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Grading of Diabetic Retinopathy in Suspected Individuals

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Abstract Diabetic retinopathy is a fast-spreading eye disease and this may lead to blindness in working-age adults. Between 32 to 40 % of about 347 million people suffer from diabetic retinopathy. It is a silent vision problem and thus, requires regular annual check-ups which will help in controlling the disease at initial stage and effective treatment will provide favorable results. The research utilizes a deep learning approach for diabetic retinopathy classification, which also will aid in addressing real-world issues. The work has already been done to solve this issue with the use of different classification techniques but somehow the efficiency of the training algorithm is dependent on the quality of feature extraction, which necessitates domain expertise. The current work solves the issue by applying a deep learning algorithm that recognizes the pattern and classifies retinal fundus images as normal or infected. In this study on the different categories of diabetic retinopathy 3662 retinal images were analyzed. The categories that are present in the data are No- diabetic retinopathy , mild, moderate, severe, and proliferative diabetic retinopathy . The publicly available retinopathy detection database and a trained model will be used in the experiments to retrieve the features of the ocular images and provide an appropriate output. The goal of this study is to apply and comprehend how the performance of a pre-trained model distinguishes between proliferative and non-proliferative diabetic retinopathy.

Keywords - Deep Learning, Diabetic Retinopathy, Eye Disease, Retinal Images.

1. Introduction

Eye conditions such as near or farsightedness, glaucoma, and cataracts may be left to worsen in areas where people lack access to regular checkups, treatment, and care, making daily life unnecessarily difficult. Those who require eye care should be able to access it without suffering financial hardship. Trachoma, acute glaucoma, macular degeneration (AMD), vitamin A deficiency, cortical cataract, hypertensive retinopathy, retinopathy of prematurity (ROP), and retinopathy due to diabetes are the top causes of chronic blindness[2]. Age-related blindness is on the rise worldwide, along with blindness caused by uncontrolled diabetes. Around the world, more than 2.2 billion populations are visually impaired, and more than a billion are forced to live in unpreventable or unavoidable conditions simply because they cannot access the support they needed. Vision loss could have been prevented or remains untreated in at least 1 billion or almost half of these cases. In 2020, the following will be the main causes of sightlessness in people over the age of fifty(50) as shown in figure 1 below: 15.2 million cases of cortical cataract, 3.6 million cases of acute glaucoma, 2.3 million cases of refractive error, 1.8 million cases of age-related macular degeneration (AMD), and 0.86 million cases of diabetic retinopathy[3].

One of the most severe eye conditions is diabetic retinopathy, as well as the most frequent retinal disease. It is the major reason for vision loss among people globally and it is a progressive disease whose severity is determined by the stages and type of lesions present in the fundus image.

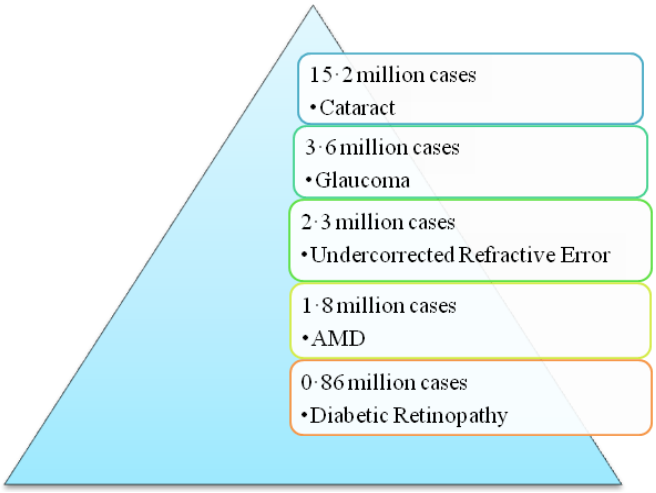

Figure 1. Leading cause of blindness in 2020[32]

There are two types of diabetic retinopathy (DR): proliferative DR (PDR) and non-proliferative DR (NPDR). NPDR, also known as Diabetic Retinopathy, occurs when the blood vessels inside the retina are severely damaged by diabetes, which tends to result in blood leakage on the uneven surface of the retina. Fortunately, early diagnosis and treatment can help stop at least 90% of DR-related blindness[32]. Detection of DR is currently reliant on well-trained practitioners inspecting eye images with advanced tools.

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Undoubtedly, it is an effective method of detection, but the whole procedure takes time. Moreover, this is a serious challenge in most rural areas leading to a shortage of well-trained ophthalmologists and specialized equipment. Over the past few decades, some important techniques for automatically identifying DR using image processing, pattern classification, and machine learning have been proposed. There are five stages of DR: 0, 1, 2, 3, and 4. The fig.2. below depicts the various stages of DR.

Finally, to identify the severity of DR, a traditional classifier such as the supporting machine (SVM) [9] or random forests [4] is used. Although these methods are highly effective, they have certain drawbacks.

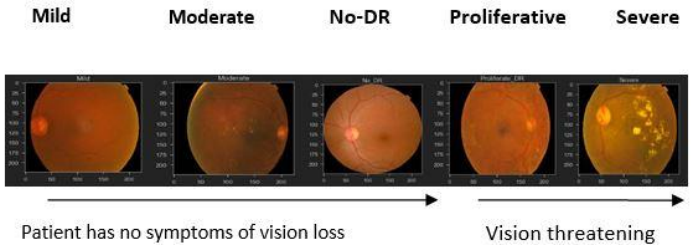

Figure 2. Stages of DR

Furthermore, feature extraction methods such as PCA-SIFT are suitable for images with large differences, making feature extraction from DR datasets difficult. Secondly, hand-crafted functions such as surface, form, fullness, noise, and exposure intensity are more sensitive to retinal image quality. Third, conventional classifiers perform poorly on huge datasets while succeeding on small datasets, limiting their generalizability. As a result, these methodologies are intended to extract general features, but may not be suitable for DR identification, and this is a much more challenging and complex task.

The convolutional neural network (CNN) [4] has recently grown in popularity in image classification, object detection, image segmentation, and other computational vision tasks. CNN's are made up of many node layers, the first of which is the input layer, followed by the hidden layer, and finally the output layer. Some of these CNN node layers were mostly preceded by pooling layers, which are used to maintain image translation invariance and increase the neuron's receptive field and dilated convolutions. In training sets, CNN is a single model in comparison with the traditional methods, combining feature extraction techniques into a single model. Among the most inherent benefits of CNN was that it could extract more discriminative capability of massive datasets and performs well in more complex problems. Therefore, CNN is task-specific and can be used to effectively detect DR.

The rest of the section is organized as follows: Section 2 deals with literature reviews on the classification of diabetic retinopathy images. The third section is a brief explanation of the proposed methodology and datasets used in this research. The fourth section is dedicated to the results. Finally, in the last section, the outcomes are presented, as well as suggestions for further research.

2. Background and Related Work

As the use of image processing methods for retinopathy detection has expanded, research has been reported to update some proposed approaches thereby developing new methods to improve precision, sensitivity, and specificity. The number of successfully anticipated fundus images out of all the fundus photos is referred to as accuracy while Sensitivity refers to the percentage of the test correctly identified those with Retinopathy (true positive rate and specificity can be termed as the capability to correctly identify those without Retinopathy (true negative rate). The higher the three factors, the better the approach is. However, not much work has been done in detecting microaneurysms and exudates; most of the research has focused on detecting vascular abnormalities using retinal images. In the literature review, some of this previous work is taken into consideration, and outcomes are also discussed. There are various approaches, in literature, which focused on retinal fundus images for the diagnosis of Retinopathy related disease.

The first attempt to detect the blood vessels from the retinal images was designed by Narkthewan et al.[19]. The study was done by analyzing a total of 40 images for performance evaluation. The results that were concluded were average specificity of 0.6392, the sensitivity of 0.9920, and accuracy of 0.9617. An accuracy of 96.17% was also recorded when the proposed method was applied for the diagnosis of diabetic Retinopathy.

Lin et al.[17] review of automated evaluation of eye image quality for diabetic retinopathy was presented in three stages. Firstly, the schematics and specifications were presented. Following that, a comprehensive evaluation of retinal image quality assessment techniques and methodologies was demonstrated. Finally, challenges and research proposals for the future were presented.

Suriyasekeran et al.[26] designed a NN (neural network) model for the grouping of normal and abnormal images. The dataset used by the author consists of 767 retinal images, out of which 484 were normal and 283 eye images with diabetic retinopathy. Consequently, the recorded sensitivity was 80.2% and specificity was 70.66%. The model's output was highly accurate in detecting diabetic retinopathy.

Carrera et al.[6] also proposed a supervised method that displays better outcomes than other algorithms. The author has also performed a variety of image processing techniques to assist individuals in detecting diabetic retinopathy using retinal images. This scheme was tested using NPDR to figure out the grade scale at 400 retinal images. The average accuracy, sensitivity, and predictive capacity of this approach were around 85%, 95%, and 94% for diabetic Retinopathy detection of the retinal images.

Dai et al.[9] proposed a deep learning method that can recognize subclinical highlights showing up beneath the limit of a person eyewitness to investigate the impact of hypertension of the retinal microvasculature. A set of 2012 retinal images, 1007 from a dataset with hypertension findings and 1005 from a normotensive control. In this approach, the author trained a CNN classification algorithm, and (Grad-CAM) was used as a deep learning technique to form a heat map of the specific region in the image. The

average accuracy, specificity, precision, and recall of this approach were around 60.94%, 51.54%, 59.27%, and 70.48%.

Rahulkar et al.[24] proposed a methodology based on a NN classifier to classify eye images into three different levels: feature extraction, classification, and segmentation. The proposed WP analyzes its execution over other traditional techniques regarding exactness, explicitness, affectability, accuracy, and FDR. As a result, it was seen that the exactness of the proposed blend was 4.81%, 10.21%, 11.53%, 12.98%, and 14.47% better from F-WPNN, F-WNN, F-SGWNN, F-GWNN, and F-PNN, separately. The explicitness of this method was highest as compared to other regular strategies, which was recorded as 2.06%, 3.12%, 10%, 12.5%, and 79%.

D. Zhang[11] proposed a ResNet model to detect or classify diabetic retinopathy. In the proposed model, three additional sets of layers were added to the moderate layers of the ResNet to give extra regularization during the cycle. The eyepieces DR training dataset was used. The accuracy rate was 94%, sensitivity rate was 67%, and specificity rate was 81% respectively.

S. Suriyal et al.[27] proposes an efficient CNN model for binary Diabetic Retinopathy screening. This scheme was tested using a retinal image dataset called, the EyePACS DR dataset. An exactness of 0.73 was accomplished by the proposed strategy.

Azar et al.[4] proposes a Non-Local method's denoising strategy was applied to the fundus picture to eliminate clamor from the EyePACS DR Dataset. AlexNet and GoogleNet were used to characterize the pre-handled retinal pictures. An AUC score of 0.78 is accomplished by the GoogleNet model contrasted with an AUC score of 0.68 accomplished by Alex Net.

3. Proposed Methodology

A) Dataset - The retinal images used here were also freely available on Kaggle [1]. The fundus images were provided by the 4th APTOS (Asia Pacific Tele-Ophthalmology Society) 2019 Blindness Detection competition. This dataset was the most comprehensive publicly available for pre-training our CNN architecture or model. Now, the eye image below in fig 3. is a sample image taken from the dataset.

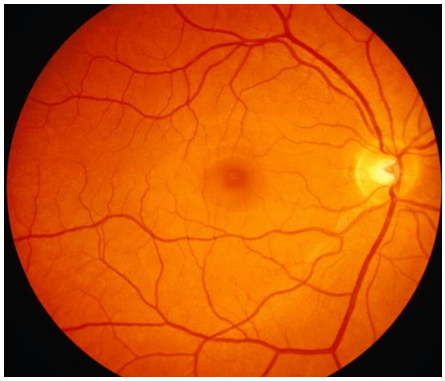

Figure 3. Retina image[31]

The dataset contains 3662 labeled color eye fundus images divided into five classes, each representing one of the five stages of the disease (see Table 1). It includes all of the classes' countings. There are 1805 images (number of people) in class 0 (No-DR), 370 images (number of people) in class 1 (Mild), 999 images (number of people) in class 2 (Moderate), 295 images in class 4 (Proliferative), and 193 images in class 3 (Severe).

On a scale of 0 to 4, a trained clinician has rated the existence of diabetic retinopathy in each image[5]. The retinal images in the dataset are from a variety of camera models and types, which can alter the appearance of the left and right retinas. Some images depict the retina as it would appear anatomically (macula on the left, optic nerve on the right for the right eye). Others are depicted as they would appear through a condensing microscope lens. Both the images and the labels had a lot of noise. All of the images in our dataset have 256X256 pixels and RGB channel color mode, the batch size is 32, and class mode is categorically divided into five classes. Fig.4 shows a pie chart depicting the percentage of samples per class.

Table 1. No of images in each class in the training dataset

Train Class	Label	No of images in each class
Number of images in No-DR	0	1805
Number of images in Mild	1	370
Number of images in Moderate	2	999
Number of images in Proliferative	3	295
Number of images in Severe	4	193

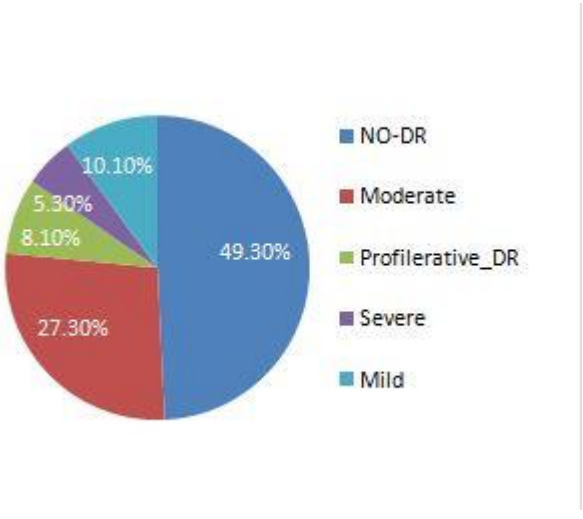

Figure 4. Percentage of samples per class.

4. Proposed Model

A CNN was used in this paper to successfully classify DR subjects into non-DR, mild-DR, moderate-DR, proliferative-DR, and severe-DR, and thus stage the disease in an automated manner. First, fundus images were resized using a pre-processor to keep the same standard size of 256X256X3. Furthermore, a data augmentation technique was being used to increase the size of the lowest category to enhance the proposed architecture's performance when applied to an unbalanced dataset. Second, fundus images were fed into a series of five convolutional layers in a row, with a single 2D max-pooling layer in between. In this architecture, a convolutional layer is made up of several filters, each of which has a size of 3×3×3.

The architecture was then validated and trained for diabetic retinopathy classification and staging on the Kaggle dataset[1], with the parameters of the entire model fine-tuned and updated. The flowchart, as shown in the diagram below, is self-explanatory; it involves preprocessing, steps show the dataset information, data exploration and visualization, imageNet, and finally running the epochs and obtaining the output as shown in figure 5.

1. Import Libraries and dataset: In this step, the necessary packages were imported. Tensor flow 2.0, a Google framework for building, training, and deploying AI/ML models at scale, was used. The Keras API was also used to create a powerful neural network model capable of replicating doctor-level intelligence or expertise.
2. Perform data Exploration & Data Visualization: In this phase, data exploration and visualization were carried out. Simply choose 5 images for each class in the dataset, along with the corresponding label, and count the number of images in each class in the training dataset as shown in fig 6.
3. Perform Image Augmentation and Create a Data Generator: This stage involves data verification and the creation of a data generator. In training and testing, our data frames or images were divided into two categories. When training AI/ML models, make sure that when testing them, we want to be able to access their performance and then create run-time augmentation on the training and test datasets. We add normalization, shear angle, zooming range, and horizontal flip to the training data generator, while we only normalize the data in the testing data generator.

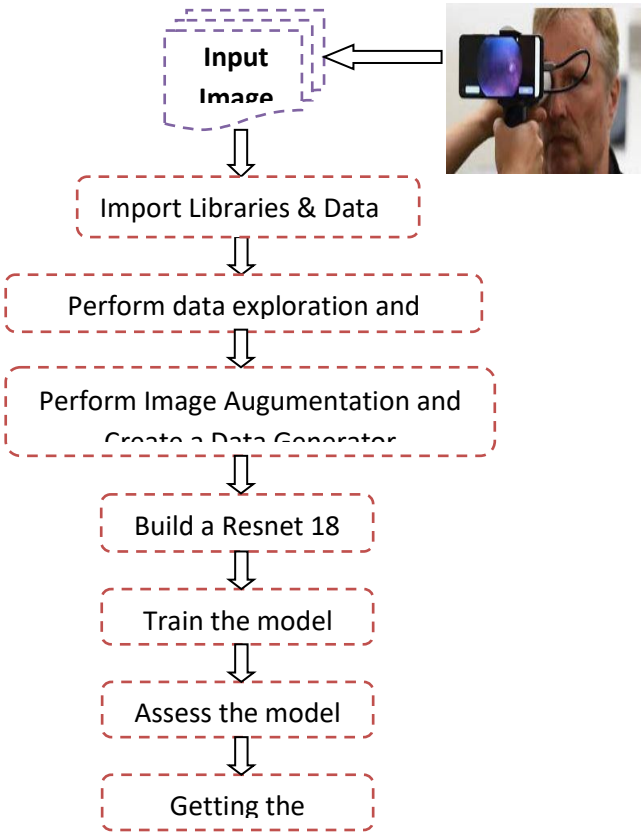

Figure 5. Overview of proposed Diabetic Retinopathy System

4. Build a Resnet18 model: Resnet functions by layering "identity mapping" on top of CNN. It has a “skip connection” feature that allows you to train 152 layers without having to worry about vanishing gradients. ResNet deep network is trained using ImageNet[6].

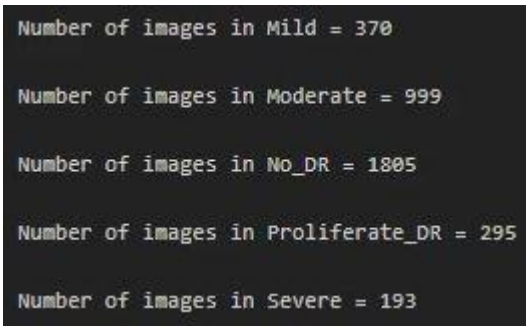

Figure 6. total number of images in an individual stage

5. Compile and Train the deep learning model: All layers must be trainable, and existing magnet weights must be used as weight Initializers for ResNet18. The Loss Functions are used to compile the model as shown in fig 7. (2 epochs with Adam optimizer).

6.

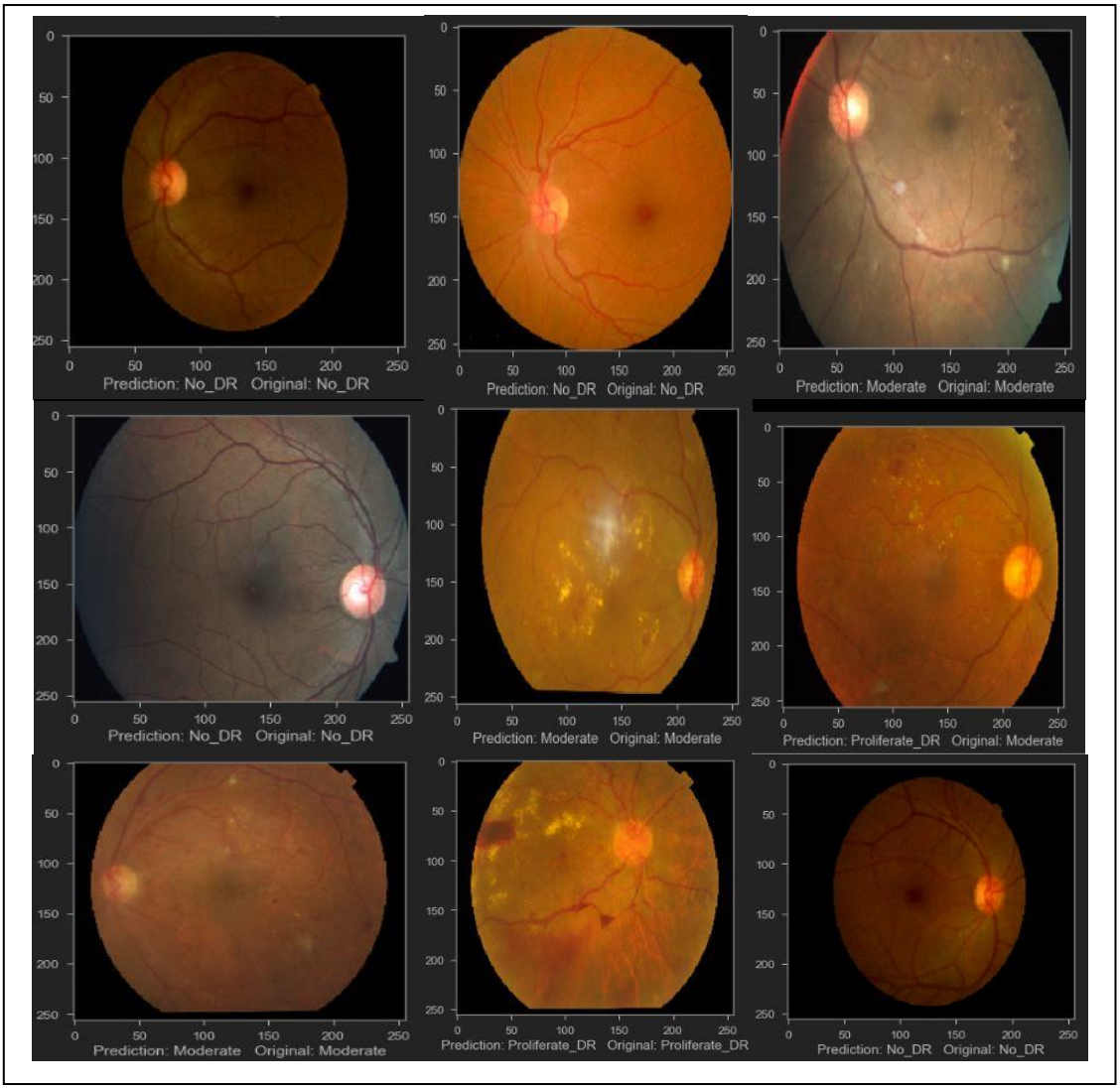

Figure 7. Predicted value vs Original value of diabetic retinopathy

7. Obtaining the accuracy of the model: To access the trained model's performance, complete the steps below.

- Restore the weight
- Evaluate the performance of the model
- Assigning label names to the corresponding indexes
- Loading image and their prediction
- Getting the text accuracy
- Visualization the results

and, to obtain results, two lists are created. The first label contains all of the different predictions generated by the model, while the second label contains our original labels as shown in figure 7 .

5. Results

Using the CNN model, the author evaluated the proposed system for categorizing diabetic retinopathy into one of five classes based on severity level. The experiment was carried out on 3662 Kaggle provided sample retinal images. The learning rate parameter and the number of epochs are tuned to train and validate the model. The loss function is calculated across all data items during an epoch and guaranteed to give the quantitative loss measure at that epoch. However, plotting the curve over iterations only shows the loss for a subset of the entire dataset as shown in fig 8. The final results show that the model outperformed with 84 percent validation accuracy. Furthermore, the confusion matrix is a precise measurement that provides additional information about the testing accuracy that has been achieved.

Performance evaluation and discussion

More performance matrices need to be investigated in this research to evaluate the performance of the proposed model. Precision, recall, and F1 score [17], which are presented from equation (1) to equation (3), are the most common performance measures in the field of DL.

Precision=TP / (TP+FP) .....(1)

Recall=TP / (TP+FN) .....(2)

F1Score=(2*Precision*Recall) / (Precision+Recall) .....(3)

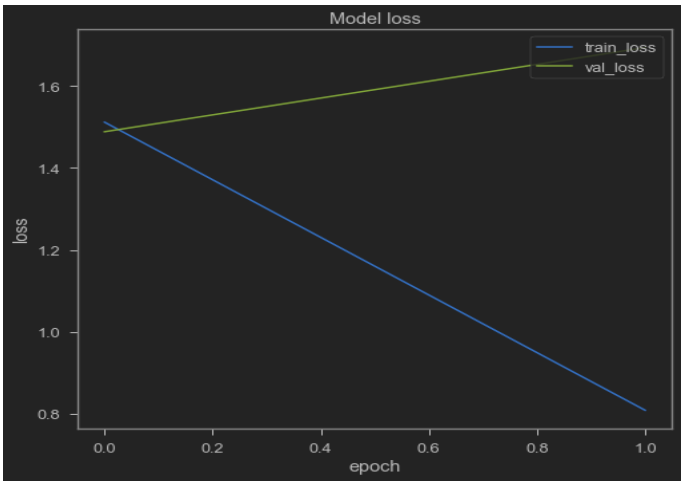

Figure 8. Loss vs Epoch

where TP represents the number of true positive samples, TN represents the number of true negative samples, FP represents the number of false-positive samples, and FN represents the number of false-negative samples from a confusion matrix. The proposed CNN model's performance metrics are shown in Figure 10. The ResNet 18 model had an accuracy of 84 percent followed by a weighted average recall of 84 % , a weighted average of F1-score of 83 % , and a precision of 84%.

	precision	recall	f1-score	support
Mild	0.81	0.61	0.69	71
Moderate	0.74	0.84	0.79	191
No_DR	0.94	0.99	0.96	374
Proliferate_DR	0.57	0.58	0.57	52
Severe	0.82	0.31	0.45	45
accuracy			0.84	733
macro avg	0.78	0.66	0.69	733
weighted avg	0.84	0.84	0.83	733

Figure 10. Performance Matrix

6. Conclusion and future work

To summarise, we have demonstrated that CNNs can be trained to recognize Diabetic Retinopathy features in fundus images. Based on the results, our work received an accuracy rate of 84 percent. Furthermore, this model only had a few layers, which reduced the training time and computational complexity, and also we can improve the accuracy with a more balanced data set with less noise. As CNN technology advances, much deeper networks will be able to learn the intricate features that this network struggled to learn. From the perspective of traditional network topology, the results from our network are very promising. Unlike previous methods, nothing specific to the features of our fundus images, such as vessels, exudates, and so on, has been used.

Experiments on various CNN architectures with a more powerful graphics processor will be conducted in the future to achieve better precision in less time. As can be seen, the training Loss does not decrease during the Main Training stage. We could address this by switching the optimizer from Adam to Rectified Adam.

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