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Glaucoma Detection Using Image Processing and Deep Learning Algorithms

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Abstract: If glaucoma is not detected and treated in its early stages, it can cause irreversible vision loss. Glaucoma is a degenerative eye condition. The proposed work uses a unique method for glaucoma detection by combining image processing techniques and deep learning methods. Using the characteristics of both domains, the proposed work aims to improve glaucoma detection's accuracy and effectiveness. The first step in our approach involves acquiring high-resolution retinal images, typically obtained through a fundus camera or optical coherence tomography (OCT). These images serve as the input data for subsequent analysis. Image preprocessing techniques enhance image quality, correct artifacts, and improve the contrast of an image, ensuring that the input data is optimal for research. Various image-processing methods strengthen the visibility of pertinent anatomical components, including contrast augmentation, noise reduction, and morphological procedures. High-level features are then extracted from the preprocessed images using a deep-learning architecture. Glaucoma-specific patterns and characteristics are automatically recognized using convolutional neural networks (CNNs). A comprehensive dataset containing standard and glaucoma-affected retinal images is employed to analyze the offered method. The use of the trained deep learning model is evaluated using metrics such as accuracy, sensitivity, precision, and recall. A comparison of the designed method with current glaucoma detection techniques shows that it is accurate and computationally efficient.

Keywords: *CNN (Convolutional Neural Networks), Deep learning, Fundus images, Glaucoma, Image Processing, LSTM (Long short-term memory networks), RNN (Recurrent Neural Network).*

1. Introduction

The second most typical disease that results in blindness is glaucoma. A rise in intraocular pressure (IOP), a glaucoma symptom, causes vision loss before the patient becomes aware that they have it. Angle-closure and open-angle glaucoma are the two main kinds of glaucoma that cause a rise in intraocular pressure. Increased pressure surrounding the eye, brought on by an obstruction in the aqueous humor's drainage system or excessive production of this fluid, harms the optic nerve. To determine the existence of glaucoma, the thickness of the retinal nerve fiber layer (RNFL) is evaluated on a retinal fundus image. It is one of the least invasive methods available, making ophthalmologists the most likely users. One of the main reasons for vision loss and blindness is glaucoma. It is necessary to have regular eye checkups because glaucoma first shows no symptoms and gives no cautions. Before feature extraction, the first stage in retinal analysis is segmenting the retinal blood vessels. In a retinal examination, segmented blood vessels are useful for microvasculature characterization, vascular geometry extraction process, and evaluation of other characteristics, including artery-to-vein ratio. The three main findings of the study are (i) the development of a new technique for segmenting retinal blood vessels, (ii) the proposed method's application to retinal images from healthy and unhealthy patients, and (iii) the evaluation of the proposed method's efficiency using performance metrics like accuracy, specificity, sensitivity, and recall.

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2. Existing System

Artificial intelligence and machine learning techniques are used in the existing approach. Convolutional neural network (CNN) techniques are used in the proposed way. After that, they utilized computer vision and artificial intelligence. Before the ImageNet competition in 2013, which had as its primary objective assessing the content of real-world images for automatic annotation, their significance had not been established. Applying GPUs, rectifiers like ReLU activation function, data augmentation approaches, and novel regularisation methods like Dropout led to success. The capacity of the CNN architectures to extract highly discriminating features at various levels of abstraction is crucial to their primary function.

3. Motivation

A primary cause of permanent blindness around the globe, glaucoma affects millions of people of all ages. Because the illness typically progresses silently and symptoms may not appear until later stages, early detection, and timely therapies are crucial to preventing eyesight loss. Traditional glaucoma detection techniques require invasive and time-consuming methods, making them less suitable for widespread screenings and standard clinical practice.

There are several reasons to use image processing and deep learning to diagnose glaucoma.

Early Detection: Early glaucoma detection provides more efficient interventions to stop the illness's progression.

Accuracy and Consistency: Deep learning-based automated systems provide objective, consistent analysis that improves diagnosis accuracy by reducing inter-observer variability. This is essential for making treatment decisions on time.

Efficiency: Traditional manual analysis of medical images can be time-consuming and resource-intensive. Deep learning algorithms are well suited for regular clinical practice and mass screenings since they can quickly process enormous numbers of images.

Personalized Treatment: Deep learning algorithms can assist clinicians in tailoring treatment plans based on accurate and detailed assessments of disease progression, leading to better patient outcomes.

Research Advancement: It is feasible to gain new insights that can aid researchers in better understanding the biology of glaucoma and developing novel treatments by analyzing an enormous quantity of medical image data.

Real-time Monitoring: Automated methods can make monitoring patients at risk for glaucoma easier, enabling quick modifications to treatment plans as necessary.

3.1. Problem Statement

Early glaucoma identification is essential to the diagnosis of the disease. Diagnosing glaucoma before eyesight is lost is crucial, and this can be done by measuring the CDR (cup-to-disc ratio). The cup-to-disc ratio is calculated manually by experienced ophthalmologists or with costly equipment like the Heidelberg Retinal Tomography (HRT). However, the availability of HRT is severely limited (cup-to-disc ratio) by an ophthalmologist's CDR evaluation. To help ophthalmologists, this study efficiently divides digital fundus images into normal or glaucomatous types.

3.2 Objectives

The main objective of our project is:

- To efficiently detect attacks based on glaucoma.
- To implement the Deep learning using LSTM, CNN, and RNN.
- To enhance the overall performance analysis.

3.3 Glaucoma Risk Factor

Optic nerve injury and vision loss can result from a series of eye conditions known as glaucoma. Numerous risk conditions can increase the chance of getting glaucoma

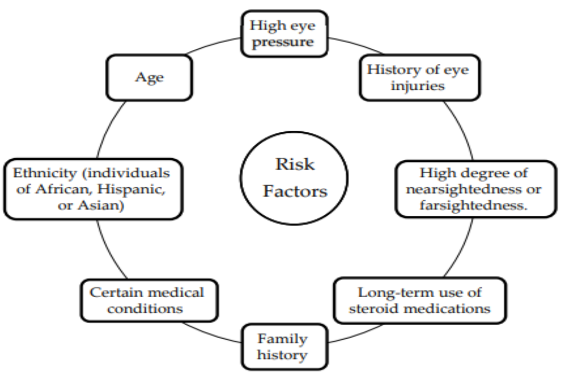


Fig 1: Glaucoma Risk factors

Age: The possibility of acquiring glaucoma increases with age. It is more common in individuals over the age of 60 or more.

Family history: If you have glaucoma in your family, your risk is higher. One has a higher risk of glaucoma if they have a close family or friend with the disease.

Ethnicity: Specific types of glaucoma, such as main open-angle glaucoma, are more common among people who are African Americans, Hispanics, and Asians.

High intraocular pressure (IOP): Glaucoma risk factors include elevated intraocular pressure, the pressure inside the eye. However, not everyone with a high IOP will acquire glaucoma; some people with a normal IOP can also have the disease.

Thin Cornea: Those who have thinner corneas have a higher risk of developing glaucoma. The precision of measurements of intraocular pressure can be impacted by corneal consistency.

Medical Conditions: Heart disease, diabetes, and hypertension can all increase the risk of developing glaucoma.

Steroid Use: The risk of developing glaucoma increases with prolonged use of corticosteroid drugs, whether taken orally, intravenously, or as eye drops, pills, inhalers, or injections.

Eye Trauma: Previous eye injuries or surgeries can increase the threat of glaucoma, especially if there is an injury to the eye's drainage system.

Thin Optic Nerve: Individuals with a thinner optic nerve may be at an advanced threat of progressing glaucoma.

Use of Certain Medications: Some medications, like antihistamines and antidepressants, may increase(higher) the threat of glaucoma.

Low Blood Pressure: Extremely lower blood pressure may limit blood supply to the visual nerve, putting you at threat of glaucoma.

Migraine: Some research suggests a link between migraine symptoms and an increased incidence of glaucoma.

4. Related Work

Several different glaucoma detection techniques have been created by researchers. These are methods based on machine learning that manually extract characteristics and carry out categorization using a variety of classifiers. For example, disease diagnostic models recently often include convolutional neural networks[1]. Many researchers have used convolutional neural networks to diagnose glaucoma. The CNN-based algorithms carry out useful computations and provide accurate results for conditions classification. A CNN is made up of several layers, including the convolutional layer, the activation layer, the pooling layer, and the fully connected layer[2]. Figure 1 shows the typical flow chart representation of the segmentation process for retinal blood vessels. It involves converting the original image to a greyscale version, improving the appearance, and extracting and segmenting the vessels. A grey-scale image is made up of a data matrix with values that indicate intensities within a certain range. The intensity of the single-color channel is changed by the intensity of the greyscale channel. Image augmentation is a technique to enhance an image's aesthetic appeal or format it more effectively for machine or human analysis. Determining the branching or structure of the retinal blood vessels requires vessel extraction and segmentation[3].

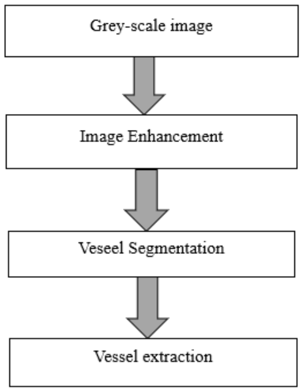


Fig 2: The process of segmenting retinal blood vessels

The colorful fundus image is converted into a grayscale image, and then the blood vessels are segmented. To complete the project on time, we must put information into many categories, such as "normal" and "glaucoma”.

An object's segmentation, form, distortion, and size must all be considered while applying this technique. These four concepts are essential for this study. Calculations must be made to achieve a precise approximation of the cup-to-disc ratio. It was also shown that a deep learning technique using pre-trained ResNet50 could recognize glaucomatous damage in fundus images. By excluding the layers and connections that may help the network learn deeper and distinct patterns from the data and reduce the number of parameters, the vanishing gradient problem can be resolved. These links can carry out identity mapping without introducing new parameters or increasing computing complexity [4]. It is the widely used and simple segmentation method. This technique converts a grayscale or color image into a binary image. Based on the intensity level, it divides the pixels in an image. The segmented image is generated by selecting the threshold value given to the color below or above that specific threshold level. Based on the features of the image, the threshold value is chosen carefully. This Thresholding is divided into global, variable, and multiple Thresholding[5]. The principal component analysis (PCA) is included in the pre-processing stage of the method that is proposed in this work, which is primarily based on morphological reconstruction. The steps in this procedure are as follows: The RGB fundus image is then processed using principal component analysis to produce a greyscale image showing the various retinal structures, including vessels. The main objective of the proposed approach is to make it easier to identify problems connected to fundus imaging in the early stages. And secondly, different morphological reconstruction-based techniques are used to locate the OD. Watersheds that are stratified and unpredictable have been employed for that purpose. Four public datasets have been used to evaluate the technique, with promising findings that complement those of previous literature approaches [6]. Four techniques can be used to locate retinal blood vessels: model-based, matching filtering, vessel tracking, and pattern morphological processing. Initially, a set of operations was used to define mathematical morphological procedures. Scales between tmin and tmax were used for the multi-scale vessel identification. (Corresponding to σmin to σmax). The goal was to examine the eigenvalues. The contrast between the blood vessels and the retinal background was improved during image processing by using the green channel of the RGB-colored retinal images [7]. In combination, extract spatial and temporal information using RNN (LSTM) and CNN (ResNet 50) architecture. It is first transformed into a series of images fed into a CNN to extract spatial features from each video. To find temporal patterns inside the image sequence, the output of the findings is input into a recurrent sequence learning model (LSTM). The pooled parts are finally transferred into a fully linked layer to predict the classification model for all input layers. Eight batches, 18 epochs, and a learning rate of 0.012 were found to be the best parameters for achieving the greatest outcomes. For the most part, segmentation-based methods and feature extraction-based techniques have been used by researchers to analyze retinal images. Feature extraction-based approaches are used to extract the data that a classifier uses to determine an image. The glaucoma field uses two different methods. These techniques analyze either a portion of an image by segmenting it or the complete image[8]. Automatic retinal blood vessel extraction is essential for the early recognition of ocular glaucoma, which, if untreated, may cause vision loss. Numerous issues with retinal images could make blood vessel extraction less accurate. The use of enhancement techniques is essential for retinal images. Despite significant advancements in image processing, several issues remain unsolved or only partially so, such as the challenge of distinguishing between healthy and diseased blood vessels during neovascularisation[9]. Mathematical morphology reconstruction methods extract features from images that help represent and recognize the region form, such as boundaries. The area of mathematical morphology operation, a neovascularization branch of image processing and computer vision, focuses on analyzing and manipulating shapes and structures in an image. Dilation and erosion are the two primary methods used in mathematical morphology. The structural elements control the dilatation and erosion processes. Combinations of dilatation and erosion processes can carry out more difficult morphological operations, such as opening (a decline followed by a dilation) and closure (a dilation followed by an erosion). These methods, which include reducing noise, segmenting objects, extracting features, and others, can improve images.

Many areas have used mathematical morphology, including video and image processing, remote sensing, computer vision, and medical imaging. Applications like noise reduction, object detection, segmentation, form analysis, and texture analysis can all benefit from it. The smoothing and removal of noise is possible with the mathematical morphology method. One of the most important first steps in morphological processing is choosing the proper structure element (SE). Based on the vessel properties, we must select a linear structural element[9]. To achieve the best results for this project, direct structure elements were convolved with the digital image in different directions. Compared to other morphological processing methods, the proposed method achieves complete accuracy.

5. Methodology

The proposed technique is shown in Figure 3. Preprocessing and segmentation are the two main divisions of the project. As shown in Figure 4, the segmentation part has four primary components, while the preprocessing part has two main features.

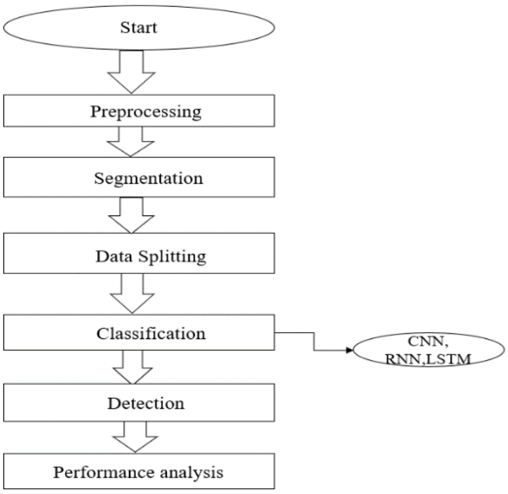


Fig 3: Proposed Methodology

5.1 Pre-Processing

The most important step in the proposed work is the extraction of the blood vessels from a color fundus image. The fundus image is an RGB (red, green, and blue) color image; RGB images have three channels (red, green, and blue), but only one is used; the other two, blue and green, have low contrast and don't transmit useful information.[3] Usually, as shown in the red channel, there is saturation or too much noise. Therefore, to transform an input image from a color to a grayscale format, the green channel of the image is used for fundus imaging. This was achieved through the green channel. The following step uses contrast-limited adaptive histogram equalization (CLAHE) enhancement to improve the greyscale image further[10].

5.2 Segmentation

Segmentation is the splitting of an image into various groups. Before an idea reaches the threshold, two procedures ensure the vasculature is retrieved. Opening-by-reconstruction and closing-by-reconstruction are techniques that are combined with morphological reconstruction. At the opening, erosion is followed by dilation. The final stage preceding dilatation is erosion. The contour object, small isthmuses, and thin protrusions are often smoothed off when analysing binary images. Closing fills up tiny holes and spaces between joined parts. Otsu is a threshold-based technique that lowers the variance of the thresholded black-and-white data within classes [11].

$$\begin{aligned} O_R^{(n)}(f) &= R_f^D[(f \ominus nb)] \\ C_R^{(n)}(f) &= R_f^E[(f \oplus nb)] \\ f_{Top-hat} &= f - (f \ominus b) \end{aligned}$$

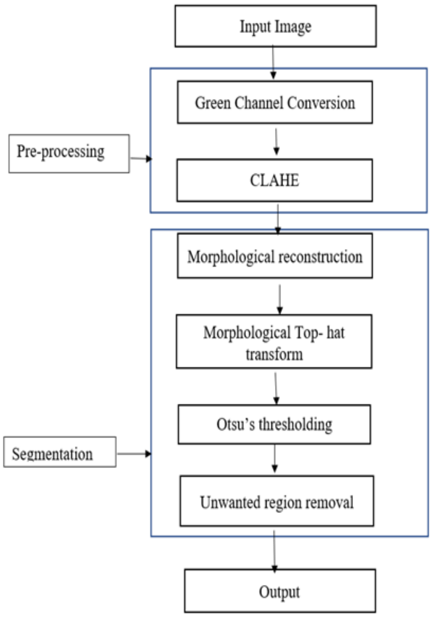


Fig 4: Proposed methodology: Preprocessing and Segmentation

5.3 Data Splitting

Here, we have split the dataset into test data for predicting a model and train data for evaluating the model. When a dataset is split into a training set and a testing set, the majority of the data, roughly 70-80% is utilized for training while very little is used for testing.[11] Training Set: Training is the most significant portion of your dataset and is used to train your model. It should comprise around 70-80% of your data. It has a balanced representation of both classes (healthy and glaucomatous eyes).
Test Set: During training, the model completely ignores the final 10–20% of your data. It's helpful to assess your trained model's ultimate performance and predict how well it will perform on newly developed, untested data.

5.4 Classification

The CNN algorithm, RNN (Recurrent Neural Network), and LSTM (Long Short-Term Memory Networks) are a few examples of deep learning algorithms used in this step.
CNN (Convolutional Neural Network) Model: A multilayer Deep Learning network called CNN gradually extracts high-dimension characteristics from input images after obtaining input from high-dimension data. As the size of the input images grows, so does the total number of layers in the (Convolutional Neural Network) CNN architecture, including convolutional layers, pooling layers, and fully connected layers. The network obtains more accurate knowledge as it goes deeper. One of the primary drawbacks of deeper networks is the longer processing time. Convolutional Neural Networks (CNNs) have shown promising properties for processing images or videos, detecting objects in images, segmenting images, classifying images, and processing natural language[12].

ResNet-50 Architecture: Figure 5 shows the ResNet-50 architecture. Using a 1x1 convolution layer and skipping three layers instead of two levels distinguish ResNet-50 from ResNet-18 and ResNet-34. Data can be categorized into seven categories using the ResNet50 design, which has 50 layers. It is frequently used in the localization of objects, image segmentation, identifying objects, and image identification processes. Costs associated with computing have consequently significantly decreased.

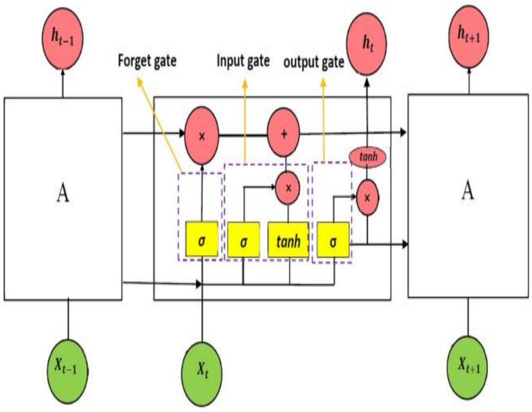


Fig 5: Block diagram of ResNet-50 architecture

RNN (Recurrent Neural Network): The segmented output from the prior CNN model is imported into the reinforcement learning model for image classification. The connected layer of the RNN model reads data one at a time. The recurrent neural network connection with hidden units containing image sequences produces a single output. The segmented output images were trained using this model, which also helped distinguish between normal and glaucoma images. Finally, to extract temporal and spatial data, we created a hybrid CNN (ResNet 50) and RNN (LSTM) model. Figure 6 shows the whole procedure for our technique[13]

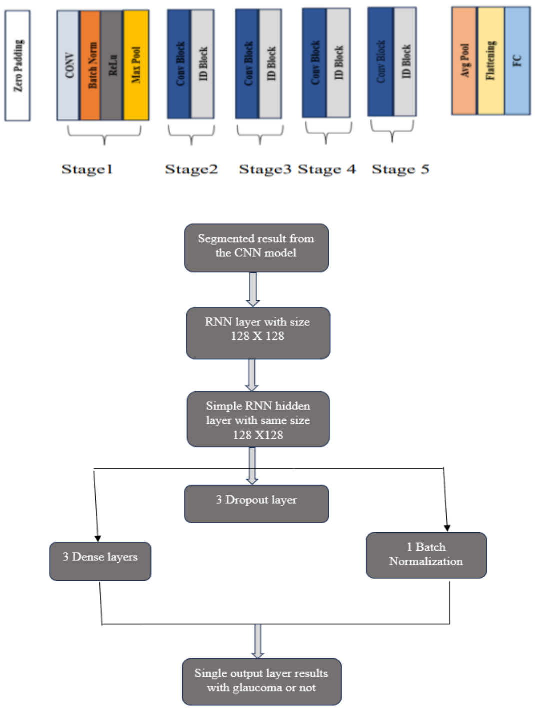


Fig 6: The workflow of the proposed RNN model

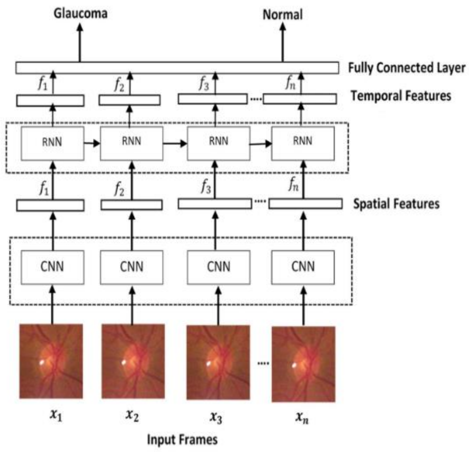


Fig 7: Overall workflow of the Convolutional Neural Network and Recurrent Neural Network (CNN- RNN)

LSTM (long short-term memory networks): The most commonly used RNN network is the Long Short-Term Memory (LSTM) network. Due to its better performance in language translation and audio processing, LSTM is presently widely used for the initial RNN tasks involving feature extraction from a sequence of data[14].

To explore Deep Learning techniques, long short-term memory networks are helpful. Recurrent neural networks (RNNs) are excellent at learning long-term dependencies in sequence prediction tasks. In addition, LSTM networks are well-suited for classifying images and prediction. The presence of glaucoma can be determined using the seven-layer RNN-LSTM for image classification[15].

The forget, input, and output gates make up the Long Short-Term Memory (LSTM) structure, which is seen in Figure 8. X stands for the input from memory, h for the prediction at time t, and for a function that decides which data should be retained or forgotten.

5.5 Performance Metrics

Many different parameters or metrics are used for calculating and evaluating the efficiency of the proposed approach. The evaluation parameters are described as follows:

Accuracy (Acc): The ability of a system or model to accurately distinguish between occurrences of glaucoma and non-glaucoma within a given dataset is known as accuracy.

$$Accuracy = (TP+TN)/(TP+FP+FN+TN)$$

Precision indicates how accurately the detecting system makes positive predictions, specifically focusing on the proportion of accurate positive predictions among all positive predictions.

$$Precision = TP / (TP + FP)$$

Sensitivity is defined as the performance metric that measures the detection system's ability to correctly identify glaucoma cases among all the actual glaucoma cases in each dataset.

$$Sensitivity = TP / TP+FN$$

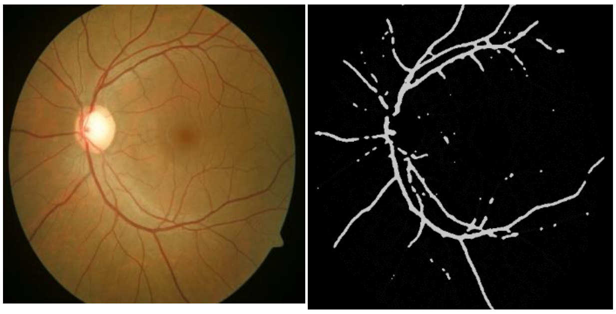
The recall is the capacity of the detection algorithm to properly identify all glaucoma-positive cases among all the actual positive patients in each dataset is measured by the recall, a critical performance indicator.

$$Recall = TP/(TP+FN)$$

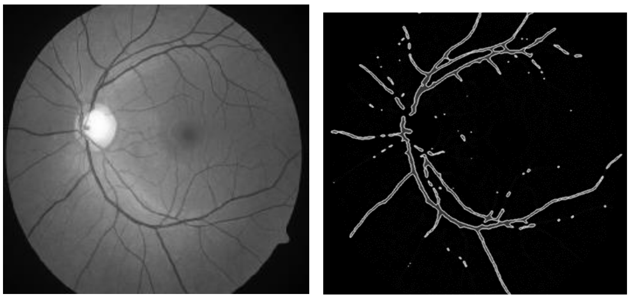
Se is the ratio of correctly categorized vessels, Sp is the ratio of pixels that are not vessels, Accuracy is the proportion of actual result, Tp is confirmed positive, FP stands for false positive, TN for true negative, and FN for false negative[16].

6. Results

In the proposed work, a combined CNN and RNN trained on a retinal image can extract spatial and temporal characteristics, greatly enhancing glaucoma detection. More specifically, combining a ResNet50 network with an LSTM architecture achieved substantially greater sensitivity and specificity rates than a base ResNet50 network. The output image from each stage is shown in the figures below. Figure (a) shows the input image, Figure (b) shows the green channel image, and Figure (c) shows the image after it has been inverted to make the background or black pixels appear dark and the vessel pixels appear white. The outcome of the morphological top-hat transform, Figure(c) shows the segmentation stage. The proposed technique's whole process is shown in Figure (e). Otsu's Thresholding completes the segmentation procedure in Figure (d).



(a) (b)



(c) (d)

Fig 9: (e) Overall procedure of the processed method

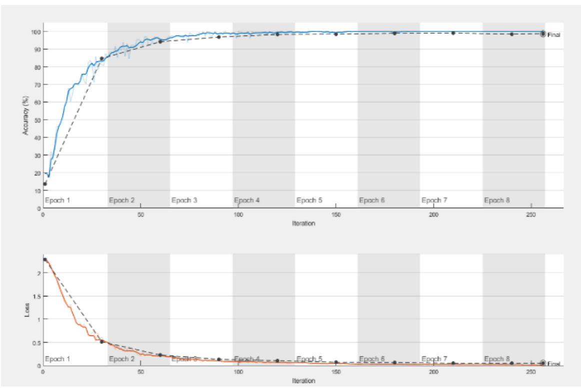


Fig 10: Training process curve for CNN

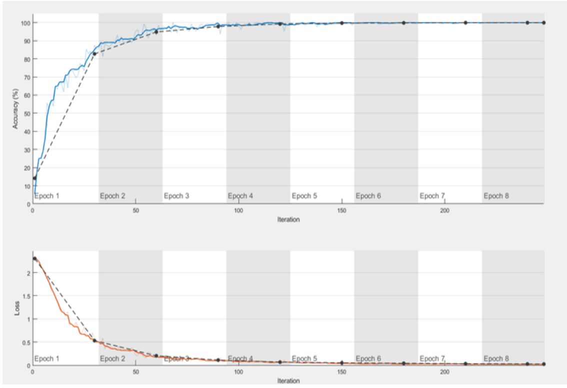


Fig 11: Training process curve for RNN

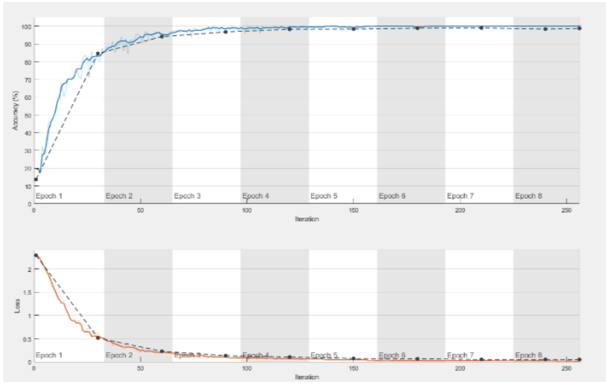


Fig 12: Training process curve for LSTM

Models	Accuracy	Sensitivity	Precision	Recall
CNN	92	93	92	93
RNN	95	92	93	94
LSTM	96	95	94	94

Table1: Performance measure of accuracy, sensitivity, specificity, Precision, and Recall

7. Conclusion

The proposed work successfully developed a new technique for splitting up retinal blood vessels. Compared to earlier methods, the proposed technique performed better than 90% of the time for all three models (healthy and glaucoma). The procedure was quicker to execute as well. On unclean datasets, the proposed method demonstrated its usefulness. The following ideas for future development of this study to improve the efficiency of the retinal blood vessel evaluation: To exclude lesions, one must i) create noise reduction techniques and ii) generalize the suggested strategy to different kinds of image databases. The proposed model achieved 93% sensitivity, 92% precision, 92% recall, and 92% accuracy. The following advice is provided for future development of this study to improve the efficiency of the retinal blood vessel evaluation: To exclude lesions, one must i) create noise reduction techniques and ii) generalize the suggested strategy to different kinds of image databases.

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