

Performance Analysis of Diabetic Fundus Images using CNN, RNN, HNN Algorithms

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ABSTRACT: Diabetic retinopathy is one of the most common eye diseases. It generally found in diabetes mellitus patients. Diabetes retinopathy is a leading cause of blindness amongst the working class (less than 55 years old) in the industrialized countries. The algorithm proposed is used to detect diabetes in fundus image using the principal of HNN (Hybrid Neural Network), CNN (Convolutional Neural Network), RNN (Recurrent Neural Network) logic. The current trend is using deeper CNN, RNN and HNN layers to improve performance. Early detection of the disease helps the optometrists to gives treatment as early as possible. This paper explores evaluation performance of system has been developed, abnormal pictures area unit thought of as input, on that pre-processing techniques area unit applied filter to get rid of noise, options extraction is completed by Top-hat filter, Region based segmentation and eventually classification is completed by HNN. This paper concludes with a comparative evaluation of CNN, RNN, and HNN classifiers in the context of MESSIDAR Datasets in order to predict the diabetic patients. Here HNN classifiers are employed in his paper out of that got best results HNN for 97.92 than compared to CNN, RNN classifiers are regarding 90.06% for CNN and 96.89% for RNN. HNN classifiers are prove to be cost effective and time saving for diabetic patients and doctors.

KEYWORDS: Fundus Images, Iridology, Top-Hat, Histogram Equalization, Statistical-Region of Interest Segmentation, Convolutional Neural Network, Recurrent Neural Network, Hybrid Neural Network.

I. INTRODUCTION

Human eye is an important sensing organ of human body that makes possible vision. It is considered as a natural camera. Theretina is highly important part of the human eye. On the other side Diabetes mellitus commonly referred as diabetes is a major and leading disease found in people due to modern life style. Diabetescan cause many serious complications related to kidney and eye. Diabetic eye disease known as diabeticretinopathy (DR), is when occurs to the retina due to diabetes. It leads to permanent vision loss. If DR is detected early, the progression of diabetic retinopathy can be restricted by providing medical treatment.

Ophthalmoscopy is one of the detection methods that can be used to detect the diseaseat an early stage. But ophthalmoscopy requires the skilled professionals and more time to analysis. For such situations, an alternate strategy is to perform fundus photography. By using fundus camera, fundus retinal images of the patientscan be captured andthose images can be analysed by the experts or doctors for taking decision. Ophthalmologist can obtain retinal images from patients to be diagnosed by using a fundus camera. From the image, symptoms will be identified manuallyby an ophthalmologist. Therefore, more time is required to diagnose number of patients. Automatic detection of clinical signs of DR can help ophthalmologists in the diagnosis of the disease, with the subsequent cost and time saving.

Hybrid Neural Network (HNN) is a prominent technique which is widely used in different biomedical signal analysis because it does not only model the signal, but also make a decision to classify the signal as normal or abnormal. Therefore, it affords significant support for medical diagnosis. While many attempts have been reported in the literature for early detection of diabetic retinopathy, none has been accurate enough to perform better than ophthalmologists. An efficient algorithm for automatic detection of diabetic retinopathy has important impact for further treatment of the patients to avoid vision loss.



This research work is aimed to design a classifier system for diagnosis of diabetic retinopathy in retinal images using HNN. The classifier system described in this research is developed for the mass screening of patients related to diabetic retinopathy. This classifier system is developed by using different neural networks like CNN and RNN.

II. OBJECTIVES

The present work is intended to meet the following objectives:

1. Detecting the type of diabetes.
2. Performing accuracy of the detected image.
3. Applying the machine learning techniques to the images.

III. OVERVIEW OF DIABETES

3.1 Diabetes

A disease in which the body's ability to produce or respond to the hormone insulin is impaired, resulting in abnormal metabolism of carbohydrates and elevated levels of glucose in the blood. There are four types of diabetes.

Type 1 - A chronic condition in which the pancreas produces little or no insulin. It typically appears in adolescence.

Type 2 - A chronic condition that affects the way the body processes blood sugar (glucose). With type 2 diabetes, the body either doesn't produce enough insulin, or it resists insulin.

Prediabetes - A condition in which blood sugar is high, but not high enough to be type 2 diabetes. Without intervention, it's likely to become type 2 diabetes within 10 years.

Gestational diabetes - A form of high blood sugar affecting pregnant women. Those who develop gestational diabetes are at higher risk of developing type-2 diabetes later in life.

3.2 The Symptoms of Diabetic Retinopathy

There may be no symptoms in the early stages, especially when the central portion of the retina is not involved. As the retinopathy progresses you may have:

- Blurred vision
- Floaters, which can look like black spots, little threads, or cobwebs
- Bleeding in the eye causing sudden loss of vision
- Temporary or permanent loss of vision

3.3 Treatment for Diabetic Retinopathy

- Anti-VEGF therapy
- Intraocular steroid injection
- Laser surgery

IV. RELATED WORK

Condition of the left body components is drawn on the left aspect Retinal, and the condition of the right body components is drawn on the correct aspect of the Retinal likewise. For organs or tissues that exist on each side of the body, the illustration of the organs and tissues are on each side of the Retinal, left and right aspect additionally. The aim of this final project is to style accurate respiratory organ disorders sports stadium detection and to establish an easy tool that will build respiratory organ disorders analysis easier for iridologists or folk toward iridology additionally. Retinal recognition, an accurate and reliable biometric system [4], identify enrolled individual based upon retinal features. Few studies [1-2] combining retinal recognition algorithms and iridology to determine the status of health of an individual have been reported. [5] used iridology to determine hearing loss and found an accuracy of 70%. [1] employed iridology in

conjunctionwith Retinal recognition system and obtained an accuracy of 94% in determining the broken tissues of pancreas.[2] reported an accuracy of 86.4% and 84.9% for Retinal based diagnosis model to determine alimentary canal disease and nerve systemrespectively. Similarly,[3] obtained an accuracy of 83.3% for their model to determine.

V.SUMMARIZED METHODOLOGY

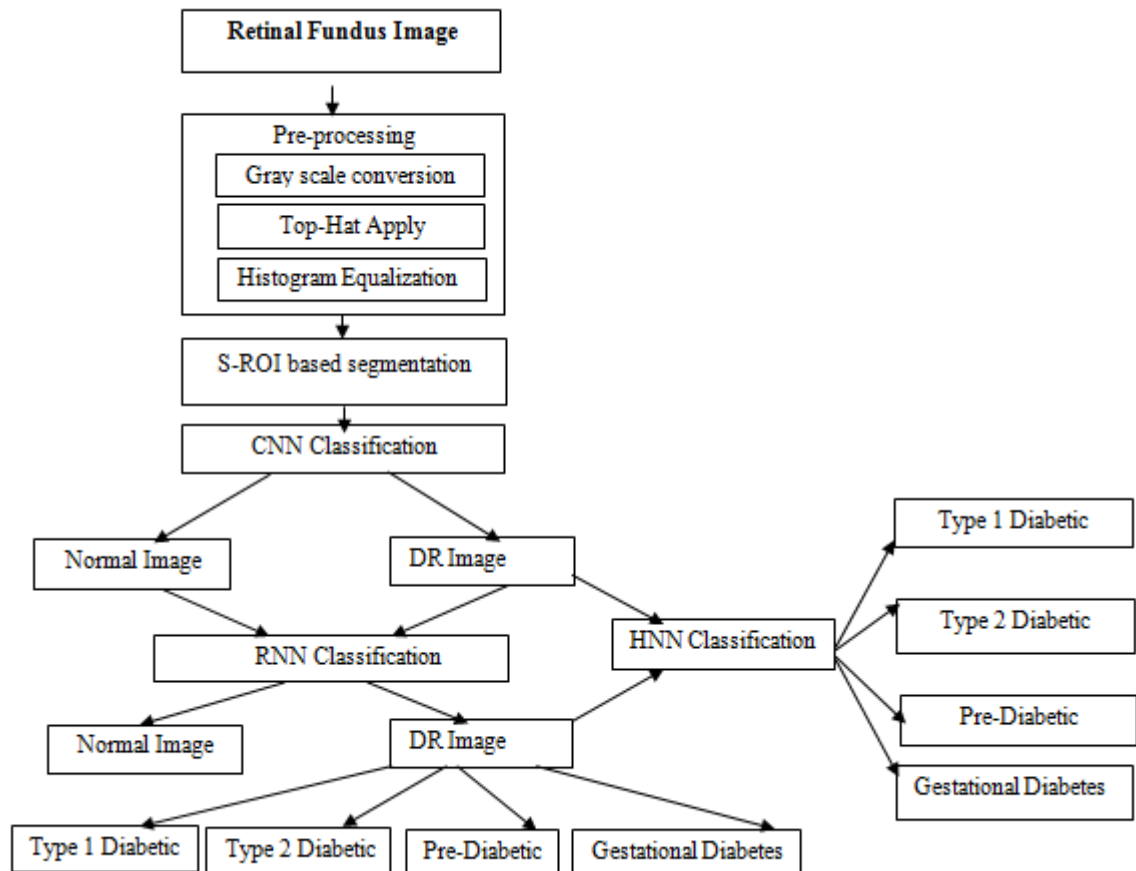


Figure 1. HNN Model

5.1 Image Acquisition

A set of elected high-quality medical images known as database is a necessary tool for the reliable evaluation and comparison of medical imageprocessingalgorithms. The retinal image databases are representatives of normal as well as diabetic retinopathy affected patient’s retinal images and those are verified by eye specialist.

The eye funduscolor images of the MESSIDOR databasewere acquiredby 3 ophthalmologic departmentsusing a color video 3CCD camera on a Topcon TRC NW6 non-mydratiac retinographwith a 45-degree field of view. The imageswere captured using 8 bits per color plane at 440*360, 400*380 or400*400 pixels. The images are packaged in 3 sets, one per ophthalmologic department. These images are also pre-processed before beingused. They are resized and converted in grayscale before the feature extraction.

5.2 Pre-processing

Image pre-processing includes various techniquessuch asgray component, image denoising and contrast enhancement. Initially we convert the RGB image into grayscale image to further process the image.



A top-hat is a residual filter which preserves those features in image that can fit inside the structuring element and removes those that cannot. The top-hat opening, h_o , is defined as the difference between the original image f , and its grayscale opening using the structure element A . $h_o = f - (f \bullet A)$ (1)

Similarly, the dual top-hat by closing, h_c , is the difference between the grayscale closing using the structure element A and the original fundus image f . The structuring element A is defined as disk like structure with size 15.

$$h_c = (f \bullet A) - f \quad (2)$$

The top-hat opening, yields an image that contains all the residual features (i.e., peaks and ridges) removed by the opening. Adding the residual feature to the original fundus image has the effect of accentuating high intensity (high) structures. The dual residual (i.e., valleys and roughs) obtained by using the top-hat by closing, is then subtracted from the resulting fundus image to accentuate low-intensity (dark) structures. $M = f + h_o - h_c$ (3)

This reduces high frequencies in image (noise). However, a drawback of the mathematical morphology technique is that a part of the noise still remains. To remove the remaining noise, we use the histogram equalization.

Contrast is the difference in luminance or colour that makes an object distinct. Contrast enhancement adjusts dark or bright pixels of an image to bring out the hidden features present in the image. For this research work, a few contrast enhancement methods have been implemented in DR fundus image to enhance the hidden features present in the image. Histogram Equalization (HE) is a contrast enhancement technique that flattens and distributes the dynamic range of intensity values uniformly among all histogram bin. Therefore, HE highlights borders and edges and also reduces the local details of the fundus image.

5.3 Segmentation

Statistical-Region of interest (S-ROI) is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. The result of S-ROI is a set of segments that collectively cover the entire image or a set of contours extracted from the image. Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. The original image is captured with the black unwanted background. Including the background reduced the accuracy of the original image, because the position of retinal blood vessels usually varies across different retinal blood vessels images, it is necessary to image segmentation in S-ROI before feature extraction and matching with database.

5.4 CNN Classification

The number of input layer neurons is equal to the number of pixels in the input image. **Convolutional Layer:** Convolutional layer makes use of the Convolutional features and computes the product between the image patches and the filter. **ReLU Layer:** For the convolutional layer ReLU (Rectified Linear Unit) can be used. ReLU layer perform a threshold operation to each element of the input where any value less than zero is set to zero. Element wise activation is applied to the output of the convolutional layer. **Pooling Layer:** The function of the pooling layer is to down convert the volume so as to make the computation faster and to reduce the memory requirement. **Fully Connected Layer:** The convolutional layer that is present just before the fully connected layer holds the information about the features including the edges, contrast, blobs and shapes. And the fully connected layer contains the aggregated information from the previous layers. A pooling layer is used as the final layer of CNN. It assigns decimal probabilities to each class. **Classification layer:** The output layer classifies the input images into two classes namely normal (without DR) and abnormal (with DR). The designed layers are used for training and testing of images. The images for training can be obtained from MESSIDOR which provides marked images of diabetic lesions. In this method are used two layers for CNN, trained it on 100 fundus images and tested on 50 images. All the images were classified into two groups i.e., with DR and without DR.

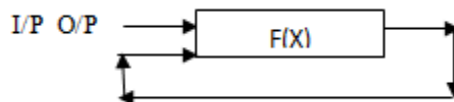


Figure 2. CNN without RNN

5.5 RNN Classification

The main use of Recurrent Neural network is in the field of fundus image recognition. The RNN is a network which has recurrent network connections. The traditional feed forward neural network does not provide good results for times series/sequential data such as stock prices, video streams etc. They do not model memory. RNN captures information from sequences and time series data from the CNN output. They can work with variable size input and work with variable size data. The concepts of hybrid neural network are also incorporated by adding recurrent connections to each Convolutional network. This can also be called as recurrent convolutional layers (RCL). Based on the weightage of time series data.

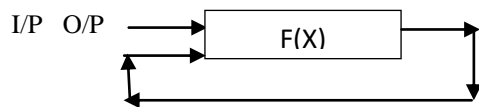


Figure 3. CNN with RNN

5.6 HNN Classification

a.convolution: The output of the embedding layer is given to each branch of b branches. Each branch starts with a 1-dimensional convolution layer of kernel size c specific to that branch. The kernel during 1-dimensional convolution is of shape kernel size by embedding size ($c \times e$). The kernel will then perform convolution on whole words instead of the typical 2-dimensional convolution that would filter partial widths and cut words into pieces. The layer produces multiple outputs with the use of multiple filters f . The purpose of the CNN layer is to view word combinations of the kernel size c . The result is an understanding of words when used with other words. For example, when $c=3$, the layer views at a time and, therefore, establishing a sense of 3-word combinations. This layer's output has a shape of input height by filters (words by f).

b.Activation: Each branch applies a rectified linear unit (ReLU) activation of the CNN layers output; this layer replaces any negative outputs with zero. The ReLU layer is used in order to introduce non-linearity into the network. The output of this layer is the same shape as the input shape.

c.Max Pooling: Each branch undergoes 1-dimensional max pooling following ReLU activation; this layer converts each kernel size of the input into a single output of the maximum observed number. The result is a reduced, down-sampled version of the input. The purpose of the layer is to reduce overfitting, while allowing for further processing. Similar to the CNN layer, the 1-dimensional max pooling kernel shape is fit to the width of the data, so that the parameter kernel size p implies a kernel shape of p by data width. This technique allows pooling to be applied with the understanding that data is composed of whole words. The output of this layer is a reduction in height according to kernel size p (input height/ p).

d. Dropout: After max pooling, each branch goes through a dropout layer; this layer randomly sets a portion of the inputs to 0. The dropout is applied to specified d fraction of the inputs. This layer serves to prevent overfitting and generalize the network to not focus on specific pieces of input. The output shape is equivalent to the input shape.

e.Batch Normalization: The next layer for each branch is batch normalization; this layer simply normalizes the distribution for each batch after dropout. The purpose of batch normalization is to reduce internal covariate shift and therefore lead to convergence at a faster rate. The output of this layer holds the same shape as the input.

f. Final Layer: The final layer for each branch is a RNN layer with a specified number of units l . The RNN is used because of the nature of sequential data. The layers persistence allows knowledge of previous input (convoluted word combinations) to influence subsequent input. The output has a length of the number of units l .

g. concatenation: The branches are finally merged together through concatenation. The RNN layers outputs are combined together in an array. The output shape of this layer is equal to the summation of the output of all branches ($l \times b$).



h. Dense: The last layer is a fully-connected layer from the concatenated input to a single output. The layer is followed by a simple sigmoid activation function to conform the output between 0 and 1.

i. Loss Function and Optimizer: The network is compiled with a binary cross entropy loss function; this loss calculates loss with two classes (0 and 1). For this paper's purposes, 0 represents negative sentiment and 1 represents positive sentiment. The loss is calculated on the single and final output of the dense layer. The network is also compiled with an optimizer; Adam, RMSprop, and Stochastic Gradient Descent (SGD) were the optimizers used for testing during the experiments. Each optimizer was used with varying learning rate decay parameters.

5.7. PERFORMANCE EVALUATION

A performance analysis methodology is a procedure that can be followed to analyse system or application performance. As such, it aims to present a balanced and complete view of the entire performance evaluation profession. i.e. Mean squared error, Peak signal to noise ratio, normalized cross correlation, Maximum difference, Average difference, Structural content, Normalized absolute error, Structural similarity.

- **MEAN SQUARED ERROR (MSE):**

MSE is a very simple and common distortion measure. MSE between the reference image and processed image with a size of a (m*n). The value of MSE measures the difference between a processed image and reference image. The smaller value of the MSE represents the better results.

- **PEAK SIGNAL TO NOISE RATIO:**

For the measurement of reconstruction quality, PSNR is one of the most extensively used metric parameter. It describes the ratio of the maximum possible power of a signal to the power of the corrupting noise and is normally represented in decibel scale. A higher value of PSNR specifies the reconstruction of higher quality.

- **NORMALIZED CROSS CORRELATION:**

NCC measure shows the comparison of the processed image and reference image.

- **MAXIMUM DIFFERENCE:**

MD provides the maximum of the error signal-difference between the processed and reference image. The higher value of the maximum difference, the poorer the quality of the image.

- **AVERAGE DIFFERENCE:**

AD provides the average of change concerning the processed and reference image. Ideally it should be zero.

- **STRUCTURAL CONTENT:**

A higher value of Structural content shows that image is poor quality.

- **NORMALIZED ABSOLUTE ERROR:**

A higher value of Structural similarity shows that image is of poor quality.

- **STRUCTURAL SIMILARITY:**

SSIM is used for measuring the similarity between two images. The structural similarity index is a full reference metric; in other words, the measurement or prediction of quality is based on an initial uncompressed or distortion-free image as reference. Structural similarity is designed to improve on traditional methods such as peak signal-to-noise ratio and mean squared error.

All the implementation work done in MATLAB. First of the entire original image is processing convolutional neural network, recurrent neural network and hybrid neural network, following are results obtained after comparison.



IMAGE	MSE	PSNR	NCC	MD	AD	SC	NAE	SSIM	ACC
1	0.158	40.437	0.068	0.158	0.407	36.311	0.973	0.032	90.06
2	0.134	65.890	0.048	0.095	2.001	42.149	0.976	0.013	90.04
3	0.059	84.976	0.046	0.085	0.001	2.955	2.955	0.013	90.04
4	0.082	74.620	0.071	0.132	0.001	2.732	2.752	0.014	90.04
5	0.068	75.590	0.065	0.110	0.001	1.396	1.396	0.015	90.04
6	0.117	59.350	0.053	0.100	0.001	2.776	2.776	0.025	90.05
7	0.070	84.259	0.065	0.112	1.000	1.756	1.756	0.013	90.05

TABLE 1. PERFORMANCE OF THE CNN ALGORITHM IN DETECTING DIABETES

IMAGE	MSE	PSNR	NCC	MD	AD	SC	NAE	SSIM	ACC
1	2.198	40.437	6.894	15.886	0.407	36.311	0.973	3.216	96.89
2	1.871	65.890	4.866	9.570	2.001	42.149	0.976	1.339	94.86
3	0.059	84.976	4.661	8.548	2.117	48.545	0.979	1.377	94.66
4	0.082	74.620	7.169	13.278	1.772	45.214	0.978	1.439	97.16
5	0.068	75.590	6.591	11.029	1.303	22.938	0.958	1.510	96.59
6	1.631	59.350	5.364	10.059	1.359	45.611	0.978	0.978	95.36
7	0.070	84.259	6.546	11.235	0.000	1.611	1.756	1.309	96.54

TABLE 2. PERFORMANCE OF THE RNN ALGORITHM IN DETECTING DIABETES

IMAGE	MSE	PSNR	NCC	MD	AD	SC	NAE	SSIM	ACC
1	2.528	46.502	7.928	18.268	0.468	41.758	1.119	3.698	97.92
2	0.068	75.774	5.596	11.006	2.301	48.471	1.123	1.540	95.59
3	0.068	97.722	5.360	9.830	2.434	55.827	1.126	1.584	95.36
4	0.095	85.813	8.244	15.7	2.038	51.996	1.125	1.655	98.24
5	0.079	86.929	7.579	12.683	1.499	26.379	1.101	1.737	97.57
6	1.876	68.253	6.169	11.567	1.563	52.453	1.125	2.945	96.16
7	0.081	96.898	7.527	12.921	0.001	2.019	2.019	1.506	97.52

TABLE 3. PERFORMANCE OF THE HNN ALGORITHM IN DETECTING DIABETES

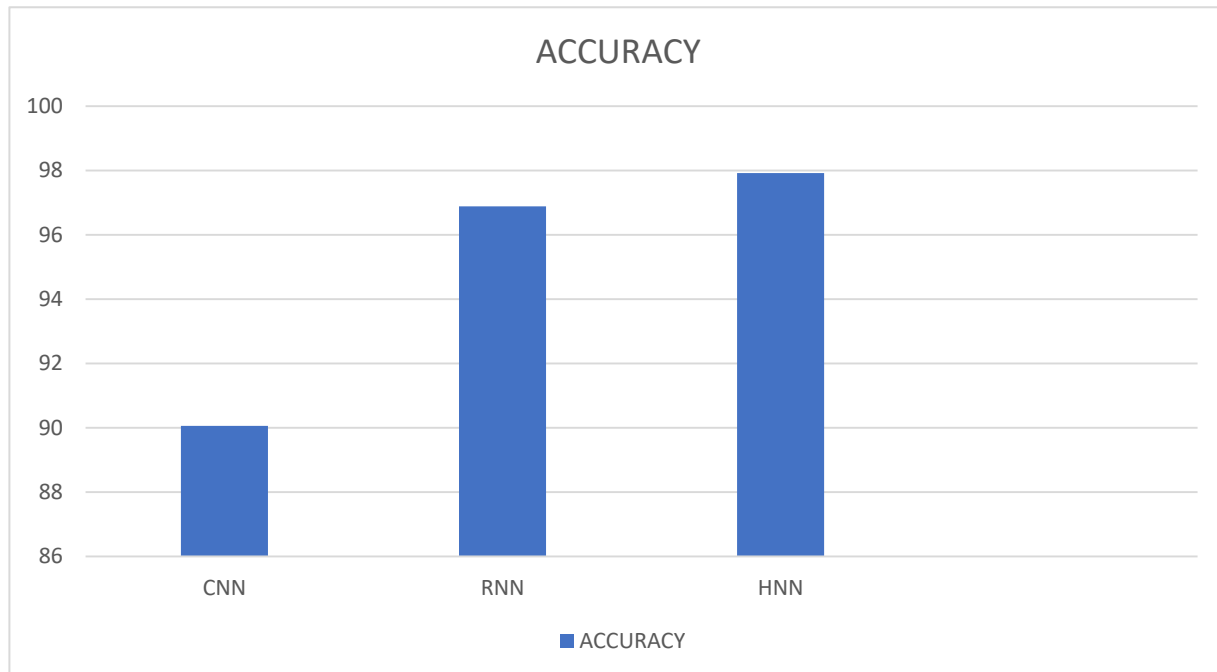


FIG. 4 COMPARISONS OF CNN, RNN & HNN ACCURACY MEASURES

VI. CONCLUSION

Diabetic retinopathy is one of the complications of diabetes mellitus that occurs due to damage of blood vessels in the light-sensitive tissues in the back of the eye (retina). At early stages, symptoms of DR may not appear and cause simple problems on vision, but in advance stages can cause to blindness. Therefore, early detection of diabetic retinopathy is important to prevent loss sight. HNN technology would act as an auxiliary assistant in screening of diabetic retinopathy and offer diagnostic support. Here three styles of neural networks are employed in this project out got best results for HNN than compared to all or any different existing strategies of classifiers, share of accuracy been obtained is regarding 90.06% for CNN, 96.89% for RNN and finally 97.92 for HNN.

FUTURE SCOPE

- In future, in work to expand the detection system to recognize microaneurysms and haemorrhages, there may be a problem in separating the pathologies from small vessels.
- If the small vessels are missed during this step and are confused with microaneurysms or haemorrhages it may be possible to combine more than one detection technique to make a final decision on the detected area being either a vessel or microaneurysm or a haemorrhage.
- Images are taken from a publicly available database domain for the experiments presented in this dissertation. It is prudent, however, to verify this technique using other databases containing DR images.

REFERENCES

1. C. Aslani, "The Human Eye: Structure and Function", Sinauer Associates, Sunderland, MA, 1999.
2. L. Zhang, M. Fisher, W. Wang, "Retinal vessel segmentation using multi-scale textons derived from keypoints", Jour. Of Comp. Med. Imaging & Grap., Vol. 45, pp.47-56, 2015.



3. C. Hassana, J.F. Boyce, H.L. Cook, T.H. Williamson, “Automated localization of the optic disc, fovea & retinal blood vessels from digital color fundus images”, British Journal of Ophthal., Vol.83, No.8, pp.902-910,1999.
4. U. Akram M. Khan, “Multilayered thresholding-based blood vessel segmentation for screening of diabetic retinopathy” Jour. of Engg. Comp., Vol. 29, No. 2, pp. 165-173, 2013.
5. R. GeethaRamani, L.Bala Subramanian, “Retinal blood vessel segmentation employing image processing and data mining techniques for computerized retinal image analysis”, Jour. of Biocybernetics & Biomed. Engg., Vol. 36, No.1, pp. 102-118, 2016.
4. DIGITAL IMAGE PROCESSING, FOURTH EDITION, RAHEL C.GONZALEZ, RICHARD E. WOODS.
5. FUNDAMENTAL OF DIGITAL IMAGE PROCESSING, Kshama pandey, prof.p.k.chaturvedi.
6. DRIVE: Digital Retinal Images For Vessels Extraction <http://www.isi.uu.nl/research/databases/drive/>
7. STARE: Structured Analysis Of The Retina. <http://www.ces.clemson.edu/~ahoover/stare/>
8. DIARETDBI-Standard Diabetic Retinopathy Database Calibration Level.<http://www.it.lut.fi/project/imageret/diaretdbl>.