Grenze International Journal of Engineering and Technology, January Issue

Detecting Microaneurysms and Exudates in Retinal Images using Deep Neural Networks, and Comparing their Performance with Alternative Neural Network Models

Mr. P. N. Maldhure[1] and Dr. S. R. Ganorkar[2]
[1-2]Electronics and Telecommunication Engineering, Sinhgad college of Engineering
(Savitribai Phule Pune University, Pune), Pune, India
Email: maldhureprasad@gmail.com, srganorkar.scoe@sinhgad.edu

***Abstract*— Diabetes frequently results in diabetic retinopathy, which, if unchecked, can result in blindness. Around one in three diabetics, according to the World Diabetes Federation, have diabetic retinopathy in some form. In affluent nations, diabetic retinopathy is the main factor of blindness among working-age individuals. With the progression of diabetes, diabetic retinopathy is more common. Two typical diabetes-related eye abnormalities are microaneurysms and exudates, which are frequently linked to diabetic retinopathy. The severity of the condition and the presence of particular retinal abnormalities are used to grade diabetic retinopathy. Machine learning algorithms are trained to examine retinal images and find particular traits connected to diabetic retinopathy, like exudates and microaneurysms. The machine learning algorithms used here are convolutional neural network(CNN), Weighted Neural Network(WNN), Hybrid Neural Network(HNN) and Deep Neural Network(DNN). Among all the used algorithms DNN shows superior results over others having Sensitivity, specificity, precision, accuracy, and Kappa value are95.74%, 92.31%, 96.77%, 94.74%, and 0.87, respectively.**

***Index Terms*— convolutional neural network (CNN), Weighted Neural Network(WNN), Hybrid Neural Network(HNN) and Deep Neural Network(DNN)..**

I. INTRODUCTION

Diabetic retinopathy (DR) refers to a condition affecting the eyes due to diabetes [1]–[4]. It manifests primarily in two forms: Diabetic retinopathy without proliferation (NPDR): The retina swells during this early stage of the disease when the retina's blood vessels leak fluid or blood. This may result in floaters, impaired vision, and trouble seeing at night[5], [6].Proliferative diabetic retinopathy (PDR) represents a severe stage of the disease where retinal blood vessels are significantly damaged, leading to their closure and thereby depriving the retina of blood supply. Because to their fragility and potential for blood leakage, new blood vessels begin to form as a result, which can cause scar tissue and even eyesight loss[7], [8].
Exudates and microaneurysms are two types of changes that can occur in the retina due to diabetic retinopathy.

Grenze ID: 01.GIJET.11.1.14_1

Microaneurysms are small, balloon-like bulges that form in the walls of retinal blood vessels as a result of damage caused by elevated blood sugar levels[9]. These microaneurysms have the potential to leak blood and fluid, which can cause retinal edoema and reduced vision. On a retinal exam, microaneurysms can be noticed. These are frequently the first indication of diabetic retinopathy[10].Exudates are deposits in the retina that are yellowish or white and frequently form rings around the macula. These deposits, which are brought on by blood vessel damage-related fluid leakage, can thicken the retina and impair vision. Exudates are seen during an eye exam and frequently indicate more severe diabetic retinopathy[11]–[13]. Figure 1 displays both Microaneurysm and Exudates.

Grading diabetic retinopathy is a method for categorizing the severity of DR based on how the retina appears during an eye exam. The grading system aids in directing care and tracking the development of illness.

Machine learning algorithms are crucial for detecting diabetic retinopathy because they can increase the precision and effectiveness of the screening procedure. In order to detect diabetic retinopathy, machine learning algorithms are crucial because they offer precise, effective, and economical screening, which can result in early detection and prompt management, improving patient outcomes[14]–[18]. Total in four ways machine algorithm is implemented i.e., CNN, WNN, HNN and DNN. Out of which DNN shows the more superior results compared to other machine learning algorithms.

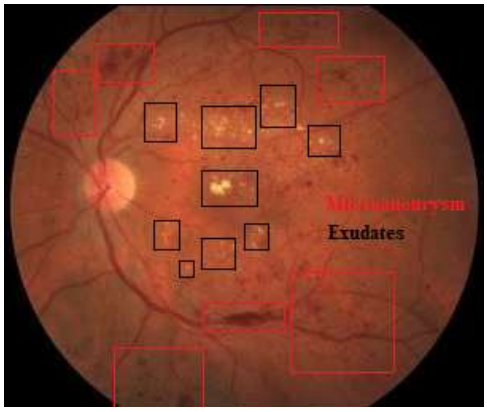

Figure 1. Microaneurysm and Exudates

A. Convolutional Neural Network

A CNN is trained using a sizable dataset of retinal pictures that have been tagged with the various disease severity levels.The following are the procedures for employing CNNs to identify diabetic retinopathy: Before sending the retinal pictures to CNN, preprocessing is required. This procedure entails scaling the image, cropping it to remove pointless portions, and changing the color balance. Data Augmentation: The images are subjected to data augmentation techniques in order to avoid overfitting and expand the dataset. To generate fresh training examples, the photos are randomly rotated, flipped, or scaled. Training the CNN: Using a labelled dataset, a CNN is trained on the enhanced and preprocessed pictures. The CNN learns to recognize the features and patterns in images that indicate different stages of diabetic retinopathy. After training, the CNN is verified on a different dataset to see how well it can recognize diabetic retinopathy. Testing: To determine the extent of diabetic retinopathy, new retinal pictures are used to test the CNN. The likelihood that an image falls within each severity category will be output by CNN. The potential to increase the precision and effectiveness of diabetic retinopathy screening has been demonstrated by the use of CNNs for the detection and grading of DR.

Several layers make up CNNs, which are used to find different features from images and make predictions. The primary categories of layers in a CNN are as follows: Continuum Layers: A collection of filters are applied by convolutional layers to the input image, allowing the network to recognize features like edges, corners, and forms. Throughout the training process, the filters are picked up. Pooling layers decrease the spatial resolution of feature maps by downsampling the output of convolutional layers, which enhances the network's robustness to small changes in the input image. Activation layers apply a non-linear function to the output of convolutional and pooling layers, enabling the network to learn complex representations of the input image. Fully connected layers, positioned towards the end of the network, generate predictions based on the learned features by combining the results of the preceding layers to produce a final output, such as a probability score for each class. Figure 2 illustrates the overall model and each layer.

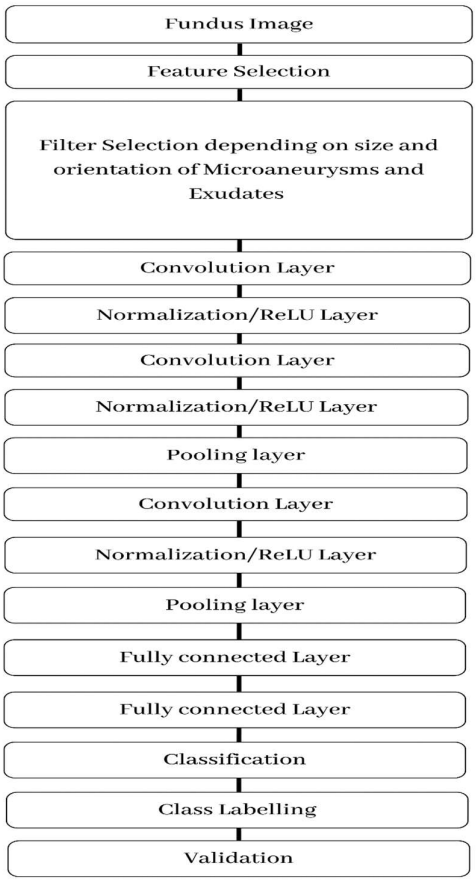

Figure 2. Convolutional Neural Network

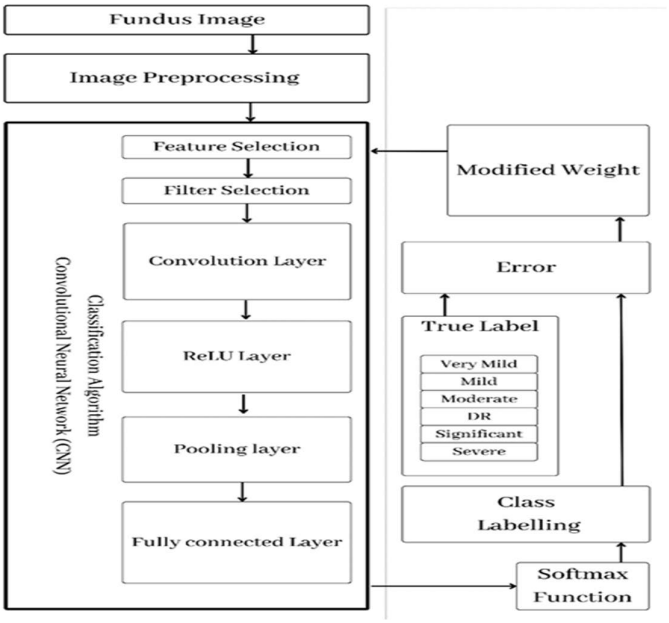

Figure 3. Weighted Neural Network

B. Weighted Neural Network

An artificial neural network that uses variable weights for its inputs, hidden layers, and outputs is known as a weighted neural network. The output of the network may change as a result of how these weights are employed to modify the strength of the connections between the neurons.

In situations where some inputs or outputs are more significant than others or where some inputs are more likely to have an impact on the output than others, weighted neural networks are frequently used.

During training, an optimization algorithm adjusts the weights in a neural network. The goal is to find the weights that minimize the difference between the predicted and actual outcomes. Figure 3 illustrates the operation of the Weighted Neural Network (WNN).

C. Hybrid Neural Network

A hybrid neural network with image split is a type of neural network architecture designed to enhance the accuracy and efficiency of diagnosing diabetic retinopathy. The input image is divided into smaller pieces in this design, and each of those pieces is processed by a different sub-network. The final forecast is then created by combining the results from the sub-networks. The split image method is based on the notion that different areas of the retina could be damaged by diabetic retinopathy differently and that by studying each area separately, the detection process can be made more accurate. This strategy and the strength of neural networks are combined in the hybrid architecture to learn intricate representations of the input data. CNNs, which are created to analyze images and develop feature representations, are used as the sub-networks in the unique architecture of a hybrid neural network with image split. The input image is initially divided into smaller portions in the hybrid architecture depicted in Figure 4, which are then analyzed by different CNNs.A fully connected layer that can learn to weight the contributions from each sub-network then combines the outputs from the CNNs. The network's final output is a classification of diabetic retinopathy. Deep Neural Network (DNN) proposed method is described in brief in methodology.

II. Related Work

This section reviews existing research on various machine learning algorithms for detecting diabetic retinopathy. In one study [19], the authors proposed an automatic classification scheme using convolutional neural networks (CNNs) to enhance the classification, segmentation, and detection of diabetic retinopathy. The performance of models such as AlexNet, VggNet, GoogleNet, and ResNet was evaluated on diabetic retinopathy images from the publicly available Kaggle platform, achieving a maximum classification accuracy of 95.68%. Another study [20] employed contrast-limited adaptive histogram equalization techniques followed by a CNN for diagnosis. This approach was tested on 400 retinal fundus images from the MESSIDOR database, resulting in performance metrics of 97% accuracy, 98% specificity, 94% precision, 94% F1 score, and 95% G-mean.

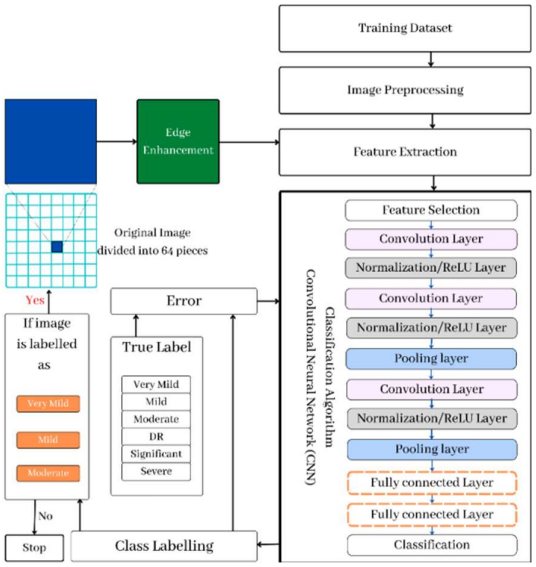

Figure 4. Hybrid Neural Network

A model proposed in another study [9] used a deep neural network that relies on score distribution from the final layer among the input pixels. It achieved over 90% sensitivity and specificity in detecting severe cases of diabetic retinopathy and could classify retinal images into five categories of disease severity. In another study [21], a method involving a group of neural networks built using CNN and typical deep neural network customizations was proposed. The DeepDR system was developed using a high-quality dataset of diabetic retinopathy medical images. The study explored the relationship between the number of class labels and optimal component classifiers, as well as the effects of various component classifier combinations on integration performance. The method reported 97.5% sensitivity, 97.7% specificity, and 97.7% area under the curve, with the grading model achieving 98.1% sensitivity and 98.9% specificity. Lastly, another study [22] presented a CNN model for diabetic retinopathy detection, trained on the publicly accessible Kaggle dataset using a graphics processing unit (GPU). This CNN achieved a sensitivity of 95% on the 80,000 training images and an accuracy of 75% on the 5,000 validation images.

III. METHODOLOGY

A. Dataset

The IDRiD (Indian Diabetic Retinopathy Image Dataset) is an essential resource for diabetic retinopathy research, specifically targeting an Indian population. Published in 2018, the dataset comprises 516 high-resolution fundus images collected from an eye clinic in Nanded, India. These images were captured using a single fundus camera with a resolution of 4288 × 2848 pixels and a 50-degree Field of View (FOV). Each image in the IDRiD dataset is meticulously labeled according to the International Clinical Diabetic Retinopathy Scale, detailing the disease's severity stages: mild, moderate, severe, and PDR (Proliferative Diabetic Retinopathy).The distribution of images across severity stages within the IDRiD dataset reveals variations in representation, with the highest numbers observed in the normal and moderate categories. Conversely, the mild stage is the least represented, comprising only 25 images. Images depicting severe and PDR stages are also included, though less frequently compared to milder stages.

B. Adaptive Histogram Equalization

The adaptive histogram equalization (AHE) technique was applied to fundus images to enhance contrast in digital images. AHE operates by segmenting a picture into small areas and separately performing histogram equalization to each area. More contrast enhancement is possible as a result, especially in low contrast or poorly lit portions of the image. Figure 5 compares adaptive and traditional histogram equalization and illustrates how AHE can be used to improve the contrast of microaneurysm and exudates in fundus images.

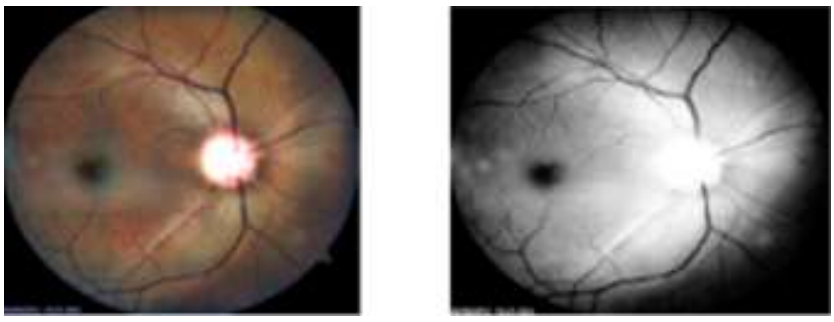

Figure 5. The difference between adaptive and conventional histogram equalization

C. Deep Neural Network

When used to analyze retinal pictures to identify diabetic retinopathy, deep neural networks (DNNs) have produced promising results. The general layout of a DNN for this task is as follows:

The first phase entails preparing retinal pictures in order to improve visibility of exudates and microaneurysms, which are hard to spot and inconspicuous. By enhancing image contrast, adaptive histogram equalization helps to make these features easier to see. Consistency in input data is ensured by standardizing pixel intensity values across images, which improves model training. By producing more training samples, data augmentation techniques including rotation, scaling, flipping, and adding Gaussian noise improve the model's resilience and capacity to generalize from a variety of retinal pictures. A neural network architecture specifically tailored to the task is intended to capture the complex characteristics of exudates and microaneurysms. Convolutional layers

with variable kernel sizes are used in multi-scale feature extraction to recognize features at different scales, such as minuscule lesions like microaneurysms and bigger, irregularly shaped exudates.
Proposed work included residual blocks that, by resolving the vanishing gradient issue, aid in the training of deeper networks. The network concentrates on pertinent retinal regions by incorporating an attention mechanism, which improves the detection of minute aberrations.
A framework is put into place to increase detection accuracy. Potential areas of interest (ROIs) where microaneurysms and exudates may be present are generated by this network. The model concentrates on these important places by reducing the scope of the examination. Next, dense probability maps for lesion presence are produced using a fully convolutional network (FCN), emphasizing regions with high lesion probability. A specialized CNN is used to extract patches from the ROIs and classify them, allowing for fine-grained lesion classification that differentiates between exudates and microaneurysms. With the aid of this design, the identified lesions are precisely segmented, revealing their regions and limits.
The layers in a deep neural network for detecting diabetic retinopathy are as follows:
Convolutional Layer: Convolutional layers are employed to extract characteristics from the input image. The layer creates a set of feature maps by applying a number of filters to the input image. A convolutional layer's equation can be written as:

$$Y = f(\sum(W * X) + b) \quad (1)$$

Where: Y: Output feature map,f: Activation function (ReLU),W: Filter weights, X: Input feature map and b: Bias term
Pooling Layer: Pooling layers downsample the feature maps generated by the convolutional layer. The layer outputs a single value that represents the maximum (Max Pooling) or average (Average Pooling) value in each small region of the feature map. A pooling layer's equation can be written as:

$$Y = f(\text{pool}(X)) \quad (2)$$

Where: Y: Output feature map, f: Activation function (e.g. ReLU), pool: Pooling function (Max Pooling) and X: Input feature map
Fully Connected Layer: The link between the features retrieved by the convolutional and pooling layers and the output class is learned using fully connected layers. The layer applies a set of weights to the previous layer's output that has been flattened in order to obtain a set of outputs. A completely connected layer's equation can be written as:

$$Y = f(W * X + b) \quad (3)$$

Where:Y: Output vector, f: Activation function (e.g. ReLU), W: Weight matrix, X: Input vector and b: Bias vector
Output Layer: The output layer, the last layer in the network, creates the output class that was expected. The output layer's equation is determined by the particular problem being solved. The output layer employs a sigmoid activation function and generates a single output value between 0 and 1 for binary classification problems like the identification of diabetic retinopathy. The following is an expression for the output layer equation:

$$Y = \text{sigmoid}(W * X + b) \quad (4)$$

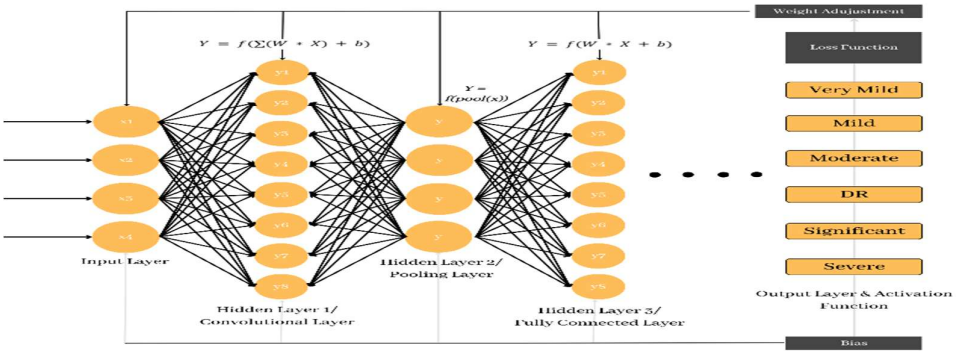

Figure 6. Deep Neural Network (DNN)

Where: Y: Output scalar between 0 and 1, sigmoid: Sigmoid activation function, W: Weight vector, X: Input vector and b: Bias scalar

IV. Result and Conclusion

In order to assess the effectiveness of the employed algorithms, many metrics are used in the detection of diabetic retinopathy. Let's start by talking about sensitivity, which is a test's ability to correctly identify patients with diabetic retinopathy [19].
The formula for sensitivity is:

$$\text{Sensitivity} = \frac{\text{truepositives}}{(\text{truepositives} + \text{falsenegatives})} \quad (5)$$

where the amount of patients with diabetic retinopathy who were correctly recognized as having the condition by the test is known as true positives, and the amount of patients with the condition who were wrongly labelled as not having it is known as false negatives.
Low sensitivity suggests that the test may fail to detect some individuals who have diabetic retinopathy, whereas a high sensitivity suggests that the test is effective at detecting patients with the condition.
Figure 7 compares the sensitivity of DNN to previously implemented CNN, WNN, and HNN for various classes.
The ability of a test to correctly identify people who do not have diabetic retinopathy is known as specificity when it comes to the diagnosis of diabetic retinopathy.The formula for specificity is [20], [21]:

$$\text{Specificity} = \frac{\text{true negatives}}{(\text{true negatives} + \text{false positives})} \quad (6)$$

False positives are the number of patients who do not have diabetic retinopathy but are mistakenly identified as having the condition by the test, and true negatives are the number of patients who do not have diabetic retinopathy but are correctly diagnosed as not having the condition by the test.
Low specificity means the test may falsely identify some individuals who do not have the condition as having it, while a high specificity means the test is effective at detecting patients without diabetic retinopathy. Figure 8 compares the specificity of DNN with previously implemented CNN, WNN, and HNN for various classes.
Precision, referred to as positive predictive value, is the percentage of patients who truly have the condition being tested for when they are classified as positive by a diagnostic test. Precision in the detection of diabetic retinopathy refers to the percentage of patients diagnosed as having the condition who actually do.The formula for precision is:

$$\text{Precision} = \frac{\text{true positives}}{(\text{true positives} + \text{false positives})} \quad (7)$$

where the number of patients with diabetic retinopathy who were correctly diagnosed by the test as having the condition is known as true positives, and the number of patients who do not have the condition is known as false positives.
Low precision means the test may misidentify some people as having the condition when they do not, while high precision means the test is good at detecting patients who actually have diabetic retinopathy. Figure 9 compares the precision of DNN with that of previously implemented CNN, WNN, and HNN for various classes.
Accuracy in the context of detecting diabetic retinopathy refers to the ability of a diagnostic test to correctly differentiate between patients who have the condition and those who do not. The accuracy equation is:

$$\text{Accuracy} = \frac{(\text{true positives} + \text{true negatives})}{\left(\begin{matrix}\text{true positives} + \text{true negatives} + \\ \text{false positives} + \text{false negatives}\end{matrix}\right)} \quad (8)$$

True positives indicate the count of individuals with diabetic retinopathy correctly identified by the test, while true negatives represent those without the condition correctly identified. False positives are instances where the test incorrectly identifies patients without diabetic retinopathy as positive, and false negatives occur when patients with the condition are incorrectly identified as negative by the test.
Low accuracy means that the test may misidentify some patients as having or not having diabetic retinopathy, while high accuracy means that the test is good at accurately identifying patients with and without the condition.
To ensure that patients receive prompt care and management of their illness, TP error analyses how frequently the system accurately identifies individuals with diabetic retinopathy. When the system accurately recognizes

people with diabetic retinopathy, as is the case when the TP error is large, the risk of vision loss and other consequences related to the condition is decreased.

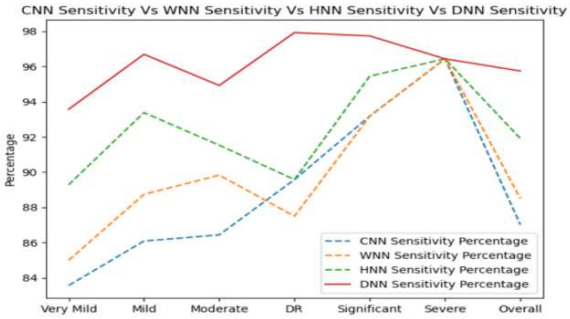

Figure 7. Sensitivity comparison of DNN with CNN, WNN & DNN for different classes.

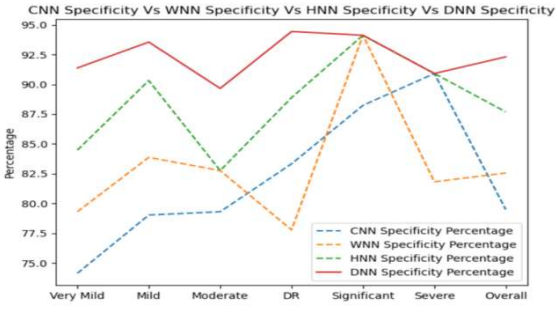

Figure 8. Specificity comparison of DNN with CNN, WNN & DNN for different classes.

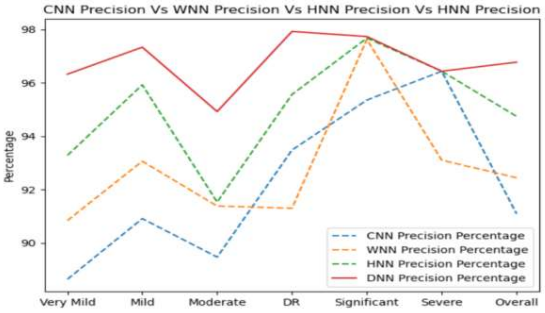

Figure 9. Precision comparison of DNN with CNN, WNN & DNN for different classes.

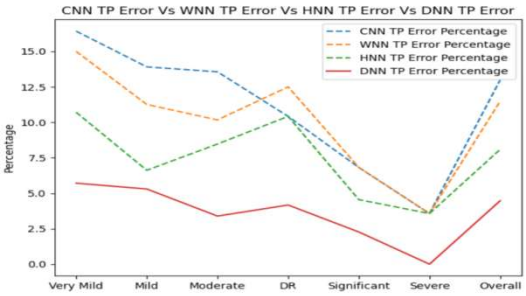

Figure 10. True Positive Error comparison of DNN with CNN, WNN & DNN for different classes.

FP error, on the other hand, gauges how frequently patients without diabetic retinopathy are mistakenly classified as having the condition by the system. Increased healthcare costs as well as unneeded testing, medication, and anxiety for those who don't genuinely have the ailment might result from this. As a result, it's critical to maximize TP error while minimizing FP error. As depicted in Figures 10 and 11, the true positive and false positive error percentages of DNN for various classes are contrasted with those of previously implemented CNN, WNN, and HNN.

Kappa value is a statistical indicator of the degree of agreement or inter-rater reliability between two observers. It can be used to evaluate the level of agreement between two or more independent specialists who are analyzing retinal pictures for the existence and severity of diabetic retinopathy in the context of detecting it.The formula for kappa value is:

$$\text{kappa} = \frac{(\text{Po} - \text{Pe})}{(1 - \text{Pe})} \qquad (9)$$

where:Po = the observed percentage of agreement between raters and Pe is the percentage of chance-based agreement amongst raters.

It needs to count the instances in which the raters agree on the classification of diabetic retinopathy and divide that number by the total number of observations in order to arrive at Po. Based on the distribution of ratings among the raters, one must compute the expected probability of chance agreement in order to calculate Pe. Kappa values range from -1 to +1, where values closer to +1 indicate higher levels of agreement, values closer to 0 indicate agreement no better than chance, and values closer to -1 indicate disagreement among raters. Kappa values between 0.40 and 0.75 are considered acceptable to good agreement, while values above 0.75 indicate outstanding agreement.

Figure 12 compares the kappa value of the DNN with the previously implemented CNN, WNN, and HNN for various classes. Figures 13 and 14 compare the statistics of DNN with CNN, WNN, and HNN for extremely mild and mild symptoms, respectivelyin view of early detection of diabetic retinopathy.

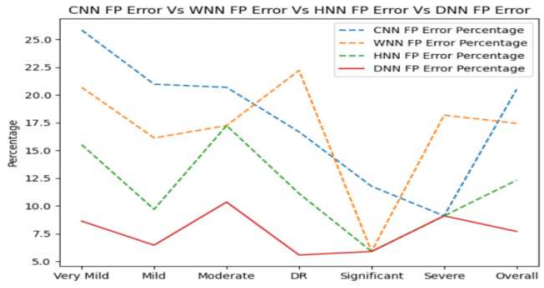

Figure 11. False Positive Error comparison of DNN with CNN, WNN & DNN for different classes.

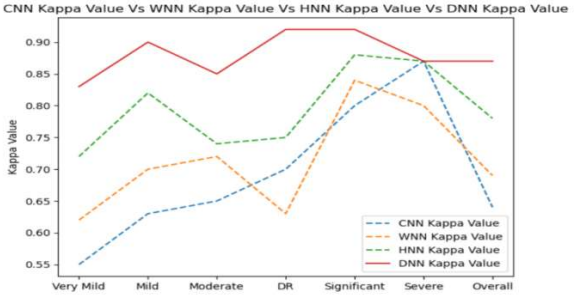

Figure 12. Kappa value comparison of DNN with CNN, WNN & DNN for different classes.

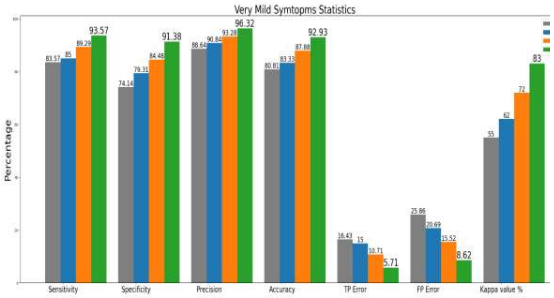

Figure 13. Very mild symptoms statistics comparison of DNN with CNN, WNN & DNN.

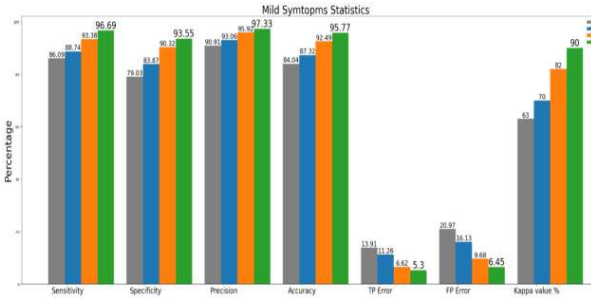

Figure 14. Mild symptoms statistics comparison of DNN with CNN, WNN & DNN.

V. Future Scope & Conclusion

Early detection and treatment are crucial for patients with diabetic retinopathy to prevent vision loss. Machine learning algorithms, particularly in the analysis of retinal images, have shown promising results in detecting diabetic retinopathy. The potential of these algorithms to predict the condition is significant, necessitating more accurate and efficient screening techniques as diabetes prevalence rises. By analyzing large volumes of retinal images and identifying subtle disease symptoms that might be overlooked by human observers, machine learning algorithms have the capacity to enhance the accuracy and effectiveness of diabetic retinopathy screening. Future electronic health records and mobile health applications may incorporate machine learning algorithms to offer patients real-time diabetic retinopathy screening. As a result, patients might receive quick medical care and treatment, which would ultimately improve their visual results. Furthermore, using machine learning techniques to diagnose diabetic retinopathy may reveal new information about the condition and how it develops. Machine learning algorithms may find novel patterns and risk factors related to diabetic retinopathy by examining massive datasets of retinal images.

References

[1] Haidar Almubarak, Yakoub Bazi, Naif Alajlan, Two-stage mask-rcnn approach for detecting and segmenting
[2] the optic nerve head, optic disc, and optic cup in fundus images, Appl. Sci. 10 (11) (2020) 3833
[3] Wentao Zhao, Zhe Zhang, Zhao Wang, Yan Guo, Jun Xie, Xinying Xu, Eclnet: Center localization of eye structures based on adaptive Gaussian ellipse heatmap, Comput. Biol. Med. 153 (2023) 106485.
[4] Anil K. Shukla, Rajesh K. Pandey, Ram Bilas Pachori, A fractional filter based efficient algorithm for retinal blood vessel segmentation, Biomed. Signal Process. Control 59 (2020) 101883.
[5] Yehui Yang, Tao Li, Wensi Li, Haishan Wu, Wei Fan, Wensheng Zhang, Lesion detection and grading of diabetic retinopathy via two-stages deep convolutional neural networks, in: International Conference on Medical Image Computing and Computer-Assisted Intervention, Springer, 2017, pp. 533–540.
[6] Xiyue Wang, Yuqi Fang, Sen Yang, Delong Zhu, Minghui Wang, Jing Zhang, Jun Zhang, Jun Cheng, Kai-yu Tong, Xiao Han, CLC-net: Contextual and local collaborative network for lesion segmentation in diabetic retinopathy images, Neurocomputing (2023).
[7] Navoneel Chakrabarty, A deep learning method for the detection of diabetic retinopathy, in: 2018 5th IEEE Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering, UPCON, IEEE, 2018, pp. 1–5.

[8] S. Gayathri, Varun P. Gopi, Ponnusamy Palanisamy, A lightweight CNN for diabetic retinopathy classification from fundus images, Biomed. Signal Process. Control 62 (2020) 102115.
[9] Varun Gulshan, Lily Peng, Marc Coram, Martin C. Stumpe, Derek Wu, Arunacha lam Narayanaswamy, Subhashini Venugopalan, Kasumi Widner, Tom Madams, Jorge Cuadros, et al., Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs, JAMA 316 (22) (2016) 2402–2410.
[10] Debiao Zhang, Wei Bu, Xiangqian Wu, Diabetic retinopathy classification using deeply supervised ResNet, in: 2017 IEEE SmartWorld, Ubiquitous Intelligence Computing, Advanced Trusted Computed, Scalable Computing Communications, Cloud Big Data Computing, Internet of People and Smart City Innovation, SmartWorld/SCALCOM /UIC/ATC/ CBDCom/IOP/SCI, IEEE, 2017, pp. 1–6.
[11] Pallab Roy, Ruwan Tennakoon, Khoa Cao, Suman Sedai, Dwarikanath Maha patra, Stefan Maetschke, Rahil Garnavi, A novel hybrid approach for severity assessment of diabetic retinopathy in colour fundus images, in: 2017 IEEE 14th International Symposium on Biomedical Imaging, ISBI 2017, IEEE, 2017, pp. 1078–1082.
[12] Zhentao Gao, Jie Li, Jixiang Guo, Yuanyuan Chen, Zhang Yi, Jie Zhong, Diagnosis of diabetic retinopathy using deep neural networks, IEEE Access 7 (2018) 3360–3370.
[13] Yung-Hui Li, Nai-Ning Yeh, Shih-Jen Chen, Yu-Chien Chung, et al., Computer assisted diagnosis for diabetic retinopathy based on fundus images using deep convolutional neural network, Mob. Inf. Syst. 2019 (2019).
[14] Avinash Kori, Sai Saketh Chennamsetty, Varghese Alex, et al., Ensemble of convolutional neural networks for automatic grading of diabetic retinopathy and macular edema, 2018, arXiv preprint arXiv:1809.04228.
[15] Along He, Tao Li, Ning Li, Kai Wang, Huazhu Fu, CABNet: Category attention block for imbalanced diabetic retinopathy grading, IEEE Trans. Med. Imaging 40 (1) (2020) 143–153.
[16] Charu Bhardwaj, Shruti Jain, Meenakshi Sood, Transfer learning based robust automatic detection system for diabetic retinopathy grading, Neural Comput. Appl. 33 (20) (2021) 13999–14019.
[17] Mukkesh Ganesh, Sanjana Dulam, Pattabiraman Venkatasubbu, Diabetic retinopa thy diagnosis with InceptionResNetV2, xception, and EfficientNetB3, in: Artificial Intelligence and Technologies: Select Proceedings of ICRTAC-AIT 2020, Springer, 2021, pp. 405–413.
[18] J. Jasper Gnana Chandran, J. Jabez, Senduru Srinivasulu, Auto-metric graph neural network optimized with capuchin search optimization algorithm for coinciding diabetic retinopathy and diabetic macular edema grading, Biomed. Signal Process. Control 80 (2023) 104386.
[19] A. Abirami, R. Kavitha, A novel automated komodo mlipir optimization-based attention BiLSTM for early detection of diabetic retinopathy, Signal, Image Video Process. (2023) 1–9.
[20] Suvajit Dutta, B.C. Manideep, Syed Muzamil Basha, Ronnie D. Caytiles, N.C.S.N. Iyengar, Classification of diabetic retinopathy images by using deep learning models, Int. J. Grid Distrib. Comput. 11 (1) (2018) 89–106.
[21] Anukriti Singh, Wooyoung Kim, Detection of diabetic blindness with deep learning, in: 2020 IEEE International Conference on Bioinformatics and Biomedicine, BIBM, IEEE, 2020, pp. 2440–2447.Wejdan L. Alyoubi, Maysoon F. Abulkhair, Wafaa M. Shalash, Diabetic retinopa thy fundus image classification and lesions localization system using deep learning, Sensors 21 (11) (2021).