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SEVERITY CLASSIFICATION OF MICROANEURYSMS USING NEURAL NETWORK

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Abstract
Diabetic Retinopathy is one of the most common causes of blindness that leads to the loss of vision to the human eye. Several methods have been proposed to detect several defects of the human eye like hemorrhages, exudates etc. which are to be considered as the major symptoms. Among them, Microaneurysms should be considered as one of the severe condition for the early blindness. Several techniques have been proposed based on this, but they have certain drawbacks. A new technique called neural network taken for presentation, helps to detect and determine the severity of Microaneurysms which would be able to give a better performance than the existing techniques.

Keywords:
Microaneurysms, Enhancement Morphological Operations, Feature Extraction, Neural Network

1. INTRODUCTION

Most of the diabetic patients are suffering from Diabetic Retinopathy that is found in the retina of the human eye. The major symptoms of the early blindness include Microaneurysms, hemorrhages, exudates, drusen, cotton wool etc. Several techniques have been proposed for the severity classification. A comparison of the results would be done by five different team of researches on the same set of data [6]. The evaluation was done in a uniform manner and the results were submitted through the website which needs certain software to determine the performance. The evaluation result shows that the detection of Microaneurysms was a challenging task for both the automatic and the human expert method. The data was also heterogeneous, because of the different cameras used that are having a high variation in the image quality.

The early detection of Microaneurysms is done through the cross-sectional scanning. Joseph M. Reinhardt [2] proposed splat feature classification method for the detection of retinal hemorrhages in the fundus image. The features should be extracted based on the filter approach and the wrapper approach.

The training sets are divided into training subset and the testing subsets. Each pixel is subjected to test fewer than two groups and the values are maintained in the ascending order which determine their effectiveness. The irrelevant features that are not very effective should be removed and different combination of features should be selected. The relevant features are forwarded to the Sequential Forward Feature Selection that covers the area under Receiver Operating Characteristics.

Macula swelling detection with multiple retinal fundus image uses uncelebrated multiple view fundus images to analyze the swelling of macula. This was proposed by Luca Giancarlo [3]. It uses a pre-processing step that shows microstructures of the macula and then the views are registered. The third step includes naïve height map reconstruction technique. The images captured with the digital fundus camera are the versatile tools for the diagnosis of the retinal diseases but it won't be able to detect the depth of the diseases.

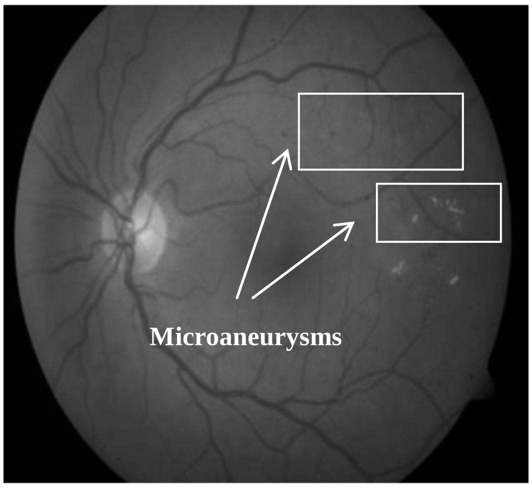

Fig.1. Fundus Image with Signs of Diabetic Retinopathy [1]

A computerized scheme forth detection of Glaucoma which is a disease caused due to the defect in the retinal nerve fiber layer was proposed by Akira Sawada [4]. The blood vessels would be left to interpolate with the other pixels. The polar transformations will make the nerve fiber into a straight nerve fiber and the enhancement should be done with the Gabor function. The multiplication of the Gaussian function and the cosine function is the Gabor function. The retinal nerve fiber layer defect was determined with the help of two classifiers called Linear Discriminant Analysis and the Artificial Neural Network and the results were plotted in the Receiver Operating Characteristics curve.

Arturo Aquino et al. [5] proposed Circular Hough Transform method for detecting the optic disc boundary. The detection of optic disc requires a fully automated system but the detection of the exact center of the optic disc is very difficult to determine. The Circular Hough Transform transforms a set of features into the accumulated votes. It should be defined as,

$$(P_c, r) = \mathrm{CHT}(I_{BM}, r_{\min}, r_{\max}) \tag{1}$$

where, $P_c = (i_c, j_c)$ and r are at the center position and the radius that is used to define the circular shape. The radius r should lie between $r_{\min}$ and $r_{\max}$ which are one-tenth and one-fifth of the image. The Circular Hough Transform method cannot be applied for the optic disc that is elliptical in shape.

The exudates are the severe condition of Microaneurysms in which the Microaneurysms burst out and the yellow patches were formed in the retina of the human eye. A comparative analysis for the exudates detection was determined. The exudates should be determined with the help of some of the morphological techniques. The pre-processing steps should be

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done to the captured image and the entire area should be equally contrasted that it gives a better appearance of the entire image. The Gabor filters are used for the vessel enhancement and it also removes the background noise.

The existing system uses the green channel of the fundus image as the input for getting a bright structure of the fundus image. The existing system uses images of different size which automatically takes different parameters and also the larger image data results in the longer execution time.

Image Preprocessing

The image preprocessing should not be considered in a proper format in the existing system. This is due to the fact that getting a very compressed format results in deformation of a small microaneurysms structure. The existing system applied a Gaussian mask having a variance of 1.0 and other enhancement techniques.This was mainly done to remove the noise on the fundus image.

Maximum Region Extraction

A local maximum region of the gray channel of the fundus image is a connected pixel component having a constant intensity value such that the pixel value of the neighbouring region having a lower intensity value. Therefore the cross-sectional scanning technique considered only the local maximum region of the preprocessed image. It uses a breadth first search algorithm for the calculation of the morphological reconstruction.

Pixels of the image are compared with their eight neighbours. If all the neighbours have a lower intensity value, then the pixel should be considered as a loacl maximum region. If the neighbouring pixels have a higher intensity value, then the current pixel should not be considered as a maximum region.

Cross – Sectional Scanning

The cross – sectional intensity profiles can be generated by examining the surroundings of a single pixel in a microaneurysms candidate region. Its intensity value with discrete line segments at different orientations should be calculated.

Feature Extraction and Non Maximum Suppression

After performing the cross – sectional scanning of each and individual Microaneurysms candidates, the features are extracted and then classified using naïve classifier. Here the training set consists of both the positive and negative examples of Microaneurysms. Based on each classification the final scores should be calculated.

The final step in the cross – sectional scanning is the non-maximum suppression. It refers to the technique of selecting a point that is having a highest score from every maximum region. The points with a non maximal score are neglected. The output of this technique is the set of Microaneurysms co-ordinates with the corresponding score value. The existing cross – sectional scanning technique has some of the drawbacks which include: the detection of Microaneurysms done manually i.e. the techniques have to individually crop each region for the detection of Microaneurysms. Secondly, the Microaneurysms are never found in the optic disc of the human eye, but this cross – sectional scanning performs the detection of Microaneurysms inside the optic disc also which increases the time complexity.

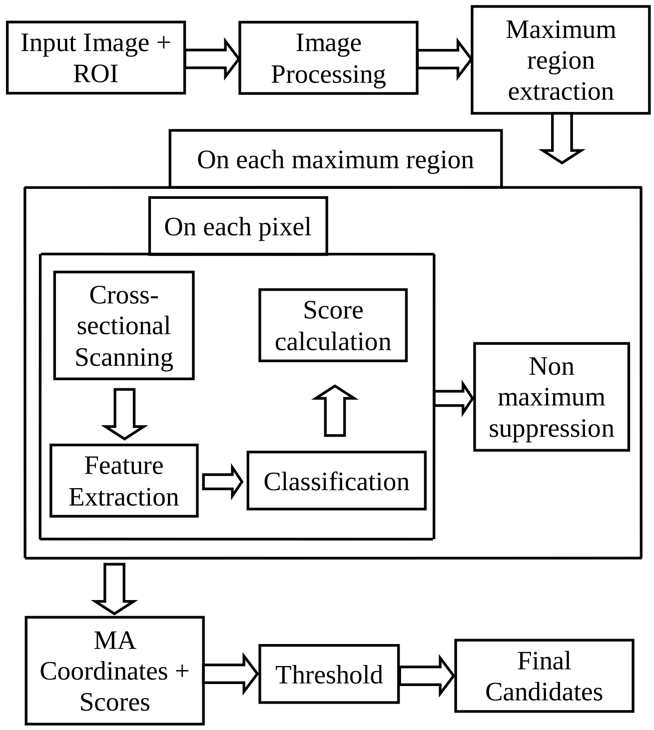

Fig.2. Workflow of the Existing Method [1]

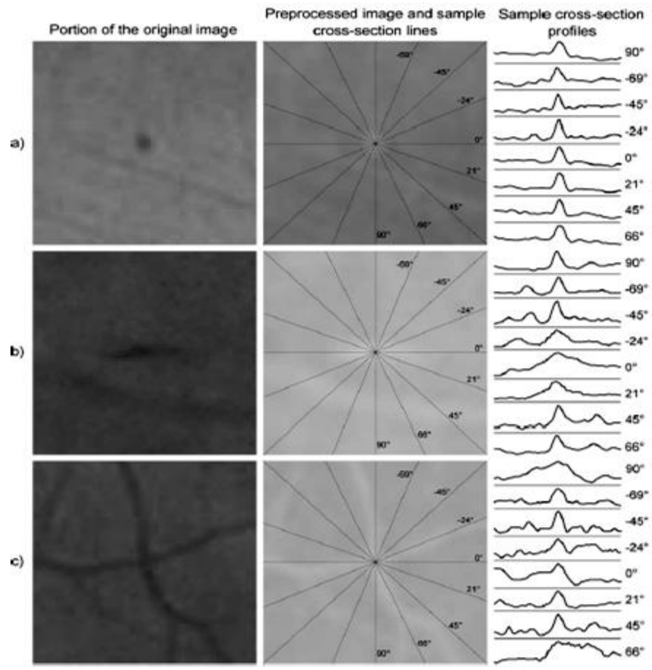

Fig.3. Cross – Sectional Scanning of Microaneurysms [1]

The cross – sectional scanning method also performs the detection of the Microaneurysms from the entire captured image which are actually not needed for the detection of Microaneurysms.

2. PROPOSED SYSTEM

The proposed system uses a new concept called the neural network which would be able to replace the existing techniques. The proposed system performs the morphological operations on the fundus image and then it extracts the feature from the fundus image using mathematical formulas. Finally the severity classification of these extracted features would be done based on the neural network.

2.1 DETECTION OF MICROANEURYSMS

The acquired input image should be preprocessed. Here it means, the image which was captured is in 1152 × 1500 pixels which should be very larger than the screen of a normal desktop system. So, to make the entire fundus image to be visible on the screen, the acquired input image should be resized. Also the resized colored input image should be converted into the gray channel through the enhancement techniques whish should be considered as an input to the morphological operations.

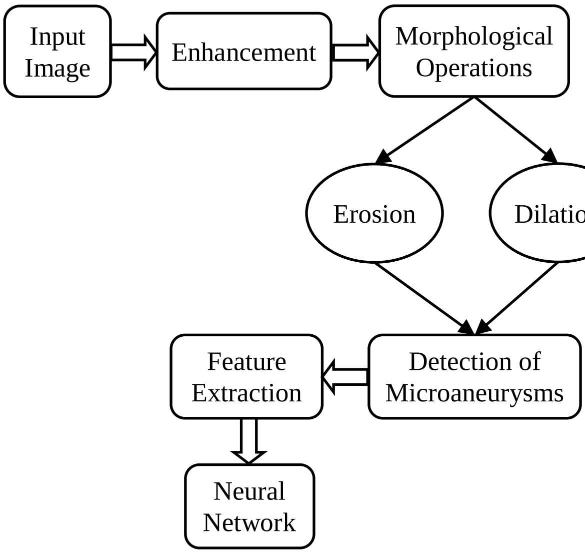

Fig.4. Workflow of the Proposed Method

The morphological operations should be done on the input image. The morphological operations include opening, closing, dilation and erosion. In order to segment out only the retinal image, the imfill operation should be used. Further, the erosion and the dilation operation would be performed on the segmented part and the difference should be taken out. Another major factor is that the Microaneurysms are never found in the optic disc of the retina. After the difference operation, the optic disc should be removed by using the closing and the removing operation. The Microaneurysms should be detected by setting a threshold value based on the intensity level of the fundus gray scale image

2.2 FEATURE EXTRACTION

After performing all the morphological operations the Microaneurysms should be clearly detected in the fundus image. Among the detected Microaneurysms, the features should be extracted using some mathematical formulas. The features include mean, variance, skewness, kurtosis and energy values, should be extracted.

The mean value should be determined by using the formula,

$$\text{Mean} = \Sigma\,(\text{Prob} \times \text{Gray Vector}) \tag{2}$$

where, $\text{Prob} = \dfrac{\text{Histogram}}{\text{Rows} \times \text{Columns}}$

Gray Vector denotes the intensity level.

The mean value in turn is used for determining the variance which should be calculated as,

$$\text{Variance} = \Sigma\,(\text{Prob} \times (\text{Gray Vector} - \text{Mean}^2)) \tag{3}$$

The energy value should be calculated as the product of its probabilities.

$$\text{Energy} = \Sigma\,(\text{Prob} \times \text{Prob}) \tag{4}$$

The skewness and kurtosis values should be calculated as,

$$\text{term1} = \text{Prob} \times (\text{Gray Vector - Mean})^3$$
$$\text{term2} = \sqrt{\text{Variance}}$$

$$\text{skewness} = \frac{\text{Prob} \times (\text{Gray Vector - Mean})^3}{\sqrt{\text{Variance}}} \tag{5}$$

$$\text{term1} = \text{Prob} \times (\text{Gray Vector - Mean})^4$$
$$\text{term2} = \sqrt{\text{Variance}}$$

$$\text{kurtosis} = \frac{\text{Prob} \times (\text{Gray Vector - Mean})^4}{\sqrt{\text{Variance}}} \tag{6}$$

The feature values should be extracted from the fundus image. These feature extraction should be done on DB1 dataset. These feature values should be given as an input to the neural network.

The classification using neural network provides a better result because here, the system is trained to provide the correct classification with some of the feature values rather than framing rules manually for the classification like in the fuzzy logic. The severity classification of Microaneurysms with these feature values using neural network concept is a new one.

i) Fundus Images from Diaretdb1 Dataset

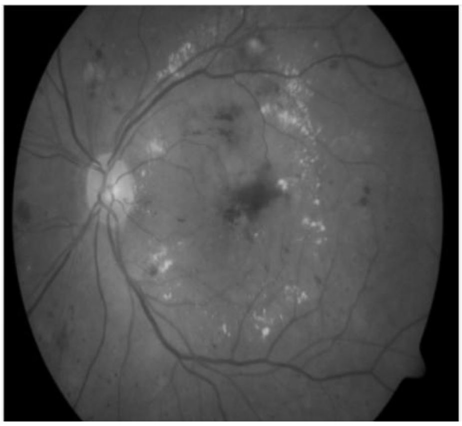

Fig.5. Fundus Image 1

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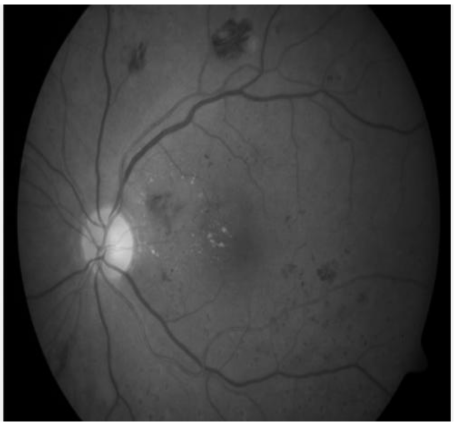

Fig.6. Fundus Image 2

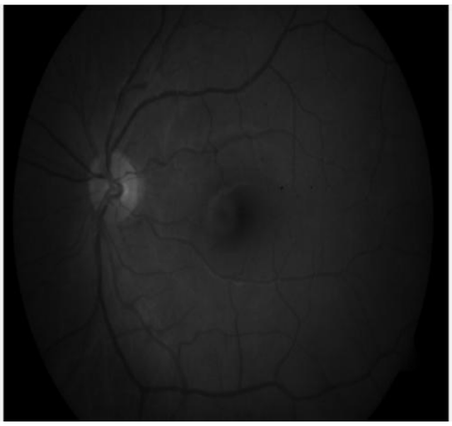

Fig.7. Fundus Image 3

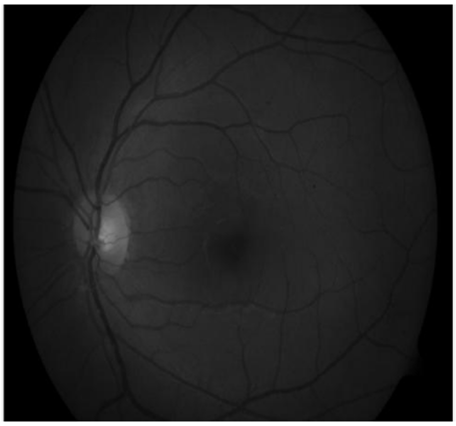

Fig.8. Fundus Image 4

ii) Feature values extracted from DiaretDB1 dataset

Table.1. DB1 Feature values

Sl. No.	Mean	Variance	Skewness	Kurtosis	Energy
Image 1	68.8574	634.5127	0.9412	5.0683	0.0116
Image 2	45.6249	540.4006	1.9343	10.1629	0.0115
Image 3	17.8513	81.3284	1.9103	7.5126	0.0242
Image 4	20.5902	97.8344	3.3863	22.3580	0.0261

Graphical Representation

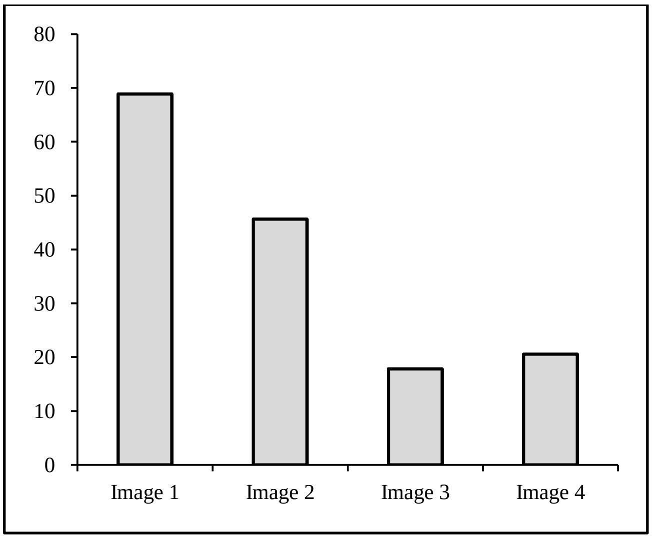

Fig.9. Graphical Representation of Mean

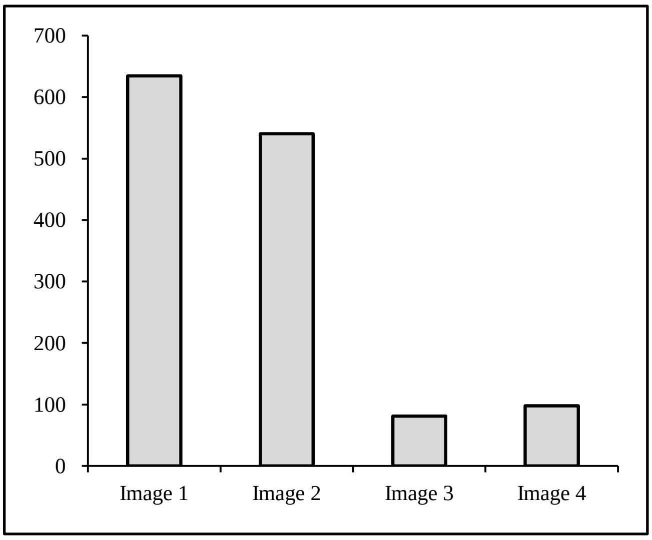

Fig.10. Graphical Representation of Variance

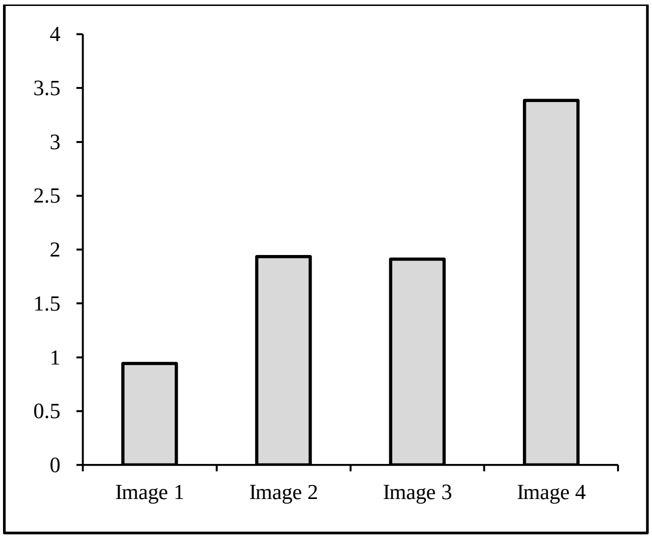

Fig.11. Graphical Representation of Skewness

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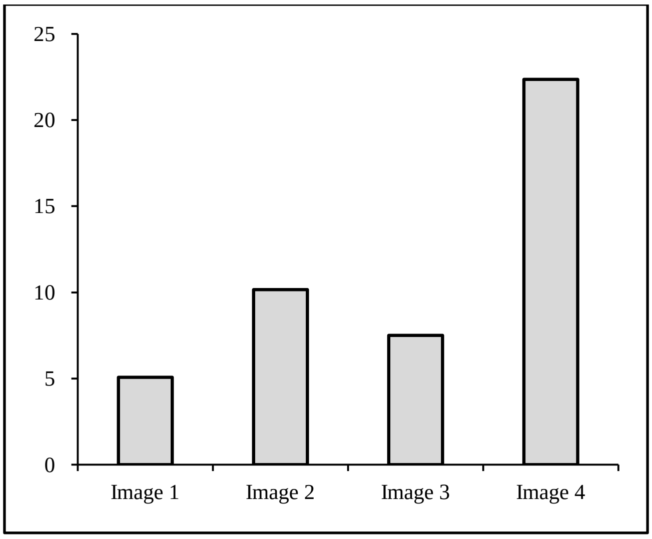

Fig.12. Graphical Representation of Kurtosis

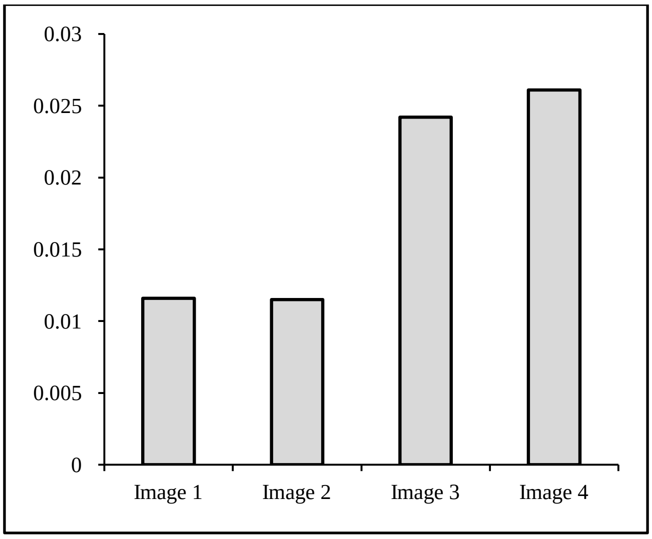

Fig.13. Graphical Representation of Energy

In the above graph, X-axis represents the four images that are taken from the DiaretD1 dataset and Y-axis represents its feature values. The feature includes mean, variance, skewness, kurtosis and energy. It was mainly calculated to get the precise information of the entire image matrix which helps to reduce the effort of training each and every pixel in the neural network.

2.3 NEURAL NETWORK

The neural network should be considered as knowledge based system. It should process the information in a similar way, the human brain does. The network is composed of a large number of highly interconnected processing elements working in parallel to solve a specific problem. Neural network is usually learned by example and they cannot be programmed to perform a specific task.

Basic Steps of Neural Network:

- The first step in developing a neural network is to create a database that contains the image.
- The created images are converted into a digital image by using any one of the scanning devices.
- Half of the image should be taken from the database to train the neural network and the reminder to test its performance.
- It includes validation test set to train the network and production test, to validate the trained network against a separate test set.

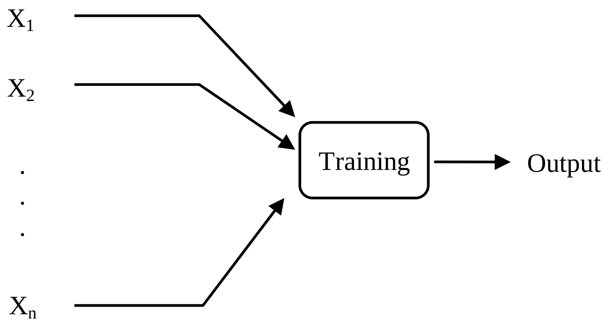

Fig.14. Workflow of Neural Network

During training, the network is trained to associate output with each of the input pattern. If any further image is used instead of the images from DB1 dataset, then it would become helpful to consider only the feature values for giving as input for associating the output rather than the entire image pixels.

3. PERFORMANCE EVALUATION

The performance evaluation was done on thirty five different images from the Diaret DB1 dataset. Among that thirty four images are correctly classified by the neural network and the one image provides the wrong classification because of the training given to the neural network so many times. If about hundred images are taken for the severity classification of Microaneurysms, nearly seventy images are used for the training the neural network with the extracted feature values. The training to the neural network system is given with the appropriate ground truth information. Fifteen images are used for validation of the neural network and the remaining fifteen images are used to test the neural network in order to identify the severity of Microaneurysms in the correct way. The Receiver Operating Characteristics graph was determined against the true positive (which indicated the presence of Microaneurysms on the fundus image, if there is) and the false positive rate (which indicates the presence of Microaneurysms on the fundus image, if there is not) for all the training, validation and the testing of the images in the neural network system from which the performance evaluation on the DiaretDB1 dataset would be able to achieve 97.1% accuracy and provides a negligible false positive rate.

Table.2. Performance Evaluation

Images	True Positive	False Positive
Image 1	✓	
Image 2	✓	
Image 3	✓	
Image 4	✓	

Image 5	✓	
Image 6	✓	
Image 7	✓	
Image 8	✓	
Image 9	✓	
Image 10	✓	
Image 11	✓	
Image 12	✓	
Image 13	✓	
Image 14	✓	
Image 15	X	✓
Image 16	✓	
Image 17	✓	
Image 18	✓	
Image 19	✓	
Image 20	✓	
Image 21	✓	
Image 22	✓	
Image 23	✓	
Image 24	✓	
Image 25	✓	
Image 26	✓	
Image 27	✓	
Image 28	✓	
Image 29	✓	
Image 30	✓	
Image 31	✓	
Image 32	✓	
Image 33	✓	
Image 34	✓	
Image 35	✓	

4. CONCLUSION

The early detection of Microaneurysms is very necessary in order to avoid the early blindness to the human eye, as it is considered as one of the major symptom. The feature extraction from the fundus image was done on Diaretdb1 dataset. These feature values should be given as an input to the neural network. By the concept of Neural Network, it should be able to produce a better performance for the severity classification of Microaneurysms in the fundus image on theDiaretdb1 dataset for the effective treatment of diabetic retinopathy and this method is found to reduce the manual effort required for the detection and also the accuracy gets increased. This work can be further proceeded with Neuro fuzzy classifier on different dataset so that the performance and accuracy gets increased.

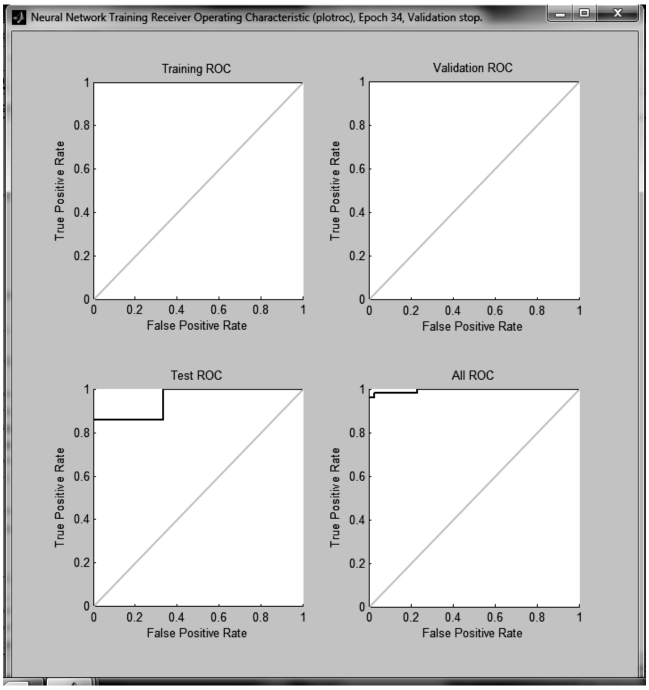

Fig.15. Accuracy Determined

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