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DETECTION AND GRADING OF DIABETIC RETINOPATHY IN RETINAL FUNDUS IMAGE USING SPIKING NEURAL NETWORK

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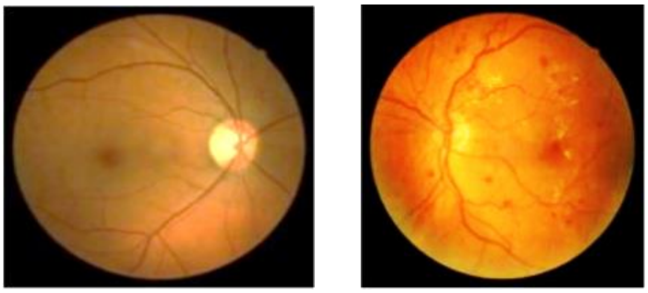
Abstract - Diabetic retinopathy (DR) is one of the world's most significant difficulties of diabetes identified with eye illness which happens when veins in the retina become swollen and release liquid which at last prompts vision misfortune. Early discovery of DR can anticipate the harm to the retina and vision misfortune or at least moderate its movement. The main objective of the proposed work is to detect the severity of Diabetic Retinopathy (DR) in the retinal fundus image using the spiking neural network. In this process, the retinal fundus images are collected from the STARE database. The data are pre-processed using the Wiener filter to extract the green channel and remove the noise. Then the Histogram equalization technique is used to enhance the contrast of the fundus image. DR is analyzed by separating blood vessels, veins, optic plates, and exudates from retinal fundus images by using mathematical morphology and finally a Prediction Spiking Neural Network(SNN) classifier and RG-based segmentation approach is implemented to segment the normal and DR from the fundus image. The performance of this segmentation approach is executed for different DR datasets and the outcomes demonstrate that; the proposed segmentation approach produces 96% accuracy for the detection of DR when stood out from different existing strategies.

***Key Words*: Diabetic retinopathy, retinal fundus image, Histogram equalization, Spiking Neural Network, RG-based segmentation.**

1. INTRODUCTION

Diabetic retinopathy (DR) is a common microvascular complication of diabetes mellitus and is the leading cause of visual loss in the elderly. Hyperglycemia and altered metabolic pathways lead to oxidative stress and the development of neurodegeneration in the initial stage of diabetic retinopathy. The World Health Organization estimates that more than 463 million people worldwide, will rank as the sixth leading cause of death globally by 2030. and this number is projected to rise to 700 million by 2045[1]. Diabetic retinopathy (DR) is a common microvascular complication of diabetes mellitus and is the leading cause of visual loss in the elderly[2]. Hyperglycemia and altered metabolic pathways lead to oxidative stress and the development of neurodegeneration in the initial stage of diabetic retinopathy [3]. Diabetic Retinopathy is asymptomatic; it does not affect view until it reaches a progress stage. Therefore, screening of Diabetic Retinopathy is crucial for type1 (non-Proliferative) and type 2 (Proliferative) diabetic patients as both types are at risk of Diabetic retinopathy [4].



(a) Healthy Retina (b)Diabetic Retinopathy

Fig.1.1 Fundus images of Healthy and Diabetic Retinopathy

Fig.1.1(a) demonstrates the healthy retina, Fig. 1.1(b) demonstrates the DR fundus retina image. Diabetes mellitus is a chronic disease characterized by hyperglycemia that causes numerous complications in humans [7-9]. Retinal fundus images are the orthoimages that are highly used to measure and detect abnormalities in the optics system. It provides detailed information about the optical blood vessels, optical disc, and optical cup [12].

The implementation of the Wiener filter and pixel correlation histogram equalization process is highly effective in removing the noise present in the retinal fundus image. The spiking neural network, a class of artificial neural networks helps to segment the blood vessels and detect the grading severity of diabetic retinopathy in the fundus image. The process typically involves preprocessing the fundus image to remove noise and baseline drift, followed by histogram equalization to enhance the contrast of the image. Feature extraction is then performed on the enhanced image, and an SNN classification algorithm is used to segment Diabetic retinopathy based on grading severity. Overall, the use of Wiener filter along with the pixel correlation histogram is used to reduce noise and enhance the contrast of the image without affecting the original data and information. The Region-based thresholding and SNN network model is used to extract features from the enhanced image and segment the DR lesions. This technique improved the accuracy of the DR lesions in fundus images.

The Order of the paper is given as follows, section 2 covers the literature review, section 3 narrates the proposed research methodology, section 4 has results and section 5 holds the conclusion part.

2. LITERATURE REVIEW

A great deal of various methodologies had been developed for identifying DR. This literature section explains some of the recent deep learning and Diabetic retinopathy research and state a few limitations faced by the current image processing technologies.
In 2017 Gargeya and leng have developed an automated deep-learning model to identify Diabetic Retinopathy. The model was tested biologically using MESSIDOR 2 and E-Optha databases for the validation process. The implementation drastically reduced the rate of vision loss attributed to DR on a global basis [10].
In 2018 Godlin Atlas L et al. had detected the DR from fundus images by using ANFIS classifier and MRG segmentation. In this method, the normal and abnormal images are classified using the ANFIS classifier. The identified DR images are then segmented using the Modified RG method. GWO technique has been used to optimize the threshold value. [11].
Qummar etal., in 2019 had put forward an automated deep learning model for detecting Diabetic Retinopathy. This technique the fundus images were selected from the Kaggle dataset and trained using the ensemble of five deep convolutions neural network (CNN) models. This classification improved the accuracy rate but affected the specificity due to the misclassification of the Positive classes [14].
In 2020, Beede, E et al. developed a Human-centered DL evaluation system deployed in Clinics for the identification of diabetic retinopathy. This sociotechnical study of a deep learning system for the detection of diabetic eye disease used with patients in clinical care. The research needed to understand how the system affects the patient experience; in particular, patients' trust of the result, and the likelihood to act on the result, and should improve the end-to-end service design of AI-based clinical products [5].
Shankar K et al., (2020) developed a Synergic Deep learning model to automatically classify the Fundus retinopathy images of diabetic patients. This method involved several processes namely preprocessing, segmentation, and classification. Synergic deep learning (SDL) model is applied to classify DR fundus images to various severity levels [15].
Bora etal., (2021) developed a deep learning approach for predicting the risk of developing Diabetic Retinopathy in patients with Diabetes within 2 years. The study screened patients with teleretinal retinopathy from the three or one field of color fundus photography. In addition, the process stated several limitations that include unavailability of comorbidities in dataset, unclear device information, second grading variability and risk of bias [6].
In 2021 Tsiknakis et al. conducted a review on Diabetic retinopathy based on the the classification of the fundus images. The review discussed the processing technique and performance of the deep learning model in the classification of the fundus image. The review discussed about the processing techniques and architectural model of the deep learning network that has improved performance and relatively high efficacy [16].
In 2021, Kumari et al., screened the selfie fundus image to detect the diabetic retinopathy. The study was undertaken over a two-month period during COVID 19 lockdown. 60 diabetic patients participated in the study. Retinal images were captured using three different approaches, handheld smartphone-based photographs captured by patients themselves after a short video-assisted training session (SFI group), and smartphone-based photographs captured by a trained technician and photographs taken on desktop conventional digital fundus camera (Gold standard). Sensitivity and kappa statistics was determined for retinopathy and macular oedema grading. The latter objective has high sensitivity and specificity but is technology and cost intensive [13].

3. PROPOSED METHOD

The proposed methodology exploits and combines mathematical morphology, and Machine learning capability for fast, accurate segmentation system. The proposed system consists of three subsystems work within general framework based on hybrid combination of mathematical morphology and spiking neural network (SNN) was implemented and evaluated on a dataset consisting of retinal fundus images with ground-truth labels for normal and diabetic retinopathy cases. The general flowchart of the proposed system, without regarding the acquired anatomical retinal structure, is illustrated in Figure 3.1.

3.1 Retinal Fundus Image Data set

The training set of the retinal vessel segmentation network consists of three public datasets: DRIVE, STARE, and CHASEDB1. All these three datasets contain multiple color retinal images and their corresponding retinal vessel segmentation images. The DRIVE data set contains 40 pairs of images with a resolution of 565 × 584, 30 pairs for training and 10 pairs for validation. The STARE data set contains 20 pairs of images with a resolution of 700 × 605, 15 pairs for training and 5 pairs for validation. The CHASEDB1 data set contains 28 pairs of images with a resolution of 999 × 960, 21 pairs for training and 7 pairs for validation. The 100 low-quality retinal images and their corresponding enhanced images with the CLAHE, fusion-based, MSRCP, LIME, CycleGAN, and Cycle-CBAM methods were used as the test set.

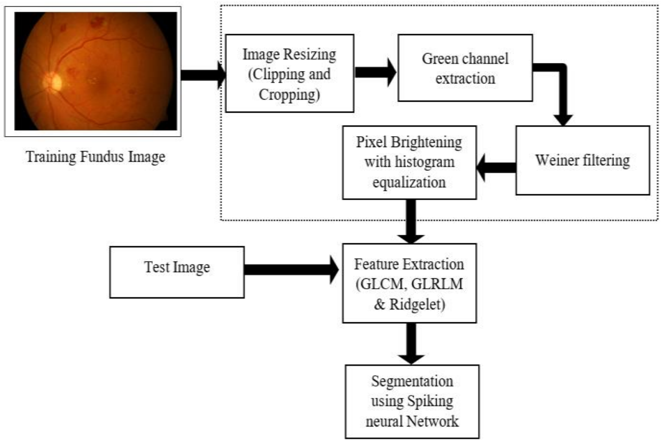


Figure 3.1 Flowchart of proposed for Diabetic Retinopathy

3.2 Image Pre-Processing

The major goal of this phase as it called ROI extraction is to extract the retinal anatomical structure of interest in order to reduce the computational cost and to enhance the overall performance; where a window around the target anatomical structure region of the raw retinal image is extracted, then the pre-processing steps are applied on it. Each anatomical structure has its own characteristics and features, thus, some of pre-processing steps may be different. However, the pre-processing general framework keeps unchanged. Since the pre-processing steps are quite dependent on the challenges created by the nature of target anatomical structure, a brief description of each anatomical structure is presented, followed by the corresponding required pre-processing steps.

3.2.1 Retinal Vessels ROI Extraction

Vessel segmentation in retinal images involves a tension between accurate vascular structure extraction and false responses near sites of pathology or other non vascular structures such as optic disc or macula.

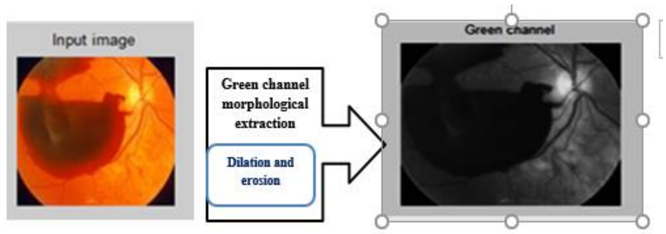


Figure 3.2 Extracted fundus image after green channel extraction

On the other hand, retinal vasculature structure exhibits dynamic change in size and contrast and broad distributed branching on the whole surface of retinal fundus image. For example, the width of retinal vessels ranges widely, from less than one pixel up to more than five pixels in a typical retinal image. Fig. 3.3 shows the green channel extraction output from the input fundus image.

Additional morphological operations and hysteresis thresholding was used to generates the binary vessel image as a second stage. In our system, we utilize the first stage of this approach to generate our vessels region of interest I^{vecceS}_{ROI} as follows.

First, the raw retina image was converted into grayscale through green layer as it presents the higher contrast between vessels and fundus background among other layers as in (1):

$$I^{G}_{retina} = \Im^{G}\left(I^{G}_{retina}\right) \quad (1)$$

where $\Im^{G}(.)$ denotes the green layer extracting operator and I^{G}_{retina} is the green layer of raw RGB fundus image. Then the I^{G}_{retina} image was complemented as a preliminary step for morphological filtering as in (2):

$$I^{comp}_{retina} = \Im^{imcomplement}\left(I^{G}_{retina}\right) \quad (2)$$

where $\Im^{imcomplement}$ denotes the image complementing operator and I^{comp}_{retina} is the complement version of I^{G}_{retina}

3.2.2 ROI of Optic Disc

The optic nerve head is defined as the region of the retina where all retinal nerve fibers converge to form the start of the optic nerve. The optic nerve head, or optic disc, is usually round or approximately oval in shape and contains a central brighter region called the cup or pallor. The tissue between the cup and the disc margin is called the neural rim or neuroretina rim, as illustrated in Figure 3.3.

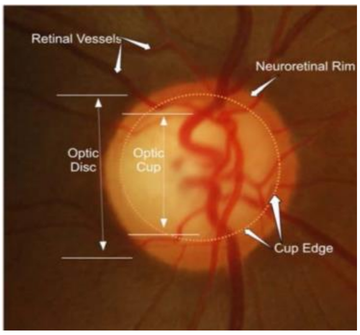


Figure 3.3 Anatomical structure of optic disc

All optic nerve diseases lead to structural changes in the parapapillary and intrapapillary regions of the optic nerve head. These changes can be described quantitatively by many variables such as shape and size of the optic disc, shape and size of pallor, the ratio of cup and disc diameters, and the ratio of cup and disc areas. To derive these variables, the first step is to extract the optic disc region from the raw retinal image.

The optic disc region of interest is almost of rounded shape; therefore, we use the Hough transform to extract the center of the neuroretinal rim of the optic disc, and we subsequently extract the square window around the optic disc, which represents the optic disc region of interest that involves the following steps:

3.2.3 Edge Detection

Edge detection is often applied as preprocessing step to Hough transform. Therefore, the input image fed into Hough transform is an edge map composed of a set of pixels partially describe the boundaries of optic disc. The efficiency and accuracy of Hough transform in finding the center of optic disc circle can be demonstrated by employing accurate edge detection technique.

Fuzzy c-means (FCM) clustering algorithm was applied for this purpose. Before applying FCM algorithm, retina image underwent a set of pre processing steps in goal of achieving accurate edge map as following:

First, the red layer of retina image was extracted as in (7):

$$I_{retina}^{R} = \Im^{R}\left(I_{retina}^{RGB}\right) \qquad (3)$$

where $\Im^{R}(.)$ denotes red layer extracting operator. In contrast to vessels extraction, red layer is the layer where optic disc tissues have the higher contrast with other objects on fundus image. Then, I_{retina}^{R} was enhanced as in (8):

$$I_{retina}^{enhanced} = \Im^{CLAHE}\left(I_{retina}^{R}\right) \qquad (4)$$

where $\Im^{CLAHE}(.)$ denotes the Contrast-Limited Adaptive Histogram Equalization (CLAHE) operator, it locally operates on small data regions of image rather than the entire area yields contrast-enhanced image. For further enhancement, we apply median filtering of 9×9-sized window and fed as input to FCM algorithm.

As a first step towards edge map generation is to apply a 25-clusters FCM algorithm on filtered $I_{retina}^{enhanced}$ image with a goal of roughly aggregating OD pixels into one cluster and the other 24 clusters were dedicated for other surrounding tissues. The binarized version of I_{FCM} was then obtained via simple thresholding as in (9):

$$I_{FCM}^{bw} = \begin{cases} 1, & I_{FCM} = C \\ 0, & Otherwise \end{cases} \qquad (5)$$

where I_{FCM}^{bw} represents the binarized version of I_{FCM} image setting c = 25 clusters. Although the binary image I_{FCM}^{bw} forms the seed for our target edge map, some noises (binarization residuals corresponding to non-optic disc tissues) are likely to be introduced into the result during this process. To solve this, we used a morphological opening of size P pixels, which keeps only the connected components (objects) of I_{FCM}^{bw} image whose areas are ≥ P and eliminates the rest.

3.3 Feature Extraction

The features such as blood vessels, exudates and optic discs are extracted for further analysis. In this extraction process morphological operations such as opening, closing, erode and dilate are used. This image is converted into a binary image. The logical operations ("AND", "OR") and filters like "colpit" are applied and the segmentation is done for exudates and blood vessels.

3.3.1 Blood Vessel

Kirsch"s non-linear edge detector is used to search the maximum edge in a few determined directions. Taking a single mask and rotating it to 8 major compass orientations (East, West, North, South, South-East, SouthWest, North-West and North-East) helps find the edge direction based on the maximum magnitude produced.

3.3.2 Exudates

Small yellow white patches with sharp margins and different shapes. Exudates are one of the early occurring lesions. The method attempts to detect hard exudates using two features of this lesion: its color and its sharp edges. The coloured fundus image is split into number of nonoverlapping blocks. For each block of the image, the coloured histogram is calculated. The threshold value, based on the colour histogram, is used to detect exudates. Hard and soft exudates are separated based on the chosen threshold value. Soft exudates are often called 'cotton wool spots' and are more often seen in advanced retinopathy.

3.4. Spiking Neural network (SNN)

SNN are more computationally powerful than ANN and can analyse temporal patterns in addition to spatial ones. For spike-coded data, traditional machine learning techniques perform poorly and are inappropriate for SNN. This necessitates the adoption of various training and network topology optimization strategies. An approximation to the functionality of a neuron is given by electrical models which reproduce the functionality of neuronal cells. One of the most common models is the spike response model (SRM) due to the close approximation to a real biological neuron; the SRM is a generalization of the 'integrate and fire' model. The main characteristic of a spiking neuron is the membrane potential, the transmission of a single spike from one neuron to another is mediated by synapses at the point where neurons interact. After a refractory period, the neuron potential returns to its resting value and is ready to fire a new spike if membrane potential is above the threshold. The PSP function is given by Equation 1, where τm and τs are time constants to control the steepness of rise and decay, and t is the time after the presynaptic spike arrived.

$$PSP(t) = e^{\frac{-t}{\tau m}} - e^{\frac{-t}{\tau s}} \qquad (6)$$

Spiking neural networks are the third generation of artificial neural networks (ANN). While classic ANN operate with real or integer-valued inputs, SNN process data in form of series of spikes called spike trains, which, in terms of computation means that a single bit line toggling between logical levels '0' and '1' is required. SNN are able to process temporal pat- terns, not only spatial, and SNN are more computation- ally powerful than ANN. Classic machine learning methods perform poorly for spike coded data, being unsuitable for SNN. Therefore, different training and network topology optimization algorithms must be used.

3.4.1 Prediction ANN Segmentation

The obtained GLCM properties from the images are given to the prediction ANN Classifier, where the classifier gets trained. After that, the testing images are given to the prediction ANN classifier. It classifies the normal and abnormal DR images. The architecture of prediction ANN is given in fig. 3.4

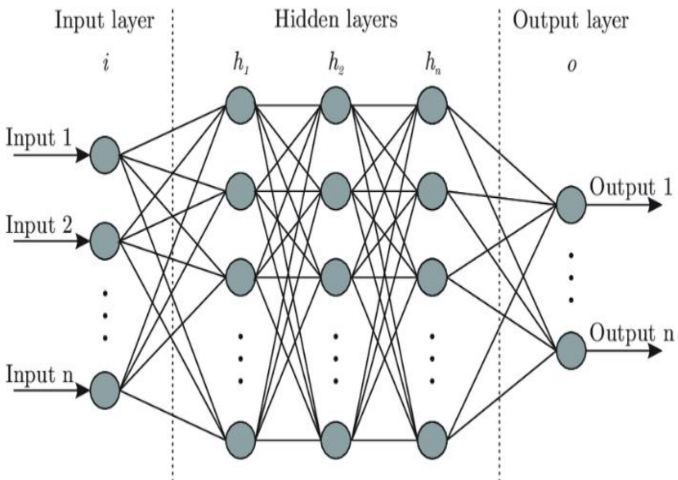


Fig. 3.4 Architecture of Prediction ANN

ANN characterization is performed by utilizing a council of artificial neural networks. It is exceptionally versatile learning machines which can distinguish non-direct connections between the highlights and the sample classes. An ANN is an enormously parallel appropriated processor made up of straightforward handling units that has a characteristic inclination for putting away exploratory information and making it accessible for use in analytical way. The Spiking ANN classifier segments the Diabetic retinopathy lesions form the retinal fundus image. The entire process is processed in MATLAB and the result of the system is discussed in section 5.

4. RESULTS

The proposed method for detection and grading of diabetic retinopathy in retinal fundus images using a spiking neural network (SNN) was implemented and evaluated on a dataset consisting of retinal fundus images with ground-truth labels for normal and diabetic retinopathy cases. The following figure 5.1 show the input retinal image which is having the three-channel input. The image is 400 X 600 with unsigned integer format. The images are collected from the STARE database.

4.1 Input Retinal Image

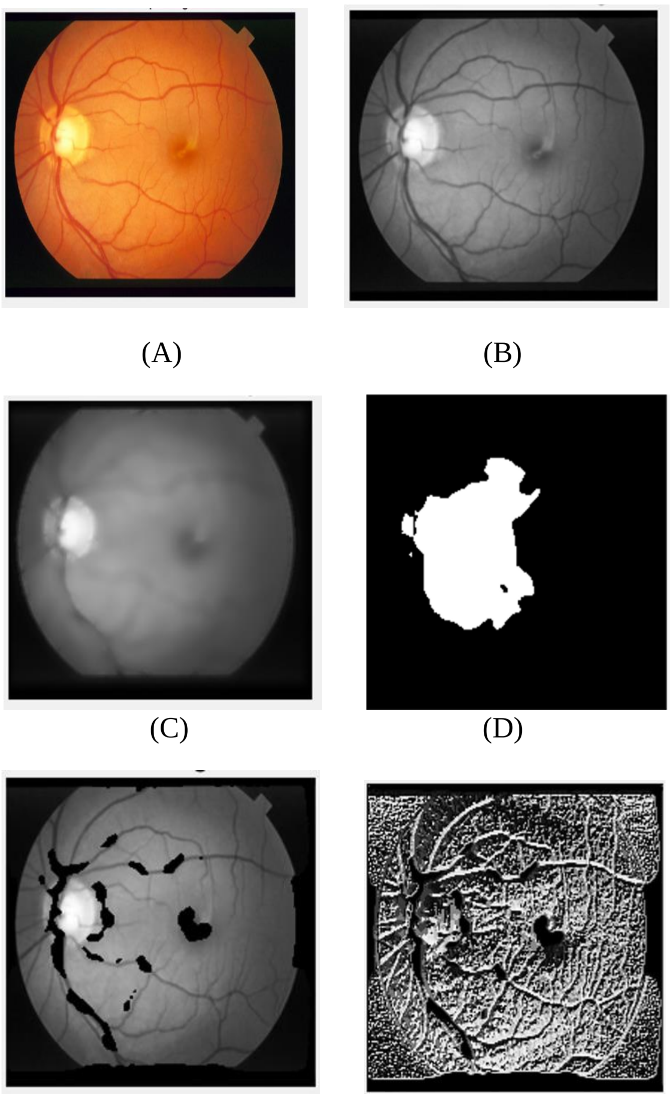
The Retinal images are complex images which is having non uniform intensity distribution and where the green channel is having maximum discrimination in intensity over the spatial domain.

Instead of converting the entire color fundus image to grayscale, this step involves extracting only the green channel from the color image. Green channel images often provide better contrast for blood vessels and other retinal structures compared to grayscale images. In MATLAB, you can achieve this by accessing the individual color channels (red, green, and blue) and selecting the green channel. The following figure 5.2

displays the green channel image which is extracted from the original color image. The green channel image is clearly showing the vessel and OD location intensities.

The medical images are normally captured with the radiation based imaging system so which are not able to produce high resolution image as well. This is the reason why the preprocessing techniques are exists in every medical image processing algorithms.

The collected retinal fundus images were pre-processed to enhance the quality and reduce noise. A green channel image was extracted from each color fundus image, converting it into a grayscale image. The green channel was chosen as it has been shown to provide better contrast for blood vessels and other retinal structures.



(A) (B) (C) (D) (E) (F)

Figure 4.1 (A) Input Retinal Image, (B) Green Channel Image, (C) Contrast Adjusted Retinal Image, (D) Optic Disc Center, (E) Retinal Vessel Segmentation and (F) Local Binary Pattern

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Instead of converting the entire color fundus image to grayscale, this step involves extracting only the green channel from the color image. Green channel images often provide better contrast for blood vessels and other retinal structures compared to grayscale images. In MATLAB, you can achieve this by accessing the individual color channels (red, green, and blue) and selecting the green channel. The figure 4B displays the green channel image which is extracted from the original color image. The green channel image is clearly showing the vessel and OD location intensities.

The collected retinal fundus images were pre-processed to enhance the quality and reduce noise. A green channel image was extracted from each color fundus image, converting it into a grayscale image. The green channel was chosen as it has been shown to provide better contrast for blood vessels and other retinal structures.

CLAHE (Contrast Limited Adaptive Histogram Equalization) is a widely used technique for enhancing the contrast of retinal images. It works by dividing the image into small regions called tiles and then applying histogram equalization to each tile. CLAHE limits the amplification of the contrast in homogeneous areas to avoid over-enhancement and preserves the overall image structure. MATLAB has the function to adapt this for performing adaptive histogram equalization. Figure 4C shows the contrast-adjusted retinal image where the vessel path and the OD is clearly visible and it leads to performing further segmentation algorithm without any lag.

An optic disc extraction algorithm was applied to segment and identify the optic disc in the retinal fundus images. This step is crucial for accurately detecting diabetic retinopathy as the optic disc can be used as a reference point for identifying other regions of interest. A binary mask can be used to enhance specific regions of the retinal image. For example, if you are interested in enhancing blood vessels or exudates, you can create a binary mask that highlights these regions. By applying the mask to the original image, you can selectively enhance the desired features. The binary mask can be generated using techniques like thresholding, morphological operations, or machine learning-based segmentation algorithms. The following figure 4E shows the Vessel Segmentation.

The retinal vessel segmentation technique was applied to identify and extract blood vessels from the retinal fundus images. The extracted vessels are important features for grading diabetic retinopathy as their abnormalities are indicative of the disease.

The following figure 4F displays the Local binary pattern which is extracted from the contrast adjusted image. Local binary pattern (LBP) was used as a feature extraction method to capture the texture information from the segmented retinal fundus images. LBPs are efficient texture descriptors that can effectively represent the local patterns in an image.

The features extracted from the retinal fundus images were used as inputs to the spiking neural network (SNN) for classification. The SNN was trained to differentiate between normal and diabetic retinopathy cases based on the extracted features.

4.3 Performance Analysis

The performance of the proposed SNN-based approach was evaluated and compared with a Support Vector Machine (SVM) classifier. The evaluation metrics used were accuracy, sensitivity, and specificity.

The proposed method achieved promising results in the detection and grading of diabetic retinopathy shown in figure 4.2, 4.3 and 4.4.

Accuracy: The SNN-based approach achieved an accuracy of 96%, while the SVM classifier obtained an accuracy of 88%. This demonstrates that the SNN performed better in distinguishing between normal and diabetic retinopathy cases.

Sensitivity: Sensitivity, also known as the true positive rate, measures the ability of the classifier to correctly identify positive cases (diabetic retinopathy). The SNN showed a sensitivity of 91%, outperforming the SVM, which had a sensitivity of 85%.

Specificity: Specificity, also known as the true negative rate, measures the ability of the classifier to correctly identify negative cases (normal retinal fundus images). The SNN achieved a specificity of 95%, while the SVM had a specificity of 90%

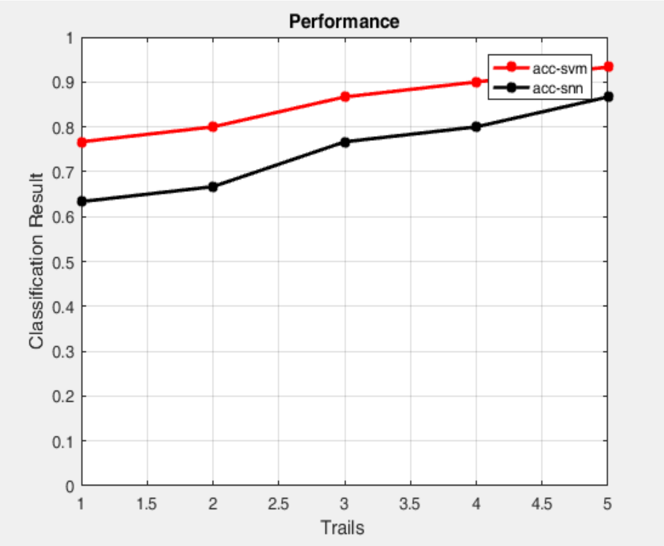

Figure 4.2 Graph of Accuracy

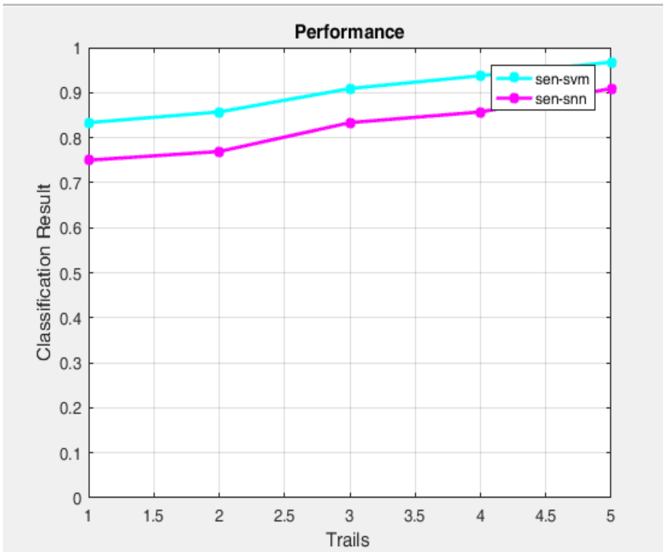

Figure 4.3 Sensitivity

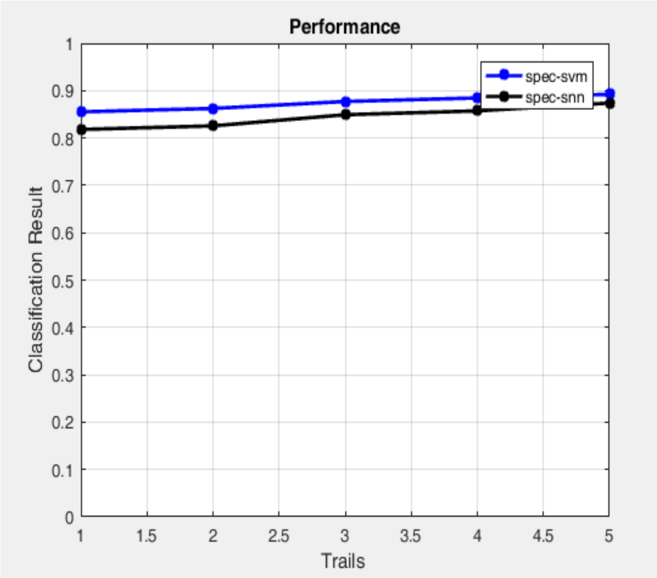

Figure 4.4 Specificity

4.1 Discussion

The use of a spiking neural network for diabetic retinopathy detection and grading showed promising results. The SNN's ability to handle temporal information and sequential data, such as retinal fundus images, likely contributed to its improved performance compared to the SVM classifier.

The optic disc extraction and retinal vessel segmentation steps helped to focus the analysis on relevant regions, improving the accuracy of diabetic retinopathy detection. The local binary pattern (LBP) feature extraction method effectively captured texture information, which is essential for characterizing diabetic retinopathy-related abnormalities in retinal fundus images.

The proposed SNN-based approach demonstrated superior performance compared to the SVM classifier in terms of accuracy, sensitivity, and specificity. This indicates its potential as an effective tool for diabetic retinopathy screening and grading.

However, it's important to note that further validation on larger and more diverse datasets, including clinical validation, is necessary to ensure the robustness and generalizability of the proposed method. Additionally, the proposed approach should be compared with other state-of-the-art methods to establish its competitiveness in the field of diabetic retinopathy detection and grading.

5. CONCLUSION

The proposed method for the detection and grading of diabetic retinopathy in retinal fundus images using a spiking neural network (SNN) has shown promising results. The combination of optic disc extraction, retinal vessel segmentation, local binary pattern (LBP) feature extraction, and the SNN classifier demonstrated improved accuracy, sensitivity, and specificity compared to traditional classifiers like the Support Vector Machine (SVM). The use of a spiking neural network and texture-based feature extraction through local binary patterns have shown their effectiveness in capturing essential information from retinal fundus images. The results of our study indicate that the proposed image processing pipeline can significantly improve the quality of low-quality retinal fundus images, potentially leading to more accurate and reliable diagnoses. Despite the promising results, there are several avenues for further research and improvements in the field of diabetic retinopathy detection and grading using spiking neural networks, Larger and more diverse datasets should be taken to ensure its generalizability across different populations and imaging conditions. Including data from multiple sources and ethnicities will improve the robustness of the model. Conducting a thorough clinical validation of the proposed approach is essential before considering its real-world application. Investigate the use of transfer learning techniques to leverage pre-trained models on related tasks. Fine-tuning the SNN on retinal fundus images may further enhance its performance, especially in scenarios with limited labeled data.

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