Diabetic Retinopathy Detection and Stage Classification Using Lenet-5 Architecture

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***Abstract*—Early diagnosis and treatment of diabetic retinopathy are made possible through retinal screening.To facilitate the screening process, we are developing a deep learning system to detect and classify diabetic retinopathy.If it is untreated it may lead to other serious eye condition like macular edema and glaucoma ultimately causing vision loss.In contrast to manually created features, we employed the convolutional neural networks (CNN) model i.e Lenet-5 architecture to automatically extract features.Techniques like edge detection,thresholding and data augmentation are applied to the model during preprocessing.The efficiency of the system is assessed using statistical metrics like sensitivity (SE), specificity (SP), F-measure , and classification accuracy (ACC).The model achieved an average accuracy of 97%,recallof 22% and f1-score of 65%.**

***Index Terms*—Keywords:Diabetic retinopathy,Dataset,CNN**

I. Introduction

Diabetes mellitus (DM) is a global chronic disease and has been identified as the fourth leading cause of death. Experts predict that there are nearly about 336 million people across the globe with DM, and this number may increase to 7.7% by the year 2030.According to the International organization for the diabetes research and education. Blood glucose levels rise as a result of abnormal metabolism, which is the causeof diabetes mellitus (DM)[9]. One of the critical symptoms of diabetes mellitus, diabetic retinopathy (DR), is a major factor in vision loss and blindness. According to research, DR will eventually develop in 97% of type 1 diabetics and 80% of type 2 diabetics with a prevalence of more than 15 years.

In order to minimize the considerable rate and prevalenceof DM and DR in India, it is necessary to develop a efficient and cross-sectoral approach. Early detection of people with diabetes, frequent DR screenings for them, and accessto treatment facilities are all necessary. On retinal scans, numerous lesions can be seen that indicate DR.Microaneurysms (MA), hemorrhages (HM), and soft and hard exudates (EX) are some of the lesions. A microaneurysm (MA), which is a precursor of DR, manifests as a tiny red dot on the retina as a result of the blood vessel wall's thinning.Sharp margins and a dimension of less than 125 m are present[10].

Clinical observations of anomalies in the blood vessels of the retina serve as the basis for the diagnosis of dia- betic retinopathy (DR). Non-proliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy are the two clinical phases of DR. (PDR). Increased vascular permeability and capillary blockage in the retinal blood vessels characterise NPDR, the early stage of DR .At this stage, retinal abnormali- ties such as microaneurysms, hemorrhages, and hard exudates can be identified through fundus photography, even if the patients do not exhibit any noticeable symptoms. Additionally, based on the severity of the condition, NPDR patients can be classified into mild, moderate, or severe categories as shown in the figure. Clinical observations of anomalies in the blood vessels of the retina serve as the basis for the diagnosis of diabetic retinopathy (DR). Non-proliferative diabetic retinopa- thy (NPDR) and proliferative diabetic retinopathy are the two clinical phases of DR. (PDR). Increased vascular permeability and capillary blockage in the retinal blood vessels characterise NPDR, the early stage of DR .At this stage, retinal abnormali- ties such as microaneurysms, hemorrhages, and hard exudates can be identified through fundus photography, even if the patients do not exhibit any noticeable symptoms. Additionally, based on the severity of the condition, NPDR patients can be classified into mild, moderate, or severe categories as shown in the figure.

This study focuses on identifying all stages of DR, using end-to-end deep learning networks .Results indicate that

Fig. 1. Stages of Dibetic Retinopathy

the proposed approach is effective than existing methods in detecting DR at all stages[11].

II. LITERATURE REVIEW

In this paper, the DR severity is automatically estimated. The INDIAN DIABETIC RETINOPATHY IMAGE DATASET was used.This methodology takes into account a modified CNN architecture with an ADAM (Adaptive MomentEstimation) optimizer. In order to prevent the issues that arise during the extraction of convolution features, modified convolution neural networks are used.The technique suggested is pre-trained on 103 total images. As neural networks suffer greatly from overfitting, the bulk of the dataset's images are simply grouped into one class even though they do not exhibitany indicators of retinopathy[1].

A Hybrid Ensemble Deep Learning system was proposed by this system for the early diagnosis of diabetic retinopathy and glaucoma. To prepare them for further processing, eye im-ages must first undergo preprocessing. The system categorises incoming input images as normal eye, glaucoma affected eye, or diabetic retinopathy affected eye based on the features obtained during training. In this study, three CNN models Lenet5,Alexnet and Mixed Neural Network are trained using the preprocessed input data.Afterwards, the ensemble voting classifier made the final prediction after classifying the test data using the three training models. As compared to the previous system, this one delivers the accuracy of 95%[2].

Imran Qureshi et al introduced an active deep learning approach that employs a convolutional neural network model to extract eye fundus features instead of relying on handcrafted features.The ADL system produces valuable prediction masks that specialists can use for annotating necessary eye samples and identifying regions- of-interest in the retinal imagefor categorizing diabetic retinopathy into five severity-levels. However, the CNN architectures developed were unsuccessful in learning complex structures of DR lesions[3].

SAJID SHAH et al. developed a cnn model which is an ensemble of five cnn architectures Resnet50, Inceptionv3, Xception, Dense121, and Dense169 to identify rich features and improve the classification of the five stages of DR. They achieved an accuracy of 80.8%, recall of 51.5%, specificity of 86.72%, the precision of 63.85%, and F1-score of 53.74%.Also, the training was done for both balanced and imbalanced data which concluded that imbalanced data led to classification biases[4].

In this paper it suggests a novel method for identifying diabetic retinopathy. To assess the effectiveness of their suggested strategy, the authors employed the DIARETDB0 and DIARETDB1 databases, which are accessible to the general public. There is one of the possible drawbacks to this article that need to be taken into account .The proposed method is highly dependent on the choice of acceptable parametersand thresholds, which can be difficult and time-consuming to identify[5].

In this paper initially have extracted the characteristics from the photos using a pre-trained convolutional neural network (CNN) named Inception-V3, and then they train a support vector machine (SVM) classifier on top of these features to determine the DR severity level.This strategy does have a few disadvantages, though. A high-quality retinal image, which may not always be available in clinical settings, especially in places with limited resources, is another constraint of the model. The model's interpretability and clinical usefulnessmay be limited as a result of the absence of information regard-ing the precise features that are being used for categorization. Finally, the use of a pre-trained CNN may restrict the model's flexibility to be modified for unique clinical requirements or to include additional data sources[6].

In particular, for binary and multi-class classification in the process of DR diagnosis, a significant amount of work has been done using a variety of deep learning methods. In order to classify 1000 retinal images for retinopathy, Dutta, Suvajit, et al. used back propagation neural networks, deep neural networks, and convolutional neural networks (VGGnet). Theyobtained 62.7%, 89.6%, 76.4% training accuracy and 42%, 86.3%, 78.3% testing accuracy, respectively.Recent increases in the number of diabetic patients have made the need for trustworthy diabetic retinopathy screening systems essential. The issue of choosing trustworthy features for ML is solved byusing DL in DR detection and categorization, but it requiresa large amount of training data. To increase the quantity of images and combat overfitting during the training stage, most studies used data augmentation[7].

Research on detecting diabetic retinopathy in Africa was given by Bellemo, Valentina, et al. VGGNet and ResNet were two of the CNN designs they employed. They conducted an experiment using the public dataset of 4504 retina images and obtained an area under curve (AUC) of 0.973 with 92.25% sensitivity and 89.04% specificity for referral DR, 99.42% sensitivity for vision-threatening DR, and 97.19% sensitivity for diabetic macular oedema [24]. The DR stages are based on the type of lesions that appear on the retina.This article has reviewed the most recent automated systems of diabetic retinopathy detection and classification that used deep learning techniques.The available therapies are only invasive procedures like intraocular injections andphotocoagulation. As it is a very serious disease, a doctor should be contacted right away[8].

III. IMPLEMENTATION

A. Acquistion Of Dataset

The proposed model is tested on the dataset collected from Kaggle recognized by aptos symposium.The dataset contains large number of retinal images taken using fundus photography

Type of DR	No. of images	class
No DR	25810	0
Mild	2443	1
Moderate	5292	2
Severe	873	3
Proliferative	708	4

TABLE I
NUMBER OF IMAGES OF 5 DIFFERENT CLASS IN THE DATASET

under many imaging conditions.It contains 35126 images with 5 classes shown in the table I.

A. Preprocessing

Preprocessing step involves resizing the images to resolution of 224*224 then cropping the images and transforming into array since the images cannot be directly fed to the model.The RGB images are converted to grayscale images.For better results data augmentation was done with help of image generator.

B. Convolutional neural network Architecture

A Convolutional Neural Network architecture is one of the type in Deep Learning architecture commonly used for image classification and recognization task.Facial and video Recognition, Analyzing Documents , Environmental Collections, study of Climate changes, Image and video identification, recommended systems, medical image categorization and evaluationare some of the applications.

Steps in CNN

- Convolution
- Max Pooling
- Flattening
- Fully connected

Convolution Layer

The convolution layer is the core building block of a Convolutional Neural Network. The parameters in this layer consists of a set of K learnable filters (i.e., “kernels”), where each filter has a width and a height, and are nearly always square.These filters are small but extend throughout the full depth of the volume. For inputs to the CNN, the depth is the number of channels in the image.At each convolutional layer in a CNN, there are K kernels appliedto the input volume. Each of the K kernels is convolved with the input volume. Each kernel produces an 2D output, called an activation map.After each convolution layer in a CNN, we apply a nonlinear activation function, such as ReLU.

Max Pooling

Another component of a CNN is the pooling layer. The proportions of feature maps are compact by using pooling layers. As a result, the parameter length and processing time in the network are both reduced. Each feature map is dealt separately by the pooling layer. In pooling operation Max pooling is the best alternative in order to retain the characteristics .In Max pooling, maximum element from the region of the feature map enclosed by the filter. As a result , the output of max-pooling layer contains the most prominent features. In the proposed work Max pooling with Fully connection 4x4 is choosing to obtain maximum value in the 4x4 window.

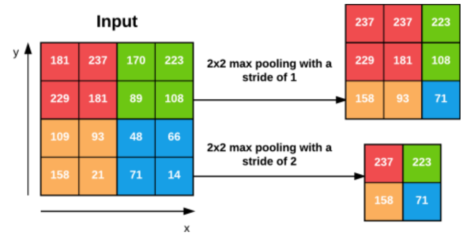


Fig. 2. Pooling Layer with stride 1 and stride 2

Flattening

Flattening is a simple step which involves taking the pooled feature map that is obtained from the pooling layer and convert them into a one dimensional vector so that it can be fed into fully connected layer in which final classification is going to be done.

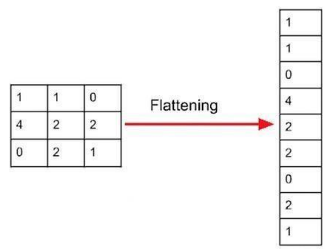


Fig. 3. Flattening

Fully connected

Fully connected layers are Feed forward neural network. The term fully connected means every node in the first layer are connected to the every node in the second layer. The out from the last pooling layer is flattened and then given to as input to the fully connected layer. Fully Connected layers classify data based on attributes acquired by preceding layers.

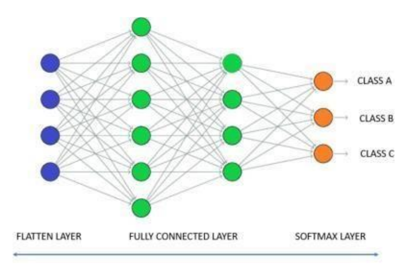


Fig. 4. Fully connected

C. Lenet-5 Architecture

Lenet-5 is a classic convolutional neural network (CNN) architecture that was originally developed for digit recognition. However, it has also been used for various image classification tasks, including diabetic retinopathy (DR) detection. The LeNet-5 architecture consists of the following layers:

- . **Input Layer:**
  This layer takes in the retinal images as input. The size of the input image can vary depending on the dataset, but it is typically 32x32 pixels or larger.
- . **Convolution Layer1:**
  The first convolutional layer applies six filters of size 5x5 to the input image. Each filter detects a specific feature in the image, such as edges or corners. The output of this layer is a set of six feature maps, each representing the presence of a specific feature.The output from this layer has a dimension of 28x28x6, which is smaller in size than the original image
- . **Max Pool Layer1:**
  After the first convolutional layer, Lenet-5 applies an average pooling or sub-sampling layer with a filter size of 2×2 and a stride of two. This layer reduces the dimensions of the image from 28x28x6 to 14x14x6.
- **Convolution Layer2:**
  The second convolutional layer consists of 16 feature maps having size 5×5 and a stride of 1. In this layer, only 10 out of 16 feature maps are connected to 6 feature maps of the previous layer. The number of training parameters in this layers are 1516 instead of 2400 and similarly, the number of connections are 151600 instead of 240000.
- **Max Pool Layer2:**
  The fourth layer is again an average pooling layer with filter size 2×2 and a stride of 2. This layer is the sameas the second layer except it has 16 feature maps so the output will be reduced to 5x5x16.
- **Fully connected layer 1:** The output of the second max pooling layer is flattened and passed through a fully connected layer with 120 neurons. This layer learns the high-level features and correlations in the input image.
- **Fully connected layer 2:** The output of the first fully connected layer is passed through another fully connectedlayer with 84 neurons. This layer further learns the complex relationships between the features.
- **Output layer:** The final layer is a softmax layer that produces a probability distribution over the five classes of DR severity. The class with the highest probability is predicted as the output.

Configuration of hyper-parameters in model

Model	Batch Size	Epoch	Learning Size	Optimizer
Lenet-5	32	100	0.001	Adam optimizer
Inception V3	8	50	0.001	Stochastic Gradi- ent Descent
Ensemble	8	50	0.01	SGD and Adam optimizer

TABLE II
COMPARISON OF HYPERPARAMETERS USED IN TUNING THE MODELS

The comparison of various configurations of the CNN architectures is done. All these pre-train CNN architectures are implemented in Python 3.8 and Keras deep library with Ten- sorflow backend. The detail of the network, batch size,epochs, and learning rate is given in Table II, respectively.

IV. RESULTS AND DISCUSSIONS

The accuracy of each class varies, as shown in the following figures, where the No DR class has an accuracy of 97.7%, the mild class has an accuracy of 94%, the moderate class has an accuracy of 98.4%, the severe class has an accuracy of 97.8%, and the proliferative class has an accuracy of 97.4%.

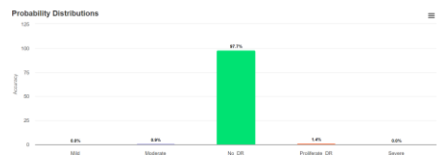


Fig. 5. Result predicted as class No DR

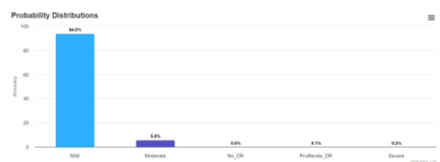


Fig. 6. Result predicted as class Mild

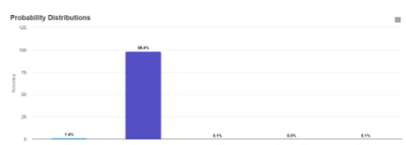


Fig. 7. Result predicted as class Moderate

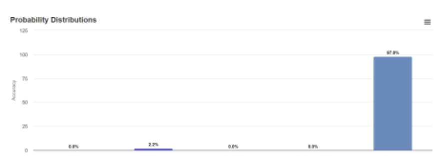


Fig. 8. Result predicted as class Severe

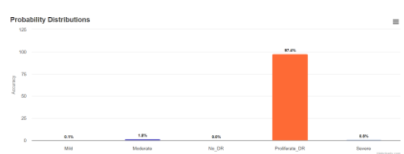


Fig. 9. Result predicted as class ProliferativeDR

In our testing, we assessed the losses for training, validation, and accuracy over the validation set. To demonstrate the suggested Lenet-5 model's applicability to identify the DR severity level, certain statistical measures including sensitivity(SE), specificity (SP), f1-score, and accuracy were also per- formed.

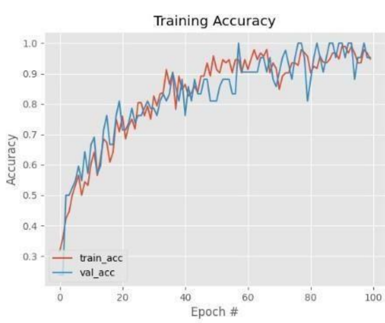
The true-positive rate (TPR) and false-positive rate (FPR) were inferred, and the SE and SP indices were frequently employed to compare the performance of the technique. FPR is defined as (1-SP), whereas TPR is the SE measure. True- positive (TP) displays the positive (P) values of the classifier estimation as well as the real instance. False-positive (FP) signals the genuine case's negative (N) value. True-negative (TN), on the other hand, displays the N values of both the actual and anticipated labels from the classifier. False-negative (FN) indicates that the real class value is positive while the classifier's N value is indicated. SE, SP, and F-measure metrics are calculated using the equations shown below.

Sensitivity or TPR=TP/(TP+FN)

Specificity or FPR =FP/(FP+TN)

Accuracy=TP+FP/(TP+FP+TN+FP)

F1-measure= 2TP/(2TP+FP+FN)



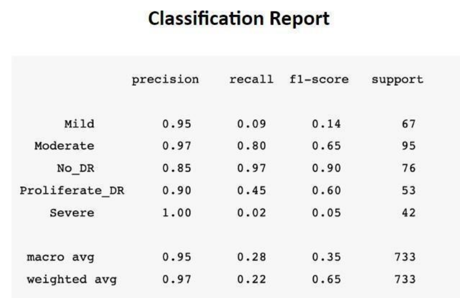
Epoch vs Accuracy

Fig. 10. Training Accuracy

Epoch vs Loss

Fig. 11. Training Loss (loss function)

Figure 10 and figure 11 depicts the accuracy curve and loss curve respectively.Accuracy curve is obtained by plotting epoch vs accuracy which indicates the change in accuracy after each epoch and it can be noted that the accuracy kept on increasing as the model was trained.In the figure 11 the loss kept on decreasing as we increased the number of epochs.



Classification Report

	precision	recall	f1-score	support
Mild	0.95	0.09	0.14	67
Moderate	0.97	0.80	0.65	95
No_DR	0.85	0.97	0.90	76
Proliferate_DR	0.90	0.45	0.60	53
Severe	1.00	0.02	0.05	42
macro avg	0.95	0.28	0.35	733
weighted avg	0.97	0.22	0.65	733

Fig. 12. Classification Report with different Evaluation Metrices

The classification report is shown in fig 12 which includes precision,recall,f1-score and support for each class.

On 35,126 digitised retinal samples, a statistical analysis based on SE, SP, F-measure, and accuracy was performed to determine how well the Lenet-5 system performed in identify- ing each class for DR diagnosis. Table III shows a significant improvement in the suggested system's accuracy (97%) f1- score (65%) and recall (22%). The results for the normal class (SE: 97%, f1-score: 90%, and accuracy: 85%), mild diabetes class (SE: 90%, f1-score: 14%, and accuracy: 95%), severe diabetes class (SE: 2%, f1-score: 5%, and accuracy: 100%), and proliferative DR (SE: 45%, f1-score: 60%, and accuracy: 90%) were compared.

Research study	Model	Recall	f1-score	Accuracy
Xiaoling Luo et al.[12]	MVDR-Net	72.48%	Not Re-ported	75.98%
Qummar et al.[6]	Ensemble Model	51.5%	53.7%	80%
K.Yazhini et al.[13]	GD-Lenet-5	72.80%	Not Re-ported	81.82%
Victor et al.[16]	Inception V3	90%	94.56	95.56%
DenseNet et al.[15]	CNN	89%	Not Re-ported	88%
Özbay et al.[17]	ADL-CNN	93.76%	94.58%	95.59%
Proposed CNN	Lenet-5	22%	65%	97%

TABLE III
PERFORMANCE COMPARISONS WITH THE STATE-OF-ART ARCHITECTURES

As demonstrated in Table III, the suggested lenet-5 system's performance has been statistically evaluated and contrasted with pre-train CNN architectures. From Table III, it can be inferred that the model's achieved accuracy in DR stage classification is higher than that of the other pre-train CNN networks, with an accuracy of 97%. These findings show that lenet may be better than known models like the VGG-16,Inception V3, ensemble models, etc.

V. Conclusion

Automated screening methods drastically cut down on the time needed to make diagnoses, saving ophthalmologists' time and money while also enabling patients to receive treatment sooner. Automated DR detection systems are crucial for spotting DR at an early stage. The stages of DR are determined by the kind of lesions that develop on the retina. This article has examined the most recent deep learning-based automated methods for detecting and categorising diabetic retinopathy. We have detailed the publicly accessible common fundus DR datasets and provided a quick introduction to deep learning methods.Due to its effectiveness, CNN has been adopted by the majority of researchers for the detection and classification of DR pictures. Additionally, the effective methods that can be applied to identify and categorise DR using DL have been covered in this review.

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