A Novel Approach based on Merging of Super pixels for Retinal Area Detection in SLO Image

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ABSTRACT

Scanning Laser Ophthalmoscope (SLO) image can be used to detect retinal diseases. Through these images a large part of the retina can be viewed, that improves the identification of the diseases. This is done with the help of advancement of SLO images. But during imaging along with the retina, artefacts such as eyelashes and eyelids are also captured. In this paper, a novel technique is proposed which detects the true retinal area with the help of image processing techniques. A framework has been developed to extract the retinal area from the SLO image. The images are initially preprocessed using Weiner filtering and the preprocessed images are then grouped into pixels based on regional size and compactness called Super pixels. After the generation of super pixels, merging of super pixel is performed. This will reduce the complexity and increase the speed of computation. Then feature generation is carried out using regional, gradient and textural features on the merged super pixels. By this proposed method artefacts are removed and highly improved detection of retinal area is achieved. Further to this process feature selection is carried out to reduce the execution time. The selected features are classified using Adaptive Network based Fuzzy Inference System (ANFIS) and its performance is compared with Artificial Neural Network (ANN). A comparative performance of 98.5% is obtained using the proposed method.

KEY WORDS: Scanning Laser Ophthalmoscope, Super pixel Generation, merging, Feature generation, Feature Selection, Classifier.

1. INTRODUCTION

The ophthalmoscope research is an emerging field where lots of research is carried out. Retinal disease is a common abnormality that leads to blindness. Vision loss can be avoided with the help of retinal disease treatment. In olden days, retinal diseases are recognized using manual techniques. Alteration of contrast and zooming are imparted by optometrists and ophthalmologists to infer images and analyze results based on experience and domain knowledge. These diagnostic methods are always a time consuming process. Mechanical examination of retinal images helps in reducing this execution time. It is better to glimpse at the images which could screen more patients and more unswerving diagnoses can be given in a time efficient manner. Scanning Laser Ophthalmoscope images gives the outcome of 2-D retinal scans. But, it contains artefacts such as eyelids and eyelashes along with the true retinal area. So the main confront is to eliminate these artefacts from the captured retinal image. In this paper, a framework has been developed to extract the retinal area from the SLO image. In this technique, Image preprocessing is done initially using wiener filtering. In the preprocessed images pixels are grouped and then super pixels are generated. A technique is developed to merge the super pixels further and the following three most important steps are performed for constructing the desired framework.

a) Generation of features is done to differentiate the retinal area and artefacts.
b) Selection of features is performed which helps to reduce time complexity.
c) Construction of classifier is carried out to classify the retinal area from SLO images.

Image based features are generated to discriminate retinal area and artefacts. It helps to determine regional, textural and gradient features. Feature selection improves classifier performance and further reduces the computational time. The Classifier construction is done using ANFIS and the developed classifier classifies the true retinal area from artefact. Finally image post processing is done using morphological filtering to determine the retinal area boundary using super pixels that are classified. To study the performance of the ANFIS classifier, a comparative analysis is carried out by comparing the results with ANN.

The paper is structured as follows. Section II introduces a detailed survey of the existing work for the retinal area detection. Section III gives an insight into our proposed framework. Section IV provides the outcome of the work with a proof of results and quantitative analysis. Section V summarizes the work and conclusion of the detection process.

Literature Survey: Many researchers have conducted various researches on the detection of retinal area and several papers have been published. Detecting and Segmenting eyelashes and eyelids were applied on the front of the eye in older method. It contains eyelids, eyelashes and pupils. To pinpoint eyelashes eight directional filter bank is used. The first step in detecting is done using edge detection methods such as Sobel, Canny and Hough Transform and wavelet transform. To remove eyelashes on iris nonlinear filtering is applied. Eyelashes can be in either separable form or they can be grouped. Hence it can be filtered using filters such as variance and Gaussian filters. It can be applied to differentiate eyelashes. Reflectance region is shown by these eyelids with superior reflectance in comparison with retinal area. The size of convolution kernels helps in detecting the eyelash. It is done using the focus

score. Separable eyelashes and multiple eyelashes are differentiated with the help of focus score. Eyelashes are concluded using features based on local standard and intensity variation. Thresholding is applied using Otstu's method and it gives better accuracy. Intensity, skewness, textural analysis, histogram analysis, sharpness are the image features that are analyzed. For the retinal areas the features including color, focus, contrast and illumination are also analyzed. In the recognition process another method called anatomical structure analysis is done. The structures such as Fovea and optic nerve head are used for analysis. Exact information about irregular regions in the image can be analyzed using a grid based technique. Classifier Construction is done using Artificial Neural Network (ANN). ANN is analogous to biological neural networks. It is a connection of neurons which exchange messages between each other. Functions are estimated using ANN depending on a large number of inputs and are generally unknown. It is a crude electronic model. It is based on neural structure of the brain. The basic unit of ANN simulates four basic functions. The first the input is processed and the second step is Summation. Thirdly summed input is transferred and then the output is obtained.

The ANN can also be used in the structure of software packages. These packages are called as the processing elements. At first input is multiplied by a weighted factor w(n). These inputs are given to summer. Summing junction will perform different operations like Sum, Max, Min, Average, AND, OR. After the operation at summing junction it is given to transfer function. Transfer function may be linear, sigmoid and sine, and final output is obtained. Three layered ANN is used to reduce complexity. There are three blocks in ANN, they are input, hidden and output layers. ANN sends signal in forward and then errors are propagated backwards. Error propagated in backwards is obtained as the output. This output is determined using back propagation algorithm. The mean square error is minimized between actual output and the desired output. It is done with the help of a Back Propagation algorithm.

$$err = \frac{1}{2}(t-y)^2 \qquad (1)$$

Where t and y are target and actual output.

To select improved pixels from the image, super pixel generation is introduced. This technique helps in grouping pixels into different regions depending upon their regional size and compactness. In this paper, the construction is created by analyzing the SLO image based features. These are considered for a small region in the retinal image. The super pixels from the images are assigned to either of retinal area class or artifact class. These assignments depend upon a majority of pixels in the super pixel belongs to a particular class. The classification process is carried based on ranking of selective features.

2. PROPOSED METHODOLOGY

A new automatic method for retinal area detection is done here using Scanning Laser Ophthalmoscope (SLO) image. The different stages of super pixel generation and classification are dealt in detail in this section. Training Stage, testing and evaluation stage and, deployment stage are three stages of this framework. The block diagram for the retinal area detector is shown in Figure.1.

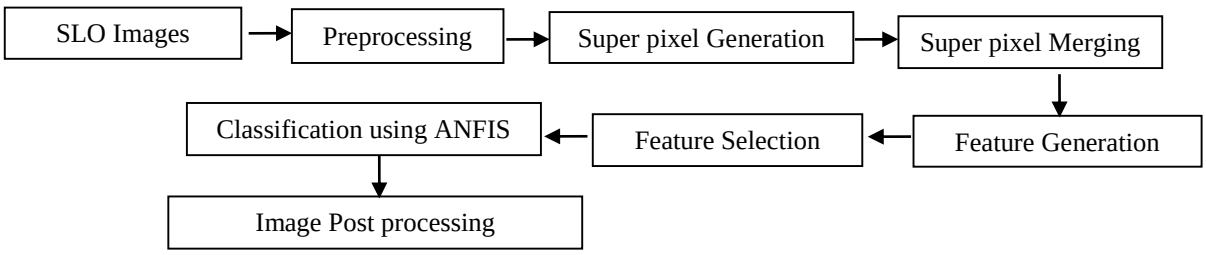

Figure.1. Block Diagram of Retinal Area Detector

Image Pre Processing: Image Pre-processing is done using Wiener filtering. Wiener filter is a linear time invariant filter that is used to remove noise. Additive noise is removed using a Wiener filter. Noise smoothening is also performed and it handles both degradation functions as well as noise. It helps in detecting Minimum Mean Square Error (MSE). More errors are reduced using Mean Square Error technique. Wiener filter has the following advantages on comparison with inverse filter. Inverse filter will amplify noise, but such amplification is not there in Wiener filter. Inverse filter will not perform well in the presence of noise because every time inverse is taken whereas in wiener filter, inverse need not be taken at every time it performs well in removal of noise.

Super pixel Generation: Super pixels are group of pixels which have analogous characteristics. To calculate image features super pixel generation algorithm is used which groups pixels into different regions. This formulation will reduce the intricacy of following image processing task. Severance in image pattern is recognized using super pixels and they provide manoeuvre original images. In this paper, Simple Linear Iterative Cluster (SLIC) algorithm is used for super pixel generation. By using watershed algorithm super pixels of artefacts are generated more than the desired, so SLIC is preferred. It is also computationally dexterous in terms of compactness and observance. Clustering is done based on their colour similarity and proximity in the image plane. SLIC works with two significant distinctions.

a) The number of distance calculations in optimization is spectacularly condensed. It is done with the off-putting search space. This makes region proportional to super pixel size. Therefore intricacy to be linear in the number of pixels N is reduced and independent of the number of super pixels.
b) A weighted distance measure joins colour and spatial proximity while simultaneously providing control over the size and compactness of super pixels.
SLIC algorithm: Compute neighbouring matrix $A\sum R^{kxk}$ for all k. Here A (i,j)=1 iand j are neighbours. Compute diffusion distance $D\sum R^{kXk}$ and average boundary strength matrix $B\sum R^{kXk}$ for all neighbouring pixels.
Super pixel merging: Next to the generation of super pixels, merging of super pixels is done to reduce the complexity. Merging is performed using Message Passing Algorithm. By this method, the original problem is split into small sub problems. Each sub problem can be solved via propagating messages among nodes. It estimates graph structure automatically and label simultaneous unique framework. The Message passing algorithm is faster and it works as follows.
a) Estimate current edge. Corresponding solution of structure variables is denoted.
b) During each iteration node pair (i,j) is selected. Variables of node (i,j) alone are unchanged.
c) The message is passed from node k to node i
d) Accumulated messages are passed from all neighbouring nodes to i and also from neighbouring nodes to j.
Feature Generation: Subsequent to the generation of super pixel the features are determined. It is done to differentiate artefacts and retinal area. Textural, Regional and Gradient features are used for this discrimination.
Textural Features: Haralick features help in analysing Texture features. It is done by the method of Gray Level Co-occurence Matrix (GLCM). The features that are proposed using GLCM are Cluster shade, Cluster prominence, Contrast, Autocorrelation, Difference Entropy, Dissimilarity, Energy, Entropy, Correlation, Homogeneity, Information measures1 and information measures2, Inverse difference normalised, Inverse difference moment normalised, Maximum Probability, Sum average, Sum Entropy, variance and Sum of variance. Texture is branded by the spatial distribution of gray levels in the neighbourhood. It is a facade property. The technique for feature extraction is GLCM. It is an algebraic technique. Textural properties of the image are discriminated using textural features. Dissimilar combinations of pixel gray levels in an image are combined using GLCM. Information about image intensities in pixels are enclosed in Haralick features. Co-occurrence matrices are calculated in directions of 0, 45, 90 and 130. Contrast measures the quantity of local changes in the image. It helps in returning the intensity difference between a pixel and its neighbourhood. The Correlation between pixels to its neighbourhood is processed using correlation. It helps in measuring gray tone linear dependencies in the image. Homogeneity gives information about the pixels which are analogous. Sum of squared elements in GLCM is returned by energy. Entropy measures the arbitrariness of intensity in an image. Linear reliance in GLCM between identical indexes is defined by Autocorrelation. Cluster shade is defined as a measure of skewness or non-symmetry. Summit in GLCM around mean for non-symmetry is shown by cluster prominence. Texture fineness is shown by Local variations. It is defined by Contrast. Difference Entropy is defined as higher weight on higher difference in index entropy value. Dissimilarity is the privileged weights of GLCM probabilities away from the diagonal. The sum of squared elements in GLCM is returned by Energy. Information measures 1&2 are entropy measures. Inverse Difference Normalised is the converse of contrast normalised. Normalized Homogeneity is defined by Inverse Difference Moment Normalised. Maximum Probability is the maximum value of GLCM. Higher weights to higher index of marginal GLCM is defined by Sum average. Higher weight on the higher sum of index entropy value is defined by Sum Entropy. Higher weights that differ from the average value of GLCM is defined by Variance. Sum of Variance is defined as higher weights that differ from the entropy value of marginal GLCM.
Regional Features: Super pixels belonging to artefacts have an irregular shape in evaluation with those belonging to retinal area so Regional Features were included. Features labelling regional attributes are area, extent, orientation, solidity, mean intensity and convex area.
Gradient Features: Irregular arrangements of artefacts are highlighted using gradient features. To calculate gradient features Gaussian filter bank response is calculated. Effective method for removing Gaussian noise is Gaussian smoothing. The weights give higher significance to pixels near edge. Gaussian Filters are efficient for computation. The Gaussian is symmetric when rotated in degrees. Sigma value controls the degree of smoothness
Feature Selection: A feature selection algorithm is a search technique. It helps in proposing new feature subsets along with estimation measure which scores different feature subsets. Feature selection helps in understanding the data, and it is also helpful in vision, reduction of data, limiting the storage requirements. Feature selection is simple and it reduces the cost. It also reduces the Computational complexity. It also helps to determine features which are more relevant to classification. Sequential Forward Selection (SFS) approach is used in this paper. Highest area under curve (AUC) is ascertained for available set of features. This process is repeated until ten features were selected. Advanced number of features results in small improvement of AUC. SFS performance is compared with Filter and SFS approach and Filter approach. Admittance to all features with minimum data consumption is permitted with the help of SFS. Data utilization is also reduced and it deals with weighted features. SFS works with the

following steps; a) Begin with blank set X=0, b) Most significant features with respect to X are appended constantly. The process is continued until the most significant features are added.

Classifier Construction: Classifier Construction is done using Adaptive Network based Fuzzy Inference System. It is a fusion between neural network and fuzzy inference system. Initial Fuzzy model along with input variables are derived with the help of rules extracted from the input and output data of the system being modelled. In ANFIS classifier Root Mean Square Error (RMSE) technique is used. It is performed by removing all antecedent clauses associated with the input variable and then performance is evaluated by checking error criterion. This process is repeated by eliminating another input variable if there is a decrease in modelling error. Eliminated variable is retained and another variable is eliminated if modelling error increases. This RMSE is minimized using this classifier.

Image Post Processing: Image post processing is performed with the aid of morphological filtering. Morphological filtering is a collection of nonlinear operations related to shape. Minute gaps among super pixels are eliminated with the help of morphological filtering. Series of operators are defined by morphological filtering. These series of operators transforms an image by penetrating it with predefined element. The result of operation is determined by the intersection of pixel neighbourhood.

3. RESULTS AND DISCUSSION

SLO images are obtained from the Optos database. The dimension of each image is 3900X3072 and the pixels are represented by 8bits. The images in the dataset comprise of both healthy and diseased retinal images. All the retinal image has resolution of 14µm. In the obtained image, the eyelashes show either dark or bright region compared to retinal area. The eyelids show the reflectance region with superior reflectance response in comparison with retinal area. In the proposed method, formulation is done to discriminate the original retinal area and the artefacts in SLO retinal scans.

These features are computed for different regions in fundas images for the quality analysis. The image pre-processing is carried out to remove the noise. It is performed using Wiener filtering. Figure.2 shows the pre-processed image.

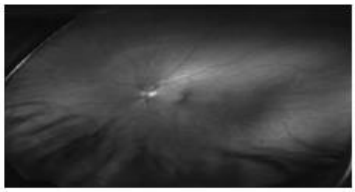

Figure.2. Pre-processed Image

Implementation of Super pixel Generation and Merging: Figure.3a shows super pixel generated image which is done using SLIC algorithm.

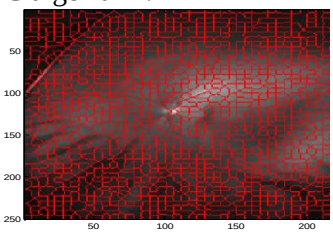

Figure.3a. Super pixel Generated Image

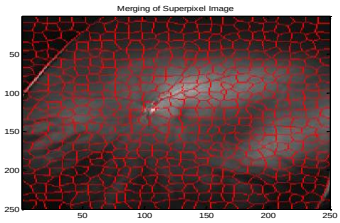

Figure.3b. Super pixel Merging

This algorithm groups the pixels into various groups that are used to compute features from the image. Redundancy of the image is confined by grouping super pixels. Suitable pattern of images is obtained by grouping super pixels. Simple linear iterative clustering (SLIC) is used in the framework for super pixel generation. It is a simple and easily understandable algorithm. The parameter k gives the desired number of equal sized super pixels. In the proposed method k=1000 is used. By choosing k initial clusters are sampled on a regular grid spaced‘s’ pixels apart. To produce equally sized super pixels the grid interval is $s=\sqrt{N/k}$ where N is the number of pixels. K is the desired number of equal sized super pixels. The centers are further moved to seed locations that have to lower gradient position in a 3X3 neighbourhood. Thus avoiding the centering of super pixel on an edge and also helps in reducing the chance of noisy pixel seeding as super pixel. The distance is calculated, that determines the nearest cluster center for each pixel. After the association of each pixel to the nearest cluster center an update step is proceeded to adjust the cluster center to the mean vector of all pixels in a cluster. This algorithm of assignment and update steps are preceded until the convergence of the error.

The performance of the algorithm is further improved by proposed merging of super pixels. In this process, a segmentation algorithm is further applied to the computed super pixel grid. The merged regions are considered as groups of constituent super pixel. This is explained in Figure 3b.

Implementation of Feature Extraction: The feature generation part of super pixels are considered by calculating the texture, gradient and regional features. Gradient feature is calculated to make artefacts even. So that it can be removed easily. By calculating the response of Gaussian filter bank gradient features are calculated. There are two first order derivatives $N_x(\sigma)$ and $N_y(\sigma)$ in the Gaussian filter bank. There are three second order derivatives $N_{xx}(\sigma)$, $N_{xy}(\sigma)$, $N_{yy}(\sigma)$ in the Gaussian filter bank. These derivatives are both in horizontal (x) and in vertical (y) directions. The mean value is obtained for each filter response over the whole pixels of each super pixel. It is done after convolution of the image. Another set of features extracted are textural features. The texture of the retinal images are analysed using Haralick features by calculating the Gray Level Co-occurrence Matrix. GLCM determines the occurrence of gray scale pixel i adjacent to pixel of value j. By setting the offset value to 1 Haralick features are performed and GLCM matrix is calculated.

Figure.4 shows the gradient filtered image. The Gaussian filter response is used for the gradient filtered image.

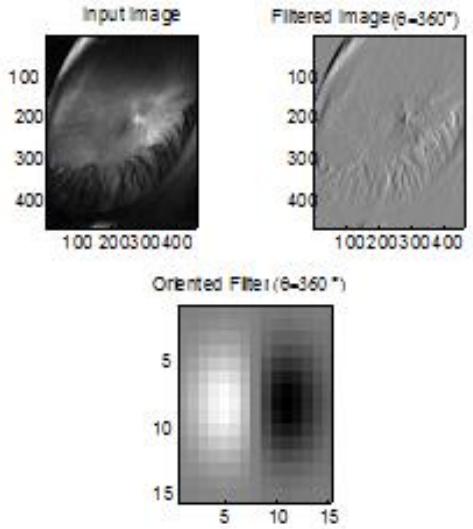

Figure.4. Gradient filtered Image

Table.1 shows the textual features calculated using GLCM. The features calculated for two images are tabulated for analysing the performance of the detector.

Table.1. Textural Features

Textural Features	Image1	Image2
Autocorrelation	7.244629032258062	6.183353901651795
Cluster shade	2.098070773598060	2.412682420915273
Cluster Prominence	2.294406704450189	1.429449639622149
Correlation	9.287663491147969	9.517543210601369
Contrast	9.559677419354840	4.198784887032467
Difference Entropy	2.878559812352725	1.740673980229120
Dissimilarity	8.182258064516128	4.184545281944180
Energy	3.143850515088449	4.435028326369404
Entropy	1.512862293333838	1.125140480808649
Homogeneity	9.603988687782807	9.790915131953676
Information measures 1	-7.368772795383040	-8.037402040662112
Information measures 2	9.106911850088186	8.829152109438851
Inverse Difference Normalized	9.910473519312231	9.953520874206275
Inverse Difference Moment Normalized	9.985666287261876	9.993542263921094
Maximum Probability	4.175806451612903	5.917742547940004
Sum average	5.146435483870968	4.803835200303778
Sum Entropy	1.439893449229493	1.095625720007778
Variance	5.146435483870968	4.803835200303778
Sum of Variance	1.632676856814376	1.544938837355699

Table.2. Regional Features

Regional Features	Image1	Image2
Mean intensity	1	1
Area	62500	211600
Convex area	6.310795302391500	6.282931383034079
Extent	6.280324087174711	1.153025706846995
Orientation	63002	212522
Solidity	9.99984127880162	9.999952946047939

Regional features are calculated one time for each super pixel. The super pixels for artefacts have an irregular shape than that belongs to the retinal area in the SLO image. Table.2 shows the calculated regional features. Mean value of super pixel is defined by Mean intensity. Number of pixels in a super pixel is defined by area. Number of pixels in convex areas of super pixel is defined by convex area. Extent is the ratio of area to a number of super pixels in a bounding box. Orientation is a super pixel angle with respect to X-axis. Ratio of area to convex area is defined as solidity.

Implementation of Feature Selection: Next in the process of feature extraction, feature selection is performed. Execution time and dimensionality are reduced by feature selection. It helps in the incarceration of the most relevant features for classification. Most important features are selected using a feature selection method, thereby reducing the computational cost. Sequential Forward Selection (SFS) approach is used for selection of features. In this approach the interactivity of features is the main consideration. The AUC is calculated for each set of features and the feature having highest AUC is selected. Area Under Curve (AUC) for SFS is higher when compared to Filter and Filter SFS approach. Filter and SFS approach will reduce the number of features that have to be tested through training of SVM. It is undesirable to discard many features using filter and SFS approach. SFS is a bottom up algorithm. SFS is a suboptimal search procedure. In SFS one feature at a time is added to current feature set. A feature to be included in the feature set is selected. The selection is done from the remaining available features at each stage. Maximum value of the criterion function used is yielded by new enlarged feature set. SFS starts from a vacant set and selects as the first feature individually. SFS approach is very fast. The next feature is chosen in such a way that when it is used with the first selected feature approach, it will give highest AUC compared to other features. This procedure is repeated further. Figure.5 shows the results of SFS filtering.

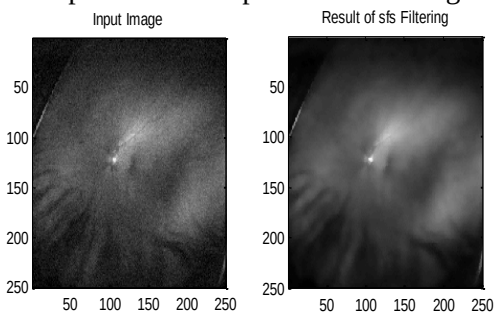

Figure.5.SFS Filtering

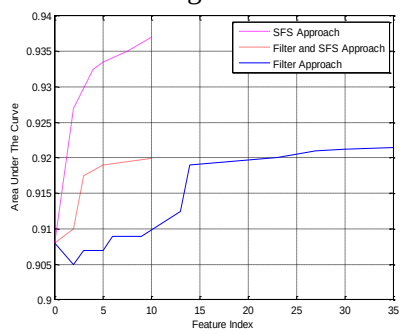

Figure.6.Comparison of SFS Approach with Filter and Filter and SFS Approach

Table.3 shows features selected using a feature selection method. SFS approach has higher AUC when compared with Filter and Filter and SFS approach. Table.4 shows various types of features across different feature set.

Table.3.Features Selected using feature selection method

Features Selected	Image1 (AUC)	Image2 (AUC)
SFS	0.935	0.935
Filter	0.923	0.923
Filter and SFS approach	0.92	0.92

Table.4. Different types of features across various feature set

Feature set	Textural features	Gradient features	Regional Features
SFS approach	92%	15%	0%
Filter approach	72.73%	24.24%	3.00%
Filter/SFS approach	100%	0%	0%

Figure.7 shows a comparison of AUC of SFS with the aid of receiver operating characteristics (ROC). This feature sets include all the calculated features. The other features are preferred by the mentioned approach. The ROC curves and AUC values give quite improved result if the features are chosen using SFS approach. It shows the higher

classification power of entire features, thereby selecting computational time and cost. The AUC obtained is 0.9638 using all features and using SFS, AUC obtained is 0.9613. AUC of 0.9549 is obtained using Filter approach and 0.9533 for filter and SFS approach.

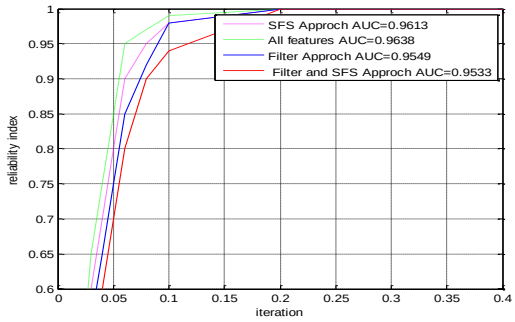

Figure.7. Comparison of SFS Approach with Filter and Filter and SFS Approach using ROC

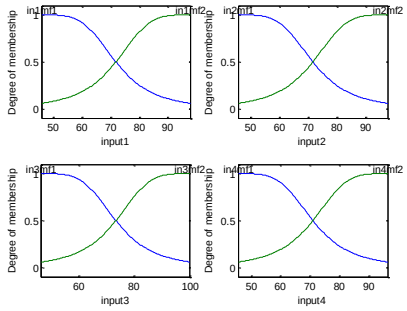

Figure.8. Degree of Membership

Implementation of Classifiers: A comparative analysis is performed using classifiers. In this paper ANN and ANFIS is used. The selected features are given as input to classifiers. The accuracy of each classifier is studied to recognize the performance of the proposed framework. The simulations are carried out in Matlab platform. Figure.8 shows the Degree of membership for ANFIS. Figure.9 shows post processed image which is done using morphological filtering. Using morphological filtering small gaps is removed in super pixels.

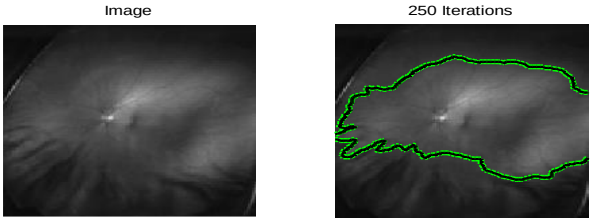

Figure.9. Post processed Image

The accuracy of classification results are 98.5% and 92% for ANFIS and ANN respectively. Figure.10 shows the comparison plot of two classifiers.

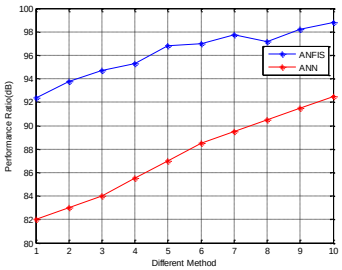

Figure.10. Comparison of ANN with ANFIS

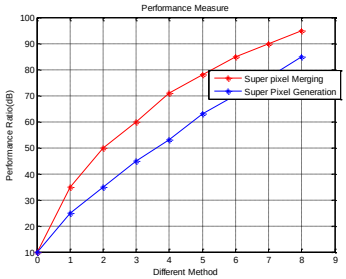

Figure.11. Comparison between Super pixel merging and Super pixel Generation

Figure.11 shows the comparison of Super pixel generation and Super pixel merging. After merging of super pixel, an improved accuracy level of 98.5% is obtained. Merging reduces the number of super pixels and further process also becomes easier. The time taken for the process is reduced and the speed has been increased which in turn helps to increase the performance.

4. CONCLUSION

The proposed framework successfully classifies the retinal area from artefacts. ANFIS is able to achieve higher accuracy when compared with ANN. Using ANFIS 98.5% accuracy is obtained and using ANN 92% accuracy is obtained. In this paper root mean square error minimization technique is used and degree of membership is plotted. It helps to achieve high accuracy when compared with ANN. By using super pixel merging, the accuracy level is further improved. By merging technique super pixels are further reduced and feature generation, selection and classification are done that help to improve performance of the proposed method. If some techniques are further developed to select the features effectively, then it is possible to increase the accuracy rate.

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