Panamerican Mathematical Journal
ISSN: 1064-9735
Vol 33 No. 3 (2023)

Microaneurysms and Exudates Detection in Retinal Images using Deep Neural Network

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Article History:

Received: *19-06-2023*

Revised: *18-08-2023*

Accepted: *23-09-2023*

Abstract:

One frequent diabetes consequence that affects the eyes is diabetic retinopathy(DR). The most frequent reasonfor blindness in working-age adults in the world is diabetic retinopathy. One in three diabetics has diabetic retinopathy to some extent. DR affects nearly all persons having type 1 diabetes and more than 60% of people having type 2 diabetes to some extent after 20 years of diabetes. In the US, approximately 4.2 million persons, 40 and older have diabetic retinopathy. In the United States, 12% of all new occurrences of blindness are caused by diabetic retinopathy.A 95% reduction in the risk of blindness is possible with a diabetic retinopathy early detection and treatment. The retina's appearance, the presence or absence of Microaneurysm and Exudates, and the degree of participation are all taken into account in the grading process. It has been demonstrated that deep neural networks (DNNs) work well for automatically grading diabetic retinopathy. The features like Microaneurysm and Exudates that are diagnostic of various stages of diabetic retinopathy are taught to these DNNs utilizing vast datasets of retinal pictures and accompanying grading information.It has been demonstrated that deep neural networks (DNNs) are efficient in automatically detecting diabetic retinopathy from retinal pictures. Sensitivity, specificity, precision, accuracy, and Kappa value are used to measure how well DNNs work in detecting diabetic retinopathy; these values are 95.74%, 92.31%, 96.77%, 94.74%, and 0.87, respectively.

Keywords: Diabetic Retinopathy (DR), Non-Proliferative Diabetic Retinopathy, Proliferative Diabetic Retinopathy, Exudates Detection, Microaneurysms Detection.

1. Introduction

Diabetes patients who have diabetic retinopathy experience ocular problems. The retina, the light-sensitive tissue in the back of the eye, has blood vessels, are harmed by high blood sugar levels[1], [2]. The retina may enlarge and become injured as a result of the damaged blood vessels leaking fluid or blood over time[3]. In severe circumstances, diabetic retinopathy can result in blindness and vision loss. People with diabetes who have poor blood sugar management, high blood pressure, high cholesterol levels, or who have long suffered with diabetes are having high probability of detecting with diabetic retinopathy[4], [5].

Laser surgery, pharmaceutical injections into the eye, and vitrectomy, a surgical operation to remove the vitreous gel and replace it with saline solution, are all available treatments for diabetic retinopathy[6], [7]. The greatest method to prevent diabetes is to maintain healthy levels of cholesterol, blood pressure, and sugar to prevent diabetic retinopathy. Patientswith diabetes also get frequent eye exams to look for any early indications of the disease.

The two primary forms of diabetic retinopathy are:

Non-proliferative diabetic retinopathy(NPDR) is the name of the early stage of diabetic retinopathy[8], during which the blood vessels in the retina weaken and leak. Microaneurysms, tiny blood vessel bulges, can develop as a result of this, and fluid and blood can accumulate in the retina. The blood arteries may obstruct as the illness worsens, reducing blood supply to the retina.

Proliferative diabetic retinopathy (PDR), the more severe kind of diabetic retinopathy, is characterized by the development of new blood vessels in both the retina and the vitreous gel. These newly develop blood vessels are fragile and prone to bleeding, which can result in the formation of scar tissue in the retina and eventual blindness. Additionally, the retina may separate from the back of the eye as a result of the scar tissue contracting and pulling on it.

Diabetic retinopathy, frequently has exudates and microaneurysms. Microaneurysms, which are tiny bulges in the retina's blood vessel walls, can develop in the early stages of DR. These lumps may leak blood or fluid into the retina, impairing vision[9]. Typically found during an eye exam, microaneurysms can serve as a marker for the severity of diabetic retinopathy.

Exudates, deposits of fluid and protein, are a potential complication of diabetic retinopathy in the retina[10], [11]. They are frequently observed as yellow or white spots on the retina and can be found through an eye exam. Exudates are fluid leaks from damaged blood vessels that might worsen diabetic retinopathy patients' vision loss.

Exudates and microaneurysms are both significant indicators of diabetic retinopathy and can be used to track the disease's development over time. The risk of vision loss and the emergence of more serious issues can be reduced with the use of diabetic retinopathy treatment alternatives including laser surgery or medicine injections into the eye[12]. The management of diabetic retinopathy and the preservation of eyesight also depend on maintaining stable blood sugar levels and having routine eye exams[13], [14].

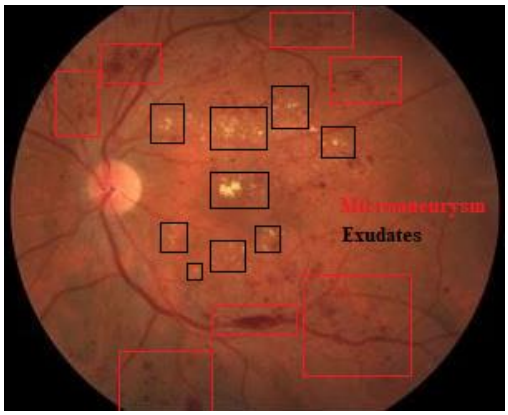

Fig.1. Microaneurysm and Exudates

Microaneurysms and exudates are frequently used in the assessment and treatment of DR to grade the condition. Here is a quick summary of the grading scheme[15], [16]:

- No diabetic retinopathy: There are no abnormalities in the retina, ruling out diabetic retinopathy[17].
- Very Mild NPDR: Miniature microaneurysms are seen in diabetic retinopathy with very mild non-proliferative changes[1].
- Mild (NPDR): Microaneurysms are present in the retina in cases of mild non-proliferative diabetic retinopathy (NPDR), but no exudates or other alterations are visible[18].
- Moderate NPDR: The retina exhibits microaneurysms and certain regions of edoema or exudates[19].
- Diabetic Retinopathy (DR) NPDR: There may be signs of blocked blood vessels in the retina, as well as more extensive areas of retinal edoema or exudates[20].
- Significant NPDR: Presence of large microaneurysm and exudates
- Severe Proliferative diabetic retinopathy (PDR): This condition combines the characteristics of Severe Nonproliferative Diabetic Retinopathy with the development of new, aberrant blood vessels in the retina, which can result in scarring and additional vision loss[1], [18]–[20].

The grading system is employed to evaluate the degree of diabetic retinopathy and choose the most effective course of action. For instance, individuals with mild NPDR might only need routine monitoring, whereas those with severe NPDR or PDR might need laser surgery or medication injections to stop further vision loss.

The identification of diabetic retinopathy has showed considerable potential for deep neural networks (DNNs). DNNs are a subset of artificial neural networks thatrecognizes intricate patterns in data and predict outcomes with accuracy. A sizable dataset of retinal pictures is needed to train a DNN for the identification of diabetic retinopathy. Standard eye exams can produce these images, which are then preprocessed to get rid of any artefacts or unnecessary features. Each image in the dataset needs to have the presence or absence of diabetic retinopathy features, like microaneurysms and exudates, annotated by a human expert. The DNN is trained using these annotations.Convolutional neural networks (CNNs), which are particularly well-suited to image analysis, are just one of the many distinct types of DNN designs that can be employed for diabetic retinopathy identification. The architecture is made to take in retinal images as input and produce either a forecast of the existence or absence of diabetic retinopathy. The annotated dataset is used to train the DNN, which then learns the intricate patterns connected to diabetic retinopathy. The weights and biases of the network are altered during training in order to minimize the difference between the expected output and the true labels. The accuracy of the DNN is checked on a different set of retinal images after it has been trained.To enhance its performance, the DNN is also adjusted or retrained with new data[13], [17], [21].

According to studies, DNNs frequently outperformed human specialists in the detection of diabetic retinopathy, achieving high levels of accuracy. DNN-based methods may help with the early diagnosis of diabetic retinopathy and lower the risk of visual loss in diabetics[19], [20].

2. Related Work

This section includes a review of existing work on diabetic retinopathy detection using machine learning algorithm.

In paper[6],It was suggested to make heatmaps displaying which picture pixels are relevant to the image-level predictions. Lesions can be found using a Convolutional Network trained for image grading. It is suggested to generalize the backpropagation method to train Convolutional Networks that generate heatmaps. The suggested remedy is used to screen for diabetic retinopathy (DR) in a Kaggle dataset. Referable DR detection was attained with Az = 0.954 in the Kaggle and Az = 0.949 in the e-ophtha.

Authors in paper[3],the findings of the proposed Dl algorithm implementation were as follows: sensitivity was 0.83 (95%CI: 0.83-0.83), specificity was 0.92 (95%CI: 0.92-0.92), and the pooled area under the receiving operating curve (AUROC) of DR was 0.97 (95%CI: 0.95-0.98). The positive-likelihood ratio was 14.11 (95% CI: 9.91-20.07), whereas the negative-likelihood ratio was 0.10 (0.07-0.16). For DL models, the odds ratio was 136.83 (95% CI: 79.03-236.93).

In paper[4], The transfer learning methodology was originally applied to the GoogLeNet,AlexNet and ResNet50. Second, examine the impact of employing images from the cross, single and multiple datasets, these frameworks trained again using retina images from a variety of datasets, including IDRiD,Messidor and Messidor-2. Third, investigate the DR detection precision of smartphonebased retinal imaging systems, the suggested ResNet50 is used onsmartphone-based synthetic pictures. Based on results from the identification of vision-threatening diabetic retinopathy, the suggested method had an AUC of 0.9978 dataset and a classification accuracy of 98.6%, 98.2% sensitivity, and 99.1% specificity.

Authors in paper[5], employed a deep network patch-based methodology, created a lesion localization model. The model's performance is to be enhanced while its complexity is decreased. designed a method, using two CNN models, for choosing the training that would priorities the difficult samples during training. A DR choice was made for the initial image using the region's labelling. TheDR Database, (DIARETDB1) database is used to train the model, and various other databases are used to test it. It reaches a area under the curve of 0:912.

In paper[2], create DeepDR, a deep learning model that can recognize diabetic retinopathy in its early to late stages. DeepDR was trained for image assessment andgrading. For the detection of microaneurysms and hard exudates, the area under the receiver operating characteristic curves is 0.901, 0.941, 0.954, and 0.967. Area under the curves for the classification of diabetic retinopathy as mild, moderate, severe, and proliferative are 0.943, 0.955, 0.960, and 0.972, respectively. The area under the curves for grading in external validations ranges from 0.916 to 0.970.

3. Methodology

1. Preprocessing

Images of the fundus, which comprises the retina, optic disc, and blood vessels, are taken from the inside of the eye. In computer-aided diagnosis systems, preprocessing fundus images is a crucial step

that increases the precision of the diagnosis. Here are the image-preprocessing methods used for fundus images:

a. Image resizing:

Fundus images are frequently huge in size, therefore downsizing them lessen the computational burden of future processing stages.

b. Denoising:

Motion blur, sensor noise, and poor illumination are just a few of the reasons that causes noise in fundus images. Wavelet denoising and median filtering are two methods that reduces noise and enhance image quality.

c. Image normalization:

Images is made uniform in terms of brightness and contrast using normalization techniques like scaling and centering, which increases the accuracy of later processing processes.

d. Image registration:

The dimensions, positions, and orientations of fundus pictures are changed as per requirement. Images are aligned using image registration techniques, making it simpler to compare them and spot changes over time.

e. Adaptive histogram equalization:

A technique called adaptive histogram equalization (AHE) is used to redistribute the pixel intensities in an image to increase contrast. AHE applies a local alteration to certain areas of the image, as opposed to typical histogram equalization, which transforms the entire image. This enables the augmentation of low-contrast areas in the image as well as the retention of local details.

The way AHE operates is to separate the image into tiny tiles and individually apply histogram equalization to each tile. The final enhanced image is created by recombining the resulting tiles. Imaging with variable illumination or contrast, such those found in medical images, benefit especially from AHE.

AHE has the potential to make noise and artefacts in the image look more prominent, which gives the enhanced image a distorted appearance.

AHE has been utilized to improve the contrast of blood vessels in the retina, which are crucial characteristics for the diagnosis of diabetic retinopathy. To increase the precision of DR diagnosis, AHE also used in conjunction with other image processing methods, such as image segmentation.

The result images and difference between adaptive histogram equalization and Normal histogram equalization is shown in figure 2[22]

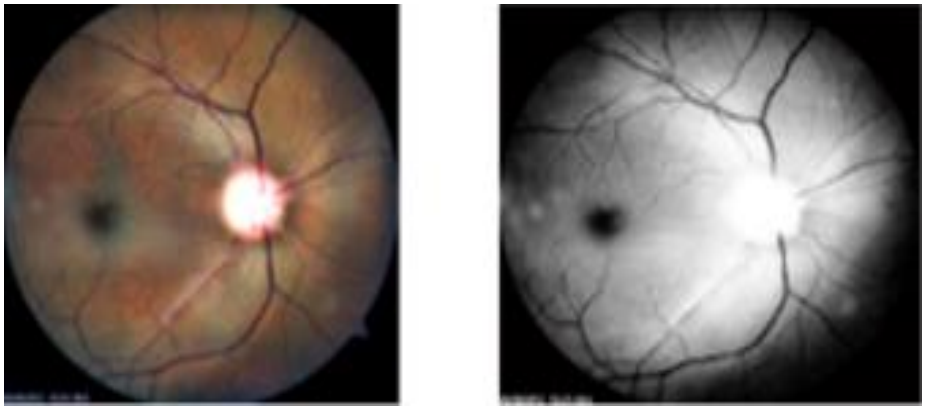

Fig.2. The difference between adaptive and conventional histogram equalization.

2. Deep neural network

DNNs are often trained for DR detection using a sizable dataset of fundus images that have been labelled with the presence or absence of DR. The network gains the ability to identify patterns and characteristics in the images that are characteristic of the condition. The network is used to categories fresh images as having or not having DR after it has been trained.

Convolutional neural networks (CNNs), a form of DNN that is particularly well-suited for image processing tasks, are one of the DNN designs that is used for DR detection. CNNs are made up of several convolutional filter layers, each of which is trained to recognize progressively complex features in an image. A classification is produced by the network's final layer using the learned characteristics.DNNs perform quite well in terms of DR detection, with high accuracy rates. Additionally, DNNs have the ability to identify DR at different levels of severity, which is critical for early diagnosis and therapy.

DNNs have the benefit of learning to notice aspects that may be challenging for human experts to recognize, increasing the precision of DR diagnosis. To minimize overfitting and get the best performance, the network design and training parameters are carefully chosen, and a significant amount of labelled data is needed to train DNNs.

A feedforward arrangement of the layers of a DNN means that the output of one layer serves as the input to the following layer.

A DNN's layers are made up of a collection of neurons, or "units," that apply a nonlinear transformation to their inputs. Each layer has a different number of neurons, which are normally determined by the difficulty of the problem being solved and the quantity of training data that is available.As shown in figure 3, the layers in a DNN are broadly divided into the following types.

i. Input layer:

In a deep neural network (DNN), the input layer is the initial layer and is in charge of taking in input data and sending it on to the succeeding layers for additional processing. The input layer is a crucial part of a DNN since it gives the network the ability to take in data from the outside world and start learning. The input layer is made up of a group of neurons, each of which corresponds to a certain

input aspect or dimension. The quantity of input features affects how many neurons are present in the input layer.

The input layer simply represents the input data, let denote the input features as

$$a^{[0]} = (x_1, x_2 \ldots . x_n)^T \quad (1)$$

No nonlinear processing of the input data is made by the neurons in the input layer. Instead, they only pass the input data as this is the network's initial hidden layer. Before being fed into the input layer, the input data is usually preprocessed and standardized.

The input layer is essential to the deep learning process since it gives the network a mechanism to receive input data and start learning. The following equation is used to mathematically represent the input layer of a deep neural network (DNN):

$$\text{x} = W_0 * a_0 + b_0 \qquad (2)$$

where x is the input layer's output, W_0 is the weight matrix connecting it to the top-most hidden layer, a_0 is the input, and b_0 is the input layer's bias vector. a_0, the input layer, receives its input as a vector of input features, with each member of the vector denoting a distinct feature.

The weight matrix, W_0, is a matrix with the dimensions n_0x m, where n_0 is the total number of input layer neurons and m is the total number of neurons in the first hidden layer. The components of W_0 stand for the strength of the connections between the input layer and the first hidden layer's neurons.

The first hidden layer's neurons' bias values are represented by the bias vector, or b_0, which is a vector of length m. To provide the model some flexibility, the bias values are added to the weighted sum of the inputs.

The input layer equation describes how the weight matrix and bias vector change the input features to create the output of the input layer, which is then sent to the first hidden layer for additional processing.

ii. Hidden layers:

layers that execute nonlinear transformations on the inputs and are placed between the input and output layers. Depending on size of microaneurysm and exudates, both the total number of neurons and hidden layers in each hidden layer are changed.

The layers of neurons between the input layer and output layer in a deep neural network (DNN) are referred to as hidden layers where $W^{[l]}$= “weight vector”, $b^{[l]}$ = “bias vector”, $a^{[l]}$= “output of the hidden layer”, $a^{[l-1]}$= “output of the previous layer”:

$$z^{[l]} = W^{[l]}.a^{[l-1]} + b^{[l]} \qquad 3$$

$$a^{[l]} = g(Z^{[l]}) \qquad 4$$

These layers are referred to as "hidden" because they perform computations on the input data to extract significant properties that are utilized to generate precisepredictions or classifications, rather than immediately interacting with the input or output.A DNN that has more hidden layers can

typically learn more intricate patterns from the data, but this also necessitates more training data and longer training cycles.

Normally, all of the neurons in the preceding layer are connected to the neurons in each hidden layer, and each connection has a weight that is changed during training to enhance the performance of the network.

A deep neural networks (DNN) equation for a hidden layer's output reads as follows:

$$z = (Wx + b) \qquad (5)$$

where W is the weight matrix, b is the bias vector, z is the output vector, and x is the hidden layer's input vector.

The hidden layer's learnable parameters in this equation, the weight matrix W and bias vector b, are tuned during training to reduce the discrepancy between the network's anticipated output and the actual data.

The output of the preceding layer, or the network's input in the case of the first hidden layer, is the input vector x. The element-wise application of the activation function f to the linear combination of the inputs and weights results in nonlinearity in the hidden layer's output. In order to induce nonlinearity, an activation function is applied after the linear combination of the input, weights, and biases in the equation for the output of a hidden layer in a DNN.

iii. Output layer:

The output prediction is produced by the last layer of a DNN. In classification issues, the number of output classes or output values is often equal to the number of neurons in this layer. The output layer is represented as:

$$\hat{y} = \sigma(z^{[L]}) \qquad 5$$

The final layer of neurons in a deep neural network (DNN) that generates the network's output or prediction is called the output layer. To reduce the error between the predicted output and the ground truth labels, the weights and biases in the output layer are also learned throughout the training phase. The loss function is used to calculate the the mean squared error. In a nutshell, a DNN's output layer is in charge of creating the network's prediction or output, and the structure, activation function, and loss function of this layer are customized for the particular gradation of diabetic retinopathy.

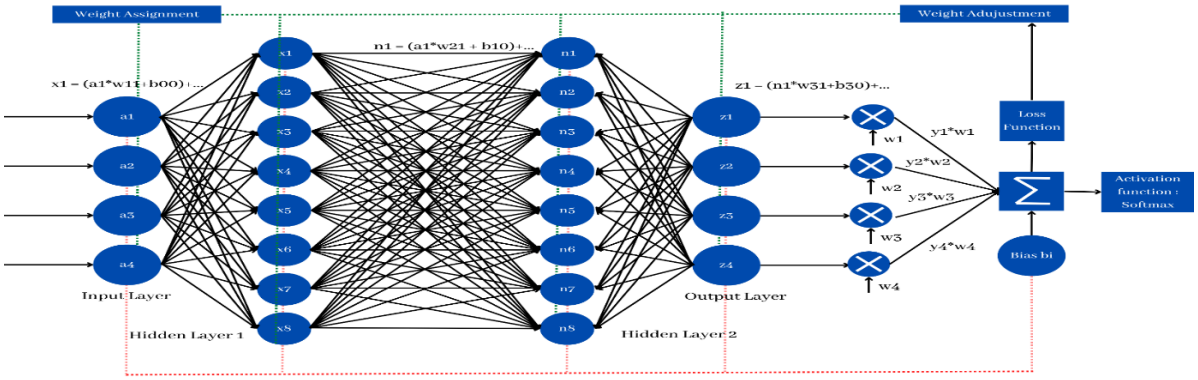

Fig.3. Deep Neural Network Architecture

iv. Loss Function

The loss function in deep neural networks (DNNs) gauges how well the network does gradation of diabetic retinopathy. The loss function provides a measure of how far the network's predictions deviate from the actual targets, which is used to direct the optimization process during training. The particular task at hand determines the loss function to be used. This function calculates the discrepancy between the actual distribution of the classes and the projected probability distribution. The cross-entropy loss is frequently employed in multiclass classification problems, when the objective is to predict one of several potential classes. For binary class cross-entropy loss is represented as:

$$J(\hat{y}, y) = -\frac{1}{m}\sum_{i=1}^{m}[y^{(i)}\log(\hat{y}^{i}) + (1 - y^{(i)})\log(1 - \hat{y}^{(i)})] \qquad 6$$

The mean squared error (MSE) loss is a popular choice for regression problems where the objective is to predict a continuous value. The average squared difference between the anticipated value and the actual value is what the MSE calculates.

v. Backpropagation

A popular algorithm for deep neural network training is backpropagation (DNNs). It is a form of supervised learning that involves modifying the network's weights and biases to reduce the discrepancy between expected and actual results. The forward pass through the network is the first step in the backpropagation algorithm's calculation of the output for a given input. The mistake is then determined by comparing the output to the actual output. In a process known as backpropagation, the error is subsequently transmitted back via the network.The algorithm determines the gradient of the error with regard to the weights and biases in each layer of the network throughout the backpropagation phase. The weights and biases are then updated using this gradient with the goal of lowering the error on the following forward pass through the network. Until weights and biases converge to levels that yield precise predictions on fresh, unforeseen data, this procedure is repeated numerous times. Backpropagation computes the gradients of the loss function with respect to the parameters of the neural network. The gradients are then used to update the parameters using an optimization algorithm (e.g., gradient descent). The backpropagation equations for the weights and biases are:

$$\frac{\partial J}{\partial W^{[l]}} = \frac{1}{m} dz^{[l]}.\, a^{[l-1]T} \qquad 7$$

$$\frac{\partial J}{\partial b^{[l]}} = \frac{1}{m}\sum_{i=1}^{m} dz^{[l](i)} \qquad 8$$

where, $dz^{[l]}$= “derivatives of the loss wrt- $z^{[l]}$ and $a^{[l-1]}$.

Stochastic gradient descent (SGD), which updates the weights and biases depending on a portion of the training data, and mini-batch gradient descent, which updates the weights and biases based on tiny batches of the training data, are examples of modifications on the backpropagation technique. Deep neural networks have been successfully trained for the diagnosis of diabetic retinopathy via backpropagation. Figure 3 illustrates it using the weight adjustment parameters.

vi. Softmax function

Deep neural networks (DNNs) uses the softmax function as an activation function in the output layer for multi-class classification problems. A probability distribution over the classes is produced from an input vector of real values.

The definition of the softmax function is as follows:

$$\text{softmax}(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \qquad (9)$$

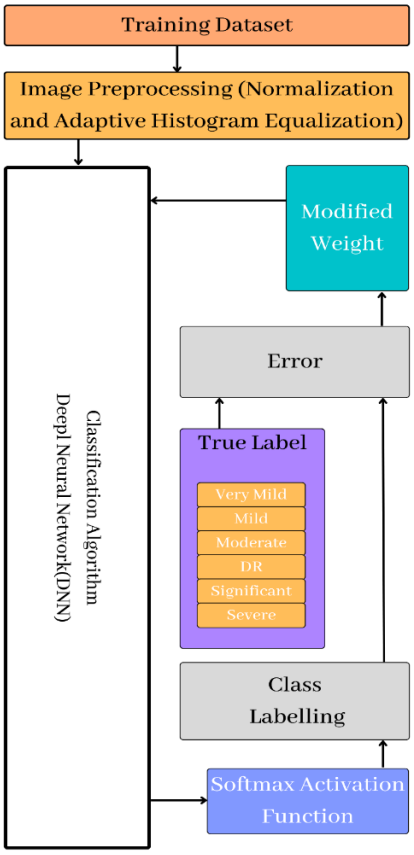

Fig.4. DR Classification.

where z_i is the input vector's ith element, K is the number of classes, and the denominator is the sum of all the input vector's exponential values.

Each member in the output vector reflects the likelihood that the input belongs to a specific class, and the softmax function transfers the input vector to a probability distribution over the classes. The output vector's elements add up to a total of one.

The probability of the various classes for a given input are computed in a DNN's output layer using the softmax function. The projected class for the input is determined by the class with the highest probability. In figure 4, it is depicted.

Given by is the softmax function's derivative with respect to the input z_i.

$$\frac{\partial \text{softmax}(z_i)}{\partial z_i} = \text{softmax}(z_i)\big(1 - \text{softmax}(z_i)\big) \qquad (10)$$

The backpropagation technique uses the derivative of the softmax function to compute the gradients of the output layer with respect to the input.

4. Result and Conclusion

Metrics like sensitivity, specificity, precision, and accuracy are used to assess how well diabetic retinopathy detection systems function.

- Sensitivity: Sensitivity is the proportion of real positive cases—patients with diabetic retinopathy—that the detection method accurately classifies as positive. A high sensitivity means that the system is capable of identifying the majority of diabetic retinopathy cases. High sensitivity, meanwhile, can sometimes lead to erroneous positive results.
- Specificity: The percentage of real negative cases—patients without diabetic retinopathy—that the detection technology accurately classifies as negative is known as specificity. A high specificity means that most non-diabetic retinopathy instances are appropriately identified by the method. High specificity, meanwhile, can also lead to false negatives.
- Precision: Precision is the percentage of cases that the system really classified as positive out of all cases. A high degree of precision shows that the algorithm is correctly classifying diabetic retinopathy instances and not incorrectly classifying non-diabetic retinopathy cases as positive. High sensitivity or specificity are not necessarily guaranteed by high precision, though.
- Accuracy: The percentage of cases that the system correctly classifies as positive or negative is known as accuracy. The system's overall effectiveness in identifying diabetic retinopathy is indicated by excellent accuracy. Figure 5 displays the DNN's sensitivity, specificity, precision, and accuracy percentages.

Precision and accuracy are measurements of the detection system's overall efficacy, whereas sensitivity and specificity are crucial indicators of the detection system's capacity to accurately distinguish between positive and negative cases. These parameters are taken into account when assessing a diabetic retinopathy detection system.

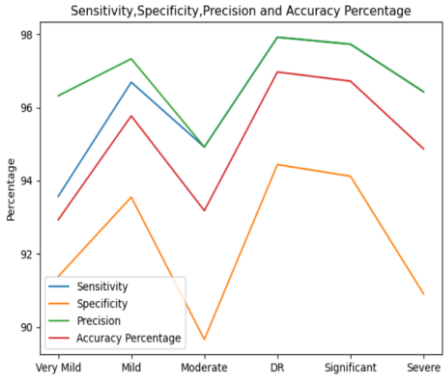

Fig.5. Sensitivity, Specificity, Precision and Accuracy Percentage.

It's critical in machine learning to assess a model's performance both during training (using training data) and after training (using unseen test data). The performance of the model on the training data is referred to as the "training accuracy," whereas the performance of the model on the test data is referred to as the "testing accuracy."

A model that performs well during training but poorly during testing is one that has overfitted the training set. In other words, the model cannot generalize to new data since it has learned the training data too thoroughly. This happens when the model is very complicated, the training data is insufficiently large or diverse, or all three.

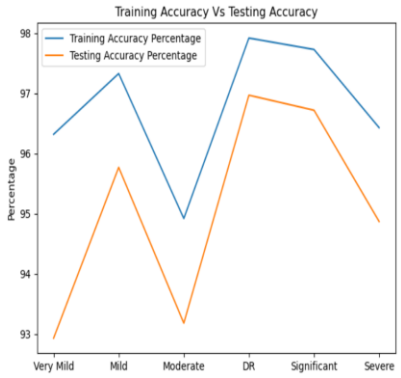

Fig.6. Training Accuracy Vs Testing Accuracy

On the other hand, a model that has low training accuracy and low testing accuracy indicates that the model is underfitting the training data. In other words, the model is not learning the training data well enough and is not able to generalize to new data.Training Accuracy Vs Testing Accuracy of deep neural network is as shown in figure 6.

As a result, a strong machine learning model needs to be very accurate throughout both training and testing. This shows that the model has mastered the training set sufficiently to generalize to fresh information. In order to improve the model's capacity for generalization, it is also helpful to determine whether the model is overfitting or underfitting and to make necessary corrections. The distribution of the real-world data the model is intended to operate on must be reflected in the test dataset in order to achieve high testing accuracy.

The percentage of samples that were wrongly classified, despite being real members of the very mild, mild, and moderate classes is shown in Figures 7, 8, and 9 for the corresponding classes.

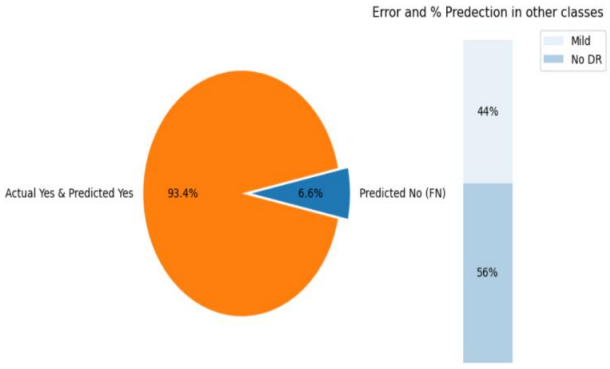

Fig.7. Actually, belongs to very mild class and % prediction in other classes.

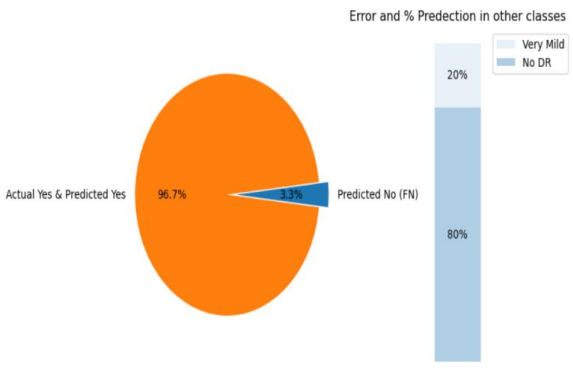

Fig.8. Actually, belongs to mild class and % prediction in other classes.

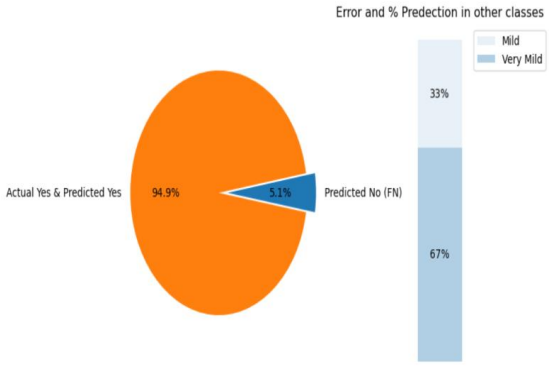

Fig.9. Actually, belongs to moderate class and % prediction in other classes.

Kappa is a statistical metric that assesses the degree of agreement in a medical diagnostic task between two observers, such as two doctors, or between an observer and an automated system, such as the diagnosis of diabetic retinopathy. The kappa value runs from -1 to 1, with 1 denoting perfect agreement, 0 denoting agreement as a result of chance, and negative numbers denoting agreement that is less than that of chance.

The agreement between a human grader and an automated system in determining whether diabetic retinopathy is present or absent in retinal images is measured using the kappa value in the detection of diabetic retinopathy. Between the automated system and the human grader, a high kappa value implies good agreement, whereas a low kappa value suggests poor agreement.

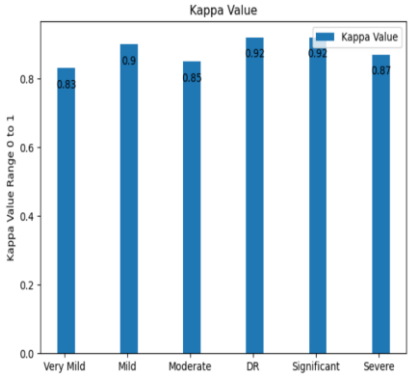

Fig.10. Kappa Value

As it accounts for the likelihood of agreement arising by chance, kappa value especially helpful when the condition being diagnosed is not common. Because there are so many true negatives in the data, accuracy alone may not be a good enough indicator of performance in these circumstances. The performance of the system is better accurately depicted by kappa, which compares the likelihood of agreement occurring by chance.

In conclusion, the kappa value statistic can be used to assess how well two observers—say, a human grader and an automated system—agree on the diagnosis of diabetic retinopathy. When the two are in agreement, a high kappa value denotes good agreement and a low kappa value, bad agreement. Kappa values for different classes is shown in figure 10.

5. Future Scope

Deep neural networks (DNNs) are being used to identify diabetic retinopathy, and there are various future paths for this technology's growth. Future applications of DNN for diabetic retinopathy detection include:

Increasing detection precision: Although DNN has demonstrated good results in diagnosing diabetic retinopathy, accuracy still has to be increased. The DNN may be trained on larger and more varied datasets, the network design can be optimized, and novel training techniques like transfer learning and semi-supervised learning can be investigated.

Investigating multi-modal imaging: Existing techniques for diagnosing diabetic retinopathy rely on retinal fundus pictures, which may not be completely accurate in detecting all forms of retinopathy. The sensitivity and specificity of the detection system could be increased by including additional imaging modalities, like optical coherence tomography (OCT).

Real-time detection development Early intervention and visual loss prevention may be possible with real-time detection of diabetic retinopathy. Real-time detection in clinical situations can be made possible by speed and efficiency-optimized DNN-based detection systems.

Including interpretability and explainability: The difficulty to interpret and explain DNN-based detection systems can be a barrier to their use in healthcare contexts. Explainability and interpretability in the detection system could boost physicians' decision-making abilities and increase their faith in the technology.

Individualized risk assessment: By locating patients who are at a high risk of developing diabetic retinopathy, earlier intervention and prevention may be possible. Personalized risk assessment models that consider unique patient characteristics and disease history may be created using DNN-based detection systems.

In conclusion, the potential for detecting diabetic retinopathy using DNN is enormous, and continuous research and development in this field may have important ramifications for the early diagnosis and prevention of vision loss in diabetic patients.

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