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Detecting Diabetic Retinopathy using Deep Learning

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Abstract*:* Diabetic retinopathy (DR) is a leading cause of vision loss in working-age adults worldwide, and timely diagnosis is crucial for preventing blindness. Current methods for diagnosing DR rely on manual grading of retinal images, which is time-consuming and prone to inter-observer variability. The development of DR is a complex process involving multiple cellular and molecular pathways, including inflammation, oxidative stress, and vascular dysfunction. Despite its significant impact on public health, there is currently no effective treatment for DR that can halt or reverse its progression. Recent advances in deep learning and image processing have opened up new possibilities for automating the detection of DR. The aim of this study is to develop a system that can accurately classify individuals suffering from diabetic retinopathy. Filtering algorithm is used to clean and preprocess the images collected by users, thereby ensuring the accuracy of the results and reducing the impact of noise on the diagnostic process. An efficient custom three layer CNN model with hyper-parameter tuning is used on kaggle 'ilovescience' dataset which gives promising accuracy of 94.45%.

Keywords: *Diabetic, Retinopathy, CNN, vision loss.*

1. Introduction

Diabetes, one of the most prevalent illnesses in the world, negatively affects several body systems and might result in new changes to micro or macro vessels. As per WHO report of estimated 382 million people diagnosed with diabetes globally, the number is expected to rise to 592 million in the future. The long-term effects of diabetes can be devastating, including diabetic retinopathy (DR), cataracts, diabetic macular edema, and glaucoma. One of the most alarming consequences of diabetes is its impact on eye health. The condition increases the risk of developing diabetic retinopathy (DR), a condition that damages the blood vessels in the retina, leading to irreversible vision loss [1].

With proper screening and regular check-ups, 90% of people can be diagnosed, and the probability of future complications is reduced. The primary problem is that DR is a quiet eye disease, meaning that it often shows no symptoms at all until it gets to the latter stages. However, evaluating books on optical images is a difficult and involved task [2]. To address this problem, a number of automated diagnostic methods have been developed recently to help doctors find irregularities in the eyes. A high blood sugar level is a chronic condition known as diabetes mellitus. Insulin is secreted by the pancreas and reduces blood glucose levels.

Diabetes, which affects people of all ages, is a condition caused by the body's inability to use insulin or by an absence or lack of it. According to a 2015 International Diabetes Federation survey, 410 million people worldwide have diabetes mellitus, which causes over 5 million deaths annually as shown in figure 1. There are two types of diabetes: insulin-dependent and non-insulin-dependent, currently referred to as type 1 and type 2, respectively. As a result, elevated blood sugar levels cause macro- and microvascular problems such as stroke, neuropathy, nephropathy, peripheral vascular disease, and retinopathy. Diabetic retinopathy (DR) is one of the four primary blindness illnesses, according to the Diabetes Control and Complication Trail (DCCT) [3].

Diabetic retinopathy results in vision distortion because of fluid leaks in the retinal blood vessels and the development of retinal lesions. It is the most common cause of adult-onset diabetes-related blindness. A great deal of research has been done on the subject of diabetic retinopathy (DR) by numerous researchers. The article shows how researchers have utilized a range of machine learning techniques to identify diabetic retinopathy (DR) and links machine learning to the medical field. Due to the field's vastness, there are still prospects for research in the field to yield practical outcomes.

Since diabetes is a metabolic syndrome associated with several consequences like nephritis, abnormalities of the eyes, and cardiovascular issues, most research efforts are directed towards automated identification. It is expected that DR will be a serious global health hazard. The known

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cause of DR is elevated blood glucose levels associated with diabetes [4].

There are various stages that DR goes through. Deviations from the usual blood distribution pattern and vascular impermeability are the hallmarks of deep vein thrombosis (DR), as evidenced by line hemorrhages, exudates, cotton wool patches and MAs. These preliminary symptoms are called non-proliferative DR (NPDR). There may be DR symptoms even early. The stage of the disease known as proliferative DR (PDR) is named for the formation of new, brittle vasculature and constriction of the retina due to clogged capillaries. New veins can form on the surface of the retina at a different position or close to the optic disc. Since the condition is treated with close observation and screening, it appears that automatic analysis and evaluation of retinal illnesses to evolving requirements is an engineering answer [3].

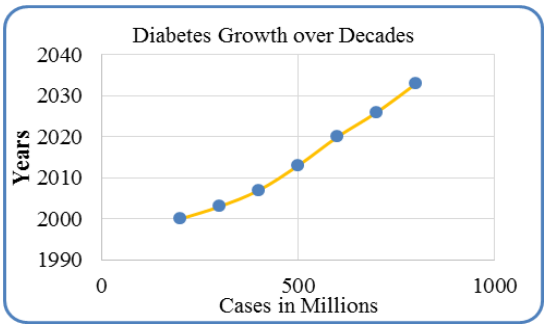


Fig 1. Diabetes Growth [1] [19]

2. Literature Review

Numerous DL-based automatic DR detection methods have been developed recently. A handful of the current research initiatives have been covered in this section.

Ying Zu's method [2] used two CNNs that were pre-trained to diagnose diabetic retinopathy or based on the probability of patches of lesions. DIARETDB1, a Kaggle dataset, was used. 91% accuracy and 94% sensitivity were achieved.

Arkadiusz Kwasigroch [3] has employed deep convolutional neural networks to identify the proper stage of diabetic retinopathy based on a colour fundus photo of the retina. By training a deep learning classifier, capable of automatically extracting relevant attributes from raw images, the model is able to extract crucial features from the data, thanks to the capabilities of convolutional layers.

Vandana Vipharti [4] published three CNN models for binary classification in addition to DR lesion identification. They also used the DiaretDb1 dataset on Kaggle for training and testing, respectively. In diabetic retinopathy, sickness onset is categorised into five (5) phases.

Using a dropout regularization technique, the CNN model is presented by Rajiv Kumar and Parvin Rai [1] and addresses the stage-wise classification. The CNN model was trained on the Kaggle dataset and assessed on the DRIVE and STARE datasets. Their model has an accuracy rate of 94%. They performed manual pretreatment and enhancement with a picture editing programme.

Yashal Shakti Kanungo [5] describes a revolutionary technique to network scalability called Rethinking the Inception Architecture for Computer Vision. When benchmarking against the ILSVRC 2012 validation set, they obtained 5.6 top-5 errors; when employing an ensemble, they obtained 3.5 top-5 errors. Because deep learning proved to have an incredible potential that was not fully explored, they were motivated to work on this problem statement using this approach.

A deep learning method for grading diabetic retinopathy (DR) based on fundus images is presented in Doaa K. Elswa's study [6]. There are three steps in the suggested procedure. First, use normalisation and intensity enhancement to preprocess the fundus images. Secondly, compact feature vectors for assessment are extracted from the pre-processed images by feeding them into a ResNet convolutional neural network (CNN) model. Lastly, DR is identified and its grade (e.g., mild, moderate, severe, or proliferative diabetic retinopathy (PDR)) is ascertained through a categorization phase. The demanding ISBI'2018 Indian Diabetic Retinopathy Image Dataset (IDRID) was used to train the suggested system. The data is balanced during training to ensure that each DR degree is represented by an equal number of photos, hence eliminating training bias. When compared to comparable techniques employing the same data, the suggested system performs better, with the greatest overall classification accuracy of 86.67%.

The work by Hanisha Thanati [7] exclusively addresses deep learning techniques and a few approaches to integrating deep learning with machine learning characteristics. The method provides an examination of each method's effectiveness. In practice, it is challenging to identify the most efficient algorithm because computer resources and performance indicators differ among algorithms and are heavily dependent on the data. But when selecting an automated drug screening system, high sensitivity and specificity are crucial considerations, and the majority of the algorithms discussed in this article fit this description.

Using colour fundus pictures, Shailesh Kumar [8] provides an enhanced technique for identifying diabetic retinopathy by precisely identifying the location and quantity of microaneurysms. Tiny red patches on the retina called microaneurysms (MAs) are brought on by the enlargement of weak blood vessels. Early detection of MA is crucial and serves as the foundation for controlling DR. Numerous techniques have been put forth to recognize and treat DR. It was decided how many and where MAs were located.

Green channel extraction, histogram equalization, and morphological processing were among the first preprocessing techniques employed. Microaneurysms were found using mean filtering, morphological process, contrast-limited adaptive histogram equalization (CLAHE), and principal component analysis (PCA).

Zago [9] created a technique that uses CNN and pre-trained VGG16 to diagnose diabetes. Fundus imaging based on retinopathy presence or absence Potential for injury. The data set DIAETDB1 was employed. for instruction. The testing targets included IDrD, Messidor, Messidor-2, GDR, DIAETDB0, and Kaggle datasets. Their accuracy was 88.21%, and their AUC was 0.946.

Jiang [10] created a model with three CNNs in it. (ResNet152, Inception-v3, and Inception-ResNet-v2) Fundus imaging datasets are categorised using it into reference DRs. or delayed delivery of DR. Jiang had introduced Adaboost with modifications, enhancements, and expansions prior to CNN image training. Integration was achieved through technology. We employed Adam's optimizer. The system updates the network weights. Their accuracy was 88.21%, and their AUC was 0.946.

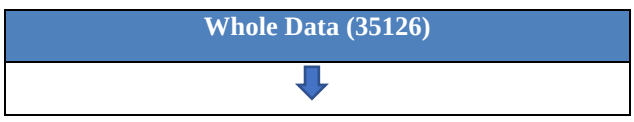
Pratte [11] created a technique with CNNs. Ten complete layers, eight max pooling layers, and ten convolutional layers SoftMax classifier with connected layer for classification DR Severity level-based Kaggle fundus picture classifications. Fundus images in color are normalized. There had been a size adjustment. L2 regularization to lessen screening techniques and over fitting. model generated There is a 95% specificity, 75% accuracy, and 30% sensitivity.

3. Pre-Processing

The 2015 Diabetic Retinopathy detection study on Kaggle provided the study's data as shown in table 1, which is derived from two datasets with thousands of retinal photos taken in a range of settings. Two images were taken from each person, one for each eye (left and right). There was a lot of noise to remove and it took a lot of steps to do so because the images originated from diverse sources (different cameras, different models, etc.).

Table 1: Database specifications [20]

Sr No.	DataSet Name	Total Images	Resolution	Extension
1	Kaggle ILOVESCIENCE	35126	1024	JPG



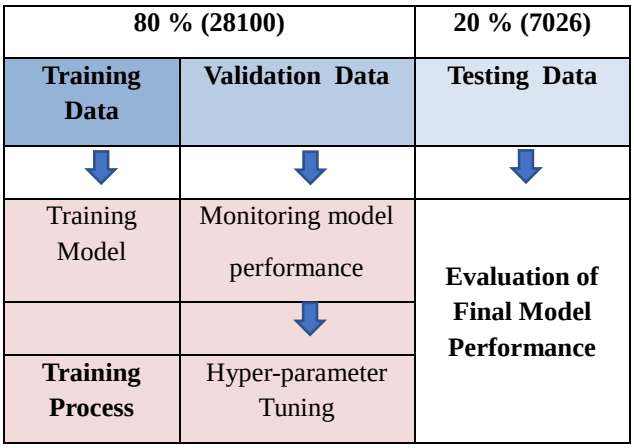


Fig 2: Dataset splitting for the experimentation

Python is utilized for the implementation, and several libraries are presented to generate images and machines are used to generate neural networks. OpenCV is the first type library used for image processing (such as translation and rotation). Nonetheless, NumPy is utilized to carry out the required mathematical operations, and Keras and Scikit-learn are additionally employed to power and comprehend the deep learning model. GPU-enabled devices are used in the model implementation for simplicity and speed. Instead of using a pre-defined architecture of CNN for our project, we decided to create a custom CNN Model of 4 Convolution Layers and 4 (Max) Pooling Layers with a regular Flatten function as the last layer. Every layer, with the exception of the final layer, sees ReLu as activation function.

Utilising ReLU's (rectified linear unit) nonlinearity is a key component of our CNN. To train neural network models, one can utilize Sigmoid or Tan activation functions. ReLU nonlinearity enables deep CNNs to learn more quickly, as demonstrated by our CNN. An illustration of a healthy eye can be found below figure 3. Owing to noise present in the set file, certain photographs may exhibit varying degrees of clarity, impact, auspicious light, dark backgrounds, and other characteristics. For this reason, we must first import them into the conventional model. Following are the steps executed as shown in figure 4:

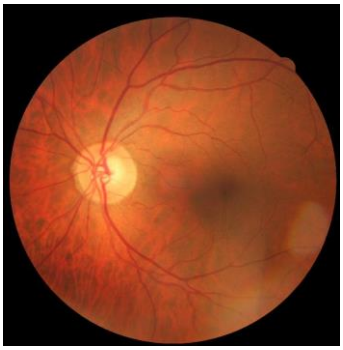


Fig. 3. Healthy Retina (Sample image form Database)

1. Cut the dark frame to size. The dark backdrop that surrounds fundus photos is removed because it serves no use and doesn't offer any information to the image.

2. Take off the dark corners. Because the fundus image is spherical, black corners persist even after the black frame is removed. The image's black corners are eliminated in this stage.

3. Image resizing: The picture is resized to 64 by 64 pixels (width by height).

4. Convert to grayscale: This reduces the image to a single channel (grayscale), simplifying the display of data. Grayscale pictures are frequently enough to identify DR-related elements and need less computer work. This lowers the dimensionality of deep learning models' input and streamlines downstream processing stages.

5. Segmenting vessels: Recognize and extract blood vessels from photographs of the retina. Vascular alterations are frequently linked to DR, and vascular segmentation is crucial for spotting anomalies such microaneurysms, hemorrhage, and angiogenesis.

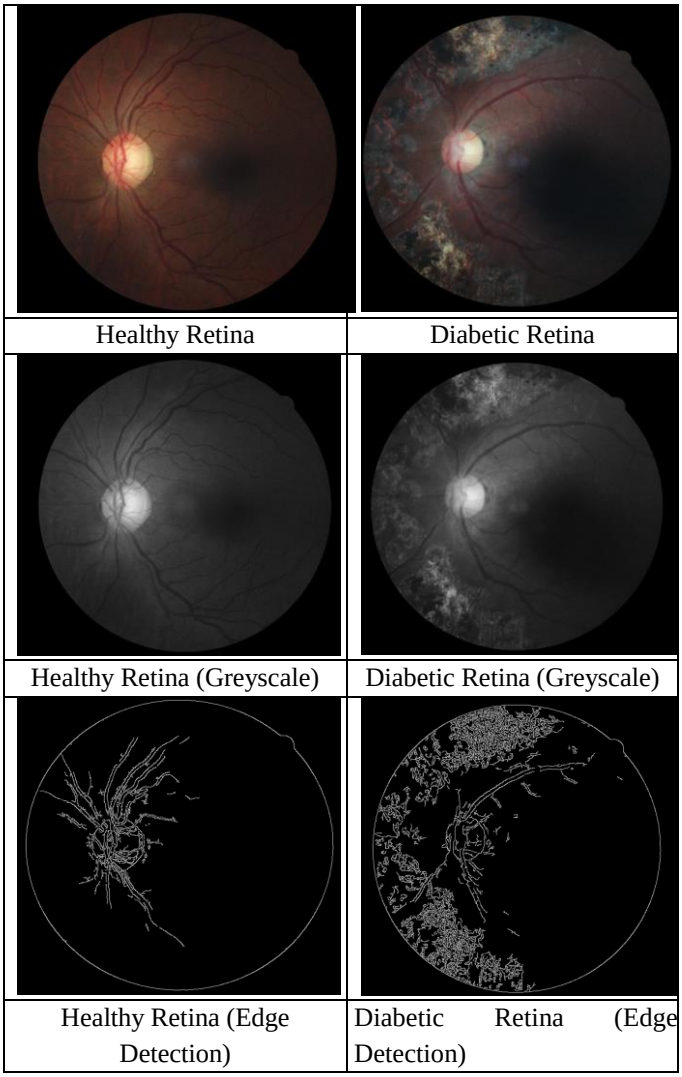


Fig 4. Preprocessing operation on retinal images

4. Methodology

Following pre-processing, feature extraction is our first step. Among processes, feature engineering is the most complicated. This is due to the fact that the features derived from this procedure, in addition to the retinal images they are based on, are utilized as input to forecast the degree of DR. Three steps are involved in feature extraction: The initial stage involves producing optical discs locally. An important aspect of diabetic retinopathy is the segmentation and localization of the optic disc, which enables the identification of areas of interest (ROIs) that can be utilized to gather comprehensive structural details on various kinds of retinal diseases. Additionally, OD localization is carried out to search for indications of fluid buildup, retinal neovascularization, retinal thickness, and venous hemorrhage. For instance, segmented and localized OD ROIs are the principal means of detecting glaucoma around the optic disc, which causes significant damage to the optic nerve.

For the following reasons, we localize optical discs as well:

The low contrast between the optic disc and fovea and the background makes them difficult to see in some situations. They can occasionally be mistaken for other structures that share a similar appearance.

The limits, structure, and form of the fovea are very changeable. They are frequently invisible to the unaided eye and are typically tiny in relation to the size of the total image.

Grain splitting is the second stage of feature development. A crucial stage in the extraction and interpretation of data from retinal pictures is vascular analysis. The majority of the images in the sample have fuzzy edges, making edge recognition challenging. Algorithms for image segmentation and edge detection offer trustworthy vessel correlation to support early diagnosis. Edges are regions of the picture where there is a clear discrepancy or mismatch between neighboring pixels. Only taking into account the grain, edge enhancement and edge detection resegment the edges as shown in figure 5.

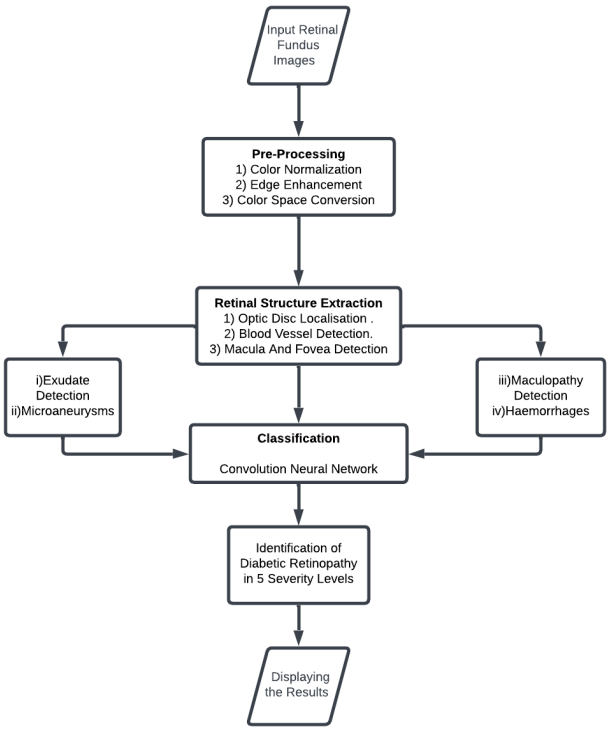


Fig 5. Block Diagram

The location of the optic nerve in the eye is known as the optic disc or optic nerve distance. In a typical human eye, nerve fibers exit the retina's optic nerve head. It connects the eye to the brain, carrying about a million neurons. It is wise to take this aspect into account. This region's cones, which are connected to ganglion cells, is called the Fovea as shown in figure 6.

We started looking into the significant anomalies that lead to diabetic retinopathy once the creation of complicated characteristics was finished. Often, the first indication of diabetic retinopathy are microaneurysms. These appear as little red spots dispersed over the retina. Solid exudate or a ring of yellow lipids may encircle it. Weakened blood arteries may produce tiny lumps called microaneurysms. People who have these microaneurysms may experience blood or fluid leakage into their retina. Additionally, the macula, a region of the retina, may experience it. High blood sugar levels in diabetics cause long-term damage to the body's blood vessels. Blood flow and damage to the retina's tiny blood vessels can both result from high blood sugar.

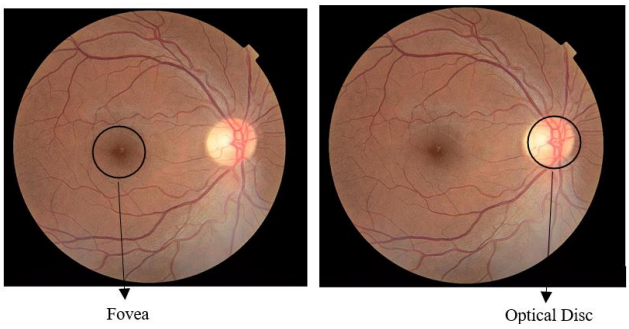


Fig 6. Retina Internal Structure

Another sign of diabetic maculopathy (DR) is the presence of retinal exudates, which are fluid-filled deposits in the macular area. Exudative diabetic maculopathy is a condition where patients with diabetic retinopathy experience visual impairments as a result of retinal capillaries reabsorbing extra fluid into the retina. Lipid and protein materials that build up in the retina's outer layer are the components of solid exudate. These plaques frequently result in significant visual loss when they build up in the central region. One of the main causes of blindness in diabetic individuals is diabetic hemorrhage brought on by proliferative diabetic retinopathy. This is a sign of diabetic retinopathy, which can lead to macular edema and neovascularization. The quantity and intensity of bleeding frequently rises from mild to moderate as DR worsens.

The blinding result of diabetic retinopathy is called diabetic maculopathy. Three categories of maculopathies exist: ischemic, edematous (diffuse), and exudative (localized). The initial symptom of diabetic macular degeneration, diabetic macular edema, is mostly covered in literature. It is typically brought on by inflammation of the retinal vessels, which disrupts the intra-retinal blood vessel barrier. Cotton wool patches are shown in figure 7.

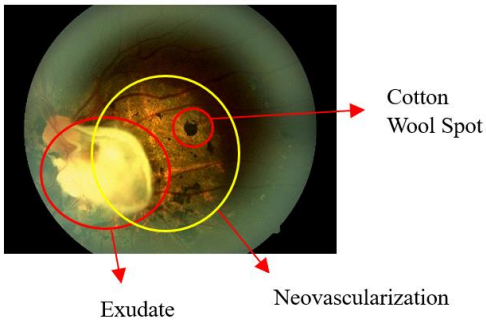


Fig 7. Exudates and Haemorrhages

Table 2: Architecture of Custom CNN

Sr. NO	***Name***	***Detail***
1	Input	64*64*3
2	Convolution2D_1	32*3*3 (32 filters & 3*3 size of kernel)
3	ReLu_1	ReLU

4	MaxPooling_1	2*2
5	Convolution2D_2	64*3*3 (32 filters & 3*3 size of kernel)
6	ReLu_2	ReLu
7	MaxPooling_2	2*2
8	Convolution2D_3	128*3*1 (64 Filters & 3*3 size of kernel
9	ReLu_3	ReLu
10	MaxPooling_3	2*2
11	Convolution2D_4	256*3*3 (32 filters & 3*3 size of kernel)
12	ReLu_4	ReLu
13	MaxPooling_4	2*2
14	Flatten	Flattening to Single 1D Vector
15	Dense_1	512 number of neurons
16	ReLu_4	ReLu
17	Dropout	Dropout Rate of 0.5
18	Dense_2	5 number of neurons
19	Softmax	Softmax activation function

Table 3: Hyper paramter tunning for custom CNN

Sr No	***Hyper parameter***	***Value Set***
1	Optimizer	Stochastic Gradient Descent (SGD)
2	Activation	Rectified Linear Unit (ReLu)
3	Loss	Categorical Cross-Entropy
4	Learning Rate	0.01
5	Epochs	300
6	Batch Size	32

5. Results

We can observe that other than our Custom CNN (table 2 and table 3), performs far better than any other CNN architecture with an Accuracy of 94.45%, Sensitivity of 93.51% and Specificity of 94.3% and Precision of 85.5% as shown in table 4 and 5.

DenseNet202 as the name suggests is a CNN architecture of densely connected by 202 layers. These densely connected convolution layers are called as DenseBlocks. DenseNet202 also has a complicated architecture which exponentially increases the computational operations performed in each layer and puts significant strain on the systems performance along with the applications performance. ResNet50's advantage lies in its ability to effectively learn and represent complex patterns in images through its deep residual network architecture. This allows it to achieve state-of-the-art performance on various image classification tasks, while also being more efficient and scalable than other deep neural networks.

Various CNN models are evaluated on ASUS F15, Intel i5 Processor, 4GB NVIDIA graphics card and 16 GB RAM with collected database and short summary of results in presented in table 4 and 5.

Table 4: Various parameters of evaluated CNN models

Sr. No	***Model***	***Accuracy***	***Loss***	***Processing Time***
1.	Custom CNN	94.45%	0.2108	120s
2.	AlexNet	73.47%	0.8742	6s
3.	DenseNet202	88.63%	0.3539	286s
4.	VGG16	77.65%	0.6595	339s
5.	VGG19	76.43%	0.6911	330s
6.	ResNet50	92.05%	0.2220	914s
7.	EfficientNetB5	83.54%	0.0601	148s
8.	InceptionV3	72.50%	0.001	228s

Table 5: Comparison of selected CNN models from table 4

Sr. No	***Model***	***Accuracy***	***Sensitivity***	***Specificity***	***Precision***
1.	Custom CNN	94.45%	0.9351	0.943	0.855
2.	AlexNet	73.47%	0.7352	0.9338	0.7352
3.	DenseNet202	88.63%	0.9354	0.9817	0.8923
4.	ResNet50	92.05%	0.6711	0.9829	0.6263
5.	EfficientNetB5	83.54%	0.9849	0.8720	0.8878

It is observed that Custom CNN performs far better than Densenet 202 and ResNet50, in matters of complexity, processing time per epoch, computational operation performed per layer and strain on system considerably lower on the system. This also helps in improving the performance of the end application. Each image's related diabetic retinopathy was identified using a scale ranging from 0 to 4, with 0 denoting no DR, 1 mild DR, 2

moderate DR, 3 severe DR, and 4 proliferative DR. There are eight stages of image pre-processing that must be completed before making the actual prediction.

The Custom CNN is with 4 layers is performing superior as compared to other selected general CNN algortihms for given database of diabetic ratinopathy. The acciracy , loss and sensitivity of custom CNN is presneted in figures 8,9,10 respectively. The results are shown in the cunfusion matrix standard format of True positive, True negative, false positive and false negative in figure 11.

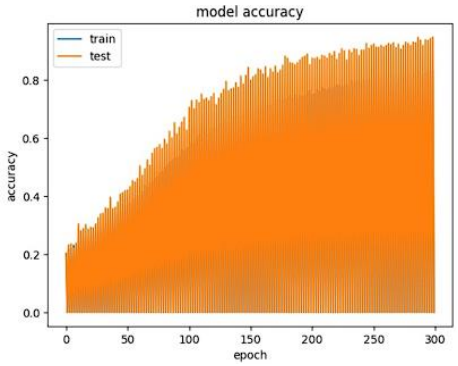


Fig 8. Accuracy Plot

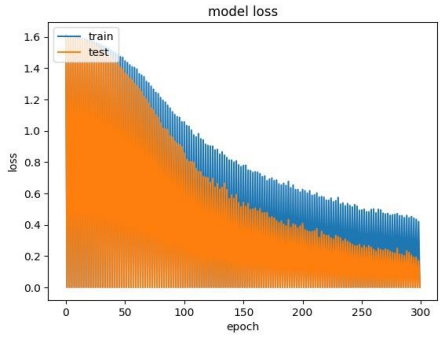


Fig. 9 Loss Function

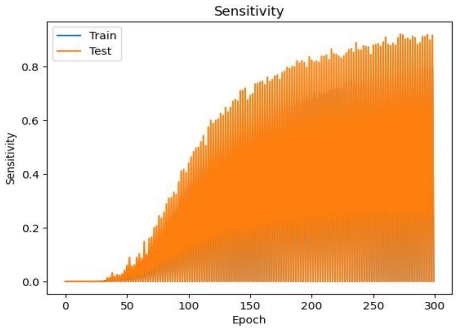


Fig. 10 Sensitivity

Predicted

Actual			
	4883	293	No DR
	109	1741	Has DR
	No DR	Has DR	

Fig 11: Confusion matrix

Table 6: Comparison of proposed CNN with other recently published papers.

Sr No.	***Paper Year and Ref no***	***Model***	***Accuracy***	***Sensitivity***	***Specificity***	***Precision***
1	Proposed Custom CNN	Custom	94.45	0.935	0.943	0.855
2	(2023) [12]	IR-CNN	92.66	0.961	0.971	0.976
3	(2023) [13]	VGG 16	81.00	0.85	0.910	0.980
4	(2022) [14]	Transfer Learning	91.56	0.856	0.974	0.971
5	(2023) [15]	ViT Model	82.50	0.825	0.956	0.825
6	(2021) [16]	EfficientNet	92.00	0.918	0.921	0.912
7	(2021) [17]	DiaNet	84.47	0.858	0.830	0.835
8	(2023) [18]	SqueezeNet	93.52	0.931	0.909	0.923

The proposed custom CNN model for selected database of diabetic retinopathy is also compared with results of other recently published papers in table 6.

6. Conclusion

Early detection of diabetic retinopathy will help the patient to avoid future complications. The automated computerized image processing based approach of detecting diabetic retinopathy will also help the medical practitioner to make the decision about the patient. Recent development in Convolutional Neural Network (CNN) deep learning make it enable to extract the minor feature difference between the diabetic retinal and healthy rational image. Selecting and training appropriate CNN model from vast available models is vital task. In this study custom CNN deep learning architecture is presented with 4 layers with proper tuning of hyper parameters, to analyze fundus images. The presented custom CNN is giving accuracy of 94.45%. Since the layers are only four the computational complexity of the presented model is also low. It also takes less time for training and testing of images. Advanced version of the presented methods may include training of CNN on many other datasets to develop more generalized model.

6.1. Acknowledgment

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Conflicts of interest

The authors declare no conflicts of interest.

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