Convolutional Neural Networks to Classify Diabetic Retinopathy Stages via Fundus Images

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Abstract- Diabetic Retinopathy has become one of the most common causes of blindness and vision loss worldwide. It is difficult to find this disease in the early stages but finding it early can make you take the step to save your vision ability. Usually, the diabetic retinopathy diagnosis requires retinal fundus images and optical coherence tomography (OCT) using images. However, (OCT) is a time-consuming technique with expensive equipment. Therefore, patients are mostly diagnosed by taking retinal fundus images. In this paper, we have shown our technique based on CNN deep learning. We used a deep learning model to evaluate diabetic retinopathy detection. The problem that we faced to do image classification was to predict which class the given image belongs to, and the classes are 0 for Normal, 1 for Mild, 2 for Moderate, 3 for Severe, and 4 for Proliferative. We used the resnet34 model, which was pre-trained on the image net dataset then we replaced the final layer of pre-trained resnet34 with new layers. To optimize the model, we called the function of train and validate for (no of epochs) times. It returns a tuple of lists containing losses for all the epochs. No of images in Training = 3302 and no of images in Validation set = 360 after 60 epochs the results are Training accuracy = 92.1865, Validation accuracy = 79.444. So, we can improve our accuracy by increasing the dataset size, increasing the model complexity, using ensemble models, and increasing the number of epochs.

***Index Terms*-** Cornea Classification, Convolutional Neural Network, Deep Learning, Diabetic, Retinopathy, Fundus images, Retina.

I. Introduction

Diabetic retinopathy (DR) is a disease that affects the blood vessels present in the retina, which are damaged due to multiple alterations by a set of metabolic disorders. The blood vessels present damage in their capillaries due to the loss of pericytes, which are contractile cells that wrap capillary endothelial cells in the body's venules. Excess glucose molecules cause this damage in the blood, which clump together in the vessels disrupting circulation, a process known as ischemia. This blood vessel deterioration produces microaneurysms, which is a saccular enlargement of the venous end of a retinal capillary by the lack of blood circulation. This process leads the vessels to lose their impermeability properties, resulting in leaks, such as hemorrhages or lipid sweating.

Long-term diabetes can become an optical eye disease called Diabetic Retinopathy. Diabetic Retinopathy is one of the most frequent causes of retinal detachment among adults of working age in the world [1]. Diabetic Retinopathy affects approximately 35% of patients with Diabetes Mellitus (DM).

As a person who has been suffering from diabetes for longer, the chance of Diabetic Retinopathy increases. According to the World Health Organization, Diabetic Retinopathy will impact more than 77 percent of people with 20 years or more of diabetes [2].

According to research conducted by the International Diabetes Federation, the rate of DR is rising every year. By 2045, more than 600 million people for 12 months will be fighting against DR [3].

The incidence of diabetes is also higher in Europe, with 60 million men and women currently suffering from this disease. Diabetic Retinopathy (DR) is a diabetes-related attention disorder. In addition, 17% to 20% of Pakistan citizens found Diabetic Retinopathy who had been suffering from diabetes before [4].

Almost (49.7%) of all men and women are suffering from diabetes and have not been diagnosed for a long time due to silent symptoms. Even so, the long-lasting blood flow will, blood vessels and nerves destroyed fundamentally, causing complications including aerobic blindness. Early recognition and diagnosis of DR are essential to preventing its growth [5]. Diabetic Retinopathy is a dangerous problem that affects people's vision, especially working-aged people. Therefore, timely identification and treatment are essential for patients to prevent blindness. Patients with Diabetic Retinopathy are believed to have a 5% chance of becoming blind if diagnosed and treated early. Fundus photography is commonly used as an imaging method to identify retinal diabetic retinopathy. Because of its reasonable price, high resolution, and large storage space, it has been used for Diabetic Retinopathy screening. There must be many functions related to the classification of Diabetic Retinopathy in fundus photography, also an efficiently trained classifier based on the vision of a computer system work in the classification. The CNN vector machine classifier is used to make promising progress in recognizing retinopathy. CNN is efficient for the classification of Diabetic Retinopathy [6].

The process is simple and can be done easily and safely through retinal photography of each center using appropriate tools. If the detection is fast enough, laser surgery can be used to resolve diabetic retinopathy (DR). However, the growth rate of demand is much faster than the quotation. The number of patients is increasing every year, and every patient needs frequent inspections. Each of these images should be carefully analyzed by the doctor. Routine measures for diagnosing DR require health professionals to manually distinguish 2D shadows on the fundus. The accuracy and analysis, in this case, are largely based on experience and ability. Patients who decide to fight with DR make up such a large population, thus it's important to investigate the category of retinopathy images for DR evaluation. As a result, it's interesting to investigate whether shallow neural companies may also get outstanding medical image classification results, even if the labeled data set isn't very huge [7].

In this research paper, we have tried to explore the detection of retinal images using CNN for the lack of high-quality or high-training samples.

II. LITERATURE REVIEW

There are many appreciable works for the process of identifying Diabetic Retinopathy. For its identification, it is important to track down the retinal vessels. We can determine whether the patient has Diabetic Retinopathy, whereas the location of the vessels can be accurately determined, also there are types of lesions that help to find Diabetic Retinopathy. Along the way of identifying DR. In paper [2], focused on a segment-based method.

This method was considered a classification model to enhance the classification of retinal images for Diabetic Retinopathy. Their method is divided into four categories. CNN-segment-based classifier, Preprocessing. In this paper [8], the author introduced the combination of two methods, skeleton detection of retinal blood vessels and multidirectional morphological bit plane slicing. Skeleton vessels were obtained by using dimensional differential operators. After that, they evaluated by the combination of derivative signs and average derivative values. To highlight the vessels in a certain direction, a multidimensional top-hat operator with rotatable design elements is performed, and information is collected using bit plane slicing.

To merge the main skeleton with the images generated from bit plane slicing of vessel direction-dependent morphological filter. The proposed method achieved an average accuracy of 0.9423 for both datasets. Whereas in [9], they proposed Deep Convolutional Neural Network (DCNN) provided high accuracy classification. DCNN is a more complicated design architecture. Among numerous supervised algorithms, the proposed approach is to create a better and more efficient way to classify the fundus image with minor pre-processing.

They achieved an accuracy of 94-96 percent. In this paper [4], the author introduced CNN models retinal fundus images based on transfer learning, and it performs partly well using a small number of a dataset with diagonal categories of 3050 images for training as well as 419 images set on validation for identifying classes of DR with hard granulation, blood textures, and vessels. This model is extremely strong, with the ability to work well in small real-time applications with limited computing resources to speed up the protection process. Whereas [10], introduced a deep convolutional neural network (DCNN). They adopted fractional max-pooling instead of the commonly used max-pooling layers. Both DCNNs are trained to extract new discriminative features from the data using the different number of layers. After comparing their forecast results, SVM is used to enhance the SVM parameters using TLBO.

Two systems are the cause of instruction, which can be distinct that system this is certainly different architectures might have their unique advantages being purpose this is certainly special area representation. The forecast accuracy is more by training two DCNNs and including their features which are certainly improved. In this paper [11], they presented another simple and effective multiscale vessel extraction approach, by combining the responses of matched filters at three scales.

So, the vessel shapes will have strong reactions to the matched filters at various scales, but it is not the background noises scale generation that could improve vessels and suppress noise. The filter responses are obtained and mixed in the scale production domain. The result of this experiment shows that the proposed method is effective for accurately subdividing vessels with good width prediction. In [5], the author introduces an algorithm that is to develop for automated recognition associated with a disc. They used neural networks, as well as other techniques. The accuracy and precision of automated techniques have never exceeded 85%. This paper includes machine vision algorithms and clinical observation also the ability to identify dot hemorrhages and hard exudates up to 100 digitized image data from a categorized database of images. The diagnosis is 95 to 100% in both sensitivity and specificity cases.

The prediction values of positive and negative were 95 to100% in both cases. This paper [12], introduced a deep convolutional neural network, to categorize the 1.2 million high-resolution images in the ImageNet LSVRC-2010 competition into 1000 different classes. The neural network consists of five convolutional layers, to make training faster, we used non-saturating neurons and a very efficient GPU implementation of the convolution operation. To reduce overfitting in the fully connected layers, we employed a recently developed regularization method called "dropout" which was very effective. In this paper [7], they introduced a new technique for detecting and computing retinal vessels that can be used on both low- and high-resolution retina images, as well as fluorescein angiograms by adjusting a few simple parameters. They proposed the basic vessel segmentation approach that was utilized for quick vessel detection and implemented in the wavelet's language.

The accuracy score for this segmentation is 0.9371, with a true positive rate of 70.27 percent, and a false positive rate of 2.83 percent. Whereas [13], introduced (ARIAS) Automated DR image assessment systems of retina images. Retina images were professionally classified using a standard unified framework for Screening and diagnosis using three ARIAS (EyeArt, iGradingM, and Retmarker. Diagnostic effectiveness (sensitivity, false-positive rate, probability ratios) and detection accuracy were 95 % evaluated. In this paper [14] author introduced a computer-based method for detecting the stages of diabetic retinopathy using fundus images. The extracted features were used in an artificial neural network (ANN) as input to make an automatic detection. They achieved 93% classification accuracy, 90% sensitivity, and 100 % specificity.

Whereas in [15], they applied a computational model based on retinal images and a neural network to predict Diabetic Retinopathy (DR). There was a feature extraction step and a classification phase in their computational model. Micro aneurysms and Blood Vessels were used to extract the most appropriate features from digital fundus images during the feature extraction phase. Diabetic Retinopathy was predicted by using CNN (DR) and they achieved 95.45% accuracy.

In this paper [16], The method corrects non-uniform illumination in color fundus images by combining intensity information from the red and green channels of the same retinal image. The proposed method evaluation was done by the datasets (DRIVE and STARE) which are publicly available.

It achieved an area under the receiver operating characteristic curve of 0.9518 and 0.9602 on the DRIVE and STARE databases, which is better than state-of-the-art unsupervised approaches and comparable to supervised methods. This paper [17] introduced optimizing and developing for image processing techniques to enhance the quality expense for screening and diagnosis of diabetic retinopathy.

This classification detects arteries around 78.4 % and vessels around 66.5 %. This paper [18], showed the evaluation of the specificity and sensitivity of the Iowa Detection Program (IDP) to identify referable diabetic retinopathy (RDR). Computer scanning of retinal images for DR and automated detection of RDR can be securely integrated into the DR testing process, thereby improving accessibility and healthcare productivity also minimizing sight loss with early treatment. Whereas in [19], they developed the CNN model to improve the classification and performance of retinal fundus images. CNN output features were utilized as input in a variety of machine learning classifiers.

KAGGLE datasets were used to create the images. Different classifiers (Nave Bayes, Support Vector Machine, Random Forest, J48, and Ada Boost) were used to evaluate this model. In paper [19], introduced a unique deep convolutional neural network approach (DCNN). They used fractional max-pooling instead of the typically used max-pooling layers. These two DCNNs, with a different number of layers, are trained to generate more discriminative classification features. They trained a support vector machine (SVM) classifier. The model was built with 34,124 training images and 1,000 validation images and tested with 53,572 testing images. The proposed DR classifier divides DR stages into five groups, each labeled with an integer scale from 0 to 4. The proposed method may achieve a detection rate of up to 86.17.

Whereas [20], showed the use of a deep learning model to evaluate the efficacy of Res Net for detection. Using the Ada boost classifier, Res Net created multiple sub-models to detect Diabetic Retinopathy. Multiclass classification Res Net models are created and stacked together for the identification of Diabetic Retinopathy prognosis.

In paper [21], presented Convolution Neural Network (CNN) models (Resnet50, Inceptionv3, Xception, Dense121, Dense169) were used to encode rich features and improve detection for different stages of DR. The experimental results showed that the proposed model detects all stages of DR and current methods performed better as compared to state-of-the-art methods on the same dataset. This paper [20] introduced a model that uses a transfer learning technique to train the architecture. To make a prediction, the proposed model accepts binocular fundus images as inputs. There are only 2804 images in the training set and 7024 images in the test set. The given monocular model yielded a receiver operating curve of 0.951, and a binocular model for five-class DR detection was also trained.

Whereas [19], the author introduced an algorithm based on deep learning, that had excellent sensitivity and accuracy for recognizing diabetic retinopathy. More research needs to be done on whether this method can be used in medical settings and, whether it can improve care and outcomes compared with existing eye diseases assessment.

Whereas [22], showed the detection results of two different classifiers, Bayesian and SVM, by using a Gaussian mixture model, they estimated class-conditional probability density functions for vessels and non-vessels. After that, they used a Bayesian classifier to perform a quick classification, then they used a Support Vector Machine. The result showed that in some instances, the SVM classifier is better than the Bayesian classifier.

Whereas [23] created an automated retinal blood vessel recognition system. A multiclass support vector machine (SVM) was used to classify the anatomical and textural features into five categories normal, mild, moderate, severe, and proliferative. This method collected fundus images quickly via mass screening, allowing ophthalmologists to work more efficiently.

There has been a lot of hype going on about artificial intelligence which is rapidly making its outstanding place in the world of technology. It includes teaching the machine that performs human-like tasks like face recognition, image recognition, speech recognition, object detection, etc. The idea is to take help from artificial intelligence (AI) in cars to make them smart [24].

According to the survey of related work, multi-class classification using CNN employs heavy and massive networks. We also used CNN to evaluate the performance in the classification of Diabetic Retinopathy [25].

III. MATERIAL AND WORKS

A. *Resources And Method*

In this section, we will share the model which we built to detect blindness caused by diabetic retinopathy using Pytorch. First, we imported all libraries for reading CSV files, plotting, and working with image files, then we use torch libraries for working with data and for pre-trained models, and image transformations. Then we printed the device which we used. We used CPU; you can use GPU if it is available. After that, we print the no of training and testing samples shown below in figure 1.

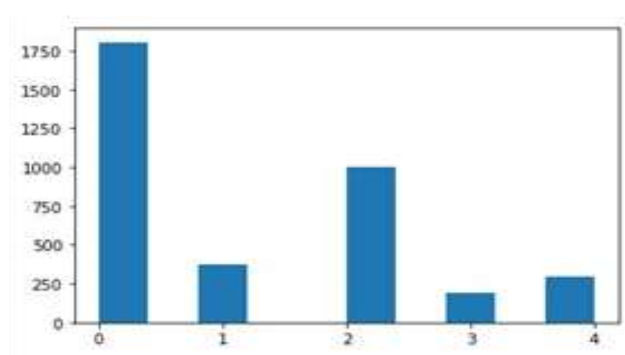

FIGURE 1. Then we showed the histogram label counts

As you can see, the data is imbalanced so we have to calculate weights for each class, which can be used in calculating loss, then we have calculated weight for each class.

tensor ([0.4058,1.9795,0.7331,3.7948,2.4827])

Then for getting a random image from our training set mentioned in Table 1, we pick a random number from the image file. The class of the random image can be shown in Figure 2.

TABLE 1. Diabetic Retinopathy Severity Level

DR GRADE	SEVERITY LEVEL	EXPECTED OUTCOMES
0	NO DR	NEGATIVE
1	MILD	POSITIVE
2	MODERATE DR	POSITIVE
3	SEVERE DR	POSITIVE
4	PROLIFERATE DR	POSITIVE

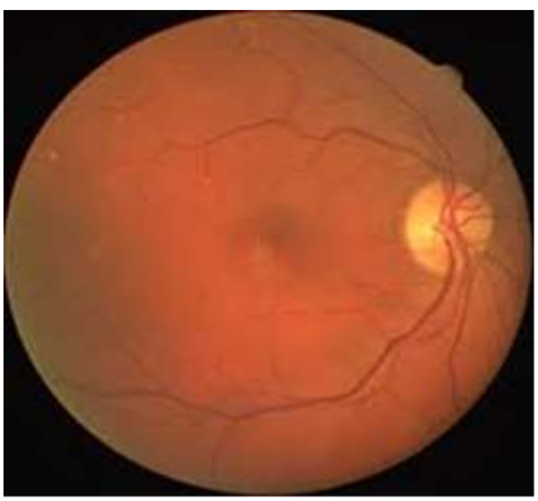

FIGURE 2. Class of the random image.

B. Pre-Processing

We inherit the Dataset class, then we used __init__, __len__, __getitem__ methods of the Dataset class.
Attributes are used, df for data frame object for CSV file, data path for the location of the dataset, image transform for transformations to apply the image, and train for a Boolean indicating whether it is a training set or not.
In __init__ () we called the constructor of the dataset class. In __len_ () return the number of samples in the dataset. In __getitem _ () applied a transformation to the image, then we split the dataset, so the valid set contains 0.1 samples of the dataset, then we use data loader for both training set and validation set. Use either SI (MKS) or CGS as primary units. (SI units are encouraged.) English units may be used as secondary units (in parentheses). An exception would be the use of English units as identifiers in trade, such as "3.5-inch disk drive."

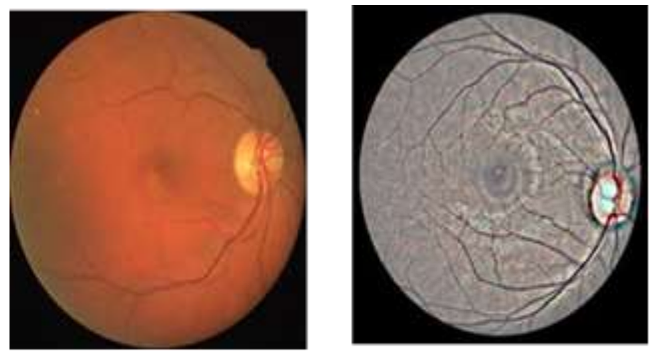

FIGURE 3. Original Image and Preprocessed image.

IV. RESULTS AND DISCUSSION

A. Build Model

A conclusion section is not required. Although a conclusion may review the main points of the paper, do not replicate the abstract as the conclusion. A conclusion might elaborate on the importance of the work or suggest applications and extensions.

B. Function Created for Training and Validation

We created a train function to update the weights of the model based on loss using the optimizer to get a lower loss. The arguments we used in the train function are:

Data loader: Iterator for the batches in the dataset.

Model: Given an input-produced output by multiplying the input with the model weights.
loss_fn: Calculated the discrepancy between the label & the model's predictions.

Optimizer: Updated the model weights.

It returned the Average loss per batch which is calculated by dividing the losses for all the batches by the number of batches. We also created validate function that calculates the average loss per batch and the accuracy of the model's predictions. Arguments we used in validate function are:

Data loader: Iterator for the batches in the dataset.

Model: Given an input-produced output by multiplying the input with the model weights.

loss_fn: Calculated the discrepancy between the label & the model's predictions.

It returned the Average loss per batch which is calculated by dividing the losses for all the batches by the number of batches.

C. Optimized Model

We created optimize function to call the train & validate functions for (nb_epochs) times. Arguments we used in optimize function are:

Train_dataloader: Data Loader for the trainset.
valid_dataloader: Data Loader for the valid set.
Model: Given an input produces an output by multiplying the input with the model weights.
loss_fn: Calculated the discrepancy between the label & the model's predictions.
Optimizer: Updated the model weights.
nb_epochs: Number of epochs.
It returns a tuple of lists containing losses for all the epochs.

D. Testing Model

We created a test function to predict the labels given an image batch. The arguments we used in the test function are:
b. data loader: Data Loader for the test set.
c. model: Given an input produces an output by multiplying the input with the model weights. It returns a list of predicted labels.

E. Data Source

We used a dataset from [26], which consists of 36,62 fundus images belonging to 5 classes.

F. Findings

Number of images in Training set = 3302
Number of images in Validation set = 360
After 60 epochs the results are as follows:
Epoch 60/60
Training Loss = 0.384221
Accuracy on the Training set = 92.186554 [3044/3302]
Validation Loss = 0.874261
Accuracy of Validation set =79.444444% [286/360]

Then we plotted the graph in Figure 4., for train losses and valid losses against nb_epochs.

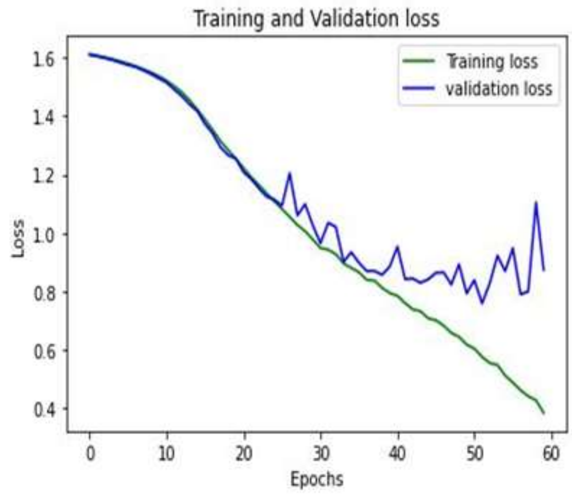

FIGURE 4. Training and Validation loss graph

V. CONCLUSION

Diabetic retinopathy is an optical eye disease brought on by long-standing diabetes that becomes blindness in those who are suffering from diabetic issues. The methodology work is easily proposed a CNN design to gather from retinal fundus images. The problem we faced to do image classification was to predict which class the given image belongs to, and the classes are 0-Normal 1-Mild 2-Moderate 3- Severe 4-Proliferative. It is important to develop automatic solutions to get better accuracy of analysis and classify the topics into different stages of DR. Number of images in the Training set = 3302 and the number of images in the Validation set = 360 after 60 epochs the results are Training accuracy = 92.1865, Validation accuracy = 79.444. This result can be better by increasing the dataset size, increasing the model complexity, using ensemble models, and increasing the number of epochs.

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