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Diabetic Retinopathy Detection through Ensemble Transfer Learning Models and Web App

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ABSTRACT

Diabetic Retinopathy (DR) is a diabetic issue that disturbs the eyes. The people with diabetics will have this eye disease. Due to extreme blood sugar level, it harms the blood vessels in the retina. The blood vessel can inflates and outflows or stops the flow of blood or there will be growth of abnormal blood vessels. The DR does not show any symptoms and it will cause a severe blindness if it is not detected earlier. Detecting DR through manual process is a takes more time and requires an expert or most skilled clinician. Hence an automated detection model will solve this problem. Therefore a Deep Learning model is proposed by ensemble three transfer learning models ResNet50, VGG16 and EfficientNet-B0. The model is trained on the pre-processed retinal images and pre-processing includes cropping, applying Gaussian blur and re-sizing the images. The model will classify the different stages of DR such as mild, moderate, severe and proliferative DR. We get training accuracy of 98%, 96% and 98% for ResNet50, VGG16 and EfficientNet-B0. We obtained an 86% of testing accuracy in ensemble model. Web interface is created for detection of DR.

Keywords: Diabetic Retinopathy, Transfer Learning, Convolutional Neural Network, Retina Images, Ensemble model.

I. INTRODUCTION

Diabetic Retinopathy (DR) is a diabetic issue that disturbs the eyes. Due to extreme blood sugar level, it harms the blood vessels in the retina. As study shows that a person has diabetes for few years then he or she may have DR. The longer a person has diabetics there are more chances for development of DR. There will be no symptoms at the earlier stage.

There are mainly two types in the DR i.e. Non Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR). The NPDR is also categorized into different stages i.e. Mild, Moderate and Severe. Mild is the first stage of DR where there is presence of micro-aneurysms. Micro aneurysms occur due to blockage of blood capillaries which leads to lack of oxygen and development of the disease, this forms tiny red spots on the retinal surface. These tiny red spots are less than the diameter of the optic vein [1]. Moderate and severe are the next stages of the DR where hemorrhage, cotton-wool spots and exudates are present. Due to leakage of lipids in the blood vessels the yellowish regions are formed knows as exudates. When there is not enough blood reaching the retina due to blockage then there will be growth of new blood vessels which is called neovascularization. This leads to PDR. This is very dangerous that can cause permanent blindness. Fig. 1 shows the different types of lesions present in different stages of DR.

Premature identification of diabetic retinopathy is essentially helpful for prognosis [2]. The manual process is time consuming process and costly. Moreover it requires a skilled clinician and normally takes a minimum of 2 days to get the results. The main problem occurs in the rural areas where people have to travel very long for check up of DR. To solve this and detect DR in early stage automatic detection will play a vital role. The automatic detection model can be kept in every clinics will help for identification in early stage. In this project the model is created using ensemble three transfer learning models i.e. ResNEt50, VGG16 and EfficientNet B0. The fundus images are pre-processed and given to the model which classifies into 5 different classes of DR. A web application is also created to make this process easy and fast.

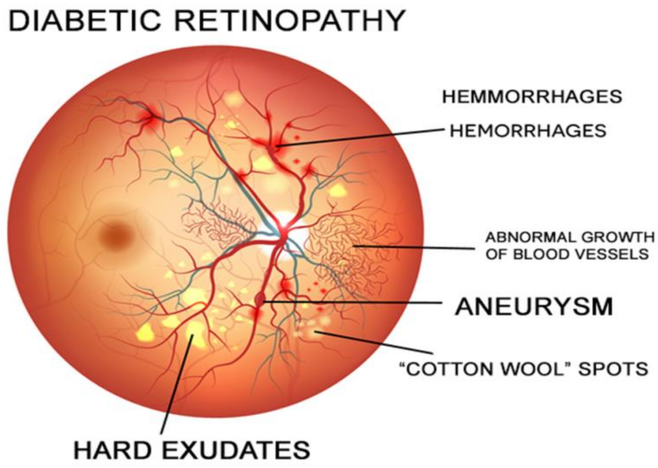


Fig. 1: Diabetic Retinopathy Lesions

II. RELATED WORKS

Sanskuthi Patel [2] used the two pre-trained models VGG16 and MobileNetV1 for the classification of DR and trained with and without fine tuning the models. In preprocessing normalization and Gaussian blur is used then images are augmented. In Revathy R *et al.* [3] method hemorrhages, exudates and micro-aneurysms are detected and classified using hybrid classifier which is a combination of support vector machine, k nearest neighbor, random forest, logistic regression and multi-layer perceptron network. Preprocessing the retinal images and image segmentation are used before training. Asra Momeni Pour *et al.* [4] described a model that uses Contrast Limited Adaptive Histogram Equalization to improve the contrast of the images and EfficientNet-B5 architecture is used for classification. They have trained the images on combining two datasets which improved AUC. A. Biran *et al.* [5] proposed a model for identification of DR using SVM classifier. In preprocessing stage several image processing techniques are used like green channel extraction, CHT, CLAHE and threshold. In this method model is classifying DR into 3 categories i.e. PDR, Normal and NPDR. Carson Lam *et al.* [6] discovered that preprocessing the images with CLAHE and ensuring datasets fidelity by expert's verification of class labels improves the recognition of subtle features. For multi classification they have used AlexNet and GoogLeNet.

III. PROPOSED METHOD

A. Dataset

In this paper, we have used Aptos-2019 Blindness Detection datasets from kaggle which consists of 3662 retina fundus images which belongs to 5 classes. We have separated the images into different classes DR i.e. NoDR, Mild, Moderate, Severe and PDR. After separation, NoDR class has 1805 images, Mild class has 370 images, Moderate class has 999 images, severe class has 193 images and PDR class has 295 images. Fig. 2 shows the histogram of the datasets.

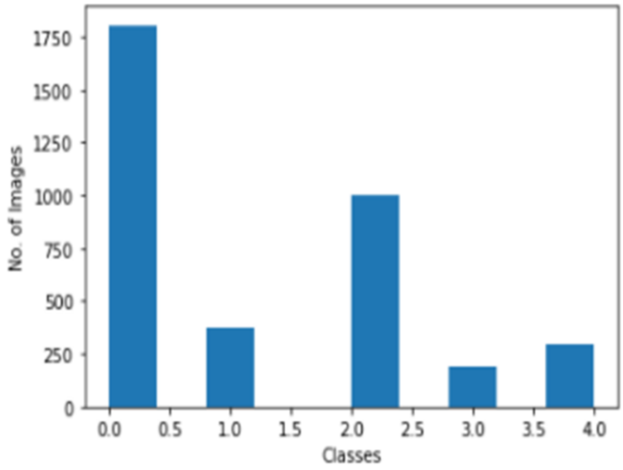
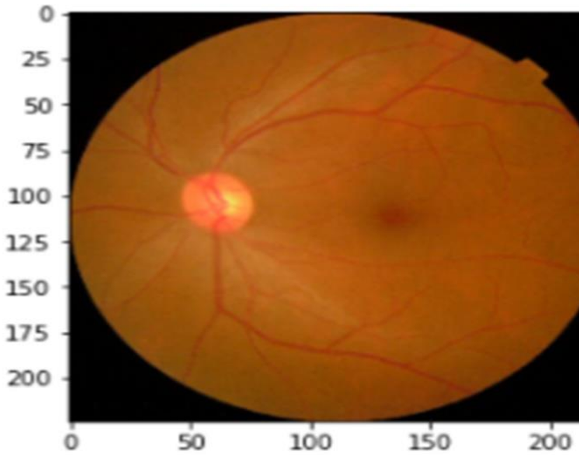


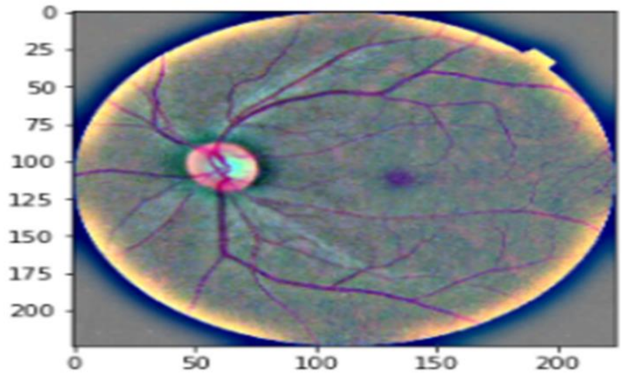
Fig. 2: Images in Different classes

B. Preprocessing and Enhancement

In the Preprocessing stage we perform cropping and re-sizing. Some images in the datasets have too much black background which may affect our model performance. So we crop out those black areas from the images and our three models takes images of 224x224 resolutions, so we resize all images into that resolution. Next step we apply a Gaussian blur filter to our images to eliminate the noise from the images. Since some of the images are dark and difficult to visualize so we used Ben Graham's preprocessing method [7] which helps to improve the lightning condition of the image. Fig. 3 shows the original image and the image after preprocessing.



(a)



(b)

Fig. 3: (a) Original image. (b) Pre-processed image.

C. Architecture

1) **ResNet50:** ResNet50 is a powerful model which is widely used in the classification and computer vision tasks. ResNet50 uses skip connection to add the output of previous layer to the next layer. This solves the vanishing gradient problem. ResNet50 is a form of ResNet which has 48 convolution layers with 1 max-pooling and 1 average pool layer [8].
2) **VGG16:** It is a convolutional neural network developed by K. Simonyan and A. Zisserma which is trained on the imagenet datasets. It takes a fixed size of 224x224 RGB image as input. There will be a combination of convolution layers and last it has pooling layer in each block.
3) **EfficientNet-B0:** It is one of the widely most used architecture. There are many types starting from B0 to B7. B0 is a baseline model and every model has their own features. Efficient-B0 architecture takes image of 224x224 sizes as inputs. EfficientNet contains a compound scaling method which increases the accuracy and makes model effective. EfficientNet-B0 is developed as baseline network by leveraging a multi-objective neural architecture search that optimizes both accuracy and flop [9].

D. Training and Classification

We have used retinal images as inputs to the models which are split into training and validation in 80% and 20%. The ResNet50, VGG16 and EfficientNet-B0 are trained separately. ResNet50 and EfficientNet-B0 are trained for 50 epochs and VGG16 is trained for 70 epochs. Using Model Checkpoint we have saved the best model which gives the best training accuracy and validation accuracy. Adam optimizer is used with a learning rate of 0.0005 and loss function as sparse categorical entropy. The three models are ensemble together and performed testing on that ensemble model.

Model	Epochs	Best Training Accuracy	Best Testing Accuracy	Precision	Recall	F1 Score
ResNet50	34	98%	83%	0.83	0.83	0.82
VGG16	41	96%	82%	0.82	0.82	0.81
EfficientNet-B0	18	98%	85%	0.85	0.85	0.85
Ensemble Model	-	-	86%	0.86	0.86	0.85

TABLE 1: Performance of the Models

IV. EXPERIMENT AND RESULT

In the previous section we have discussed about datasets used, pre-processing methods and the models used and the particular parameter values. TABLE 1 shows the performance metrics of our models. Initially we have taken three separate transfers learning models with imagenet weights and then finetuned the layers then performed training for collected images. In ResNet50 model we have gained a 98% training accuracy in 34 epoch and 83% of validation accuracy. Fig. 4 shows the line graph of training and validation accuracy of ResNet50 model for 50 epochs. We have calculated the precision, recall and f1 scores for that model which gives 0.83, 0.83 and 0.82 respectively.

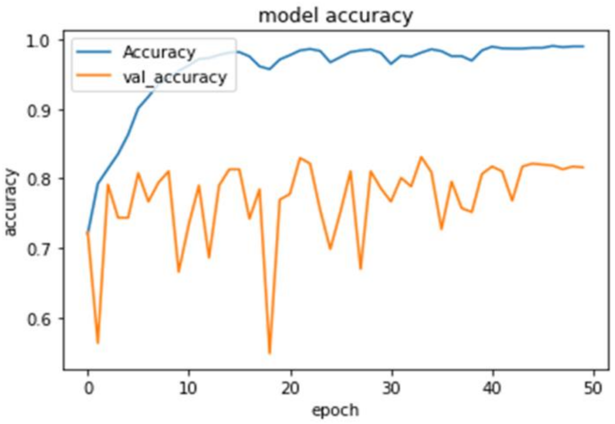


Fig. 4: validation and Training accuracy graph of ResNet50

In VGG16 model we have trained it for 70 epochs as we know that VGG16 is slightly slow in reaching the accuracy because of its structure. We obtained a training accuracy of 96% and testing accuracy of 82% in 41 epochs. We obtained the precision of 0.82, recall of 0.82 and f1 score of 0.81. Fig. 5 shows the line graph of training and validation accuracy of VGG16 model for 70 epochs. We can see a gradual increasing the training and validation accuracy while training.

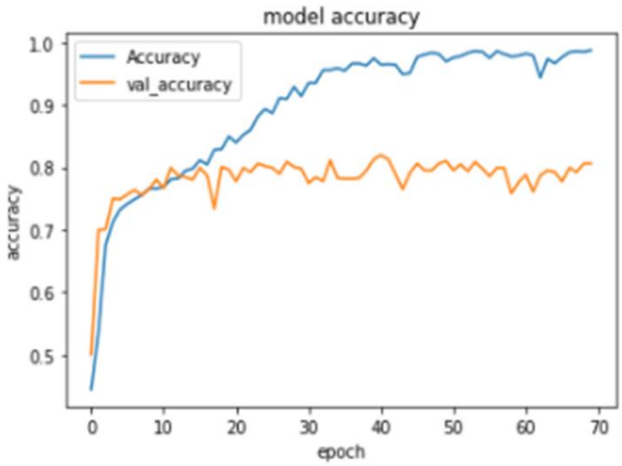


Fig. 5: Training and validation accuracy graph of VGG16

In EfficientNet-B0 model we overall trained it for a 50 epoch but we have got a best model in 18 epochs. That model provides 98% training accuracy and 85% training accuracy. As we know that EfficientNet is a faster network and provides an efficient result. As comparing individually, this model gives greater validation accuracy. The model has a 0.85 of precision, 0.85 of recall and 0.85 of f1 score. Fig. 6 shows the graphical representation of training and validation accuracy of EffiicientNet-B0 model for 50 epochs.

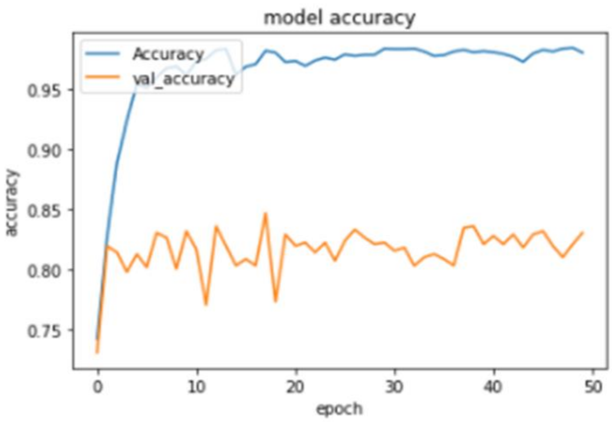


Fig. 6: Training and validation accuracy graph of EffiecientNet-B0

We have used Google Colab Notebook for training the model. After training of each individual model we now perform testing on ensemble model. Ensemble is a process that we use predictions of three models together and get the output. By ensemble model we can achieve a better prediction and better performance. Ensemble model provides robustness to models which can able to reduce the variance in our model helps in increasing the accuracy. After performing testing using ensemble model we get a testing accuracy as 86%. We can observe an increment in the accuracy as compared to individual models. We obtain a precision of 0.86, recall of 0.86 and f1 score of 0.85.

A. Web Application

We have created a web application to predict the types of DR by uploading the retinal image. A user interface will make very flexible and easy to make use of our model. The application was created using python flask library. The front end was created using HTML and CSS.

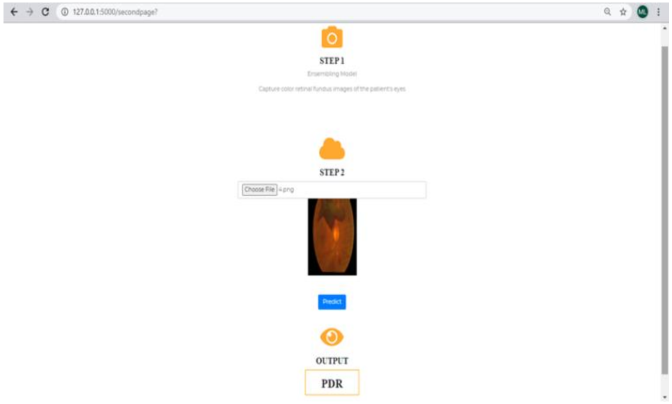


Fig. 7: Web application prediction page

Fig 7 shows the prediction page of the web application where the prediction is performed. This is interface for uploading the image and getting the predicted output.

V. CONCLUSION

In this paper, we have created an ensemble model using three transfer learning models ResNet50, VGG16 and EfficientNet-B0. The retinal images from APTOS datasets are taken and images are pre-processed and used for training. After training each individual model we perform testing by ensemble model. We have obtained an accuracy of 86% for test data and precision, recall and f1 score of 0.86, 0.86 and 0.85. As compared to individual model the ensemble model performs best. We use ensemble model because it increases the performance and makes model more robust. If we train using large amount of datasets this model will become more robust and accurate. We can train on larger Efficient Net networks which are more efficient and accurate using high resolution images.

VI. REFERENCES

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