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Modified Alexnet architecture for classification of diabetic retinopathy images☆

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ABSTRACT

Diabetic retinopathy (DR) is an illness occurring in the eye due to increase in blood glucose level. Among people in the age group of 70, 50% of deaths are attributed to diabetes. Early identification and appropriate treatment can reduce the loss of sight in many DR patients. Once the symptoms of DR are recognized, the severity of the disease should be evaluated for administering the right medication. This paper focuses on the classification of DR fundus images according to the severity of the disease using convolutional neural network with the application of suitable Pooling, Softmax and Rectified Linear Activation Unit (ReLU) layers to obtain a high level of accuracy. The performance of the proposed algorithm has been validated using Messidor database. In the case of healthy images, images of stage1, stage 2 and stage 3 of diabetic retinopathy, classification accuracies of 96.6% and 96.2%, 95.6% and 96.6% have been achieved.

1. Introduction

1.1. Diabetes

Diabetes is caused by increase in the glucose level in blood. If this abnormality persists for a long period of time, it will bring about irreversible damage to the blood vessels. A diabetic person is prone for kidney failure, vision loss, bleeding gums, lower limb confiscation, wounds in the feet, and nerve damages. There is a high risk of even heart attack and stroke among diabetic patients. On the basis of the parts that are affected by rise in the blood glucose level, the diseases are named as Diabetic Nephropathy (nephrons in the kidney are damaged), Diabetic Neuropathy (neurons in the brain are affected), and diabetic retinopathy (retina of the eye is affected). The World Health Organization (WHO) predicts that diabetes will be the 7th leading fatal disease [1]. In 1980, there were 108 million diabetic patients only, but in 2014, the diabetic patients population increased by four folds to 422 million. According to statistics, an increase in diabetic patients above 18 years age from 4.7% to 8.5% has been observed. People below poverty line are the major victims of diabetes. In India, there are about 61.3 million people falling in the age group of 20–79 identified as diabetic patients. It is estimated that this figure is likely to increase to 101.2 million by 2030 [2].

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Table 1
Different stages of DR.

Stages of DR	Ophthalmoscope recordings	Corresponding label in the proposed algorithm
Normal	Without any abnormalities	Healthy retina
Mild NPDR	Presence of micro aneurysms only	DR stage 1
Moderate NPDR	Microaneurysms are present but in a smaller amount as compared to severe NPDR.	
Severe NPDR	• Venous beading in two or more regions • Prominent intraretinal microvascular abnormality (IRMA) in one or more regions	DR stage 2
PDR	• Vitreous/pre- retinal hemorrhage • Neovascularization	DR stage 3

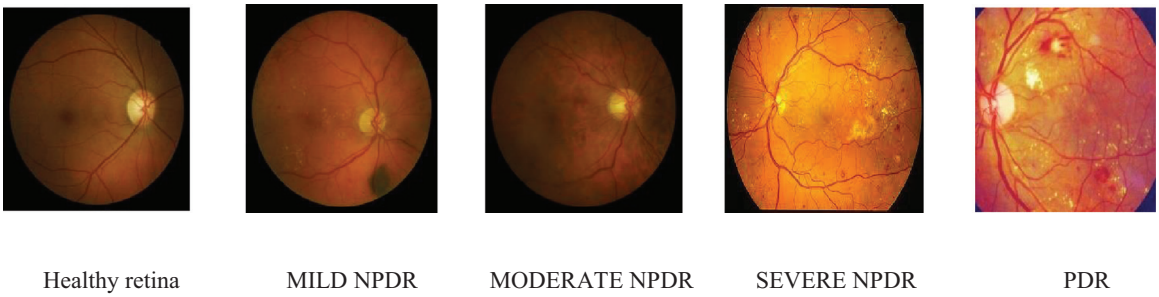


Fig. 1. Stages of DR starting from healthy fundus image [17].

1.2. Diabetic retinopathy

Persistent increase in the blood glucose level damages the retinal blood vessels. This increase in blood glucose level mainly punctures the blood vessels causing leakage of blood into the eye and thereby weakening the vision system. The human body inherently is capable of curing itself. When the brain finds a leakage of blood, it activates the nearby cells to control the situation. This activity leads to an abnormal growth of new blood vessels [3]. The newly formed vessels are weak. They affect the vision of the person in due course. Hence it is imperative that a diabetic patient should always take up a regular eye test. The patient's retina should be checked and monitored regularly by an ophthalmologist. Slit lamp bio microscopy, optical coherence tomography (OCT), fundus fluorescein angiography (FFA), and fundus photography are some of the eye testing techniques used to diagnose the disease in its early stage itself.

1.3. Phases of diabetic retinopathy

The presence of abnormalities and their magnitude define the severity of the disease. The identification of manifestations like micro aneurysms, hemorrhage, neovascularization, venous beading is a major process in diagnosis. Micro aneurysms refer to blood clots of size 100–120 μm that are usually circular in shape. Leakage of blood from a broken blood vessel is called hemorrhage. Abnormal growth of tiny blood vessels is termed as neovascularization. Venous beading refers to the central expansions of the veins lying adjacent to the occluded arterioles. Diabetic retinopathy patients are categorized as Non-Proliferative Diabetic Retinopathy (NPDR) patients and Proliferative Diabetic Retinopathy (PDR) Patients. Further, depending on the severity of the disease, NPDR patients are distinguished as mild-stage, moderate-stage, and severe-stage NPDR patients. Stages in the severity of diabetic retinopathy are described in Table 1. Images of different stages of diabetic retinopathy [17] appear in Fig. 1.

The remaining part of this paper is organized as follows: Section 2 provides a literature review of the research area. The Materials and the proposed method are explained in Section 3. The results and discussion explained in Section 4. Conclusions are finally given in Section 5.

2. Literature review of existing methods for automatic DR detection

Diabetic retinopathy is one of the most prominent ailments among the diabetic patients and patients can be prevented from vision loss if the disease is diagnosed at an earlier stage. Once the disease is diagnosed the patient has to be evaluated for every six months to know the progress of the disease [18]. An efficient algorithm to detect and classify the fundus images will be helpful for the ophthalmologist to a greater extent in eradicating the vision loss due to DR. Researchers have developed a number of algorithms for application in the study of images to facilitate precise diagnosis of diabetic retinopathy. The configuration of human eye includes optic disc and optic nerves. Detection and classification of DR can be carried out by segmenting the images of the portions of the parts from the fundus image or by examining the fundus image for the occurrence of hemorrhages, lesions, micro aneurysms, exudates, etc.

The authors in [5] have presented an algorithm that computes several features such as area occupied by blood vessels, foveal zone irregularities, and micro aneurysms. The proposed method utilizes curvelet coefficients of fundus image and angiograms. Three-stage (Normal, Mild NPDR, and PDR) classification is adopted. The study has been carried out among 70 patients. The proposed method has achieved 100% sensitivity. The researchers in [4,19] have classified DR images on the basis of the presence of micro aneurysms. Features such as circularity and area of micro aneurysms are considered in feature extraction. Datasets namely DRIVE, ROC, and DIARETDB1 are used in this research. The algorithm introduced by the authors has produced 94.44% and 87.5% sensitivity and specificity respectively. The proposed method employs principal component analysis (PCA) to segregate the image of the optic disc from the fundus image. Using Enhanced MDD classifier, the authors have achieved an increase by about 25–40% in the detection probability of exudates near the region surrounding the optic disc in the image. A set of 39 pictures has been taken up for study; the images have been classified using proposed algorithm into 4 normal fundus images and 35 images showing fundus with exudates.

In [6,7], the researchers have described the application of SVM, Bayesian method, and PNN for identifying the stages of DR as NPDR or PDR from the study of fundus images. The database DIARETDB0 pertaining to 130 images has been used. Initially the portions of blood vessels, exudates, and hemorrhages from the images of DR have been segregated. The accuracy obtained by using the proposed method involving the application of PNN, SVM, and Bayes classification techniques is 87.69%, 95.5%, and 90.76% respectively. In [8], the author discusses the validation of results obtained from using trained SVM classifier. Three public datasets, namely, MESSIDOR, DIARETDB1, and DRIVE have been used. An accuracy of 93% has been achieved in classifying exudates and micro aneurysms by segmenting the images of blood vessels.

Reference [9] explains the application of local binary pattern texture feature to detect exudates and reports that an accuracy of 96.73% has been obtained. In Reference [10], a dual classification method is introduced. This method involves boot strapped decision tree to classify the fundus images. Two binary vessel maps are created by reducing the feature vectors dimensionally. The suggested method has produced an accuracy of 95%.

In Reference [11], the author has proposed an algorithm that employs Gabor filtering technique and SVM classifier to categorize the DR images. Prior to the application of classifier, Circular Hough Transform (CHT) and CLAHE techniques are applied to the input images. An accuracy of 91.4% has been realized for the images drawn from STARE database. In Reference [12], the application of Multi-Layer Perception Neural Network (MLPNN) to detect diabetic retinopathy is explained. Nine statistical features are extracted through 64-point Discrete Cosine Transform (DCT) operation. The statistical features thus obtained are fed to the neural network.

In Reference [13], morphological operation using the intensity of the image as threshold to segment is described. The process of segmenting the portions of exudates in the HIS space is explained. Reference [14] discusses the application of CNN architecture along with data augmentation techniques in the classification of DR images. The severity of DR is classified into five stages. Kaggle database is used. An accuracy of 75% is produced.

The researchers in [15] have proposed a method of grouping a set of error dependent networks for image classification. The system is tested with the dataset that contains remote sensing images taken from an agricultural land in a village near Feltwell (UK).The classification was done by pixel basis. Based on the elements of feature vectors the pixels were characterized as one of the five different agricultural areas like sugar beets, carrots, potatoes, bare soil and stubble. Three different types of ensembles (E1, E2&E3) were created. The classification accuracy obtained was 89.83%, 87.87% and 90.46% for E1, E2 and E3ensembles respectively. The authors in [15] have attempted to recognize macular disorders from SD-OCT images using recombined convolutional neural network. The preprocessing stage uses BM3D filter for noise removal. In BM3D approach the image is initially divide the image into 2D blocks and then recombined to form 3D blocks based on the similarity. The low level, mid-level and high level features are extracted sequentially from 18 layered residual networks. The network was tested for different kernel sizes like 3×3, 5×5, and 7×7. Accuracy, precision and recall were used as performance indicators. The kernel of size 3×3 in the recombined residual network achieves a better accuracy of 90%.

3. Materials and the proposed method

3.1. Dataset description

Messidor [16] dataset consists of around 1190 color fundus images with annotations in Excel file. It has been used for testing and training the proposed Alexnet architecture. A camera having three separate charge-coupled devices and attached with Topcon TRC-NW6 Non-Mydriatic Retinal Camera has been employed to take photographs of FoV images at 45°. The images to be fed as input have been taken in 8 bp color level at 1390 × 1040, 2160 × 1884, and 2216 × 1166 pixels. Each dataset has been distinguished into four different subsets, namely, Healthy retina, DR stage 1, DR stage 2, and DR stage 3, according to the annotations given for the respective images. Grades on the basis of presence of micro aneurysms and hemorrhages have been assigned to the images. Images showing no signs of micro aneurysms and hemorrhages represent healthy retina. Images containing only a few micro aneurysms correspond to DR stage 1. Images presenting more (between 5 and 15) micro aneurysms and few (less than 5) hemorrhages are classified to stand for DR stage 2. Images showing more (greater than 15) micro aneurysms, more (greater than 5) hemorrhages, and very few neovascularization locations are considered to denote DR stage 3.

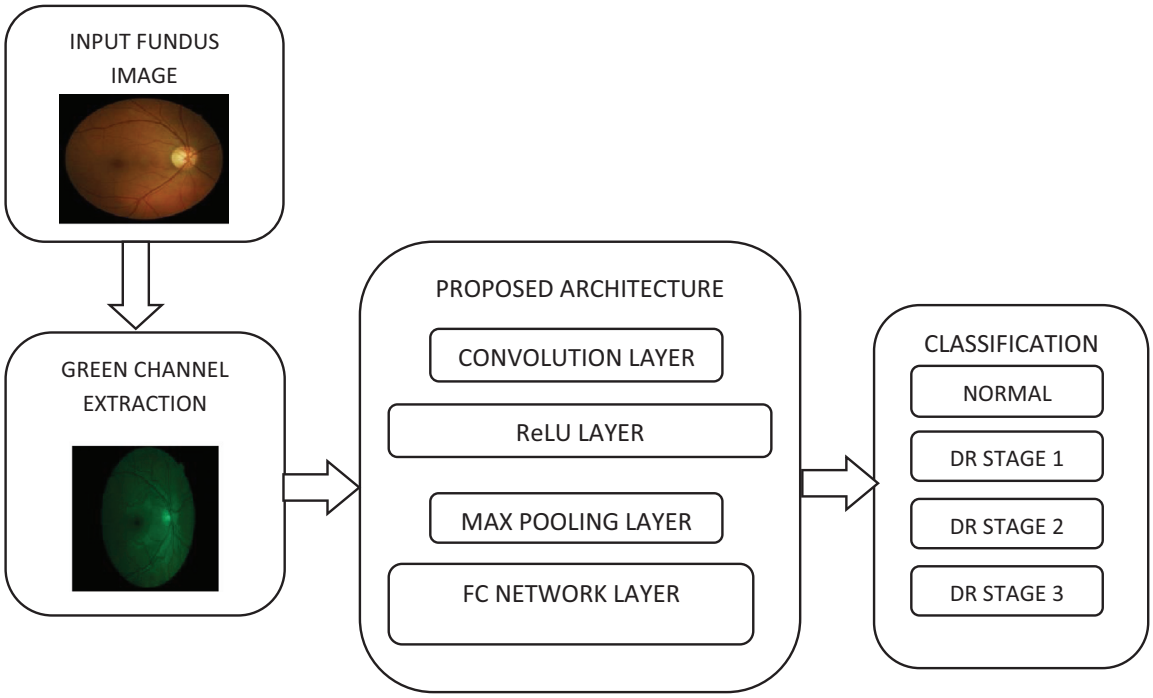


Fig. 2. Flow diagram of the proposed method.

3.2. Method proposed

The present research aims to classify the fundus images with high accuracy into various stages of diabetic retinopathy. There is a massive growth in patients affected by diabetic retinopathy. It is necessary to categorize the patients into different stages of diabetic retinopathy in a swift manner. Through the present research with the application of a modified Alexnet architecture we have striven to increase the classification accuracy in the study of DR images.

3.3. Preprocessing

The Messidor dataset has been arranged into four different subsets, viz., Healthy retina, DR stage 1, DR stage 2, and DR stage 3. The annotations are given for all the images in the Messidor dataset in Excel file. These particulars are much useful in the grouping of subsets. The green channel provides finer details of the optic nerves and other features of the retina. Initially the images are split into RGB channels. Using the green channel, the input fundus image is refined so as to get a higher accuracy in classification. Improved images in different stages are fed to the modified Alexnet architecture to categorize the fundus images into the corresponding stages of diabetic retinopathy. The stages followed in the present research are depicted as a flow chart in Fig. 2

3.4. Convolutional neural network

A convolutional neural network is a deep-learning neural network. It has been emulated from the observation of biological process. It mimics the functions of different layers in the human brain. CNN has been proved to be very efficient in all image processing applications like face recognition, pattern recognition, etc. The proposed architecture carries out the image processing through different layers. The input image is fed to the initial convolution layer and successive output is processed in different layers in the proposed architecture. Convolutional layer takes out a patch of input fundus image, and different filters are applied to the input images. The output from the convolutional layer is fed as input to maximum pooling layer where unwanted pixels are removed.

CNN has different architectures like Le-Net, Alex-Net, Google-Net, Conv-Net, Res-Net, etc. In the present research we have employed Alexnet architecture because it has better computational ability to address complexities than other architectures. CNN works with three-dimensional (length, width, and depth) values. For a normal color image, the dimensions of the image are denoted by a, b, and c, where ‘a’ stands for the length of the color image, ‘b’ represents the breadth of the color image, and ‘c’ denotes the number of color channels present in the input. The primary layer receives the input image, and after processing the final layer of the architecture provides the prediction. Generally, Alexnet architecture has eight layers,

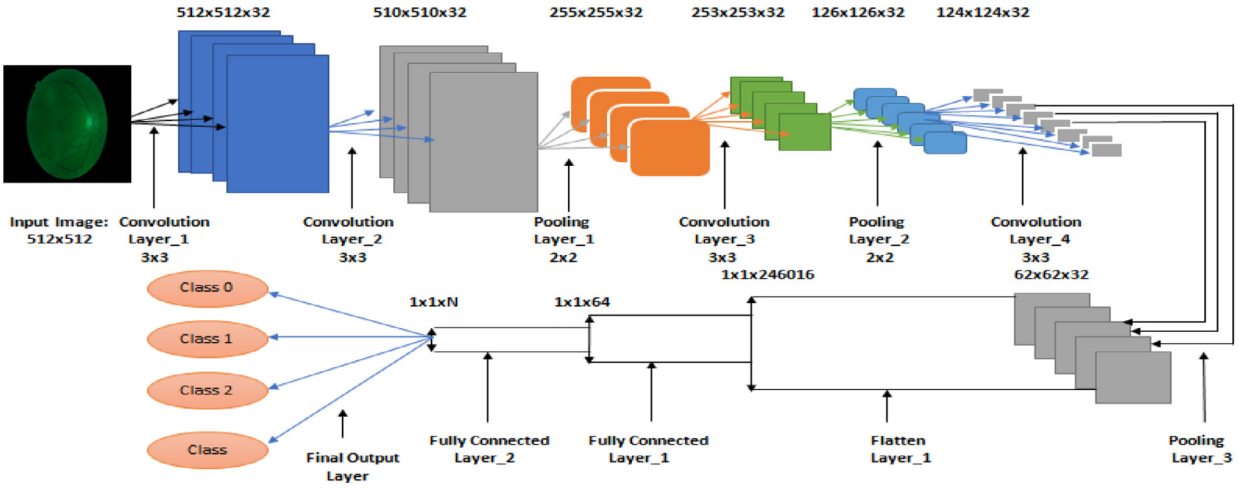


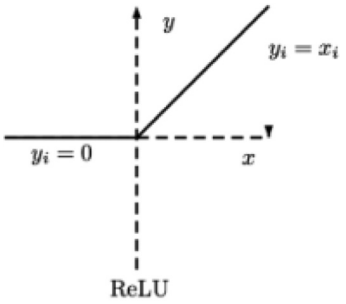
Fig. 3. Modified Alexnet architecture for classification of diabetic retinopathy images.

in which the first five layers are convolutional and maximum pooling layers, followed by three layers fully connected to the neural network.

3.5. Proposed Alexnet architecture

Among various CNN architectures, Alexnet is one of the most efficient architectures that are widely employed to address problems in image classification. The Fig. 3 depicts the Modified Alexnet architecture for classification of diabetic retinopathy images. The operations involved in the implementation of the proposed Alexnet architecture are described below:

- The first step is to resize the input fundus image to the size of 259 × 259 pixels corresponding to the breadth and height and the three color channels representing the depth of the input fundus image.
- The output of neurons is computed as a scalar product of a small portion of the image with their corresponding weights. This process is repeated along the length and breadth. This operation is performed in convolutional layer.
- In Rectified Linear Unit (RELU) layer, an element-wise activation function is employed. This layer replaces all the negative activations with 0 by introducing nonlinearity to the system and by applying the function – $f(k) = \max(0, k)$.

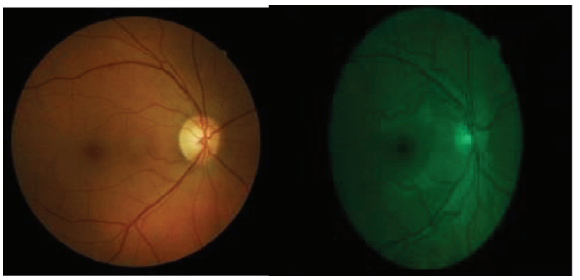


Activation function

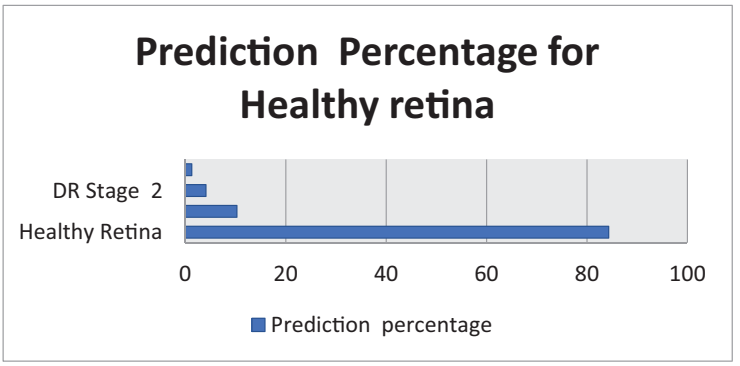
- In pooling layer, the samples are reduced along the spatial coordinates. This process is known as decimation.
- Fully Connected (FC) layer computes the Class scores for each image and gives the prediction. The probability score for each of the prediction class is computed and the class that is scoring maximum probability score is chosen as the predicted class as shown in Fig. 4.

3.6. Performance metrics

The performance of the architecture is assessed in terms of accuracy, specificity, sensitivity, and precision factor in respect of all DR stages. Alexnet architecture has been employed to train 710 input fundus images. Of these 710 images, 303 input fundus images have been used to evaluate the performance of the algorithm. Such a sample size is necessary to realize perfect classification with minimum computational error. True positive (TP), true negative (TN), false positive (FP), and



(a) (b)



(c)

Fig. 4. Prediction for testing image (Healthy retina) (a) input RGB fundus image (b) green plane of the image (c) the test image is predicted as healthy retina as per the prediction percent.

false negative (FN) values for each class of input images vary according to the values obtained through confusion matrix. If a healthy retina is predicted as healthy retina, then it represents a true positive value for that class; all other correct predictions for other classes are called as true negative with respect to this class (healthy retina). When an input healthy retina image is predicted as DR image of any stage (DR stage 1, 2 or 3) then it is termed as false positive. On the other hand, if a DR input image of any stage (DR stage 1, 2, or 3) is predicted as healthy retina, then it is termed as false negative. Once all these values are obtained for each class of images, then the performance metrics like sensitivity, specificity, accuracy, and precision factor determined using the following equations:

$$\text{Sensitivity} = \frac{\text{True Positive}}{\text{True Positvie} + \text{False Positive}}$$

$$\text{Specificity} = \frac{\text{True Negative}}{\text{True Negative} + \text{False Postive}}$$

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{True Positive} + \text{False Postive} + \text{True Negative} + \text{False Negatvie}}$$

$$\text{Precision factor} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

Sensitivity measures the proportion of correctly classified images that are correctly identified to the total number of positive classification. Specificity measures how well the algorithm predicts the other classes. Accuracy measures the total prediction rate of the algorithm.

4. Results and discussion

Training the architecture has been carried out with 710 fundus images from the given dataset. The performance of the proposed architecture has been evaluated by testing it on 303 fundus images. It is found that among the 303 images of

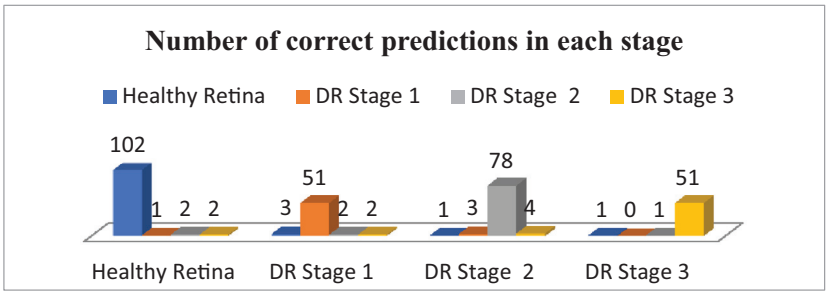


Fig. 5. Classification of different DR grade images.

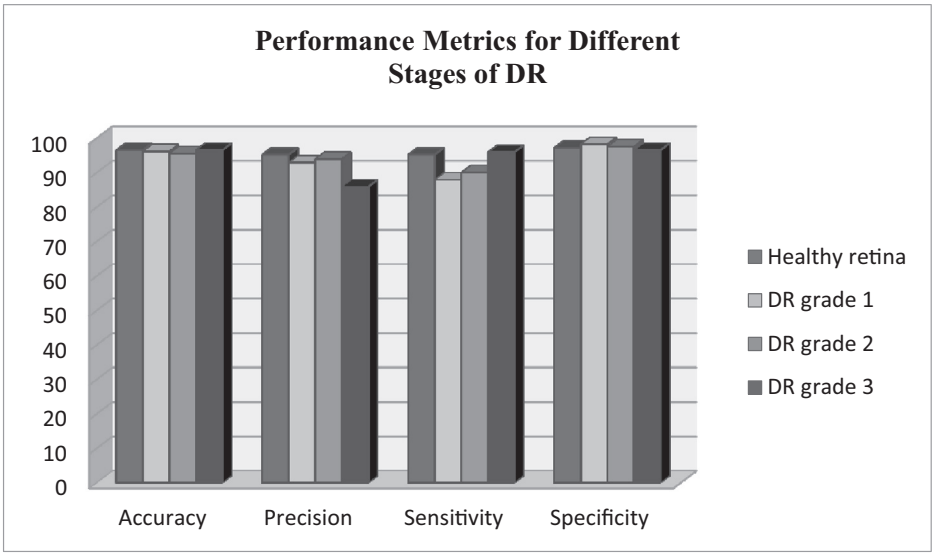


Fig. 6. Performance metrics for different stages of DR.

Table 2
Confusion matrix.

Input class	Different level of diabetic retinopathy				Total no. of images
	Healthy retina	DR stage 1	DR stage 2	DR stage 3	
Healthy retina	**102**	1	2	2	107
DR stage 1	3	**51**	2	2	58
DR stage 2	1	3	**78**	4	86
DR stage 3	1	0	1	**51**	53
Total no. of images	107	55	83	59	303

Table 3
Manipulations from confusion matrix.

Input grades →	Healthy retina	DR grade 1	DR grade 2	DR grade 3
TP	102	51	78	51
TN	180	231	204	231
FP	5	4	5	8
FN	5	7	8	2

fundus tested with the application of the proposed Alexnet architecture, 107 images are images of healthy retina, 58 images belong to DR stage 1, 86 images pertain to DR stage 2, and 53 fundus images fall in the category of DR stage 3.

Table 2 and Fig. 5 show that 102 images out of 107 are correctly predicted as Healthy retina, 51 images out of 58 are correctly predicted as DR stage 1 image, 78 images out of 86 are correctly predicted as DR stage 2 image, 51 images out of 53 are correctly predicted as DR stage 3 image. Table 3 shows observations from the confusion matrix.

Table 4
Performance metrics for test images with different DR grades.

Input grades	Accuracy	Precision	Sensitivity	Specificity
Healthy retina	96.6	95.3	95.3	97.3
DR grade 1	96.2	93.0	88.0	98.3
DR grade 2	95.6	94.0	90.1	97.6
DR grade 3	96.6	86.0	96.0	96.6

Table 4 presents the performance metrics obtained through using the proposed algorithm. Fig. 6 shows the performance metrics for different stages of DR.

5. Conclusion

Severe vision loss in diabetic patients can be avoided by detecting and treating diabetic retinopathy at an early stage. The method proposed in this paper aims at providing an optimal solution for the classification of diabetic retinopathy patients according to the severity of the disorder. Deep learning is one of the state of the art techniques to address classification problems and it provides better accuracy. Efficient convolutional neural network architecture to detect and classify the fundus images will be helpful for the ophthalmologist to a greater extent in eradicating the vision loss due to diabetic retinopathy. The probability score for each of the prediction class is computed by the final fully connected layer of the deep learning architecture and the class that is scoring maximum probability score is chosen as the predicted class. The testing and training the evaluation of proposed Alex net architecture is done using Messidor dataset. The dataset from Messidor dataset s segregated into two, 70% of the fundus images are trained by Alexnet architecture and 30% of the fundus images from Messidor dataset are used to evaluate the performance of the algorithm. A modified Alexnet architecture that is used to categorize the input fundus images is employed in the present research and the results obtained are discussed in this paper. The performance of the modified Alexnet architecture is evaluated in terms of performance metrics like accuracy, specificity, sensitivity and precision. Accuracy in classifying the images collected from the Messidor dataset into Healthy retina, diabetic retinopathy stage 1, diabetic retinopathy stage 2 and diabetic retinopathy stage 3 using the proposed modified Alexnet architecture is 96.6%, 96.2%, 95.6% and 96.6% respectively. The results can be improved further by increasing the size of a dataset. In future the algorithm can be tested with Kaggle dataset with more of images.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.compeleceng.2019.03.004.

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