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IMPROVED CNN BASED DATA ANALYTIC MODEL FOR DIABETIC RETINOPATHY PREDICTION

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Abstract

Big Data Analytic model examines large datasets and reveals the hidden information like hidden patterns and their correlations in it. Especially in the healthcare analytics, they are widely used for analyzing and predicting the diseases from the data that are being collected from various sources like electronic health record, patient's insurance claim, scan reports, pharmaceutical, and research development data, emails, mobile devices, databases, applications, server and by other means. Diabetes is a chronic, incurable disease due to the abnormal levels of glucose in the blood. Diabetes is a major health problem that is increasing worldwide as it is a stern difficult complaint distressing the whole body. It needs regular care by ourselves. It would significantly impact the quality of life if complications are developed as it would also reduce life expectancy. Diabetic patients majorly suffer due to the problem of Diabetic Retinopathy which causes vision loss. To overcome the problem of Diabetic Retinopathy, diabetic patients should have a periodic ophthalmologic examination. Basically, detection of diabetic retinopathy (DR) through color fundus images and identifying the current status of the eye requires highly experienced physicians. The proposed Diabetic Retinopathy prediction model applies Modified Convolutional Neural Network(M-CNN). This model analyses DR from digital fundus images and correctly categorizing its severity. Also, the model will recognize the complex structures convoluted in the cataloging task such as micro-aneurysms, exudate, and bleedings on the retina and subsequently recognizes the problem without the need of manual intervention. The system is

trained using publicly available Kaggle Dataset and the result is validated with the original fundus images of 100 patients.

1 Introduction

1.1 Diabetes and its Complications

Diabetes Mellitus is the major health care issue in India compared with other countries. According to the World Health Organization's statistical report, 80% early death is due to diabetes and its complications and it will be double by 2030[1]. According to the report of the Centre for Disease Control (CDC), in 2015, it is calculated that nearly 30.3 million people have diabetes and 23.1 million people were diagnosed and 7.2 million people were not diagnosed. Out of this diagnosed category, nearly 95 % of those are suffering from Type 2 Diabetes Mellitus (T2DM). Diabetes is the main driver for the prevalence of various diseases [2]. The majority of diabetic patients will suffer from complications related to Diabetic Mellitus (DM). The complications may be long term or short term. By maintaining glucose level of blood in a correct range by planning good and periodic meals, exercises and by proper pills we can circumvent extended term difficulties of diabetes. The microvascular complication is diseased due to the damage of tiny blood vessels. The damage to large vessel damage is macrovascular diseases. Microvascular complications include disease related to eye, kidney, nerve, heart diseases, etc. Especially in the eye, If the Blood glucose level is high for a long time then it causes Cataracts and/or retinopathy in the eyes either in a single eye or both the eyes.

Diabetic Retinopathy (DR) is the utmost public optical weakness of diabetes which causes loss of the sight. There is no much complex problem until the patient gets visual impairment. If the diagnose of DR is delayed due to poor awareness or due to lethargic diagnostic approach the patient will be suffered by sight illness. An early diagnose and treatment of DR is very very important. Frequent screening of Diabetic patients for DR care is more cost-effective and time-consuming. The prediction accuracy also plays an important role in the detection and treatment of DR. If the detection is early and accurate the visual threatening complications of Diabetic Retinopathy can be easily overwhelmed and it should be a vital process [4-6].

It is advisable to do eye examination twice per year to prevent aggressive damages due to diabetic illness. The main mode of detecting diabetic retinopathy is fundus analysis. Due to the huge number of diabetic patients and the lack of awareness, many patients with DR cannot timely be diagnosed and treated, which results in irreversible visual loss, as well as even the consequences of blindness. For the past few years, the Convolutional Neural Network-based fundus image analysis plays a vital role in fundus image analysis and prediction of Diabetic Retinopathy [7]. The proposed system utilizes a big image dataset of 10,000 Fundus from Kaggle data set and that is processed with the CNN algorithm and trained for providing better accuracy. Since the images are of mass in size an effective deep learning technique will be most essential for accurate analysis of images. It is an unconventional form of analytics it has various components that are predictive and claims that are complex and also perform analysis through statistical algorithms that are driven by high-performance analytics systems. It empowers analytical modelers, data scientists, statisticians, and other analytics professionals to analyse the increasing volumes of data in many models. The data to be processed may be structured and unstructured.

The modified Convolutional Neural Networks (CNNs) is a division of deep learning techniques which produces an effective result in fundus analysis and its interpretation. The main idea of this paper is to implement an automatic diagnosis of Diabetic Retinopathy. The classification of fundus image is based on the severity and features of symptoms like microaneurysms, hemorrhages, exudates, retinal edema. Here the image is pre-processed to important features and then classified into respective classes. Here the Convolutional Neural Network is used to analyze the fundus images. The analyzed results are evaluated by the parameters like Sensitivity, Specificity and Receiver Operating Curve.

2.Structure and Function of Human Eye

The cross sectional view of eye is as shown in Fig.1. In our eye structure when the light reaches ,first it hits on cornea which is on the center of the eye.When light strikes the eye, the first part it reaches is the cornea, a dome positioned over the center of the eye. Then the light reaches pupil and the iris through cornea.The amount of light that pass through is basically limited by these portion of eye.When there is the chance of observing more and very bright light, the muscular iris shrinks the pupil and expand it when needed. This activity is managed by brain. Eye lens is the in-depth part of eye, which helps to create images more precisely. Depends on the objects proximity the shape of the lens is handled. When we view the distance object, the lens becomes flat shape and when we see the nearer object, lens becomes rounder.

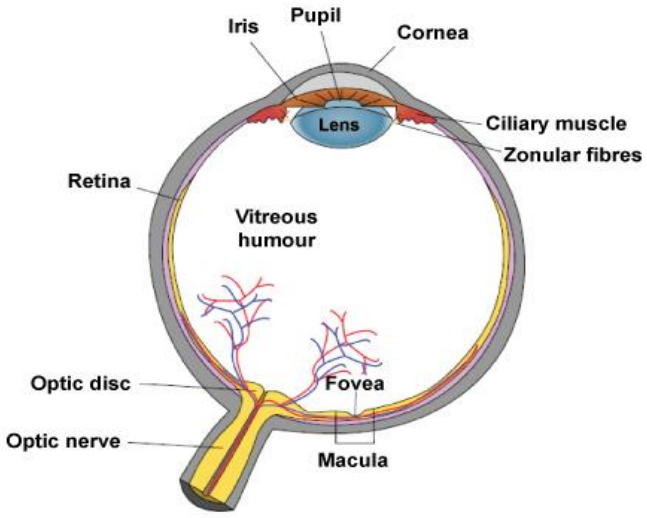


Fig. 1:Human Eye Cross Section[9]

In the same way, the camera regulates the amount of light entering the camera with the aperture. In order of the eye to focus on objects at different distances, the ciliary muscle reshapes the elastic lens through the zonular fibres. For objects in short distances, the ciliary muscle contracts, zonular fibers loosen, and the lens thickens into orb-shaped which results in high refractive power. When the ciliary muscle is relaxed, the zonular fibers stretch the lens into thin shaped and the distant objects are in focus. This is corresponding to focal length .When there is correct focus on object ,then the corresponding light passes through retina which consists of several layers of transparent tissue which converts the light into neural signals.[8]The furthest layer of the retina called photoreceptor cells immediately responses the conversion of light through all layers of retina. Inner layers of retina are processing the electric impulse created

during the transmission of light from photoreceptor cells to the optic nerve.The central region of retina forms the detailed central vision[11].Fovea is the central part of the macula in which we can find cones. The optic nerve begins next to macula through which the main blood vessel and vein emerge in the retina.

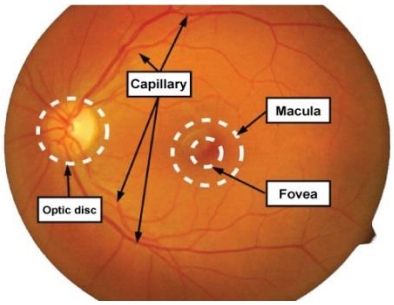


Figure 2: Normal physiological parts of the eye fundus [9]

There aren't any traditional membrane layers .So when there is no photoreceptor cells the retina will be affected directly and a it seems to get a blind spot .There are two capillary networks such as the nerve fiber layer network which supports membrane[10].A densest network will be formed over macula which intensively increases the capillary density. So the choroid ,a tube shaped layer behind the membrane relies on the choroidal blood from central part of fovea.The afore mentioned anatomical parts such as macula,fovea,capillaries and optic tract head are as shown in Fig.2.

3. Diabetic Retinopathy (DR)

Diabetic retinopathy may be a microvascular complication of polygenic disorder, inflicting abnormalities in the membrane. usually, there aren't any salient symptoms within the early stages, however, the number and severity preponderantly increase in time. The diabetic retinopathy usually begins as tiny changes within the retinal capillaries. the littlest detectable abnormalities, microaneurysms (MA), seem as tiny red dots within the membrane and square measure native distensions of the weakened retinal capillary (Fig. 3)).

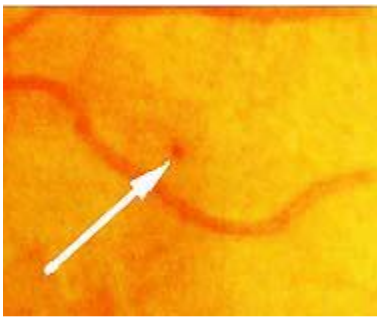


Fig. 3:Microaneurysm[9]

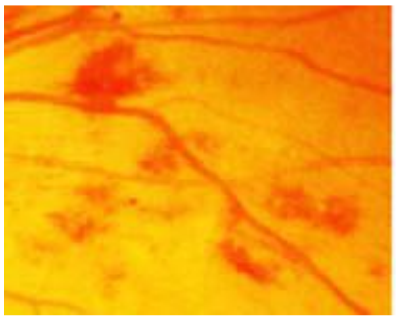


Fig. 4: Haemorrhages[9]

Due to these broken capillary walls, the tiny blood vessels could rupture and cause intraretinal haemorrhages (HA).Within the membrane, the haemorrhages seem either as tiny red dots indistinguishable from small aneurysms or larger round-shaped blots with irregular outline as shown in Fig.4.

3.1 Stages of Diabetic Retinopathy and Maculopathy

The severity of diabetic retinopathy is split into two stages: Non Proliferative Diabetic Retinopathy(NPDR) and Proliferative Diabetic Retinopathy(PDR). The NPDR indicates the presence of diabetic retinopathy within the eye and contains microaneurysms, haemorrhages, exudates, retinal swelling, IntraRetinal Microvascular Abnormalities (IRMA), and venopathy. The microaneurysms and particularly exhausting exudates usually seem within the sight region (macula) that predicts the presence of macular swelling (macularoedema). The symptoms of nonproliferative retinopathy and therefore the macular swelling characterize the individuals [12].

Although the maculopathy could occur at any stage of the diabetic retinopathy, it's additional probably within the advanced stages of the malady. within the worst case, it may end up irreversible harm to the fovea centralis. A membrane with nonproliferative retinopathy is illustrated in Figure.5 and a membrane with maculopathy is illustrated.

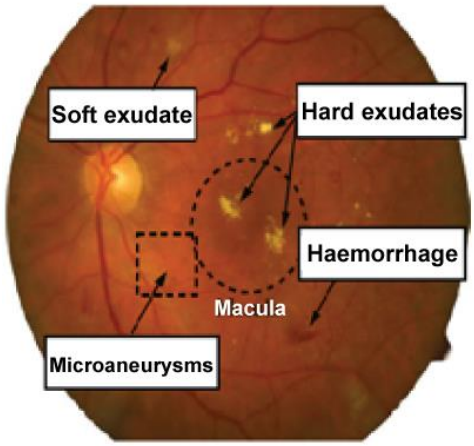


Fig. 5: Eye Fundus image with maculopathy showing haemorrhages, microaneurysms, exudates [9]

If the NPDR is untreated or unknown it'll be converted into PDR that is additionally associate degree eye-sight threatening condition. In PDR due to high blood sugar levels the veins, arteries and capillaries which carries blood throughout the body will be damaged severely. Due to this there is the growth of new blood vessels .But these are the abnormal blood vessels over the surface of retina which are highly weakened .So that they are not able to supply blood to retina.

This stage is taken into account if neovascularization or vitreous/preretinal hurt is a gift within the membrane [12]. A membrane with proliferative retinopathy is illustrated in Fig.7.

3.2 Diagnosing Diabetic Retinopathy

The designation of diabetic retinopathy relies on clinical eye examination and eye structure Photography. Neural Networks have conjointly been utilized in classification of DR. Early space of exudates and also the square measure of blood vessels are the 2 parameters thought-about for classifying pictures into traditional, proliferative or non-proliferative retinopathy and it's obtained that of ninety-three, sensitivity and specificity of 100% [13]. Another work on Funds image analysis influenced 5 specific options with Support Vector Machine that is an automatic technique of distinguishing 5 categories. There was a model that extracts data exploitation higher-order spectra technique that inputs SVM classifier and captures the variation [14]. Another 5-category classification model calculates the realm of varied options like haemorrhages, micro-aneurysms, exudate and blood vessels [15].

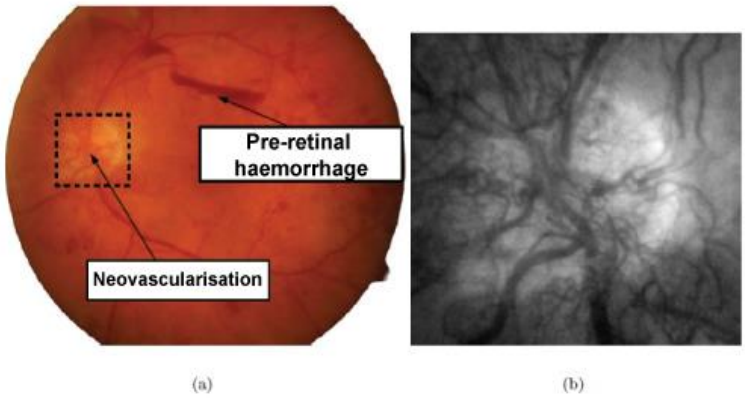


Fig. 6: Example of proliferative diabetic retinopathy: (a) Preretinal Haemorrhage and Neovascularisation; (b) Close up view of Neovascularization.[9]

Image process technique conjointly effectively used to provide automatic detection of Diabetic Retinopathy through the analysis of retinal blood vessels, exudate, micro-aneurysms, and texture options. the realm of lesions and texture options were accustomed to construct the feature vector for the multiclass SVM. This achieved accuracies of ninety-six and ninety-four.6% on the general public eighty-nine and one hundred thirty image databases. These ways square measure less period applicable than a CNN [16].The five stage prediction models together with OLR, LR-BS, ridge, elastic web, and LASSO. The thin learning model exploitation LASSO was effective in analysing the medical specialty underlying

patterns of DR. After the coaching method, the best prediction model was known to support the Bayesian data criterion (BIC) within the internal validation dataset [17]. Another model that proposes CNN for identification retinopathy from structure pictures and accurately classifying its severity. Here the network of CNN has framed the information augmentation identifies the sophisticated options concerned in structure detection. So there will not be any support to input.

3.2.1 Modified CNN Based Classification Model

A changed version of the Convolutional Neural Network was designed with seven layers of classification. Seven Classification includes options for distinguishing retinopathy as Blur structure while not Diabetic Retinopathy (BFPDR), Blur structure with suspected PDR(BFWPDR), Hardexudates, Maculopathy, Opticatrophy, Tessellatedfundus. These featured pictures were compared with traditional structure image.80 five of the on top of pictures were thought-about for coaching and 2 hundredths of the pictures were used for testing. The normal fundus image is as shown in Fig.7 and retinopathy connected images are shown in Fig. 8(a)-(f).

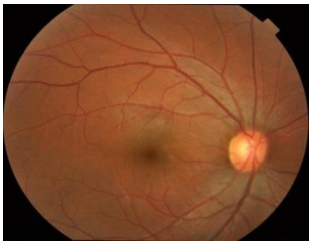
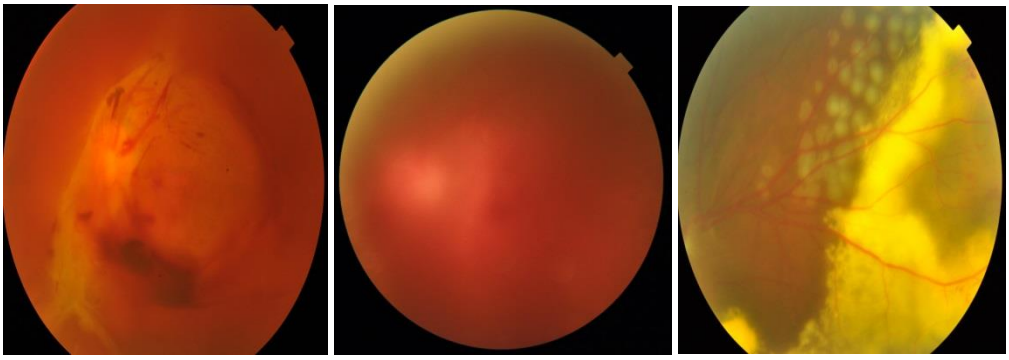
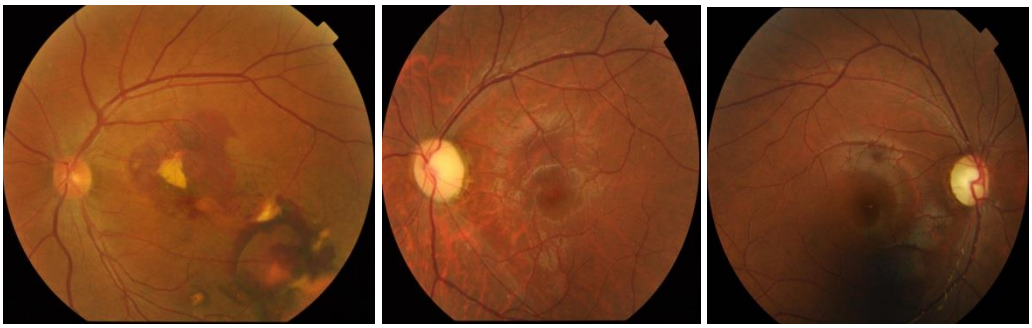


Figure 7: Normal Fundus Image



a). BFPDR **b). BFWPDR** **c). Hard Exudates(HE)**



d). Maculopathy e). Opticatrophy f). Tessellated fundus

Fig. 8(a): Blured Fundus without Diabetic Retinopathy(BFPDR) 8(b): Blur Fundus with suspected PDR(BFWPDR) 8(c): Hardexudates 8(d): Maculopathy 8(e): Opticatrophy 8(f): Tessellatedfundus

3.2.2 Network Architecture and implementation

The network structure of the Modified Convolutional Neural Network was shown in Fig.9. The fundus image of size 96 ×96 ×3 (A three channelled image) is taken as an input for processing. Here the filter of size 5*5*3 is taken and it is slide over the complete image and there the dot product is computed between filter and image chunks. To improve the performance of the network, the number of layers in-network is increased. By the way, the deepest analysis of the inner feature is achieved. The leading layer will identify the edges in-depth and the last layer will learn the features such as Blur Fundus without Diabetic Retinopathy (BFPDR), Blur Fundus with suspected PDR(BFWPDR), Hardexudates, Maculopathy, Opticatrophy, Tessellated Fundus. To gain the accuracy the six main features were considered for classification. There is a normalization process after each convolution activation function. The normalization process will be handled after each convolution layer. After the convolution activation process, the max pool is performed with a kernel size of 3×3 and 2×2 strides.

Pre-processing

Data set has a total of 10000 images of various age groups, ethnicity and at different lighting levels. To avoid irrelevant classification levels color normalization is implemented. The dataset is resized to 96 ×96 pixels which involve complex features that are to be analysed.

Training

The modified Convolutional neural network is trained with 80 % of the images with the epoch of 75 until it reaches a significant level of accuracy. During training at a first epoch, the loss is 11.94% and the accuracy rate is 46.18%. At the 25th epoch, the loss value is 64.72% and the accuracy rate is 85.71%. The loss decreases the accuracy increases. At the time of the 50th epoch, the loss rate is 30.40 and accuracy is 92.37%. Finally, the 75th epoch has a loss rate is

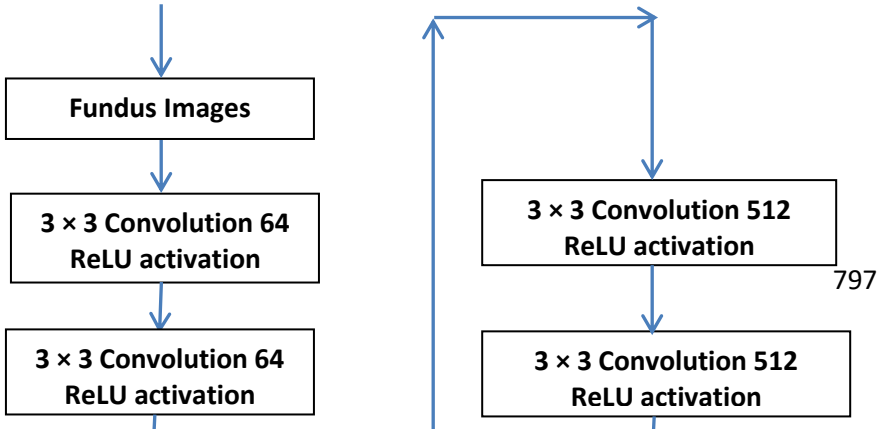


Fig.9: Network Structure of Modified Convolutional Neural Network

reduced to 7% and accuracy is 97.77%. Thus, the accuracy increases when the number of epochs increases. During the training process, the class-weight was adjusted concerning several images in each training batch.

4. Result and Discussion

Nearly 8,000 images were taken for training and 2000 images were taken for testing. Here we have seven layers of classification. In the field of diagnosing diseases basically, there are two main classifications such as whether the disease is existent or not. The sensitivity and specificity are the two main measures to measure the accuracy of the analysis. Here the fundus image analysis related to the existence of Diabetic Retinopathy is evaluated by those to measures in image basis. Sensitivity deals with the correct classification of the correct data. It says the percentage of naturally abnormal fundus images is classified as it is abnormal. Specificity is the percentage of normal fundus images classified as normal. When the sensitivity and specificity are high, the accuracy of the analysis is better. Thus, the accuracy is derived from sensitivity and specificity as below,

$$\text{Accuracy} = \frac{Sensitivity+Specificity}{2}$$

Sensitivity is measured by,

$$\text{Sensitivity(SN)} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{Specificity(SP)} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

Here, the number of abnormal fundus images found as abnormal is termed as TP, the number of normal fundus images found as normal is termed as TN, the number of normal fundus images found as abnormal is termed as FP, and the number of abnormal fundus images found as normal is FN.The distribution of output classes and its respective representations such as No diabetic Retinopathy (NR-0), Mild (1), Moderate (2), Severe (3), Proliferative DR(PDR)-4 are as shown in the figure below.

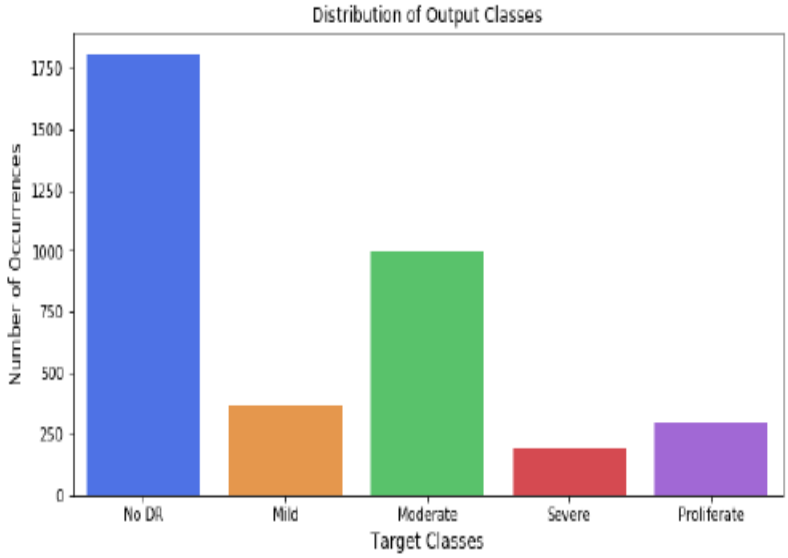


Fig. 10:Distribution of output classes

Confusion matrix calculation with the above-mentioned parameter is as shown in Table 1 below. The below table 1 shows the confusion matrix, which has two axis x and y which indicates output class and target class respectively. The value '0' in output class indicates that the normal fundus image given to Convolutional neural Network and '1' indicates that the fundus image with symptoms like Blur Fundus without Diabetic Retinopathy (BFPDR), Blur Fundus with suspected PDR(BFWPDR), Hardexudates, Maculopathy, Opticatrophy, Tessellated fundus.

Table 1:Confusion Matrix

Predicted Value (89.46%)		Actual Value (86.24%)	
		Positives	Negatives
	Positive (6500)	TP (74.28%)	FP (36.71%)
	Negative(3500)	FN (76.88%)	TN (36.56%)

4.1 Visualization and Validation of data

Training data is visualized based on the severity level as severity 0, severity 1, severity 2 and severity 3.This is as shown in Fig.11 below.

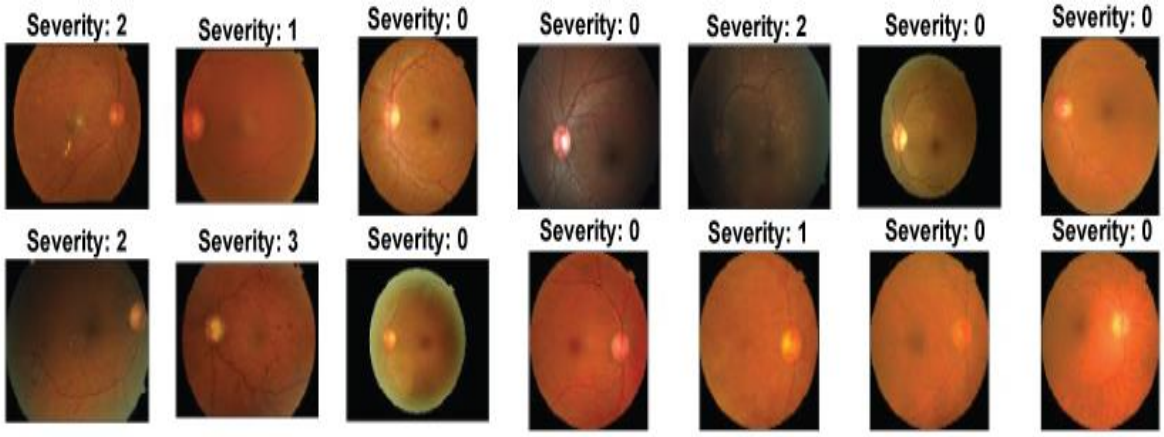
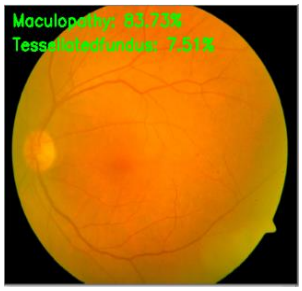


Fig.11: Severity Level

In the case of the target class,'0' indicates the CNN target for Blur Fundus without Diabetic Retinopathy (BFPDR), Blur Fundus with suspected PDR(BFWPDR), Hardexudates, Maculopathy, Opticatrophy, Tessellated fundus. For the matrix position [0,0] the value is True Positive (TP) means correct classification that was tested by CNN with normal fundus image. True Negative (TN) is indicated at the matrix position [0,1],) which indicates the misclassification by CNN for the available symptoms of Diabetic Retinopathy in fundus images. For the position [1,0],the value is False Positive(FP),it shows the correct classification tested with normal images. In the matrix position [1,1] is the False Negative(FN), the miss classification, it is been tested by CNN for the images with the symptoms of DR.

(a) **(b)** **(c)**



(d)

Fig.12 : Fundus image identified as a) normal(99.39%) b)Tessellated Fundus(87.82%) c) Tessellated Fundus(51.99%) , d)Maculopathy (3.30%)

In the above Fig.12, 99.39% indicates that fundus is normal and there is only 3.76% of chances for optic atrophy. Similarly, Figure (b) shows that the tested image would be of Tessellated fundus with an accuracy of 87.82%, (c) Tessellated fundus with an accuracy of 51.99% and image (d) is the Maculopathy of 83.73%.The obtained result is as shown in Fig.13 below.

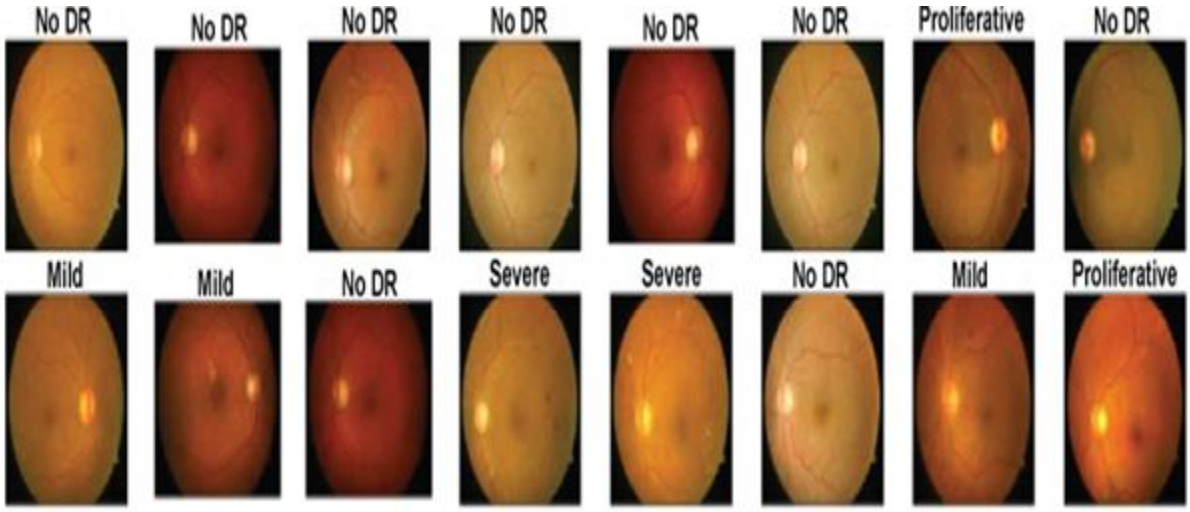


Fig.13:Diagnosed Result

Table 2 below shows the performance wise difference between Convolutional Neural Network and Modified CNN in terms of accuracy, precision, recall, and F-Measure. This performance variation is as shown in Fig.14.

Table 2: Performance measure

Metrics	CNN	Modified CNN
Accuracy	72.56	89.76 %
Precision	52	86%
Recall	42	62%
F-measure	31	71.5%

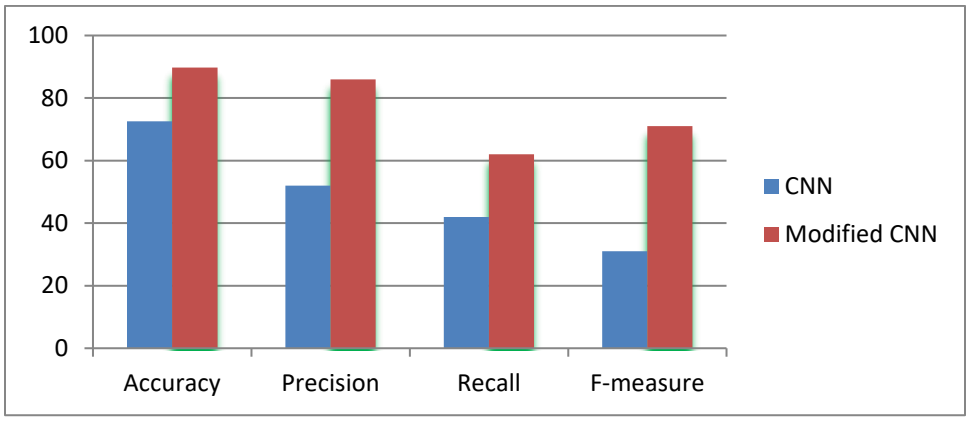


Fig.14:Performance of Modified CNN

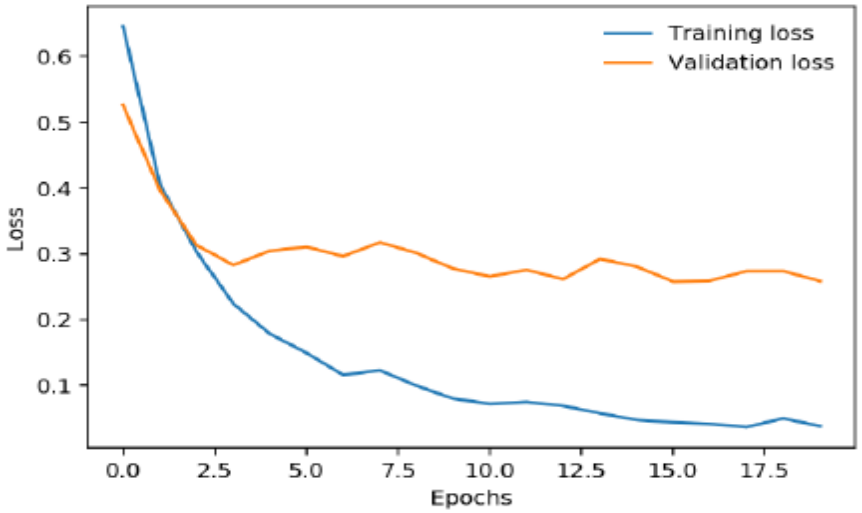


Fig.15 :Training Loss Vs Validation Loss

Here the variation in validation loss and training loss based on epochs is shown in Fig.15. The sample diagnosis result for patients is as shown in Fig.16 as below.

	id_code	diagr
0	vijayakumar_jain_15-10-1960_108994_(0001).jpg	
1	geetha_s_11-11-1956_108418_(0000).jpg	
2	image010.jpg	
3	Kandasamy_R._01-01-1967_107314_(0000).jpg	
4	Velusamy_A._01-01-1960_108951_(0002).jpg	

The value 0 indicates No DR, value 1 indicates mild stage of Diabetic Retinopathy,2 indicates moderate stage of Diabetic Retinopathy.

5. Discussion and Conclusion

The proposed Modified Convolutional Neural Network-based prediction system has seven classes of screening. The network shown will effectively classify the dataset based on the basic features required for the identification of DR. Based on the features it properly identifies the possibility of Diabetic Retinopathy based on Blur Fundus without Diabetic Retinopathy (BFPDR), Blur Fundus with suspected PDR (BFWPDR), Hard exudates, Maculopathy, Opticatrophy, Tessellated Fundus. Since the study uses 10,000 images for training and testing overall, specificity has come with a balance of lower sensitivity. The trained Modified CNN supports for fast diagnosis and immediate response to patients. This net result is evaluated with the original hundred images which are received from eye-hospital. The proposed CNN can classify thousands of images every minute and supports for real-time decision making for physicians.

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