Deep Learning-Based Early Prediction of Diabetic Retinopathy: A Novel Approach

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Abstract

Retinopathy is a progressive eye disorders that mainly effect the retina, afterward effects on sensitive tissue lining the back of eye, caused by various factors such as diabetes, genetic predispositions, hyper tension. Over 75% of people effected by the diabetes for about 20 years and globally 1.8 million people are blinded due to diabetic retinopathy. The seriousness of eye conditions can be neglected by taking preventive methods such as early detection, proper screaming and timely diagnosis. Currently, researchers developed automated diagnostic systems on the purpose of monitoring the advancement of eye diseaseusing machine learning techniques to differentiate retinal fundus images based on the severity, howeverhaving many drawbacks on DR evaluation, including un necessary training time, Reduced sensitivity performance, use of data annotation. Thus, proposed a technique which is automated diagnostic system by using the CNN, way to identify the symptoms of DR at the initial stage from the fundus images and to classifies DR irregularities in database as non-DR, moderate NPDR, severe NPDR, mild non-proliferative DR (NPDR) and proliferative DR (PDR). The productiveness of proposed technique is investigated by contrasting its effectiveness with other state-of-the-art ways in terms of varied performance metrics such as accuracy, sensitivity, specificity with 95%, 93.2% and 92% respectively.

Key words

Diabetic Retinopathy (DR), Convolution Neural Networks (CNN), Diabetes, vision loss.

Introduction

From recent survey, 170 million of the people throughout the world effected by retina diseases which are diabetic retinopathy, age related macular degeneration (AMD), retinal detachment, macular edema, etc., probably most of the people suffering from diabetic retinopathy (DR), where diabetic people getting vision impairment. Light sensitive tissue and blood vessels are responsible for sending information to the brain. Sometimes increasing sugar levels in blood can responsible for blocking and swelling in blood vessels. Due to not having any symptoms, it is very important to regular checking of eye, else, it will be very severe. It is very important to detect the disease from fundus samples in early for curable treatment.

The four stages are involved in diabetic retinopathy shown in Fig.1. illustrating that Mild NDPR (Non-Proliferative Diabetic Retinopathy) is the first stage of DR, appearing swelling and slightly fluid leakage in fundus image, the condition develops to Moderate NDPR showing that more swelling and fluid leakage such as fats and proteins as compared to Moderate NDPR represented by red and yellow spots respectively. PDR (Proliferative Diabetic Retinopathy), the third stage, starts breakdown of blood vessels on retina and leading to higher risk of bleeding and vision loss. and the last stage is Severe NDPR, where the extensive damage, fluid flow, low blood circulation and high vision impairment.

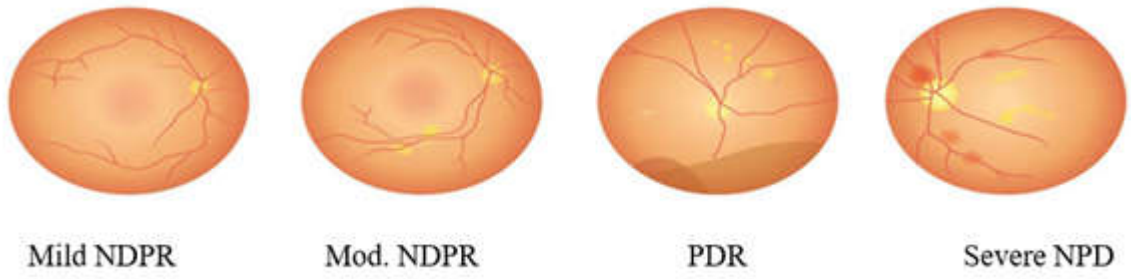

Figure 1 four stages of diabetic Retinopathy

The diabetic retinopathy could be cure by utilizing advanced techniques such as generative adversarial network (GAN), convolution neural networks (CNN) which is adapt for the classification of eye disease

The proposed method, Optimized Deep Learning Method for diagnosis of Diabetic Retinopathy overview presented in below sections. Section 2 handles with present available techniques for prediction of diabetic retinopathy with various technologies, section 3 deals with one of recent available system and drawbacks of existing system. Section 4 concentrates

on complete process of proposed technology Optimized Deep Learning Method for diagnosis of Diabetic Retinopathy, section 5 represents on process flow of proposed method and input samples for prediction of disease through novel technology. Section 6 follows results obtained by proposed system, and conclusion follows section 7.

Literature review

Diabetic retinopathy (DR) is an eye condition that can cause vision loss and blindness in people suffering from diabetes. Matheus H. Tempone, et al,[1] reviewed that retina is a sensory organ which is accountable for the first stage of visual perception. 170 million of people throughout World are effected by retina diseases like age related macular degradation, glaucoma, diabetic retinopathy etc., which effects vision impairment. Akanksha Bali, et al, [2] proposed Vision problems can seriously effects quality life of a person. deep learning tool come out as a powerful tool for examine medical images, encompassing retina images and forecast different diseases of eye. The technique talks though incorporate Generative adversarial networks (GAN), Recurrent neural networks (RNNs), convolution neural networks (CNNs), explainable deep learning and attention mechanics.S. Karthika, et al,[3] evolved Various fundus options available in proliferative, which combines growth of new arteries in retina and bleeding. Openly approachable images of fundus database from Kaggle (EyePACS). Recommended prototype is helpful for categorized the disease in initial level by automated transformer network. Recent SE-ResCA-GTNet technique is recommended for categorize different types of retinopathy diseases.

Sharjeel Sulthan, et al, [4] recommended Retinopathy could be divided as subtle non proliferative diabetic retinopathy (NPDR), proliferative diabetic retinopathy (PDR), severe NPDR, and moderate NDPR. The suggested enquiries are fluorescent angiography, B-scan ultrasonography and optical coherence tomography angiography (OCT) scans. Jyothsna Devi Bodapati,et al[5] Introduced a self-adaptive ensemble proceeding towards retinopathy seriousness grading by assemble few dual attention-based models. The suggested dual attentional novel contains double techniques. Where the first level focusing on damaged particular areas. And second one focus to determine correlations between spatial descriptors. Ramya Navaneethan, et al,[6] Proposed a new method, for predicting early and predict errorless grouping by using fundus images a method is used called “Modified Generative Adversarial-Based Crossover Slap Grasshopper”. Later, convolution Neural Networks (CNNs) is helpful for extracting of features.

Ramazan incir, et al, [7] evaluate Tissues and organs of the body cannot be damaged only by high glucose levels. But also cause undesired harmful effect on the eye. Classification is done

with seven different types of pre-trained deep learning architectures. Each technique of an experimental study was done on the EyePACS using dataset. The overtrain issue was cleared in results when compared with the original data. Nicola tecce, et al, [8] reviewed this indicates about the struggles of type 1 diabetes. A particular portion of review dedicated to advanced technologies in diabetes. Mainly, the importance of hybrid closed -loop system (HCLSs) having the capability for open source HCLSs, which different patient needs should be modified by using data analytics and machine learning. Naomi Wijesingha, et al, [9] evaluate review confers about the use of optical coherence tomography angiography (OCTA) as a diagnostic device to detection of disease initially. It is speedy, conservative and that enables informative visualization of macular microvasculature in dissimilar plexuses.

Guangyi HU, et al, [10] proposed a theory about DR, the main reason for vision less in the aged people. Even though blood glucose levels can be control to reduce the development of DR. due to unavailable of diagnostic indicators or improved treatment for diabetic retinopathy improvement in Glucose Well-Controlled Diabetic patients (GW-DR). in this case, They proposed intended GW-DR cohort by stick firmly to glycaemic regulate instructions. Federico Manai, et al, [11] reviewed, in this extracellular vesicle are engaged to moving of lipids, proteins from contributor to beneficiary, and nucleic acids. Yaojie Liy, et al, [12] suggested Hyperglycaemia is a disease which is related to retinopathy with high vision less rate. To know the symptoms of retinopathy they conducted few tests which were feed diet with hat fat, which contains quercetin about to 12 weeks, and injected with streptozotocin. Toan Duc Nguyen, [13] et al proposed a theory about the Ultra-wide field fundus imaging (UFI) supplies thorough imagination of critical components of eye, incorporating optical disk, macula and fovea. Through these the doctor can diagnose the disease accurately. This review exploring the various applications for classifying eye diseases using UFI.

Barbara detric, et al, [14] shift attention to experimental coronavirus retinopathy. It is the first technology to connect the relation between retinal autoimmunity and viral infection. Extracellular vesicles (EV) plays a versatile role in intercellular communication. Siyao Wang, et al,[15] introduced two step verification technique which can be using ultracentrifugation (UG) to separate samples of crude extracellular vesicle.Data of Present available system for prediction of diabetic retinopathy used and compared with various classifiers, proposed a method with CNNs classifier for prediction of diabetic retinopathy in early stage.

System model

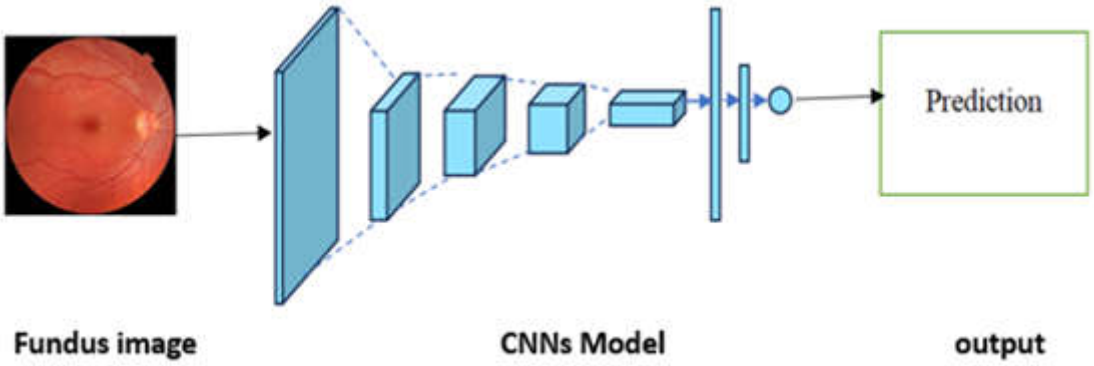

Figure 2 system model of diabetic retinopathy

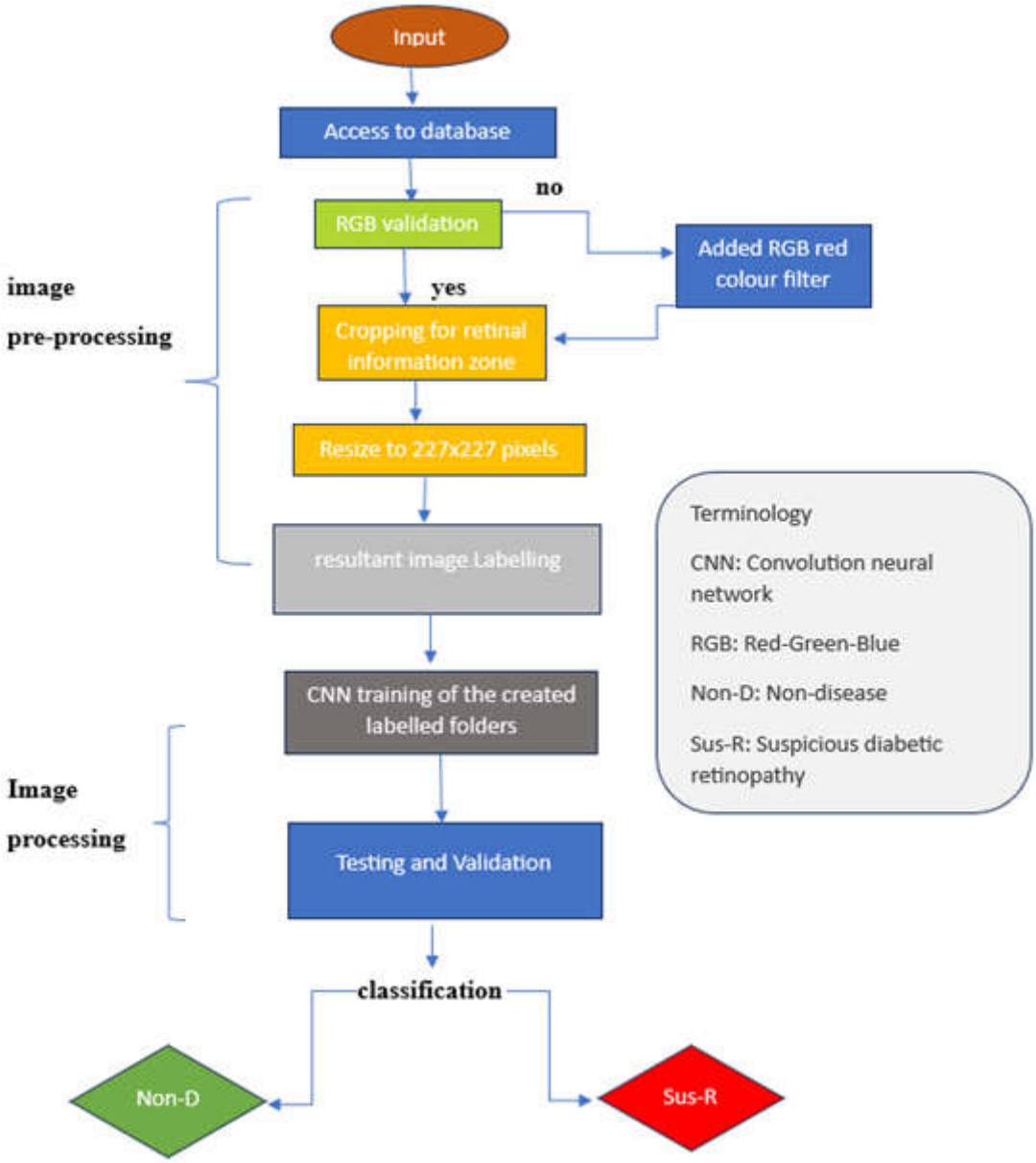

Figure 3 Proposed system for glaucoma and diabetic retinopathy detection

The existing methods for diagnosing Diabetic retinopathy (DR) in early stage, facing various challenges such as delayed disease prediction, false alarms, lack of accuracy leads to increasing the risk of vision impairment. To overcome the drawbacks, proposed a technique by using Neural Networks. Methodology is represented as system model in Figure 2. Utilized Convolution Neural Networks (CNN) to improve the prediction and diagnosis of diabetic retinopathy through processing retinal images. The main reason for utilizing CNN is compatible for the task because of their capability to automatically acquire features from fundus image which are crucial for recognizing complex patterns related with diabetic retinopathy.

The patient's fundus image had given to the CNN model as input. CNN architecture processes retinal images by passing through different layers to detect and classify different stages of diabetic retinopathy. By leveraging large datasets of labelled fundus images, the CNN trained to identify features, such as microaneurysms, hemorrhages, and exudates, which are indicative of DR. This model Performed many functionalities like classification of fundus, detection of images, and segmentation based on the requirements. Here the samples of fundus image which are collected from retina are applied to the convolution neural network (CNNs). Where the CNNs can be operates by sequentially processing input data through a series of layers.

- **Dataset**

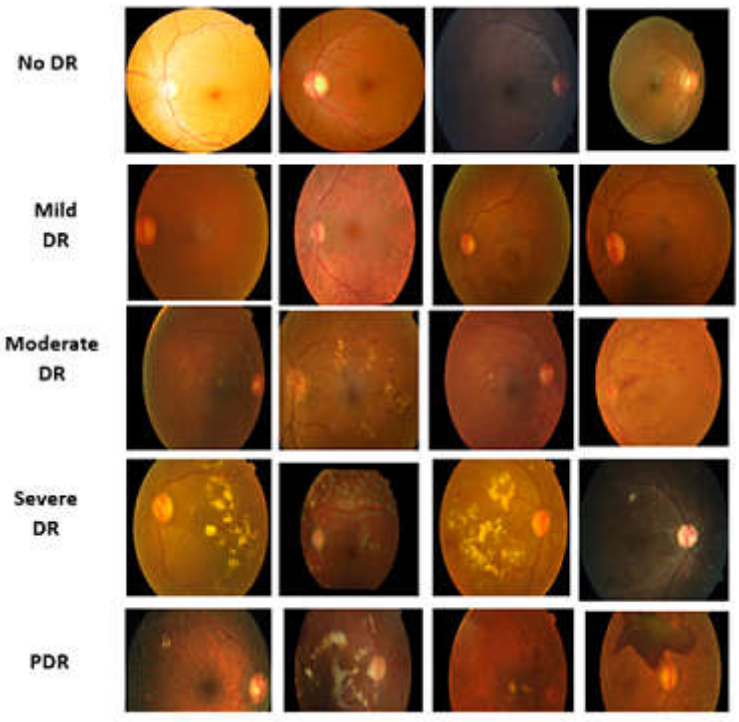

Figure 4 Fundus images of Different stages of DR

The Kaggle retina scan image dataset for diabetic retinopathy is divided into five categories: NO DR, which contains 370 images of healthy retinas; Mild DR, which contains 999 images of early stages of retinal images; Moderate DR, which contains 1805 images of damaged retinas; Severe DR, which contains 193 images of significant retinal images; and Proliferate DR, which contains 295 advanced stage retinal images. The dataset of different stages of Diabetic Retinopathy is shown in Figure 5.

- **Pre-processing**

Image Preprocessing is technique to prepare the data for analysis from raw data. Various steps involved in pre-processing such as Image Resizing, Normalization, Colour histogram equitation, data augmentation, Gaussian blurring, mean subtraction and colour balance adjustment.

(i) Image Resizing: Retina images were resized to uniform dimension, i.e,. 224x224 pixels to match input data, helps in reduce computational cost. The expression for resizing expressed in Euation (1).

$$I'(x',y') = \left(\frac{x'.W}{W'}, \frac{y'.H}{H'}\right) \quad (1)$$

Where, $I'(x',y')$ represents resized image, W, H represents width and height of real image, W' and H' represents width and Height of resized image.

(ii) Normalization: Normalization is the process of measuring data pixel values in a range between 0 and 1 or -1 and 1 in order to facilitate faster training convergence. The normalization expression shown in equation (2) applies if the pixel value falls between 0 and 225.

$$I_{norm}(x,y,c) = \frac{I(x,y,c)}{255} \quad (2)$$

Where, I(x,y,c) represents the pixel value in c^{th} channel at position x,y, $I_{norm}(x,y,c)$ represents the normalized pixel value.

(iii)Contrast enhancement: Histogram Equalization utilized to enhance the image contrast, making features more visible. Distributes the intensity values across the images to improve contrast in low intensity areas. Histogram Equalization is expressed in Equation (3).

$$I_{eq}(x,y,c) = round\left(\frac{CDF(I(x,y,c)) - CDF_{min}}{(M \times N - CDF_{min}}\right) \quad (3)$$

Where, I(x,y) represents input pixel intensity, CDF represents cumulative distribution function of pixel intensity, CDF_{min} represents the minimum value of cumulative distribution, M×N represents total number of pixels in image, L represents the possible intensity values, typically 256 for 8-bit image.

(iv) Data Augmentation: Data augmentation is utilized to improve the size of dataset and make model more vigorous. Augmentation includes rotation, flipping, brightness adjustment and cropping. Data Augmentation can be expressed in Equation (4), (5),(6) and (7).

Rotation: the image sis rotated by small angle θ to simulate different angles of camera.

$I_{\theta}^{'}(x^{'}, y^{'})$ = I (x cos θ – y sin θ, x sin θ + y cos θ) (4)

Flipping: Flipping can be done in two ways, vertical flipping and horizontal flipping.

Horizontal Flipping $I^{'}(x, y) = I(W - 1 - x, y)$ (5.1)

Vertical Flipping $I^{'}(x, y)$ = I(x,H-1-y) (5.2)

Where, original pixel value denoted by I(x,y), Flipped pixel value is denoted by $I^{'}(x, y)$, height denoted by 'H' and Width of image denoted by 'W'.

Brightness Adjustment: the brightness of image such as reducing or increasing had done lur by factor 'β'.

$I_{bright}^{'}(x, y, c) = I\ (x, y, c)\ \times \beta$ (6)

Cropping: cropping selects interest of region (ROI) from image and discard the rest.

$I^{'}(x^{'}, y^{'}) = I(x + x^{'}, y + y^{'})$ for

$0 \leq x^{'} < (x_{max} - x_{min}), 0 \leq y^{'} < y_{max} - y_{min})$ (7)

Where, original image is represented by I(x,y), cropped images are represented by $I^{'}(x^{'}, y^{'})$.

(v) Image Denoising: Gaussian blurring utilized to reduce the noise in image, eliminates unwanted features. Gaussian blur is expressed in equation (8).

$I_{blur}(x, y, c) = \frac{1}{2\pi\sigma^2} \exp(-\frac{x^2+y^2}{2\sigma^2})$ * I(x,y,c) (8)

Where, σ indicates standard deviation of gaussian kernel, convolution indicated by *.

(vi) mean subtraction: Mean subtraction used to remove the mean pixel value in each colour channel and make the data cennter, pre-channel is expressed in equation (9).

$I_{mean}(x, y, c) = I(x, y, c) - \mu_c$ (9)

Where, mean pixel value is denoted by μ_c, and $I_{mean}(x, y, c)$ represents centered pixel value.

(vii) Grayscale Conversion: to reduce computationa; complexity of images, gray conversion has done, expressed in equation (10)

$I_{gray}(x, y) = 0.2989\ .R\ (x, y) + 0.5870.\ G(x, y) + 0.1140.\ B(x, y)$ (10)

Where, red, blue and green images are indicated by R(x,y), B(x,y) and G(x,y) respectively, gray scale value indicated by $I_{gray}(x, y)$.

(viii) Colour Balance Adjustment: colour balance adjustment has done when the images have colour imbalance, expressed in equation (11).

$$I'_{balance}(x,y,c) = I(x,y,c) \times \alpha_c \quad (11)$$

Where, α_c represents scaling factor.

- **Feature Extraction using CNN**

CNN abbreviated as Convolution Neural Networks, deep learning neural network which contains multiple layers such as input layer, convolution layer, pooling layer and fully connected layer shown in Fig.5.

(i) Convolution layer: extraction of low level features has done in this layer, apply kernels to input layer to create feature maps. Convolution operation can be expressed in equation (12).

$$F(x,y) = \sum_{i=-k}^{k} \sum_{j=-k}^{j} I(x+i, y+j).K(i,j) \quad (12)$$

Where, $I(x+i, y+j)$ is determined as pixel value at $(x+i, y+j)$position, K(I,j) is represented as filter applied to image, k is the sized of filter and f(x,y) represents convolution output.

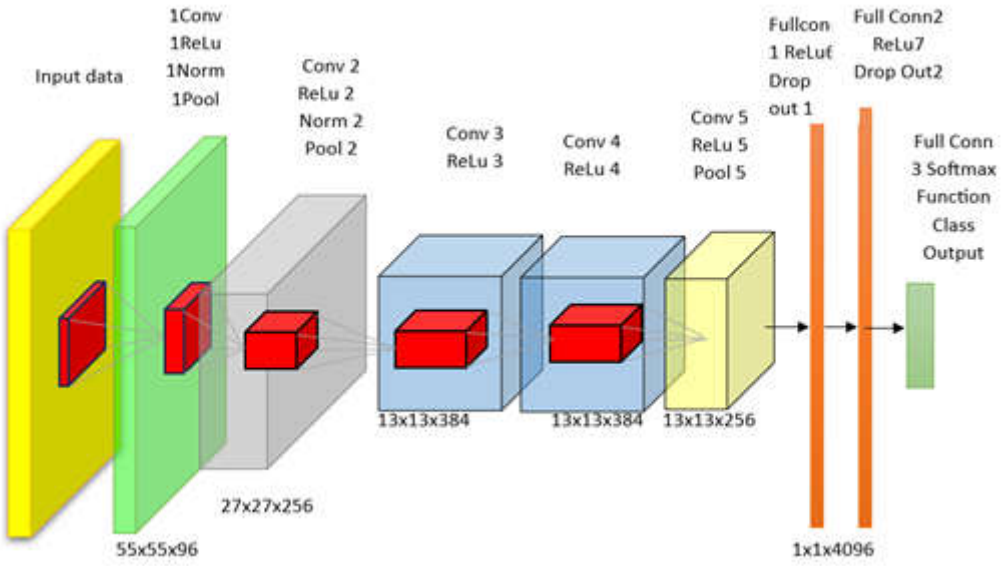

Figure 5 Architecture of Convolution Neural Network (CNN)

(ii) Activation Function (ReLU): ReLU function is utilized to present non-linearity into network. It converts all negative features to zero and positive keeps unchanged. The ReLU function can be expressed in equation (13)

$$g(x) = \max(0,x) \quad (13)$$

where, x represents input to activation function and g(x) represents output of activation function.

(iii) Pooling Layer: pooling layer reduces the spatial size of feature maps, expressed in equation (14).

$$P(x,y) = \max\{f(x,y), f(x+1,y), f(x,y+1), f(x+1,y+1)\} \quad (14)$$

Where, f(x,y) represents input feature map, p(x,y) represents pooling layer output.

(iv) Fully Connected layer: every neuron is connected to previous layer neurons alternately, classify the input image by combining extracted features. The expression represented in equation (15)

$$Z = \sum_{i=1}^{n} w_i x_i + b \quad (15)$$

Where, z represents weighted sum, input feature is represented by x_i, weight of the neurons is represented by w_i, b represents bias.

(v) Softmax activation: softmax activation function is utilized for classification of Retinopathy, expressed in equation (16).

$$P(y = c/x) = \frac{\exp(z_c)}{\sum_{i=1}^{C} \exp(Z_i)} \quad (16)$$

Where, z_c represents the output of fully connected layer, P(y = c/x) represents probability of input and total number of classes represented by 'C'.

(vi) Loss Function: to reduce the difference between predicted output and actual output, utilized cross- entropy loss, expressed in equation (17)

$$L(y, \hat{y}) = -\sum_{c=1}^{C} y_c \log(\hat{y}_c) \quad (17)$$

Where, true label is denoted by y_c, predicted label denoted by y_c.

(vii) Back propagation and Gradient Descent: determines the gradient of the loss function with regard to the network's weights and biases. Then, gradient descent is used to update the weights, expressed in equation (18)

$$\theta_{t+1} = \theta_t - \eta \frac{\partial L}{\partial \theta} \quad (18)$$

Where, η represents the learning rate, $\frac{\partial L}{\partial \theta}$ represents gradient loss and θ_{t+1} indicated updated parameter.

- **Performance metrics**

The performance obtained for diagnosis of diabetic retinopathy in terms of True Negatives (TN), True Positive (TP) false negative (FN) and false positive (FP) for accuracy, precision, recall, F1-Score expressed in equations (19), (20), (21) and (22).

Accuracy: Accuracy is defined as the ratio of sum of True positive and True negative to the all possible outcomes.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \quad (19)$$

Precision: precision is defined as the ratio of True positive to the sum of true positive and false positive.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (20)$$

Recall: Recall is defined as the ratio of True positive to the sum of true positive and false negative.

$$\text{Recall} = \frac{TP}{TP+FN} \quad (21)$$

F1-Score: F1-score is defined as the merging of precision and recall.

$$\text{F1-score} = 2 * \frac{Precision*recall}{Precision+recall} \quad (22)$$

Selection of appropriate performance metrics is essential for accurately evaluating the effectiveness and efficiency of systems, continuous monitoring and refinement of metrics ensure relevance and reliability over time. Ultimately, a well-defined set of performance metrics enables organizations to track progress, identify areas for improvement, and drive overall success.

Result

The newly introduced model demonstrated exceptional performance for different stages shown in Table 1. Model achieves an accuracy of 98%, precision of 92%, recall of 95% and F1-score with 92% for No DR stage, accuracy for Mild NDPR slightly reduces to 88%, precision and recall balancing at 90% along with F1-score of 88%, model achieved 82% of accuracy, precision of 87%, recall of 87% and F1-score of 95% for severe NDPR, and for PDR, model obtained accuracy of 93%, Precision of 89%, recall of 92% and F1-score of 93%, showing that strong performance in advanced stages of condition.

Table 1 Performance for Various stages of Diabetic Retinopathy

Stage	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
No DR	98	92	95	92
Mild NDPR	88	90	90	88
Moderate NDPR	82	87	85	83
Severe NDPR	90	85	87	95
PDR	93	89	92	93

The performance metrics for various stages of Diabetic Retinopathy in graphical form is shown in Figure 7, illustrating those different types of stages such as No Diabetic Retinopathy (No DR), Mild Diabetic Retinopathy (Mild DR), Moderate Diabetic Retinopathy (Moderate DR), Severe Diabetic Retinopathy (Severe DR) and Proliferative Diabetic Retinopathy (PDR) represented on x-axis and the accuracy in (%) are represented on y-axis.

From this graph, accuracy showing more accurate results in No DR, F1-score in Severe DR and overall, showing strong performance in advanced stages of Diabetic Retinopathy.

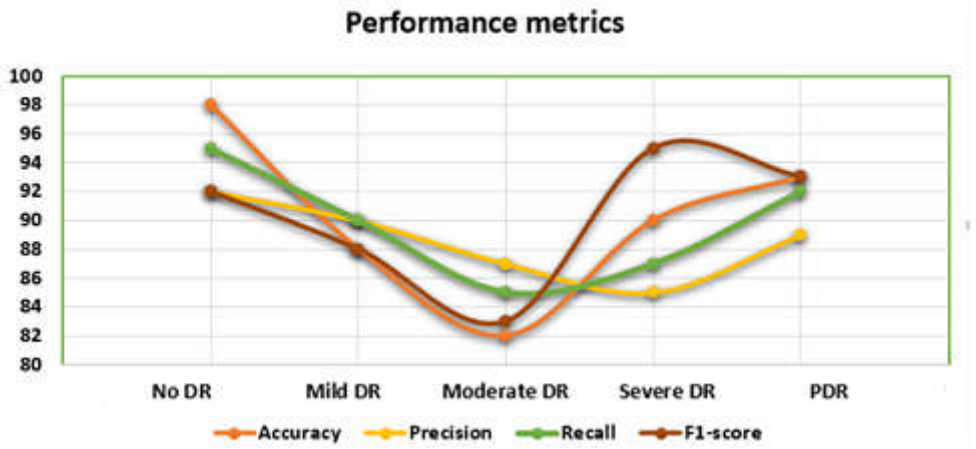

Figure 6 Graph of Performance Metrics of different stages of DR

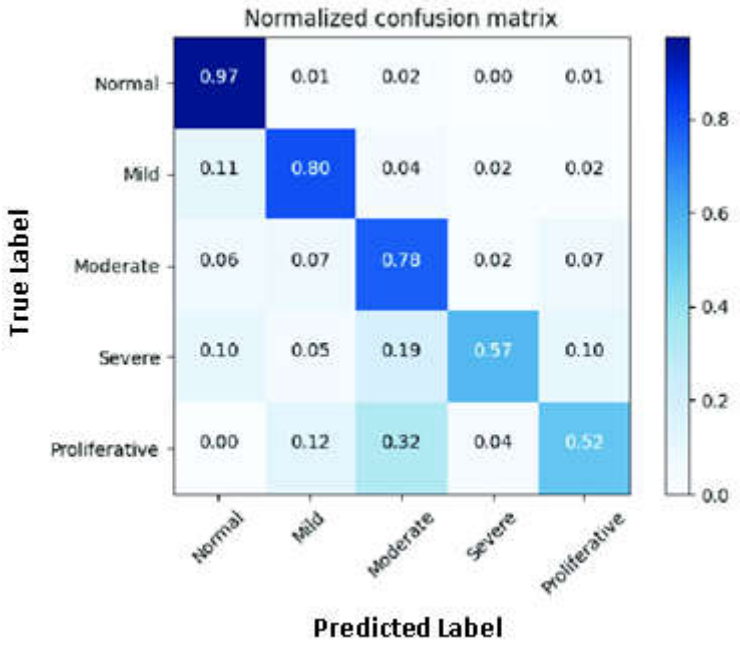

Figure 7 Confusion matrix of CNNs

In the valuation of Convolution Neural Networks for the prediction of diabetic retinopathy in early-stage is shown in Figure 8.

Confusion metrics deliver a inclusive breakdown of model performance by classifying predictions into four key consequences, such as True Positives (TP) which represents correct predictions of DR cases, true Negative (TN) indicates accurate predictions of non-diabetic retinopathy cases, false Negative (FN) and False Positive represents instances where non-diabetic retinopathy cases incorrectly classified as diabetic retinopathy (FP) represents instances where diabetic retinopathy cases incorrectly classified as non-diabetic retinopathy. Different performance metrics derived by using this matrics such as, accuracy, precision,

recall, F1-Score, offered exclusive perceptions into CNN's efficiency in precisely identifying cases of Diabetic retinopathy.

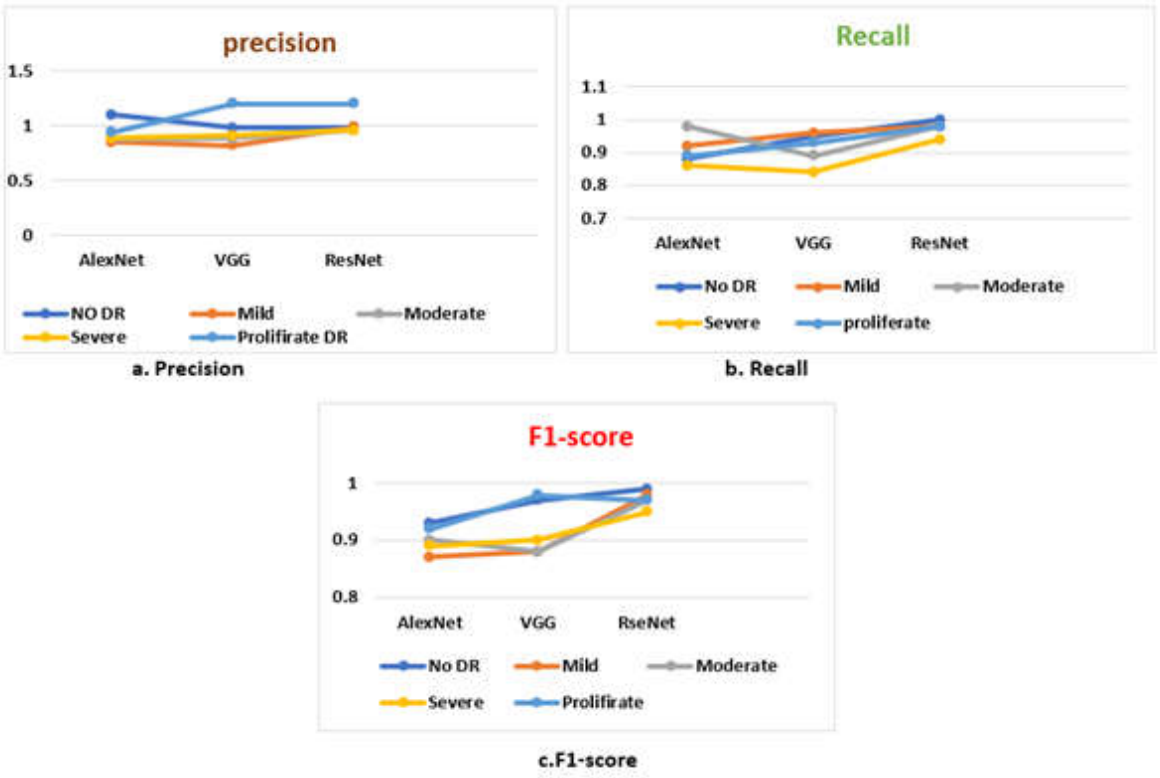

Figure 8 (a)Precision, (b)Recall and (c)F1-Score for Various deep learning techniques for Prediction of DR

Figure 9 (a), (b), (c) shows the precision, recall and F1-score by using CNNs algorithms for diagnosis of classification of diabetic retinopathy. Precision measures the accuracy of positive predictions, i.e., the ratio of true positive predictions to the total predicted positives.

Table 2 Performance of Machine Learning algorithms

Model	AUC	Accuracy	Sensitivity	specificity
SVM [16]	0.83	0.90	0.834	0.791
Chat GPT and Automated Machine Learning [17]	0.772	0.84	0.771	0.752
artificial intelligence-based reading system [18]	0.95	0.90	0.90	0.7

Recall defined as the positive predictions, assessing the capacity of model to comprise patient cases.

The F1-score defined as the harmonic mean of precision and recall, provides a reasonable evaluation of system efficacy by considering false positives and false negatives. F1-score can classify and reduce the incorrect predictions leads to accurate identification of DR stages.

To illustrate the efficiency of the system and compare the results to industry standards, tests were carried out on the fundus data. The data set is divided in to five sub sets according to the required training method. Various techniques utilized to identify the diabetic retinopathy in shown in Table 2, such as SVM, ChatGPT and Automated machine learning and Artificial intelligence-based reading system (AIRS) with the parameters like AUC, accuracy, Sensitivity and specificity.

Illustrated that SVM and AIRS performed accurately as compared to ChatGPT and Automated Machine Learning.

Table 3 A review of the literature comparing different DR diagnostic methods

Year	Technique	Total no. of images	classes	database	accuracy	precision	recall	Receiver operating characteristics ROC
2021	Multi-scale attention network (MSA-Net)		5	APTOS	85%	91%	92%	-
				Eyepacs	88%	79%	91%	77%
2022	Local binary convolution neural network (LBCNN)		2	APTOS	98%	96.9%	95%	98.81%
2022	VGG-16	Test-1728	5	APTOS	75%	84%	85%	-
2022	DenseNet201	3662	5	APTOS	94%	91%	81.5%	-
		2355	3	New Dataset	95%	95%	95%	-

Table 3 represents the performance metrics for different techniques with a different data sets for prediction of diabetic retinopathy. This shows that every year researchesrs introducing various methodologies for early prediction of disease.

Table 4 comparison of conventional deep learning methods for DR recognition and classification

Methods of DL	Data base	Accuracy	specificity	sensitivity	AUC
VGGNet	5-class (EyePACS) 2-class (EyePACS)	96.2%	98%	87.02%	0.981
Fully CNN	STARE (20) CHASE DBI (28)	0.9843% 0.9773%	0.9831 0.9931	0.8990 0.7842	0.9880 0.9734
CNN	DRIVE (40)	94.98%			
CNN	CHASE (28)	97.24%	99.80%	81.02%	99.94%

The comparision of performance analysis among different types of convolution deep learning techniques for prediction of diabetic retinopathy shown in table 4.

Conclusion

Diabetic retinopathy is a very complication of diabetes that leads to vision impairing. Now-a-days many people facing this situation like elder age people and diagnostic people. The early detection of diagnosis is very difficult.so, to simplify the problem of identifying the fundus of retinal image in the image and diagonalising the diabetic Retinopathy. The Proposed novel is Five-fold cross validation CNN, for early detection of disease of the eye. It is a technique to assess the performance of our diabetic detection model by portioning the data into five Subsets and alternatively training the CNN on other four folds.there is a classification in retinopathy that can be detect easily by using five-fold cross validation. CNN exhibits consistent and dependable predictive performance throughout all folds, demonstrating its ability to generalize well to unseen data. This suggests CNN relatively Learns relevant features from retinal image to closely classify the diabetic retinopathy with 93.2%, 92%, and 95% of sensitivity, specificity and accuracy respectively.

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