2020 Emerging Technology in Computing, Communication and Electronics (ETCCE)

Identifying the Level of Diabetic Retinopathy Using Deep Convolution Neural Network

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2020 Emerging Technology in Computing, Communication and Electronics (ETCCE) | 978-1-6654-1962-8 /20/$31.00 ©2020 IEEE | DOI: 10.1109/ETCCE51779.2020.9350905

***Abstract*— Diabetic Retinopathy is the leading cause of blindness in the last 100 years. The traditional screening process for DR and its stages takes a lot of time, and it is not practical. Using machine learning techniques and image processing, we can automate detecting diabetic retinal disease and disease stage with acceptable performance. In this work, we have used multiple deep convolution neural networks (CNN) with the same architecture of InceptionV3. Each of the pre-trained InceptionV3 architecture is retrained with 2200 preprocessed and leveled images. The dataset is preprocessed using multiple high performing and effective image processing techniques. Then the newly trained models are used for identifying the level of DR. In the final stage, we use a voting scheme for classifying the level of DR from the output of each model. We have achieved 90.5% accuracy in binary classification (Normal/DR) and 81.1% accuracy in 5-class classification.**

Keywords*— *Diabetic Retinopathy, Convolution Neural Network (CNN),* InceptionV3, *Contrast Limited Adaptive Histogram Equalization (CLAHE).

I. INTRODUCTION

Diabetes is a chronic disease, and it is common these days. The complications that may come from this disease are many, the most important of which is diabetic retinopathy. The diabetic retinopathy is the leading cause of blindness in the past 100 years for born without vision problems. Identifying diabetic retinopathy in earlier stage is 95% effective in treatment. But early detection, which requires medical image skilled readers and is both labor and time consuming. Manual examination methods do not meet the required speed in diagnosing the disease and giving the necessary treatment.

Hence automatic technique for identifying diabetic retinopathy in earlier level is essential for solving these problems. Deep learning has got higher accuracy for binary classification while it is hard to identify in earlier levels. In our work, we have demon-started multiple deep convolution neural networks (CNN) with same architecture for identifying the specific level of diabetic retinopathy. We have applied most used and effective image preprocessing techniques for processing the retinal images and then trained the pretrained InceptionV3 architecture. The pretrained models are used for identifying the level with voting technique.

A. Diabetic Retinopathy

People with diabetes are prone to developing diabetic retinopathy. This development occurs when blood sugar levels rise sharply, causing damage to the blood vessels in the retina. Fig. 1. shows the differences of normal retina and the affected retina.

As a result, the blood vessels swell and leak, or they get clogged, preventing blood flow. Sometimes new abnormal blood vessels grow. All of these changes may lead to blindness. Eighty percent of people who have had diabetes for 20 years or more may develop diabetic retinopathy. The longer a person has had diabetes, the greater the chances of developing diabetic retinopathy.

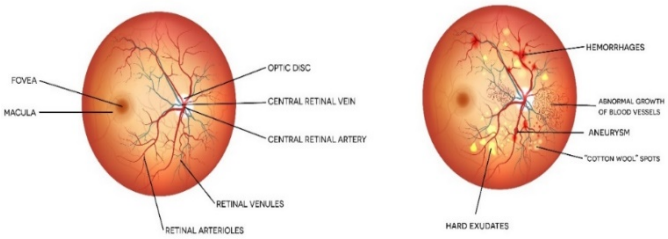

Figure 1 Normal eye (left) and eye with Diabetic Retinopathy (right)

B. Levels of Diabetic Retinopathy

When the diabetic eye is diagnosed for the detection of diabetic retinopathy, there are two main stages in which it is possible to describe the diseased eye's condition. The first stage is a small leak in the blood vessels, which makes the retina swell. This stage is called Non-Proliferative Diabetic Retinopathy (NPDR). At this stage, the macula may have swollen; then it is called macular edema. This is the most common reason why people with diabetes lose their vision. In some cases, the retina's blood vessels may become blocked, preventing blood flow to the macula, which is called the macular ischemia. Sometimes tiny particles called exudates can form in the retina. These can affect your vision too.

In the advanced diabetic retinopathy stage, the retina produces new blood vessels; this stage is called Proliferative Diabetic Retinopathy (PDR). These new blood vessels usually bleed into the vitreous. If these vessels bleed a little, he may see some dark floaters. If the bleeding is a lot, it is possible to block the vision completely. These new blood vessels can form scar tissue. Scar tissue can cause problems with the macula or lead to a detached retina.

PDR is very dangerous, and the patient may seriously lose his central and peripheral (side) vision. In general, the stages of diabetic retinopathy can be classified into five stages, as

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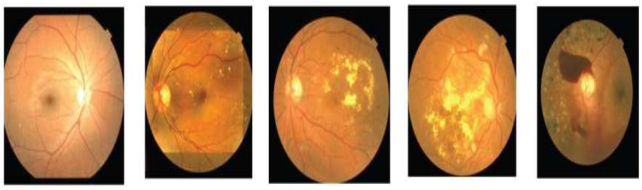
follows: (i) Normal, (ii) Mild NPDR, (iii) Moderate NPDR, (iv) Severe NPDR, and (v) PDR

Figure 2 shows medical images of the eye in the mentioned stages.



(a) (b) (c) (d) (e)

Figure 2 Levels of DR (a) Normal (b) Mild (c) Moderate (d) Severe (e) PDR

C. Symptoms of Diabetic Retinopathy

The most common symptoms that accompany diabetic retinopathy are:

i. Seeing an increasing number of floaters,
ii. Having blurry vision,
iii. Having vision that changes sometimes from blurry to clear
iv. Seeing blank or dark areas in your field of vision,
v. Having poor night vision, and
vi. Noticing colors appear faded or washed out losing vision.

In Fig. 3. the vision of normal people and vision of people affected by diabetic retinopathy are shown.

(a) (b)

Figure 3 (a) Normal Vision (b) Vision affected by DR

Diabetic retinopathy symptoms usually affect both eyes. In worse case, it will lead to blindness. So, the impact of DR is very serious.

D. Current diagnosis system

The current diagnosis system requires skilled ophthalmologists. Fig. 4. depicts the processes. At first, patients have to take doctor's appointment. Doctor scans the eyes of the patient and evaluates the scanned images. Then doctor makes schedule follow up for the patient. In each term, doctor reviews the result. After all these steps, patient is able to pursue treatment. It takes about 2 weeks for getting overall treatment.

The current diagnosis process takes hard manual labor and it is also time consuming. But skilled ophthalmologists are not available in all regions. As a result, it is hard for people who are affected by diabetic to screening their eyes in a regular basis.

E. Background and Present State of the Problem

Diabetic retinopathy is diagnosed by reading images captured by a fundoscopy, and it depends on a complex set of features and localization within the image. The difficulty of diagnosis is in distinguishing the presence of microaneurysms, small saccular outpouching of capillaries, retinal hemorrhages, ruptured blood vessels, among other features on the fundoscopic images. Computer-aided diagnosis of diabetic retinopathy has been explored for decades to help reduce diagnostic errors in manual readings. Automated methods of detecting diabetic retinopathy symptoms from the fundoscopic images have been active computer vision research areas [1].

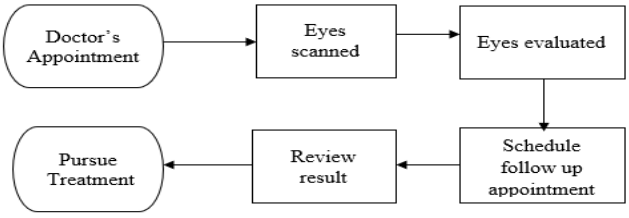


Figure 4 Current diagnosis system

Previous studies using digital image processing techniques with high bias and low contrast have performed well in identifying a specific feature used in detecting microscopic diseases, such as the use of the top-hat algorithm to detect microscopic aneurysms [2]. However, a variety of other features besides a microscopic aneurysm are useful in detecting disease. Additional methods for detecting microscopic aneurysms and DR classification using k-NN [3], support vector machines [4], and group-based methods yielded sensitivities and properties within the range of 90% using various feature extraction techniques and pretreatment algorithms. Previous CNN studies [5] of DR fundus images had investigated sensitivities and specificities in the 90% range of normal or mild versus moderate or severe binary classification categories over the much larger private datasets.

At present, it is trying to improve the quality of the retinal fundas images which are used as dataset for training neural networks using various improved image preprocessing technique. Convolution neural network performs very satisfactory performance in image classifying [6]. Transfer learning is a popular approach for training neural network. Pretrained model is a good example of transfer learning.

II. LITERATURE REVIEW

The literature review gives a clear picture of the problem to be solved as a prerequisite for the study's actual planning and conduct. A review of previous investigations serves as a guide for researchers as it avoids duplication in this area. Knowing what has already been accomplished in the field of investigation regarding the methods used for the data collections and their analysis results keep the researcher systematic in his endeavors. Thus, a review of the relevant literature is an indispensable step in the research.

The use of CNN to classify diabetic retinopathy stages on color fundus images has been explored [7]. They also explored polynomial classification models and found that due to the inability of CNNs to identify subtle disease characteristics, errors occur primarily in the misclassification of mild disease as normal. They discovered that CLAHE pretreatment and ensuring the dataset's consistency enhance fine features identification by expert verification through labels. Transferring the learning from

ImageNet to pre-trained Goog-LeNet and AlexNet models increased the peak test's accuracy to 74.5%, 68.8%, and 57.2% over the 2-ary 3-ary and 4-ary classification models, respectively. Transferring the learning on pretrained Goog-LeNet and AlexNet models from ImageNet improved the peak test's accuracy to 74.5%, 68.8%, and 57.2% over the 2-ary 3-ary, and 4-ary classification models, respectively.

They tried to incorporate a computer vision model of this issue in [8] and to minimize the human resources needed to diagnose the disease. The images are from various sources in the dataset and have different dimensions. The first task was to ensure that the same radius (200px and 500px) should be sampled for all images. These images were then preprocessed via learning transfer to train a convolutional neural network. ImageNet-trained Inception V3, for a Class 5 severity rating, performed better with 48.2% accuracy.

In order to support medical diagnostic decisions, a deep learning framework applied to human retina images [9] has been developed. EyePACS (EyePACS, LLC) has provided Retina images. These images were used for a Kaggle competition (Kaggle INC, 2017), intended to identify signs of diabetic retinopathy through an automatic detection system. They implemented a model that successfully detects diabetic retinopathy from retinal images using one of the contest's solutions as inspiration. After carefully designed pretreatment, CNN carried out a feature extraction process followed by a classification step, which required the system to use five categories to classify healthy and ill patients, the images were used as input to a deep CNN. Their model was able to identify diabetic retinopathy in patients with an agreement rate of 76.73% regarding clinical expert designations for test data.

Gabriel Garcıa et al. [10] attempted to develop a computer-aided tool to classify the retina's medical images to rapidly and accurately diagnose diabetic retinopathy. By training with labeled samples provided by EyePACS, a free platform for detecting retinopathy, the neural network detects exudates, microaneurysms, and hemorrhages in a retinal picture using the CNN architecture. The database consists of 35,126 images of a high-resolution grid recorded in different circumstances. The network showed 93.65 percent specificity after training and 83.68 percent precision in the verification process.

Darshit Doshi et al. [11] presented GPU design and implementation provided deep convolutional neural network acceleration to automatically diagnose and classify high-resolution retinal images into five disease severity stages. The accuracy of the single convolutional neural network model presented in this paper is 0.386 on the weighted quadratic kappa scale, and the synthesis of three similar models yielded 0.3996.

Ramachandran Rajalakshmi et al. [12] used three hundred and one of the people with diabetes of type 2 who underwent retinal imaging using a 'fundus on phone' Remidio (FOP), a smartphone-based device, at a tertiary care Diabetes Center in India. DR classification was performed by ophthalmologists using the DR (ICDR) International Medical Classification methodology [13].

In our methodology, we have used three image preprocessing techniques and three deep convolution neural networks with same architecture. All procedures are de-scribed in this section.

III. METHODOLOGY

A. Flow chart

The overall process consists of two parts. First part is training and the second part is testing. The flowchart of the overall methodology is depicted in Fig. 5.

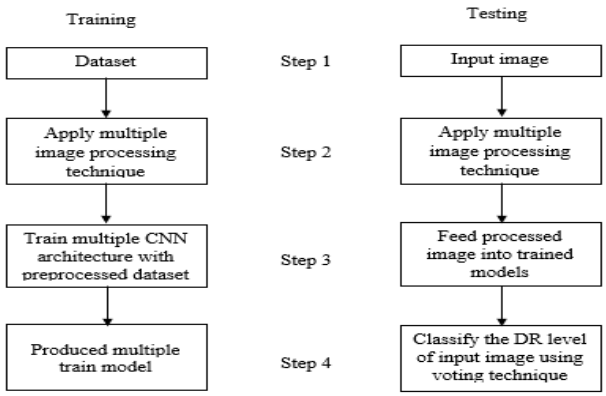


Figure 5 Flowchart of overall procedure

B. Dataset

The dataset contains a wide range of high-resolution retina images captured under a variety of imaging conditions. For each subject, the left and right areas are given. Images are labeled with subject ID and either left or right (e.g., the left eye of Patient ID 1 is 1_left.jpeg). On a scale of 0 to 4, the clinician measured the presence of diabetic retinopathy in each picture according to the following scale: 0 - No DR, 1 – Mild NPDR, 2 – Moderate NPDR, 3 – Severe NPDR, and 4 – PDR.

C. Training Phase

In training phase, first we preprocess the dataset using three (3) different image preprocessing technique. Then each of the preprocessed dataset is feed to three (3) different deep convolution neural network with same architecture. The neural networks are trained with the given dataset and produced three different individual model. In Fig. 6. the whole process is depicted.

D. Identifying the Level

Each input image is preprocessed using the same preprocessed techniques used for dataset preprocessing. Then the preprocessed images are feed to the specific model which used same preprocessing technique in training phase respectively. Fig. 7. shows the entire process of testing.

Each model is independent regarding to the classification purpose. Since the dataset is preprocessed with different preprocessing techniques, each model can classify different level for the same input image. For getting the best result, we have applied voting technique.

E. Voting Technique

We use voting technique for identifying the final level of the input image [15]. The voting technique find the majority of the output of each model. Fig. 8. demonstrates the voting technique.

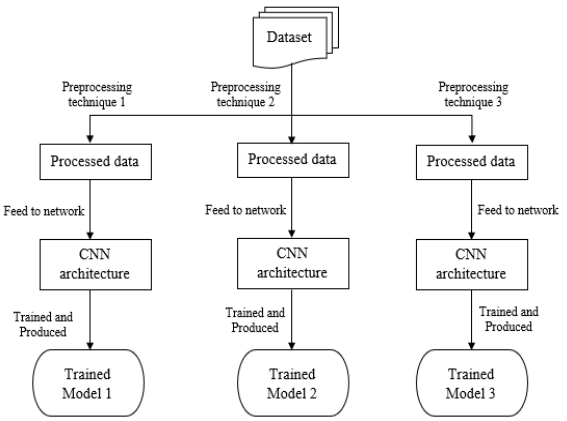


Figure 6 Training steps, these three (3) trained models are used for classifying the level for each respective input image.

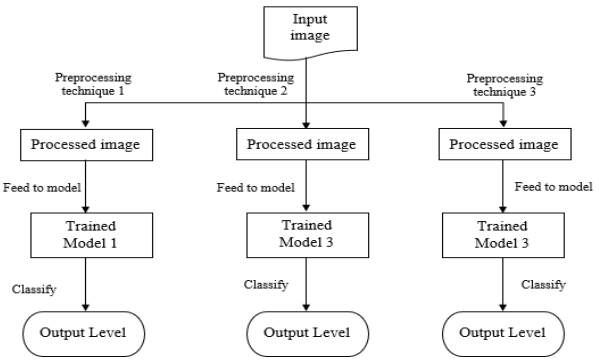


Figure 7 Testing phase using multiple model

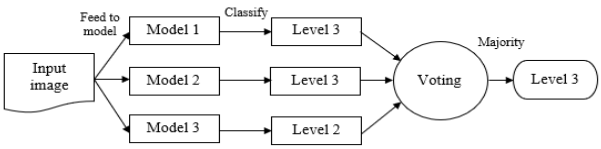


Figure 8 Voting technique

Let, for a same input image the output of model 1 is level 3, the output of model 2 is level 3 and the output of model 3 is level 2. Since two models (model 1 and model 2) classify the input image as level 3 and it is the majority, the final output is level 3 [16]. If the three models produce three different, then we average the classifying percentage of each class. The higher percentage for a class is then the final level. In general voting among 3 is normal where increasing further might make it ambiguous and as an alternate to make the second approach of taking averaging increases the reliability of the voting technique due to having an alternate scheme rather than one.

F. Inception V3 architecture

In our experiment we have used pretrained InceptionV3 architecture as the deep convolution neural network.

Inception-v3 is trained to use 2012 data for the ImageNet Large Visual Recognition Challenge. In computer vision, this is a typical task [17], where models attempt to classify whole images into 1000 groups, such as "Zebra," "Dalmatian," and "Dishwasher".

To compare models, as one of their top 5 guesses called "top-5 error rate," it is important to analyze how much the model fails to predict the correct response. In the 2012 validation data collection, AlexNet achieved a top-5 error rate of 15.3 percent; Inception (GoogLeNet) reached 6.67 percent; BN-Inception-v2 achieved 4.9 percent; Inception-v3 reached 3.46 percent.

With 42 layers, the lower error rate is achieved and makes it the 1st runner up for image classification in ILSVRC (ImageNet Large Scale Visual Recognition Competition) 2015[19].

Support: In several other scientific fields, good support for machine learning and deep learning and the versatile numerical computing center is used [18].

G. Proposed diagnostic system

In our proposed diagnostic system, it is simple to get treatment. After making appointment, doctor will scan patient eyes. Then using the classifying system doctor's will be able to easily classify the patient eye condition. Fig. 10. shows the steps.

It will take less than one (1) hour to purse treatment, where the present procedure takes over two (2) weeks to purse treatment.

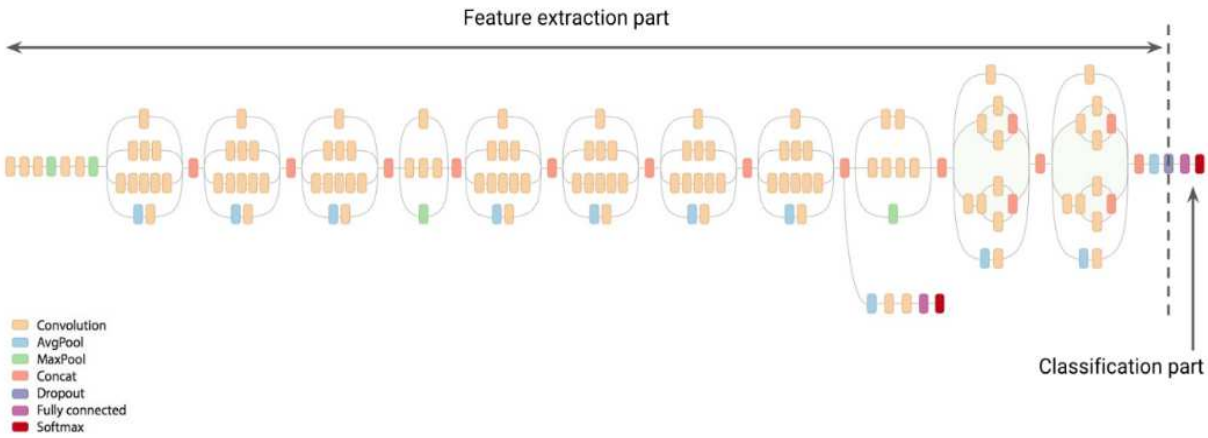


Figure 9 Architecture of InceptionV3

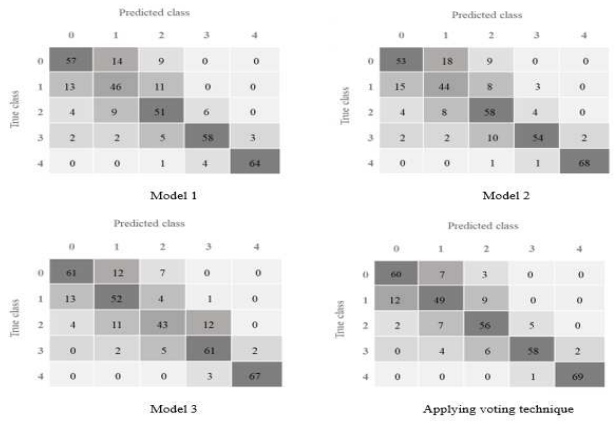


Figure 11 Confusion matrix for each model

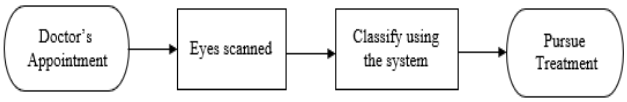


Figure 10 Proposed diagnostic process

IV. IMPLEMENTATION

The implementation process consists of several steps. From environment setup to data testing, the required steps are described in this section. The steps are given below:

A. Preprocess dataset:

We preprocess the images using following steps: (1) Cropping image, (2) Resizing image, (3) Apply technique, (4) Apply technique 2, and (5) Apply technique 3. Retinal images in the dataset requires preprocessing because: (i) Pupil dilated, (ii) Variation in the reflection and diffusion of light, (iii) Noise, (iv) Low contrast ration, and (v) Retinal pigmentation variations and camera variations.

Limitations of the tool as the lighting pattern of the ring-shaped model and imaging related to the difference of the eye's lighting axes concerning optical axes.

We have applied three high performing image processing techniques for preprocessing the image dataset [14]. The techniques are given in Table. 1.

Table 1 Number of images in dataset

No.	Image preprocessing technique	Method
01	Technique 1	Apply Adaptive Histogram Equalization to green channel
02	Technique 2	Subtract local average color from each RGB channel
03	Technique 3	Apply Contrast Adaptive Histogram Equalization

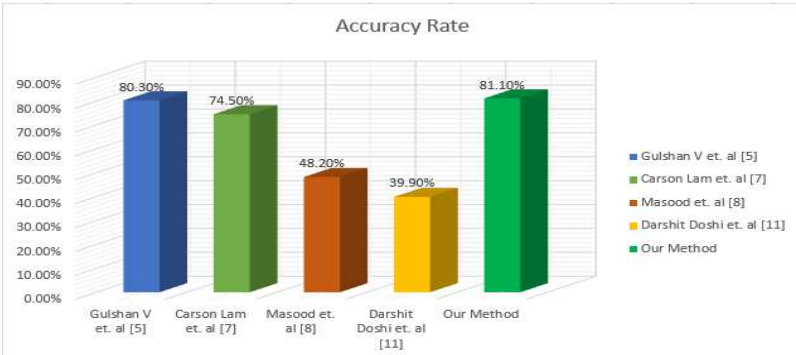


Figure 12 Accuracy rate in term of comparison with previous work

V. EXPERIMENTAL RESULT ANALYSIS

We have experimented our method in various aspects. In this section some of experimental results are depicted. We consider some metrices of result analysis such as confusion matrix, accuracy of our method, and Comparison with other methods.

A. Confusion Matrix

In our experiment, we have tested individual level of DR with images. The number of images used in our experiment is given in Fig. 11.

From the above confusion matrix of each model, it is showing that for level 0, 1 and 2 have much confusion in model 1 and 2. But when we have applied voting technique, this confusion has reduced in almost cases.

B. Accuracy

We have considered both for binary classification (Normal or DR) and 5-class classification (Normal, Mild, Moderate, Severe, PDR).

We have achieved better result in binary classification than the 5-class classification. The testing accuracy of each individual model are given in Table 2.

Table 2 Testing accuracy of individual model

Classification		Binary	5-Class
Number of test images		360	360
Individual Model Accuracy	Model 1	87.5%	76.6%
	Model 2	87.2%	76.9%
	Model 3	90%	78.8%
Accuracy after applying voting technique		90.5%	81.1 %

C. Comparison with previous works

The comparison between our work and some previous works are given in Table 3. In comparison, we have considered 6 metrics. These are (i) method, (ii) Train mode, (iii) Number of train images, (iv) Number of test images (v) Classification type, and (vi) Accuracy. We have comparatively gain higher accuracy than the others.

Combined results from the three models has produced a better result.

VI. Conclusion and Future Work

Though we have achieved an accuracy with a satisfactory level in the identification of diabetic retinopathy in retinal images, there are some points which can be improved in further future. For improving accuracy of our work, we will have to work with larger dataset. Training from scratch will also be able to produce better result. We want to build a real system based on our work so that it can assist doctors. A system based on deep learning will be helpful to people to get treatment with an ease. Identification of diabetic retinopathy in earlier level is effective for treatment. In our work, we have tried to identify DR level in earlier stage. We used three effective image preprocessing techniques for getting best result from the models. Not depending on a single model, we used three models with same architecture. As a result, we have been able to get a satisfactory level of accuracy. We conclude that our experiment will play an essential role in using a Computer-Aided Diagnosis (CAD) method in the identification of diabetic retinopathy. In the 5-class classification, the 83.4 percent precision is much higher than the previous one.

VII. Acknowledgment

This work is supported by Universiti Malaysia Pahang RDU190333.

Table 3 Comparison with previous works

Authors	Method	Train Mode	Training images	Testing images	Classes	Acc
Gulshan V et. al [5]	Single CNN	From scratch	9963	1748	5 Class	80.3%
Carson Lam et. al [7]	Multiple CNN	Pretrain	1077	269	5 Class	74.5%
Masood et. al [8]	Single CNN	Pretrain	800	Unreported	Binary	48.2%
Darshit Doshi et. al [11]	Multiple CNN	From scratch	72390	5000	5 Class	39.9%
Our Method	Multiple CNN	Pretrain	2200	360	5 Class	81.1%

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