood vessels of the retina due to long term Diabetes is the complicated case called Diabetic Retinopathy (DR) [3].
Diabetic Retinopathy (DR) is divided into two main categories mainly Non-Proliferative (NPDR) and Proliferative (PDR) stages in which microaneurysms (MAs), Hemorrhages (HAs), exudates (Exs) and Neovascularization are the main features seen in the retinal images of patients suffering from diabetic retinopathy [6].

A. Diabetic Retinopathy Features

The PDR (proliferative diabetic retinopathy), PDR is an extreme level of diabetic retinopathy. PDR occurs when the retina membrane starts growing a new network of blood vessels called **Neovascularization** [7].

Microaneurysms: They are red and resemble a sac-like structure. They are 1-3 pixels in diameter that is 100 µm. It is the first-over symptom of Diabetic Retinopathy [7].

Haemorrhages: They are blood vessels with risk of leakage from the network of blood vessels. Thin blood vessels may get rupture and bleeding may happen which will lead to vision problems. It is characteristic of PPR (Pre-Proliferative Retinopathy) also it is the second symptom of DR. They are 3-10 pixels in diameter [7].

Exudates: They are yellowish-white discrete intra-retinal features. They are ring-like 1-6 pixels in diameter [7].

Cotton Wool Spot: They are the largest, cloudy, irregular structures. They are grey-white in colour patches, leads to the pre-proliferative stage of diabetic retinopathy [2].

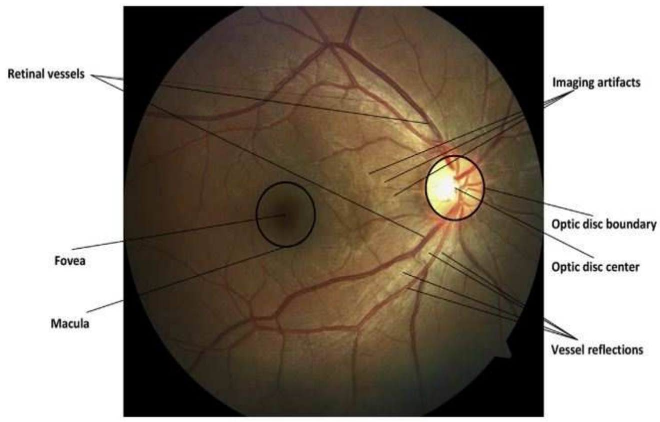

Fig. 1. Anatomy of Human eye [5]

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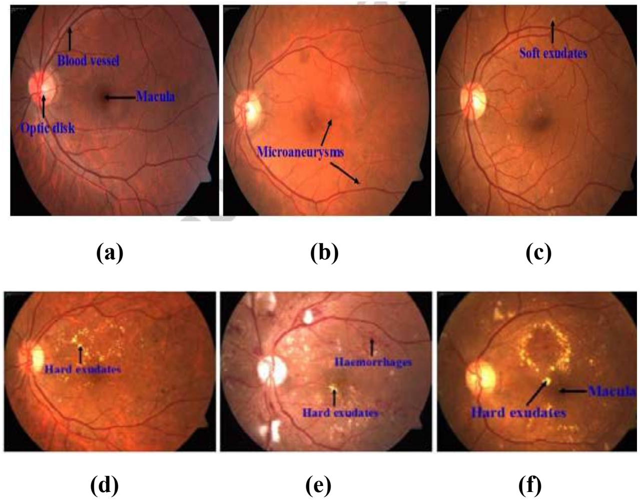

Fig. 2. Typical retinal image showing features of Diabetic Retinopathy [8]

II. Literature Review

DR is the significant condition of diabetes mellitus if not detected at early stage will lead to complete vision loss. Hence it is very important that patients suffering from diabetes should do regular retinal checkups. Automatic analysis and detection of DR will surely help doctors in screening patients. There are multiple studies available focusing on detection of DR. These studies are mainly focusing on recent trends and technologies like machine learning, advance image processing, deep learning, and neural network algorithms etc. This section of paper focuses on recent trends and technologies used for DR detection.

Basic stages involved in DR detection are (1) Preprocessing of retinal image (2) Segmentation of normal retinal features optic disc, blood vessels, macula etc. and abnormalities such as microaneurysms, hemorrhages, Exudates, Cotton Wool Spot (3) Training (4) Classification.

Manual diagnosis takes much more efforts for detection and classification of DR. Automated diagnosis and screening will surely reduce the cost, time in the process also will assist doctors making their work easier [2].

Seoud et al. [11] proposed a method to classify DR lesions using dynamic shape features where multiscale ring-shaped matched filter used to extract features and RF classifier is used for classification. Gangwar et al. [12] proposed a novel method with the help of transfer learning pre-trained Inception-ResNet-v2 and added CNN block layer above pre-trained model and tested the performance on Messidor and APTOS dataset got 72.33% and 82.18% accuracy, respectively. Qureshi et al. [13] used active deep learning CNN model for detection of DR and tested method on EyePACS dataset and got 98% accuracy. Z. Khan et al [14] proposed a VGG-NiN model for DR detection which is a combination of VGG16, spatial pyramid pooling layer (SPP) and network-in-network (NiN) which gave average accuracy for DR classification as 83.8% on Kaggle dataset. X. Luo et al. [15] proposed a novel method using combination of deep learning and mixture loss function for eye disease screening. K. Shankar et al. [16] proposed a novel synergic deep learning model for classification of DR and combined it with preprocessing techniques histogram-based segmentation and got 99.28% accuracy on Messidor daaset. Shaik, N.S et al. [17] proposed a Hinge Attention Network which uses pre-trained VGG16 model for DR grading. The accuracy achieved by this model is 85.54% and 66.41% on Kaggle APTOS and IDRiD datasets, respectively.

Boukadida et al. [18] proposed a smartphone base DR detection method with the help of optical lens attached to phone and applied 10 cross validation method and achieved 98.69 % accuracy on publicly available dataset. Elloumi et al. [19] proposed a mobile based DR screening system called as NasnetMobile which uses transfer learning method where they got 95.91% accuracy on dataset consisting of 440 images.

After going through the exiting methods, it is observed that developing automatic screening system is very important as DR is silent disease with the main cause of blindness for people suffering from diabetes. It is being predicted that by year 2030 and 2045 there will be 578 and 700 million people suffering from diabetes and approximately 193 million people will be suffering from DR [23]. Hence it is very essential do develop automatic screening system for DR detection and classification.

III. Methodology

After going through exiting methods we understood that deep learning methods or transfer learning methods have given more promising results in detection and classification of DR. Hence, we focused on detection and classification of DR with the help of deep learning models and developing an android application for the same. This section gives the details about methodology and dataset used by us for carrying out the research.

A. Dataset

We used publicly available Kaggle dataset known as “APTOS 2019” which consists of 3662 DR sample images [20]. Mentioned dataset is a part of EyePacs dataset consisting of 35676 retinal images. Summary of the dataset is shown in fig. 3. The dataset used contained 5 classes as per the severity of DR,

0 - No DR

1 - Mild

2 - Moderate

3 - Severe

4 - Proliferative DR

Dataset consists of different CSV files such as test.csv, train.csv and valid.csv which provides the information about ground truths of images.

B. Implementation

To train the model dataset is split into 85:15 ratios. We used 85% of a sample for training and 15% for testing. Then, we resized the image into 224 x 224 x 3 with MobileNet Architecture to train the model with 50 epochs and batch size of 60 with the learning rate of 0.001. To use that same model into a mobile application, we converted this model into the TensorFlowlite (TFlite) model which helps to build android app, also analyzes live image capture feed, and identifies the object using machine learning technique.

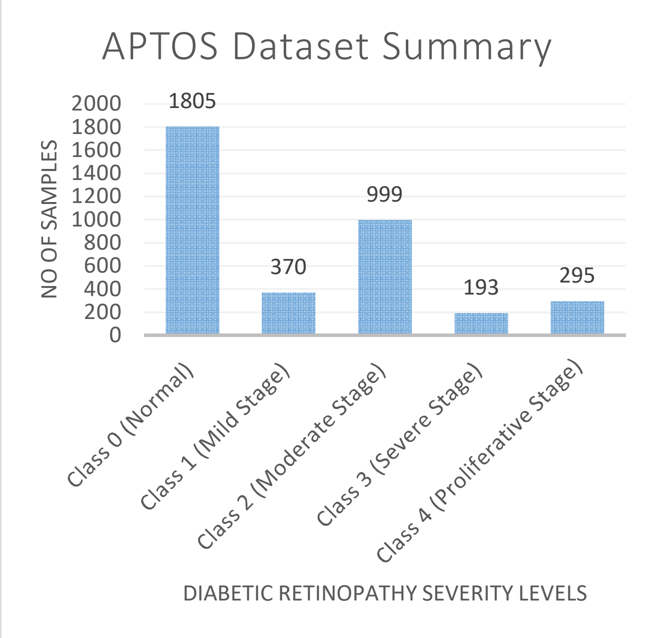

Fig. 3. Classification of Train and test images in dataset

We tried to reduce class imbalance in dataset by performing mirroring and rotation of class images. Following table classifies the whole dataset into two classes- No DR & DR

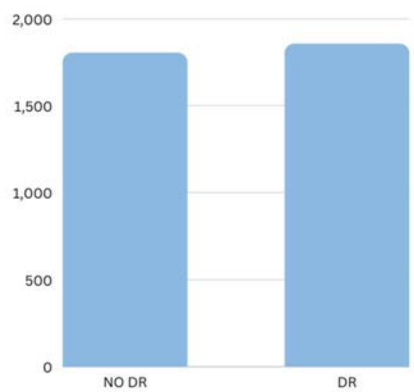

Fig. 4. No DR vs DR

We tried to detect DR using different CNN models which were maximum of the times used in literature review such as MobileNet, VGG16, InceptionV3 and Resnet50.

MobileNet is 53 layers deep [21]. We can load the pre-trained network of model on more than a million images from the ImageNet database and load other images into it and train our model with our respective dataset of 5 classes. VGG16[22] is the most famous model used for image classification by the researchers as it gives 92.7% top-5 test accuracy in ImageNet dataset. InceptionV3 is mostly used for transfer learning and Resnet50 is a 50-layer residual network which rather than learning features it learns residual [22]. Fig. 5 shows the basic structure of mobile application model for DR detection and classification.

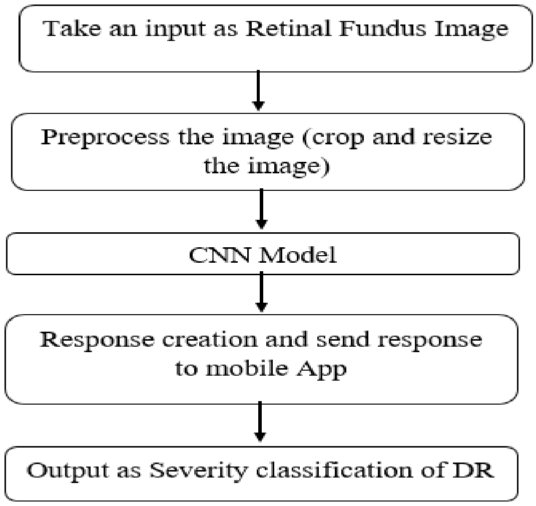

Fig. 5. Basic strusture of mobile application model for DR classification

IV. RESULTS AND ANALYSIS

We experimented the results on MobileNet, VGG16, InceptionV3 and Resnet 50 models. We found the best model at 46th epoch with f1-score of 0.91 with VGG and 0.9 with MobileNet. After testing and converting the models to TFlite model, we found, MobileNet is the lightest model among them, providing accuracy of 0.9, with the precision and recall value of 0.89 and 0.91, respectively.

The first step to start with the application is open the app, select the retinal image to be classified or detected and click on detection. Tools and technologies to develop application are Android OS (Min 10), Python, Flutter, TFlite and Colab. Fig 6, Fig 7, Fig 8, Fig 9 and Fig 10 are the screenshots of the results obtained through developed application where we can see that developed application have successfully classified retinal input images in respective DR classes from 0 to 4. With loss and test loss, we can say that good performance, in later training process loss is very low as compared to test loss.

So, we can say that this is a good model to detect and classify. In the last section we saw implementation of the model into a mobile app. We have divided our dataset into two parts: training & testing dataset. After training a model for 50 epochs with a learning rate of 0.001, we are discussing results for the same model as we can see the relation between accuracy and test accuracy. Also, with loss and test loss, we can say that we obtained a good performance. In later training process loss is very low as compared to test loss. We can say it is a good model to detect and classify the classes.

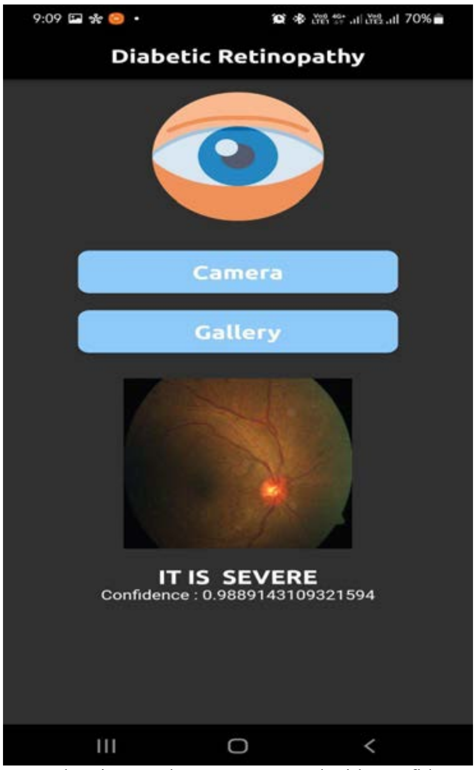

Fig. 6. Output Showing result Severe Detected with Confidence –Class 3

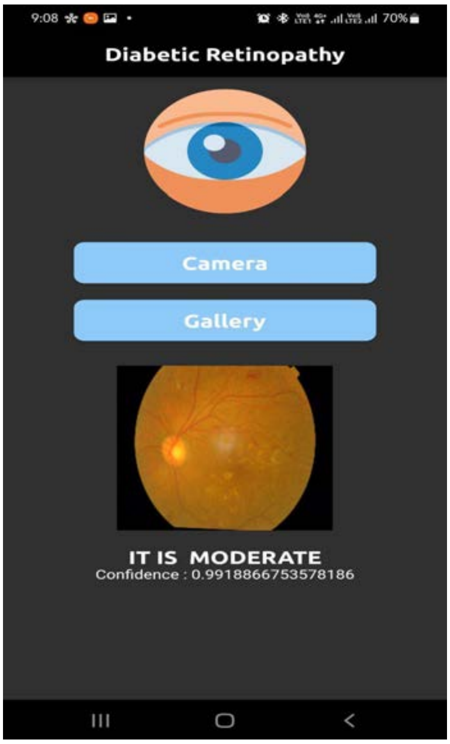

Fig. 7. Output Showing result Moderate Detected with Confidence-Class-2

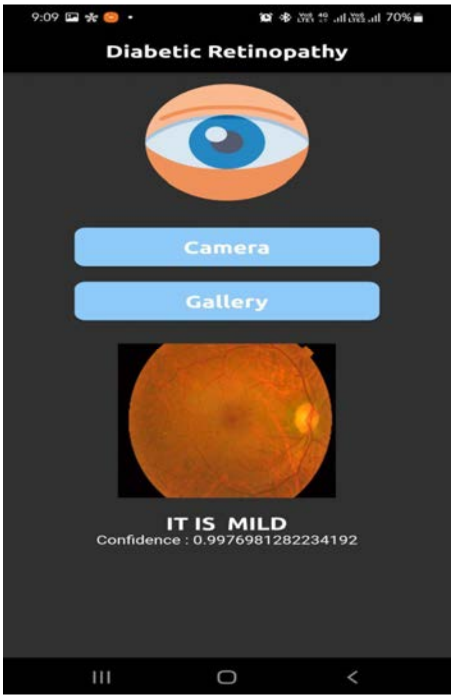

Fig. 8. Output Showing result Mild Detected with Confidence- Class 1

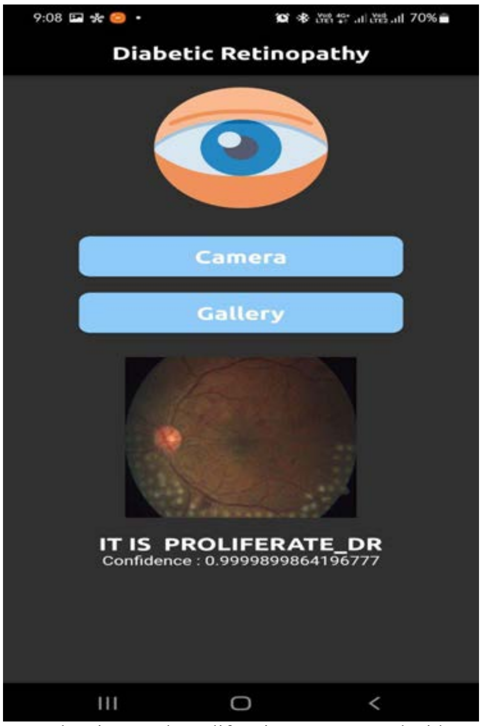

Fig. 9. Output Showing result Proliferative DR Detected with Confidence-Class 4

Experimental results of MobileNet, VGG16, InceptionV3 and Resnet50 are shown in the table I.

TABLE I:Comparative Study

Architecture	Dataset	Loss	Accuracy (%)
MobileNet	Kaggle	0.3648	89.03
VGG16	Kaggle	0.1123	90.14
InceptionV3	Kaggle	0.411	85.18
Resnet50	Kaggle	0.586	84.7

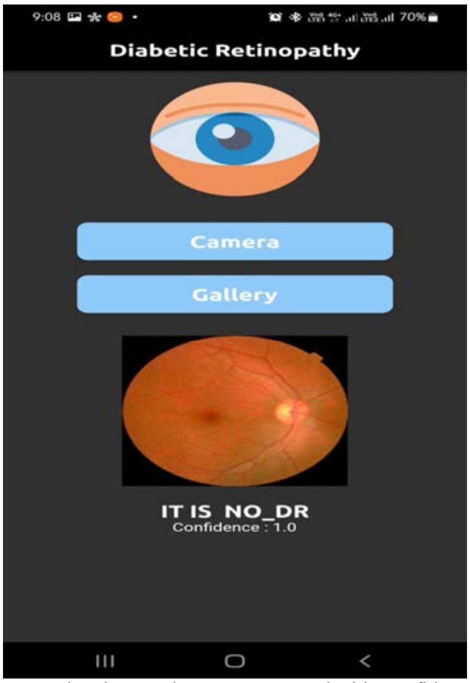

Fig. 10. Output Showing result No DR Detected with Confidence- Class 0

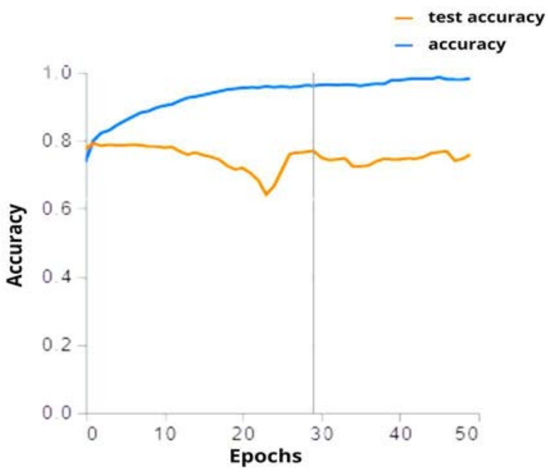

Fig. 10. Accuracy graph

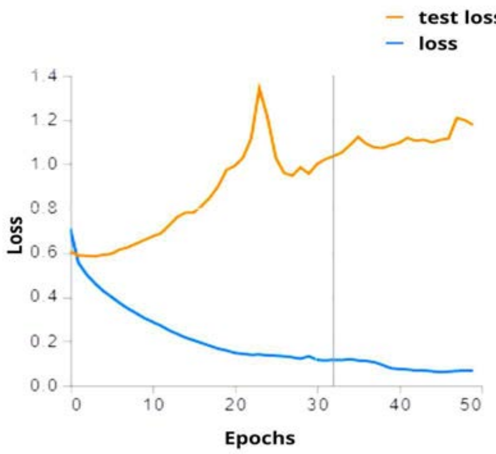

Fig. 11. Loss graph

V. Conclusion

With maximum use of smartphones and availability of the smart gadgets we conclude that disease detection with android application will surely help doctors to speed up the screening process. We experimented and compared four deep learning models MobileNet, VGG16, InceptionV3 and Resnet50 and which gave us 89.03 %, 90.14 %, 85.18 % and 84.7 % accuracies, respectively on Kaggle dataset. In future more advance model can be developed by applying more preprocessing and segmentation techniques to improve the accuracy of the model.

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