

Computerized Sensing of Diabetes Retinopathy with Fundus Images Using CNN



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1 Introduction

In the current scenario, we are all aware that diabetes is one of the worst and most deadly diseases not only in India as well as in the world. A large number of people are diagnosed with this disease, and from this, the chance of other problems or other medical problems is also there [1, 2]. Diabetes may lead to a higher chance of many eye diseases; one such is diabetic retinopathy. Screening and testing of eyes are not as cheaper as it is also a time and cost-effective procedure. Apart from screening and testing of eyes, a clinical person needs a required lot of experience so that they could detect whether either person is suffering from diabetic retinopathy or not. Several models and techniques have been introduced using DL models to discover DR.

However, DR is irreversible blindness, and it is mostly in the mid-age population; DR is one of the major causes of unrepairable visual deficiency. Figures 1 and 2 show the normal and diabetic retina images. As diabetes is a chronic disease, severe and systemic disease, it affects different organs like kidneys, eyes, and systems never still as the heart. Diabetic retinopathy may create no side effects or fair minor visual anomalies at, to begin with.

However, it can cause blindness. Unquenchable diabetes and its complexity led to DR [3]. According to a report, there are 103.12 million people are suffering from diabetic retinopathy, and by the year 2045, it will increase to 160.50 million. It is one of the driving causes of visual insufficiency in people.

DR might happen in type-1 and type-2 diabetes patients; it happened since of the high level of sugar inside the blood [4].

In diabetic retinopathy, the retina's blood vessels are harmed due to the increased level of sugar in the blood. Diabetic retinopathy is broadly separated into parts

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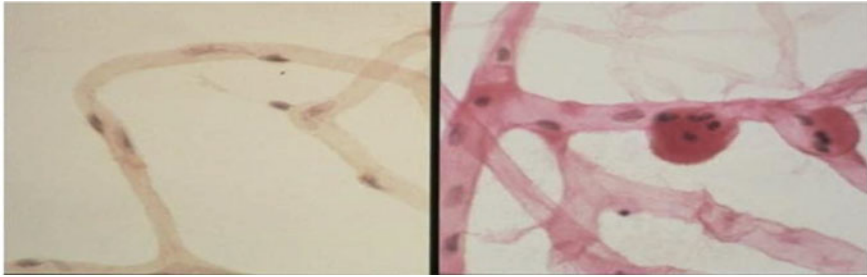


Fig. 1 Normal and diabetic retina veins image



Fig. 2 Normal retina and diabetic retina

named pre-diabetic retinopathy and post-diabetic retinopathy. Diabetic retinopathy is additionally alluded to as non-proliferating diabetic retinopathy (NPDR), and post-diabetic retinopathy is alluded to as proliferative diabetic. Table 1 represents the different severity scales of diabetic retinopathy. In the first category of diabetic retinopathy, the new blood vessels are not developed which is called proliferating. In this, the walls of the veins in our retina get weakened [5]. Diminutive bulges are obtruded from the walls of the tiny vessels. Often it seems that leaking of blood and fluid into the retina. Broad retinal vessels can begin to widen and may lead to unpredictable shapes as well. NPDR can be taking place from mild to severe as a large number of blood vessels become blocked.

Though inside the post-diabetic retinopathy can reach out to this more serious sort. In this, impeded veins are cut off, which bring practically the improvement of present-day, untypical veins inside the retina [4].

These as of late made veins are fragile and can drain into the reasonable, jam-like substance that fills the focal point of our eye (glassy). In case the as of late made veins barge in into the standard stream of fluid out of the eye, the oblige can build

Table 1 International clinical DR disease severity scale (ICDRDSS)

Disease severity level	Finding upon dilated ophthalmoscopy
0 = No DR	No abnormality
1 = Mild DR	Micro-aneurysms only
2 = Moderate DR	More than micro-aneurysms but less than NPDR
3 = Severe DR	Any of the following and no sign of proliferative retinopathy: more than 20 intraretinal hemorrhages in each of four quadrants Definite venous beading in two or more quadrants Prominent IRMA in one or more quadrants
4 = Proliferative DR	One or both of the following Neovascularization vitreous/pre-retinal hemorrhage

inside the eyeball. It can harm the nerve that takes a picture from the eye to our brain (optic nerve), which comes about in glaucoma.

In spite of the fact that screening and rescreening of an individual experiencing DR is an exorbitant and exceptionally tedious cycle.

In this manner, numerous pseudoscientists have explored different avenues regarding scientific methods and the programmed discovery of DR [1]. As the screening of DR is the time taken to handle it likewise expected a thoroughly prepared clinician to check and confirm the computerized fundus image of the retina. Figure 3 shows the various instances of DR, by the time human per user presents their survey, which might prompt the postponed results lost to follow-up, miscommunication, and deferred treatment [4].

An expert ophthalmologist can find DR by the closeness of wounds related with the vascular combinations from the standard brought around by sickness. As this approach is sensible, its resource demands are particularly tall. The expert ophthalmologist and contraption are regularly lost in the locale where how much diabetes inside the local people is tall and DR exposure is required. As how much of people with diabetes increments bit by bit, the system is expected to stay missing people from visual needs since DR will get the opportunity to insulant be for unquestionably more [6].

The rate of increment of diabetes among adults from 4.7% in 1980 to 8.5% in 2014. The experienced clinician is very less and is unevenly distributed. The general number of experienced ophthalmologists all over the planet in the year 2012 was 210,730 which proposes that 29 ophthalmologists. The differentiation between the general population of diabetes patients and the expert clinical can be greater, which mirrors the expectations for a squeezing structure for the area of diabetic retinopathy thusly [2]. Figure 4 represents the clinical protocol chart.

Deep learning methods rapidly become the most interesting as well as a promising technique for pseudoscientists and are acquiring acceptance in countless practical applications in engineering [5].

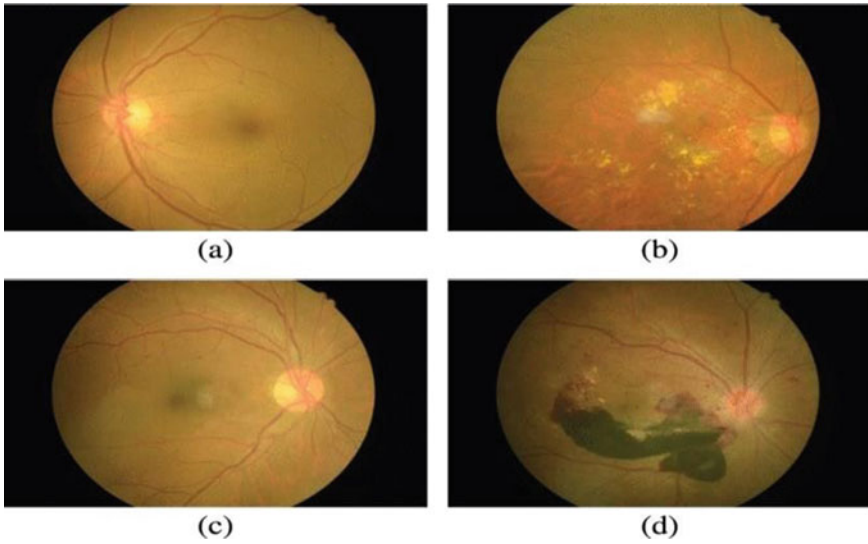
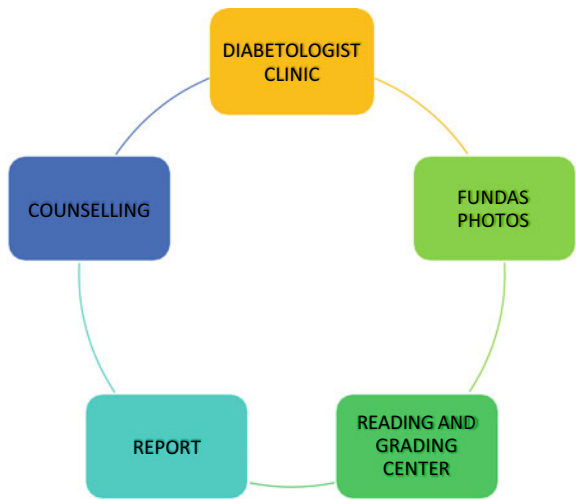


Fig. 3 Different cases of diabetic retinopathy

Fig. 4 Clinical protocol chart



So much work is done in computers to detect automatically diabetic retinopathy diagnoses. Earlier models removed different features to at first remove significant information from the fundus pictures. From that point forward, these features are sustained to specific kinds of classifiers. What is more, these hand-planned highlight-based procedures are troublesome and routinely miss the mark to abandon far-off better; much better; a higher; a stronger; an improved a far-off improved outcome.

Inside the seem decade, fabricated pieces of data have achieved directly arrives at the place of understanding in various zones. Artificial neural networks and deep learning are ideally and structurally influenced by traditional neural systems; they become an interesting and promising technique for pseudoscientists in different fields including analysis of medical imaging [7]. Deep learning means learning the representation of data. Figure 5 shows what is deep learning?

Most deep neural networks are based on neural network architecture that is so often called DNN. The word significant suggests there are a small bunch of disguised layers inside the mindset up. The timetable mindset up s so to talk dealing with 2–3 up layers, disregarding the way that it can have as various as 150. Figure 6 seems the neural frameworks, which are worked with in layers containing a lot of interconnected focus centers. Frameworks can have tens or various covered layers [5].

Fig. 5 What is deep learning?

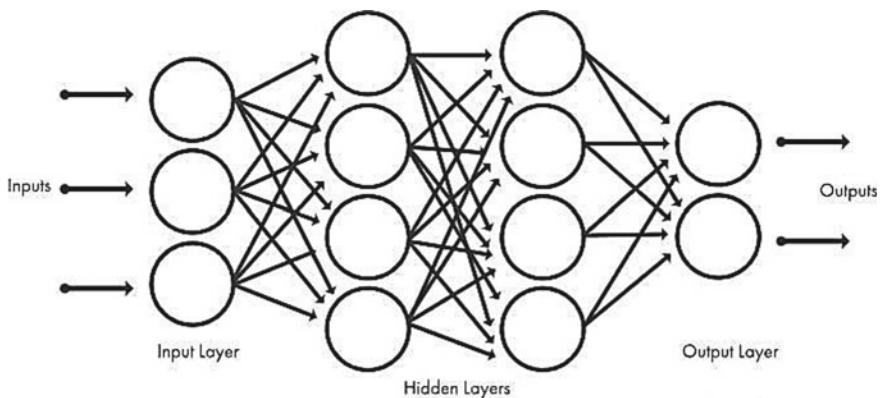
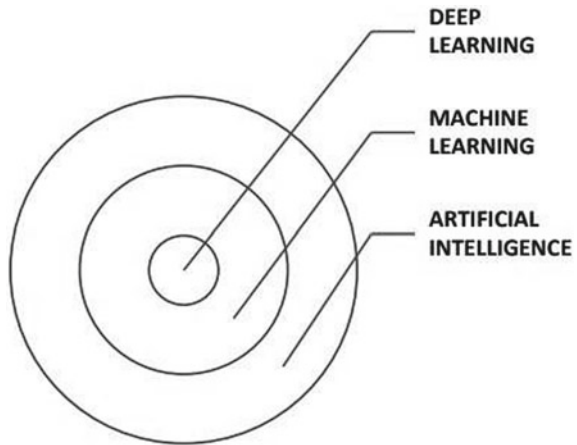


Fig. 6 What is a neural network?

Countless named datasets are used for the getting ready of significant learning models. The brain coordinate plan will clearly gain from the data with no manual feature extraction [5]. It has performed mostly well as a classifier for image-processing applications and as a function estimator for linear as well as nonlinear applications.

In the recent decade, the deep neural network has found revolutionary outcomes in different fields. In the 1970s, coordinate models were arranged that work on picture data with important applications and different ways to deal with testing tasks like physically composed character affirmations. It brings around leap forwards in defy affirmation, talk affirmation, PC vision, trademark lingo taking care of, and various more [5, 7].

The different application of deep neural networks surprises humans such as COVID detection, face recognition, and wide-scale visual recognition. The utilization of significant brain frameworks inside the assurance of diabetic retinopathy has in addition gotten much captivated, and much development has been made. Notwithstanding the way that various impels have been made, clinical utilization of customized diabetic retinopathy end structures stays blocked off; thus, much work is as yet expected to be finished [7]. Figure 7 represents the various ways for DR detection.

A branch of a DNN, i.e., known as a convolutional neural network. A convolutional brain orchestrate basically has a spot to the feed-forward made brain organize, which has a spot to significant brain frameworks. The CNN might be an incredibly notable significant learning plan that can get familiar with a food chain of features that is used for picture grouping [2]. As a show learns more complicated features, understanding, and other mutilation features in advanced layers, the precision of the exhibit can be higher. Moreover, in light of this suspicion, we explore the working of the convolutional brain put together for diabetic retinopathy [8]. Regardless, an essential multi-facet CNN show is framed, and tests are taken a stab at interesting retina data.

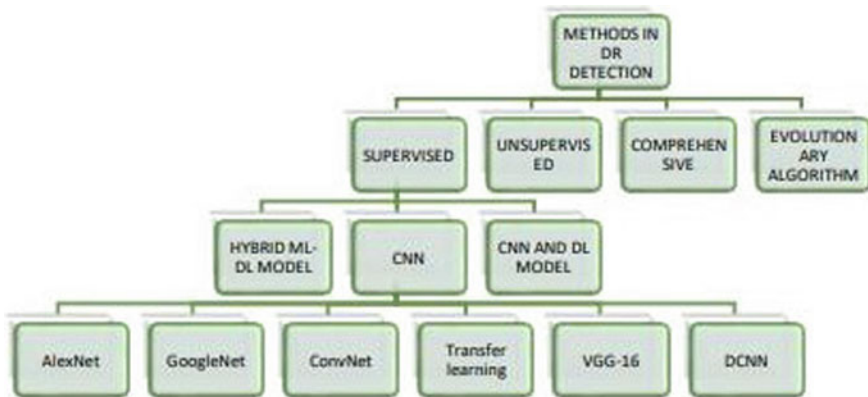


Fig. 7 Different methods for DR detection

Inside the ongoing circumstance, especially broad CNN was used to actually deal with really complex picture affirmation issues with unmistakable dissent classes to an imperative norm. It is used in various present statuses of craftsmanship picture characterization work, for example, COCO challenges and the yearly ImageNet.

There are a few issues within the automated grading and particularly with CNN. The first one is to achieve a required offset insensitivity which means the person is correctly identified as either it going through DR or specificity which means a person is not going through DR. That is strikingly convenient for public measures which might be a five-name issue from common, delicate, immediate, outrageous, proliferative diabetic retinopathy classes [5]. In addition, the overfitting of the dataset is one more issue in brain organizations. Slanted datasets may prompt the brain organization to overfit the class which is most conspicuous in the dataset [3]. Large datasets are frequently hugely slanted. In this paper, we take a significant learning-based convolutional brain coordinate show to recognize particular kinds of diabetic retinopathy with the help of fundus pictures. Typically, a remedial imaging handle with creating indicative importance, as we discussed earlier, and one that has been exposed to various things about inside the past.

At particular phases of the CNN procedure, it contains an extensive number of teachable boundaries which are used to find essential features from retina pictures at unmistakable reflection levels. The most downright horrendous piece of the CNN-based technique is that it needs an epic dataset to get ready [9]. Isolated from this, it required speedy registering resources for planning and tuning with the hyperparameters.

It could produce a good result in different disease diagnoses like the categorization of pneumonia as well as COVID-19 patients with the help of analysis of chest X-ray image, blind patients' differentiation with analysis of retina image, classification of brain tumor with MRI image analysis, and many more. CNN's methods are also very helpful to find the classes of DR severity from the original retina images [10].

2 Related Work

This part discusses CNN-based models for DR severity classification.

An exhaustive examination has been performed on the model for double separation of DR with a promising end.

Gardner et al. used brain networks as well as pixel values power to achieve responsiveness and particularity aftereffects of 88.4 and 83.5% individually for 0 or 1 arrangement of DR.

They utilized the restricted dataset of pictures and parted each picture into patches and afterward expected an ophthalmologist to confirm the patches for the component before the execution of SVM.

Within the three-class classification of DR, neural systems have moreover been connected. The range of exudates and the zone of blood vessels, as well as textural

parameters, were utilized by Nayak et al. To classify pictures into typical, non-proliferative retinopathy, and proliferative retinopathy, highlights are embedded into the neural arrangement. These characteristics were utilized as categorization input by the neural organization [8].

The detection results were confirmed by comparing them to professional ophthalmologist grading. They achieved 93% classification accuracy, 90% sensitivity, and 100% specificity. This was done on a dataset of 140 photographs, and highlight extraction was required on all of them in both preparing and testing, which took a long time [6].

Support vector machines have been employed in the great bulk of studies on the five-class categorization (SVMs) [11]. The five classifications have been identified using an automated approach developed by Acharya et al. The SVM classifier businesses feature taken from the unrefined data utilizing a higher-request range way to deal with catching the data.

The precision, affectability, and explicitness of this SVM approach were all over 80% typical. Acharya et al. made a five-class order strategy by evaluating the zones of a couple of qualities like hemorrhages, micro-aneurysms, exudate, and veins [12]. The principal basic attributes, veins, miniature aneurysms, exudates, and hemorrhages, were recuperated from crude pictures with the help of picture-getting-ready techniques.

These were by then set into the SVM to be arranged. This approach achieved an affectability of 82%, particularity of 86%, and precision of 85.9%. These methodologies were associated with astoundingly little datasets, and the reduction in affectability and explicitness was in all probability connected with the intricacy of the five-class issue [4].

Adarsh et al. used pictures dealing with gadgets to supply a robotized determination for DR by perceiving retinal veins, exudate, miniature aneurysms, and textural attributes. The incorporate vector for the multivariate data SVM was constructed using the zone of wounds and textural attributes. On average citizens 89 and 130 picture datasets DIARETDB0 and DIARETDB1, are made precision paces of 96 and 94.6%, independently [8].

Every one of the first five class methods required picture highlight extraction prior to being taken care of into an SVM classifier, and they were just confirmed on minuscule test sets of around 100 photographs. These methodologies are less material continuously than a CNN [13].

The researchers proposed a graph neural network (GNN)-based approach for DR severity classification in their paper. The method initially determines the ROI from imagery which target the regions that identify lesions [8]. Following that, the technique employs the GNN for fundus image categorization.

A deep learning approach for detecting and classifying DR fundus was proposed by the researcher. The procedure began by reducing the excess noise that emerges on the edges. The image's important sections were then retrieved using histogram-based segmentation. Finally, in the DR fundus pictures, the synergic deep learning (SDL) approach is employed to identify severity classes [8].

The pseudoscientist proposed a procedure for diagnosing DR in view of two specific variables: (1) dim level concentrated and (2) surface features removed from fundus pictures. These qualities are by then used to order data utilizing a choice tree-based outfit learning approach. Subsequently, the show achieves 94.20% order accuracy and an F-proportion of 93.51%.

The KNN classifier was used by the maker to recognize DR illnesses by removing attributes of the optic plate, veins, and exudates from retina pictures. The DR-impacted picture order showed by the expert depended on the stationary wavelet change and the discrete wavelet change coefficient. The model's precision was 94.17% [8].

The authors created a classification approach that combined SVM and neural network models [12]. They investigated feature extraction and segmentation processes before applying model pre-processing. The model has an accuracy of 80%.

The scientists outlined a methodology for recognizing drusen, cotton-fleece fixes, and exudates in retina pictures [4]. The estimation gets 0.95 inside the Recipient Working Characteristics (ROC) score and performs so likewise to an expert. The makers showed a constant procedure for fundus picture order in view of an AM-FM modified assessing structure [8]. Sometimes as of late applying the retinal features to the illustration, the makers removed them regardless.

Mehedi et al. [12] demonstrated the approach with area under the receiver operating characteristics (AUROC) which is used to classify the true and false cases. Figure 8 represents the AUROC graph of the model. The methods represent the fair performance in comparison between the different cases of DR [8].

3 Methodology

3.1 Dataset, Hardware, and Software

The dataset of retina pictures that we used during the testing and getting ready for the show was taken from the Kaggle people group. Until later times, sets of remarked on pictures of diabetic retinopathy were confined. We had the option to get ready in the general dataset by resizing these photos and running our CNN on a top-of-the-line GPU, the NVIDIA GTX. The NVIDIA GTX contains 1344 CUDA focuses and integrates the NVIDIA CUDA Profound Neural Organize (cuDNN) library for GPU learning.

About 15,000 photos were traded onto the GPU memory out of nowhere by using this program. Keras's (<http://keras.io/>) significant learning PC program was joined with the Theano (<http://deeplearning.net/programming/theano/>) AI back end. This was picked since it has good documentation and a quick calculation time. An image might be arranged in 0.04 s, allowing for continuous contribution to the calm.

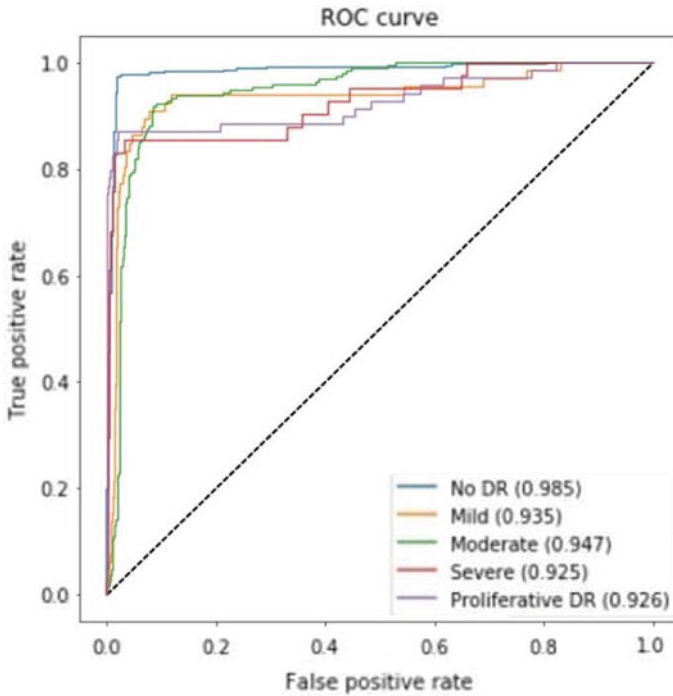


Fig. 8 AUROC score of the proposed method for variety of DR classes

3.2 Preprocessing

The collection comprises photos from patients of multiple ethnicities, ages, and illumination levels in fundus photography. This has an effect on the gray levels in the photos, causing additional variance unrelated to categorization levels. To overcome this issue, we rescale the images. Using rescaling, we treat all the images in a similar way because some images are a high pixel range, while others are a moderate pixel range. These images are sharing the same method.

3.3 Training and Proposed Model

In this study, CNN is employed for feature studying of referable DR. Four convolutional layers are used for each channel, with the number of filters increasing in succeeding layers to 32, 64, 120, and 256. To keep away from overfitting, most limit pooling, revised direct unit authorization work, and dropout are used.

The completely connected layers are coupled after flattening from the two channels to statistically finding the detection of referable diabetic retinopathy. TensorFlow

software and Python are used to code the suggested referable DR detection technique. For training the network, the binaryCross_Entropy loss function and the ReLu algorithm with a learning rate of 0.001 are used. The CNN was pre-trained on the number of retina images at first until it achieved a substantial level.

This was required in order to produce a pretty speedy classification result without spending a significant amount of training time. After 120 epochs of preparing on the first photographs, the organization was prepared for one more 40 epochs on the total 5000 preparation pictures. Neural networks suffer from significant overfitting, especially in a dataset like ours, where the bulk of the photos are categorized in one class that displays no evidence of retinopathy.

To deal with this issue, we joined ongoing course loads inside the network. The class weights were updated using a ratio proportional to the number of images in the training batch and were differentiated as having no evidence of DR for each batch applied for back-propagation. This considerably lowered the possibility of over-fitting to a specific class. A modest learning rate of 0.001 was utilized for three epochs to stabilize the weights.

A couple of specific CNN models have been suggested and assessed in our tests. The significance of the attempted brain arrangement runs from 9–18, though the convolution part measure goes from 1 to 5. To meet the information gauge of the CNN, we scale the image measure to $200 \times 200 \times 3$. Figure 9 seems a definitive coordinate arrangement used in our research [2]. The sort-out returns two probabilities for each piece of information that incorporates dependent upon one, one for each class (our issue might be a twofold grouping issue). In our attempt, we used various marked photos which are used to prepare the brain coordinate, while a couple of the photos are utilized to evaluate the execution of the arranged brain sort out.

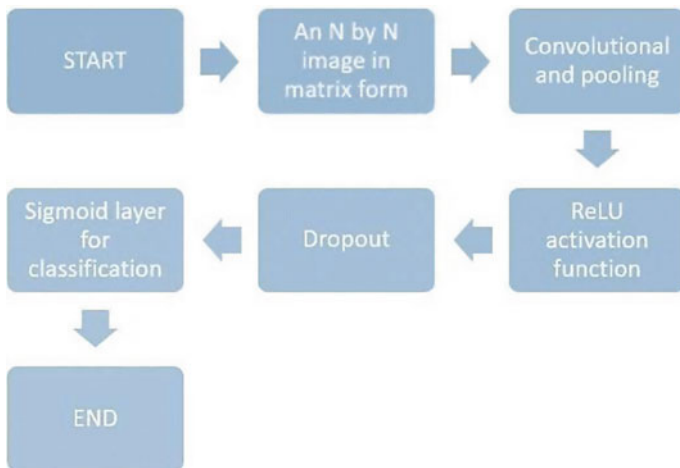


Fig. 9 CNN architecture used in our experiment

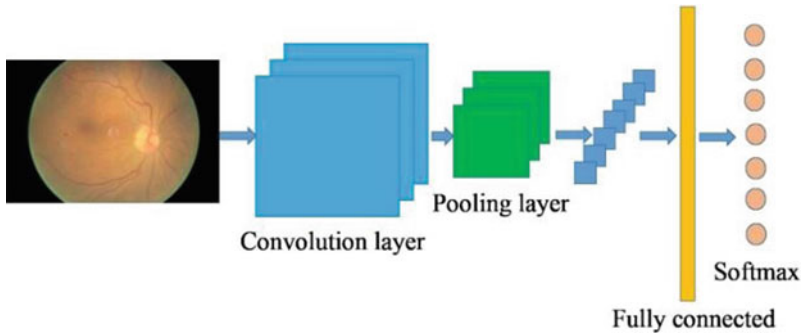


Fig. 10 Exemplary Architecture of convolutional neural network

The model was then trained with a low studying rate on the whole training set of pictures. Within a few huge epochs of the whole dataset, the network’s accuracy had grown to almost 98%. When compared to other approaches, the CNN-based models outperform them, supporting the premise made in the introductory section.

The entropy picture of the brightness of fundus picture indicates the complexity of the actual retinal picture and aids in the training of the convolutional neural network-based DL. To quantify the heterogeneity, the merit in the entropy picture is computed locally from $n \times n$ blocks. Entropy is decided by the probability distribution of the local intensity.

In this paper, a lightweight CNN model for identifying the severity of DR from retina pictures. Figure 9 depicts the suggested custom model. The model contains four 2D convolutional layers. In each\’s layer, the filter size is 3×3 , and a similar padding is used. A “ReLU” activation function is used by each layer.

In extension, the show uses the MaxPooling2D approach after the second and fourth layers, as well as dropout regularization after the occasion, fourth, and completely associated layers. The softmax activation work is associated with the grouping layer due to the staggered order.

In the model, the (RMSprop) optimizer is used. RMSprop eliminates oscillations and automatically adjusts learning rate. The studying rate in RMSprop is divided by an exponentially decaying average of squared gradients. RMS propagation prevents you from searching in the direction of oscillations. RMS propagation additionally chooses a unique learning rate for each parameter. Figure 10 represents the basic model of the CNN [2].

3.4 Result

A large dataset of retina images was saved for the validation and training process. Moreover, the training dataset of retina images is divided into 80% to train the network and rest 20% for the validation of the network. Working on the validation images

dataset on the network took a few seconds. For this, we define two-class specificity either the patient is suffering from diabetic retinopathy or the patient is not suffering from diabetic retinopathy. The final trained model acquired almost 98% accuracy, i.e., shown, in Fig. 11 and model loss which shown in Fig. 12.

Our trained convolutional neural network has the potential benefit of being able to categorize hundreds of pictures per minute, allowing it to be utilized in real-time anytime a new image is collected. Pictures are given to specialists for exploring in sharpen; however, they are not appropriately assessed when the tranquil come in for screening. The trained CNN allows for a speedy diagnosis and immediate reaction to

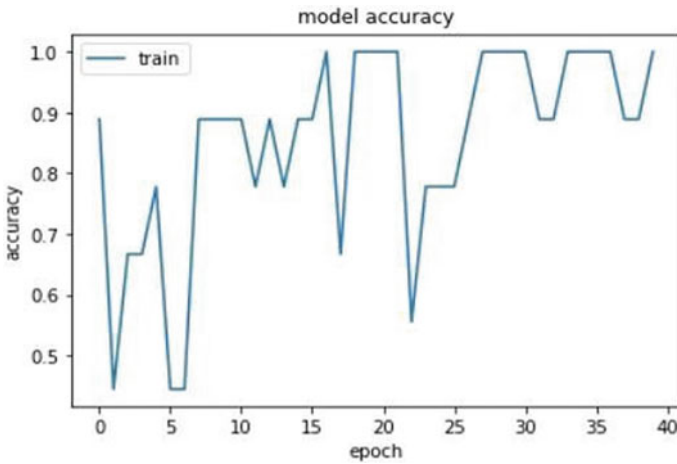


Fig. 11 Model accuracy graph

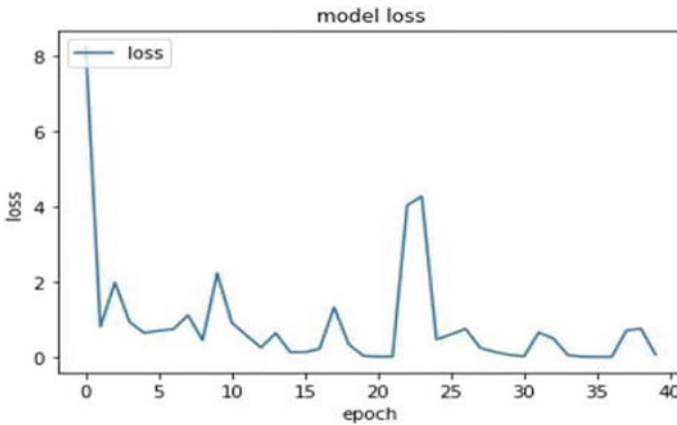


Fig. 12 Model losses graph

Table 2 Performance differentiation with different approaches

Methods	Accuracy (%)
Hard exudates + GBM	89.4
Red lesions + GBM	88.7
Micro-aneurysms + GBM	86.2
Blood vessel detection + GBM	79.1
CNN without data augmentation	91.5
CNN with data augmentation	94.5

a patient. These results were likewise attained by the network with only one picture per eye.

Pictures are given to doctors for reviewing in home, but they are not suitably evaluated when the quiet comes in the continuous advancements in CNNs enable for far deeper networks that can learn the nuanced properties that this network was unable to understand. The findings of our network from an orthodox network topology are highly encouraging. Unlike earlier techniques, nothing explicitly connected to the properties of our fundus photos, such as vessels, exudate, and so on, has been utilized. This makes the CNN results outstanding, but we have plans to tailor our network to this specific purpose in the future in order to learn the more nuanced categorization criteria screening.

The system has no difficulty learning to recognize a picture of a normal eye. This is most likely because the sample contains a significant proportion of healthy eyes. The training required to categorize photos at the extreme ends of the spectrum was substantially less during training. The difficulties arose while attempting to train the network to discriminate among moderate, mild, and severe cases of diabetic retinopathy.

DR is a serious medical health issue that causes blindness, and DL approaches can play a more vital role in its diagnosis and early identification than traditional procedures. This document covers DR in detail, including its symptoms, characteristics, form, size, and location, as well as how DR causes blindness. It also explains numerous ML and DL strategies for detecting aberrant RBV and OD behavior in order to diagnose DR lesions. Table 2 represents the performance differentiation with different approaches.

4 Conclusion

With a certain number of medical personnel, an automation model can considerably reduce the time-consuming human work needed in diagnosing large numbers of retinal pictures. In prior investigations, feature extraction-based diabetic retinopathy diagnosis was dominating. Our model has shown good evidence of learning the characteristics needed to classify fundus pictures, correctly distinguishing the bulk

of proliferative cases and patients with no DR. Our research has demonstrated that the challenge for nationwide diabetic retinopathy screening may be handled using a convolutional neural network method. As in other large dataset research, increased specificity has come at the expense of poorer sensitivity. Our strategy achieves an equivalent that happens to these earlier methodologies notwithstanding the non-attendance of element explicit conspicuous evidence and the use of a stunningly greater dataset.

The results are positive when compared to human grading reports; hence, a clinical study will be conducted in order to include the given method into a tool for diagnosing diabetic retinopathy. To sum up, we represented that CNNs can be told to perceive diabetic retinopathy attributes in fundus pictures. CNNs have the capacity to enhance beneficial to diabetic retinopathy physicians in the future when models and datasets improve and they can provide genuine-time categorization.

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