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Variational Mode Decomposition Based Retinal Area Detection and Merging Of Superpixels in SLO Image

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Abstract: Scanning Laser Ophthalmoscope (SLO) image can be used to detect retinal diseases. However identifying retinal area is a major task as retinal artefacts such as eyelashes and eyelids are also captured. Major part of retina can be viewed if detection is done with the help of images of SLO. In this paper our novel technique helps in detecting the true retinal area based on image processing techniques. To the SLO image two dimensional Variational Mode Decomposition (VMD) is applied. As a result of this different modes are obtained. Mode-1 is chosen because it has high frequency. Then mode1 is pre-processed using median filtering. After this preprocessed model image is grouped into pixels based on regional size and compactness called superpixels. Superpixels are generated to reduce complexity. Superpixel merging is done next to Superpixel generation. It is done to reduce further difficulty and to enhance the speed. From the merged superpixels feature generation is performed using Regional, Gradient and textural features. It is done to eliminate artefacts and to detect the retinal area. Also feature selection will reduce the processing time and increase the speed. A classifier is constructed using Adaptive Network Fuzzy Inference System (ANFIS) for classification of features and its performance is compared with Artificial Neural Network (ANN). By this novel approach we got a classification accuracy of 98.5%

Index Terms: Scanning Laser Ophthalmoscope, Superpixel Generation, Superpixel merging, Classifier construction

I. INTRODUCTION

Retinal disease treatment helps in avoiding vision loss. Manual techniques were used to detect retinal diseases previously. Better zooming and contrast are imparted by Optometrists and ophthalmologists to give better results. Diagnosing processes are very time consuming to diagnose for single patients so Scanning laser ophthalmoscope avoids this difficulty. Scanning Laser Ophthalmoscope images gives the outcome of 2-D retinal scans. However it contains artefacts such as eyelids and eyelashes along with true retinal area. So the challenge is to remove the artefacts for better diagnosis. Research was done to segment retinal area. To detect artifacts, eight directional filter banks are used. The following methods were used previously to detect artefacts. By using eight directional filter bank shapes modeling becomes inaccurate and it is a time consuming process. First step in detecting is done using edge detection methods such as Sobel, Canny Hough Transform [1] and wavelet transform [2]. To remove eyelashes on iris Nonlinear filtering is applied [3].

Gaussian filters [4] and convolution Kernels [5] are used to detect eyelashes but Size of Kernel is not fixed so results are inaccurate. Min and Park [6] detected eyelashes using local standard and intensity variation but results were not proper. In Otsu’s method [7] eyelashes are detected based on thresholding but due to variation in threshold value results are not accurate. Optic nerve head and fovea [8] structure is also used for detection of eyelashes but results are not accurate. Grid analysis is another method used to generate features of particular region rather than each pixel. However, the exact information about irregular regions in the image cannot be analyzed. So superpixels are generated for further analysis. The classifier construction is done using ANN SVM and PLS. In PLS classification results are not accurate. Classification of retinal area using ANN results in an accuracy of 92.5% [9]. To select improved pixels from the image superpixel generation is introduced [10]. This technique helps in grouping pixels into different regions depending upon their regional size and compactness. In this paper, the classifier construction is created by analyzing the SLO image-based features.

In our proposed work, VMD is applied in SLO image as a result six different modes are obtained. Mode-1 is chosen because it has high frequency. This process helps to separate high frequency region of the image. Mode-1 is preprocessed using median filtering. Then the superpixels are generated. After this generated superpixels are merged. This helps to reduce the area to be detected and utilize less time for computation. Superpixels are generated to analyze retinal hemorrhage detection [14]. Further feature generation and selection process are performed. The selected features are classified using ANFIS. Thus, a better accuracy of 98.5% is obtained. Our approach helps to increase the speed of computation with less complexity. The paper is structured as follows. Section II gives an insight into our proposed framework. Section III provides the outcome of the work with a proof of results and quantitative analysis. Section IV summarizes the work and conclusion of the detection process.
II. PROPOSED METHODOLOGY

A new automatic method for retinal area detection is done using Scanning Laser Ophthalmoscope image. Our proposed algorithm for the accurate detection of retinal area in SLO is explained below.

Proposed Algorithm

i) Scanning Laser Ophthalmoscope images are obtained from optos database.

ii) Variational Mode Decomposition is applied to SLO image. This results in different modes.

iii) Choose mode-1 because it has high frequency

iv) Group the pixels based on region size and compactness to generate superpixels.

v) Then the generated superpixels are merged using message passing algorithm.

vi) Features are generated from the merged superpixels

vii) Feature selection is done based on ranking of AUC.

viii) After feature selection Classification is done using ANFIS.

ix) The data are trained and tested using ANFIS.

x) RMSE is calculated then Degree of membership curve is plotted which is the output of ANFIS.

xi) Performance graph is compared with ANN and ANFIS and also between superpixel merging and generation.

xii) Finally post processing is done and retinal area is detected.

The flow chart of proposed retinal area detector is shown in Figure 1

A. Variational Mode Decomposition

2D-VMD is used because it helps in image segmentation and it is non recursive [13]. It is free from explicit interpolation and it is adaptive. Higher dimensions are generalized by the gradients and modulation is straight forward. In EMD band limits of wavelet are hard and recursive shift limits backward error correction. VMD balances this error [15].

To the SLO image 2D-VMD is applied. 2D-VMD is an extension to one dimensional VMD. 2D-VMD helps in smoothening the image and it gives sharp edges. The 2D analytical signal is given by a real term and its imaginary term which is a Hilbert transform

\[ f(t) = (t) + jH\{f\}(t) \]

\( \{f\}(t) \) is a Hilbert transform

In spectral domain analytical signal suppresses the negative frequencies and it gives unilateral spectrum. As a result of VMD, different modes are obtained. Based on frequency the modes are distinguished and its residue is obtained. Mode 1 has high frequency. So, it is selected for pre-processing and for further steps.

![Flow chart of proposed Retinal Area Detector](image)

**Fig. 1.** Flow chart of proposed Retinal Area Detector

B. Pre-processing

Image pre-processing is done using median filtering. It is a nonlinear digital filtering it helps to remove noise. In median filtering neighboring pixels are ranked according to intensity and median value becomes the new value for center pixel. The median is calculated by first sorting all pixel value from window into numerical order and then replacing pixel being considered with median pixel value.

C. Superpixel generation

Superpixels are group of pixels which have analogous characteristics. To calculate image features super pixel algorithm is used which groups pixels into different regions. This formulation will reduce the difficulty of following image processing task. Severances in image pattern are recognized using superpixels and they provide scheme of images.
E. Feature generation
discrimination is done to distinguish artefacts and retinal area. Textural, plane. It works with two significant distinctions.

1) The number of distance calculations in optimization is spectacularly condensed. It is done by off-putting search space. This makes region proportional to super pixel size. Therefore, intricacy to be linear in number of pixels N is reduced and independent of number of super pixels.

2) A weighted distance measure joins color and spatial proximity while simultaneously providing control over size and compactness of super pixels.

Algorithm for SLIC works as follows:

i) Compute neighboring matrix \( A \sum R^{x,y} \) for all \( k \). Here \( A(i,j) = 1 \) if \( i \) and \( j \) are neighbors.

ii) Compute diffusion distance \( D \sum R^{x,y} \) and average boundary strength matrix \( B \sum R^{x,y} \) for all neighboring pixel.

\[ S = \sqrt{N/K} \] N: Number of superpixels K: Initialisation clusters

D. Superpixel merging
After this generated superpixels are merged to reduce complexity. Merging is done using Message Passing Algorithm [11]. It lies in splitting original interference problem into small subproblems. Each subproblem can be solved via propagating messages among nodes. Our message passing algorithm do not require Markov Random Field (MRF). It estimates graph structure automatically and label simultaneously unique frame work. It works faster as message passing is performed in dual space. This algorithm works as follows.

1. Estimate current edge. Corresponding solution of structure variables is denoted.
2. During each trial node pair \( (i,j) \) is selected. Variables of node \( (i,j) \) alone are unchanged.
3. Message is passed from node \( k \) to node \( i \)
4. Accumulated messages are passed from all neighboring nodes to \( i \) and also from neighboring nodes to \( j \)

E. Feature generation
Next to super pixel merging the features are determined. It is done to distinguish artefacts and retinal area. Textural, Regional and Gradient features are used for this discrimination [12].

1) Textual Features
Haralick features helps to analyze Texture features. It is done by the method of Gray Level Co-occurrence Matrix (GLCM) and it is an algebraic technique. The features calculated using GLCM are Cluster shade, Cluster prominence, Contrast, Autocorrelation, Difference Entropy, Dissimilarity, Energy, Entropy, Correlation, Homogeneity. Informationmeasures1 and information measures 2, Inverse difference normalized, Inverse difference moment normalized, Maximum Probability, Sum average, Sum Entropy, variance and Sum of variance. Texture is branded by spatial distribution of gray levels in the neighborhood. It is a facade property. 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 image. It helps in returning the intensity difference between pixel and its neighborhood. Correlation between pixels to its neighborhood is processed using correlation. It helps in measuring gray tone linear dependencies in image. Homogeneity gives information about the pixels which are analogous. 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 are shown by Local variations. It is defined by Contrast. Difference Entropy is defined as higher weight on higher difference of index entropy value. Dissimilarity is privileged weights of GLCM probabilities away from diagonal. The sum of squared elements in GLCM is returned by Energy. Information measures 1&2 are Entropy measures. Inverse Difference Normalized is the converse of contrast normalized. Normalized Homogeneity is defined by Inverse Difference Moment Normalized; Maximum Probability is maximum value of GLCM. Higher weights to higher index of marginal GLCM is defined by Sum average. Higher weight on higher sum of index entropy value is defined by Sum Entropy. Higher weights that differ from average value of GLCM is defined by Variance. Sum of Variance is defined as higher weights that differ from entropy value of marginal GLCM. GLCM is applied to each feature. The values are calculated separately for each feature.

2) Regional Features
Superpixels belonging to artefacts have uneven shape in consideration 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. Number of pixels in Super pixel is defined by area. Extent is the division of area to number of superpixels in bounding box. Number of pixels in convex area of Super pixel is defined by convex area. Orientation is Super pixel angle with reverence to X-axis. Ratio of area to convex area is defined as Solidity. Mean value of super pixel is defined by Mean intensity. The values are calculated separately for each feature.

3) Gradient Features
Uneven arrangements of artefacts are highlighted using gradient features. To estimate these features, Gaussian filter bank rejoinder is premeditated. Effective method for removing Gaussian noise is Gaussian smoothing. Gaussian
Formulas for regional features are provided below

\[
\text{Area} = \sum_{i=1}^{N_S} \sum_{j=1}^{N_S} p(i,j)
\]

\[
\text{Sum average}=\sum_{i=1}^{2N_g} \sum_{j=1}^{N_g} p_{x+y}(i)
\]

\[
\text{Variance} = \sum_{i=1}^{2N_g} \sum_{j=1}^{N_g} (p(i,j) - \mu)^2
\]

\[
\text{Sum of variance}=\sum_{i=1}^{N_g} (i - H_{sum}) p_{x+y}(i)
\]

Formulas for textural features were provided below

\[
\text{Autocorrelation}=\sum_{i=1}^{N_S} \sum_{j=1}^{N_S} \frac{i(j)p(i,j)}{\sigma x \sigma y}
\]

\[
\text{Contrast}=\sum_{i=1}^{N_S} \sum_{j=1}^{N_S} \frac{p(i,j)}{1+(i-j)^2}
\]

\[
\text{Cluster prominence}=\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} (i-j)p(i,j)
\]

\[
\text{Energy}=\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} \frac{1}{N_g} P_{xy}(i)
\]

\[
\text{Inverse difference normalized}=\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} \frac{p(i,j) - \mu}{1+\sigma_x \sigma_y}
\]

\[
\text{Inverse difference moment normalized}=\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} \frac{p(i,j)}{1+\sigma_x \sigma_y}
\]

\[
\text{Correlation}=\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} \frac{i(j)p(i,j)}{\sigma x \sigma y}
\]

\[
\text{Information measure2}=\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} \frac{p(i,j)}{\sigma x \sigma y}
\]

\[
\text{Dissimilarity}=\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} \frac{(i+j)p(i,j)}{\sigma x \sigma y}
\]

\[
\text{Variance} = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} (i-j)^2 p(i,j)
\]

\[
\text{Energy}=\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} \frac{1}{N_g} P_{xy}(i)
\]

\[
\text{Inverse difference normalized}=\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} \frac{p(i,j) - \mu}{1+\sigma_x \sigma_y}
\]

\[
\text{Inverse difference moment normalized}=\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} \frac{p(i,j)}{1+\sigma_x \sigma_y}
\]

Formulas for feature selection

\[
\text{Area} = N_S
\]

\[
\text{Extent} = \frac{N_s}{N_{sb}}
\]

\[
\text{Convex Area} = N_{sc}
\]

\[
\text{Orientation} = \theta_s
\]

\[
\text{Solidity} = \frac{N_s}{N_{sc}}
\]

\[
\text{Mean Intensity}= I_{\mu} = \frac{\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} I(i,j)}{N_s}
\]

**F. Feature selection**

Feature selection is done to explore features and it helps in generating new feature subsets. Computational complexity is reduced with the help of feature selection. It also helps to establish features which are more appropriate for classification. Sequential Forward Selection (SFS) approach is used in this paper. Highest area under curve (AUC) is certain 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 reduced with the help of SFS. It deals with weighted features. SFS works with the following steps.

1. Start by means of blank set X=0
2. Most important features with respect to X are appended constantly.
3. This process is repeated until the most significant features are included.

Algorithm for SFS filter was provided

1. Begin with empty set \( Y_0 = \{ \} \)
2. Select the next best feature \( X^+ = \arg\max[J(Y_k + X^) \cap X \in Y_k] \)
3. Update \( Y_{k+1} = Y_k + X^+ \backslash \{X\} \)
4. Go to second step

Formula for SFS filtering

\( X^+ = \arg\max[J(Y_k + X^) \cap X \in \text{input}] \)

In SFS filtering following features were selected and fed as input for ANFIS. They were autocorrelation, difference entropy, sum of variance, variance, sum average, entropy and gradient features.

**G. Classifier construction**

Classifier Construction is done using Adaptive Network based Fuzzy Inference System (ANFIS). It is a combination between neural network and fuzzy inference system. The selected features were trained and checked from image in optos database. The features which were selected were trained and when checking error was calculated. Only selected features were given for input to both ANFIS and RMSE. The output of ANFIS is RMSE whose value is 2.2. RMSE= \( \text{norm of checked data/ sqrt of checked data} \). These features were trained and checked for different candidates. Preliminary Fuzzy model along with input variables are derived by means of rules extracted from input output data of system being modelled. In this ANFIS technique Root Mean Square Error (RMSE) technique is used. It is performed by eliminating all antecedent clauses linked with 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. Here RMSE is minimum.

**H. Image Postprocessing**

Image postprocessing is performed with the support of morphological filtering. Morphological filtering is a group of nonlinear operations associated to shape. Tiny gaps among superpixels are removed with the help of morphological filtering. Morphological opening is used as operator in this work. Series of operators are defined by morphological filtering. These series of operators performs image transformation by penetrating it with predefined element. The result of operation is determined by junction of pixel neighborhood.
III. RESULTS AND DISCUSSION

The images for performing training and testing are collected from optos database [12]. 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. From the database 70 retinal images are trained and 26 images are tested and validated using this method. 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 our proposed method formulation is done to discriminate the original retinal area and the artefacts in SLO retinal scans.

Following the analysis from visual representation of the image, the features reflecting the structural and textural regions are the recommended features. These features are computed for different regions in fundus images for the quality analysis. Figure 2 shows the SLO image which is given as input.

To this input image 2D-VMD is applied. As a result six different modes are obtained. The reconstructed composite is obtained if we sum all modes. The solution for 2D-VMD is done using Alternate Direction Method of Multipliers (ADMM)[16]. ADMM is nothing but saddle point of augmented Lagrangian. Modes are differentiated based on frequency. Modes which have high frequency have sharp edges and it is well smoothed.

Let the problem be
\[ \min_{u_k, w_k} \{ \Sigma \alpha k \| \nabla [uAS,k(x)e^{-\langle \omega, \kappa(x) \rangle}] \|_2^2 \} \] (2)

To the above problem ADMM algorithm is applied.

\[ L(\{u_k\}, \{w_k\}, \lambda) := \Sigma \alpha k \| \nabla [uAS,k(x)e^{-\langle \omega, \kappa(x) \rangle}] \|_2^2 + \| f(x) - \Sigma u_k(x) \|_2^2 k + \langle \lambda(x), f(x) - \Sigma u_k(x) \rangle \] (3)

After applying ADMM algorithm the problem is solved and the result is obtained as
\[ \min_{u_k, w_k} \max_{\lambda} \{ \{u_k\} \{W_k\}, \lambda \} \] (4)
Fig 2b Mode 2 of 2D-VMD

Fig 2c Mode 3 of 2D-VMD

Fig 2d Mode 4 of 2D-VMD

Fig 2e Mode 5 of 2D-VMD
Among these six different modes are obtained. Mode 1 has high frequency and it is selected for further processing. Mode 1 is pre-processed using median filtering. Figure 3 shows the pre-processed image.

Figure 4a shows superpixel generated image which is done using SLIC algorithm. 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 superpixels. Suitable pattern of image is obtained by grouping superpixels. Simple linear iterative clustering is used in our framework for superpixel generation.

`Computing cost is reduced by grouping superpixels. It represents different irregular regions in a compact way. By generating feature vector for each superpixel the process becomes`
efficient. Figure 4b shows Superpixel merging. Message Passing algorithm is used for Superpixel merging. By this merging process time is reduced and speed is improved. In message passing algorithm the original problem is divided into sub problems. To each sub problem message passing algorithm is applied and finally messages are accumulated. Then the accumulated messages are passed and finally superpixels are merged using message passing algorithm. By this merging space and time complexity is reduced hence feature generation is done with help of these reduced pixels.

To the generated superpixels message passing algorithm is done. Figure 5 shows Gradient filtered image in degrees. Gaussian filter response is used for Gradient filtered image.

To make artefacts even, Gradient features are calculated. Hence it can be removed easily. There are two first order derivatives. They are $N_x(\sigma)$ and $N_y(\sigma)$ in Gaussian filter bank. There are three second order derivatives $N_{xx}(\sigma)$, $N_{xy}(\sigma)$, $N_{yy}(\sigma)$ in 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 superpixel. It is done after convolution of image. GLCM is used for calculating textural features. All these features are calculated separately. By setting offset value as 1 Haralick features are performed and GLCM matrix was calculated. Table 1 shows the Textual features calculated using GLCM. The features calculated separately for mode 1 images are tabulated for analyzing the performance of the detector.

| Textural Features | Image 1 |
|-------------------|---------|
| Autocorrelation   | 4.01643270676691 |
| Cluster shade     | 2.797387467486687 |
| Cluster Prominence| 5.325728571498190 |
| Correlation       | 9.854400023615023 |
| Contrast          | 1.400717703349282 |
| Difference Entropy| 1.645832369572792 |
| Dissimilarity     | 5.249487354750513 |
| Energy            | 3.056804442218841 |
| Entropy           | 1.601903290244610 |
| Homogeneity       | 9.809655688216060 |
| Information 1     | 8.903483141784686 |
| Information 2     | 9.60995654959921 |
| Inverse Difference Normalized | 9.949457518254512 |
| Inverse Difference Moment Normalized | 9.982433821278121 |
| Maximum Probability | 4.975734791524265 |
| Sum average       | 1.190364832535885 |
| Sum Entropy       | 1.563274698632190 |
| Variance          | 1.260238858838883 |
| Sum of Variance   | 4.004861822747565 |
Regional features are calculated one time for each super pixel. They are not related to channel variation. Table 2 shows calculated Regional features. Mean value of super pixel is defined by Mean intensity. Number of pixels in Super pixel is defined by Area. Number of pixels in convex area of Super pixel is defined by convex area. Extent is the ratio of area to number of super pixels in bounding box. Orientation is Super pixel angle with respect to X-axis. Ratio of area to convex area is defined as Solidity. All these feature values are calculated separately.

### Table 2 Regional Features

| Regional Features | Mode 1 |
|-------------------|--------|
| Mean intensity    | 1      |
| Area              | 235200 |
| Convex area       | 6.15275914418755 |
| Extent            | 1.202963480356445 |
| Orientation       | 4.934367452495153 |
| Solidity          | 9.999999999999980 |

Figure 6 shows result of SFS filtering.

**Figure 6. SFS Filtering**

Execution time and dimensionality are reduced by feature selection. It helps in identification of most relevant features for classification. Most important features are selected using Feature selection method which helps to reduce the computational cost. Sequential Forward Selection (SFS) approach is used for selection of features in our work. In these dealings among features selected features are taken for consideration. Area under Curve (AUC) for SFS is high when compared with “Filter” and “Filter SFS approach”. “Filter and SFS” approach will reduce the number of features that has 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. Feature to be included in feature set is selected. This selection is done from the remaining available features at each stage. Maximum value of criterion function used is yielded by new enlarged feature set. SFS starts from vacant set and select as first feature individually. SFS is very fast. The next feature is chosen in such a way that when it is used with first selected feature approach it will give highest AUC compared to other features. This procedure is repeated further. Figure 7 shows how AUC of SFS is high when compared with other two methods.

### Table 3 Features Selected using feature selection method

| Features Selected | Image1(AUC) | Image2(AUC) |
|-------------------|-------------|-------------|
| SFS               | 0.937       | 0.937       |
| Filter            | 0.924       | 0.924       |
| Filter and SFS    | 0.92        | 0.92        |

Table 4 shows time comparison of different methods.

### Table 4 Time comparison of algorithms

| Algorithm | Computational time |
|-----------|--------------------|
| ANFIS     | 0.5S               |
| ANN       | 0.015S             |
| SVM       | 8.5S               |
| kNN       | 1.45S              |

Figure 7 shows result of SFS filtering method. SFS approach has higher AUC when compared with “Filter” and “Filter and SFS” approach.
Figure 8 shows the comparison of AUC of SFS with the aid of Receiver Operating Characteristics (ROC). The feature sets include all the calculated features. The other features are preferred by the mentioned approach. The magnified version of comparison of SFS approach with “filter” and “filter and SFS” approach is shown in Figure 9. Figure 10 shows ANFIS selection process.

Figure 11 shows selection of two input from Five candidates and Root Mean Square Error is calculated.

Figure 12 shows three inputs from Five candidates and their Root Mean Square Error is calculated.

Figure 13 shows Degree of Membership for Five candidates with degrees.
Figure 14 shows post processed image this process is done using morphological filtering. Using morphological filtering small gaps were removed in superpixels.

![Image](image1.jpg)  ![Image](image2.jpg)

**Fig. 14** Post processed Image

Accuracy is calculated by $\frac{TP+TN}{TP+TN+FP+FN}$. TP: True Positive, FP: False Positive, FN: False Negative, TN: True negative. TP is pixels calculated as retina. TN: artefacts calculated as retina. FP: Retina calculated as artefacts. FN: artefacts correctly calculated as artefacts.

Figure 15 shows comparison of ANN with ANFIS. Accuracy level of ANFIS is 98.5%. Accuracy level of ANN is 92%. Thus in the proposed method by the selection of high frequency and merging the superpixel gave more accuracy in classification. Hence computational complexity was reduced.

![Graph](graph1.png)

**Fig. 15** Comparison of ANN with ANFIS

Figure 16 shows comparison of Superpixel generation and Superpixel merging. After merging of superpixel accuracy level is improved to 98.5%. Merging reduces the number of superpixels and further process also becomes easier. Time is reduced and speed is increased which in turn helps to increase the performance.
IV. CONCLUSION

Thus 2D-VMD gives six different modes. Based on high frequency model is chosen. This further makes process easier and it helps to achieve accuracy level higher. ANFIS is able to achieve higher accuracy when compared with ANN. Using ANFIS 98.5% accuracy is obtained. Using ANN 92% accuracy is obtained. Thus using RMSE technique errors are checked and degree of membership is plotted. It helps to achieve high accuracy when compared with ANN. By using superpixel merging accuracy level is improved. By superpixel merging technique superpixels are further reduced and further feature generation, feature selection and classification is done which helps to improve performance to 98.5%.

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