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# A Fuzzy Imaging Technique for Image Understanding

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**Abstract:-Diabetic retinopathy (DR) is a microvascular problem of long-term diabetes which is the primaryroot of visual lossdue to theabnormalities in blood vessels of the retina. The detection of DR in early stages is the most important to prevent visual impairment. In this paper, a Fuzzy Naive Bayesian (FNB) classifier is proposed to classify the four types of retinal abnormalities such as Hordeolum, Seborrheic keratosis, Xanthelasma and squamous Cell Carcinoma. The proposed method includes four main stages to detect DR. At first, Discrete Wavelet Transform (DWT) based Bayes Shrink thresholding method is applied to the retinal images for reducing noise and improving the quality of the image. In the second stage, a hybrid retinal image segmentation algorithm is used which is the integration of active contour with Fuzzy C-Means (FCM) algorithm. In the third stage, texture based features are extracted from the segmented image using Gray-Level Co-occurrence Matrix (GLCM). Finally, based on FNB model four abnormities are detected.The classification of the proposed FNB classifier achieves an accuracy of 98.7%, sensitivity of 98.2%, and specificity of 96% which is better than the other existing techniques.**

**Keywords:**-Diabetic Retinopathy (DR),Fuzzy Naive Bayesian (FNB) classifier, Discrete Wavelet Transform (DWT),Fuzzy C-Means (FCM), Gray-Level Co-occurrence Matrix (GLCM).

## I. INTRODUCTION

Diabetic Retinopathy (DR) is a significant problem of diabetes where the blood vessels provide oxygen to the retina of the eye are injured. It can be happened due to the high levels of blood sugar in the body is not concealed correctly by the pancreas (Yun et al., 2008 &Sangwan et al., 2015). The early stage of DR is called as Non-Proliferated Diabetic Retinopathy (NPDR) in which hemorrhages due to bleeding of the capillaries and exudates due to protein deposits in the retina occur (Hann et al., 2009). As the disease developments, new abnormal vessels grow in the retina is called as neovascularization. These vessels often leak into the vitreous that is called Proliferated Diabetic Retinopathy (PDR), and it may cause severe visual problems on the retina (Zhang et al., 2014 &Garcia-Ramirez et al., 2007).

If the people who have diabetes for 20 years or more, they have more possibility to suffer DR (Kertes& Johnson, 2007). Fig.1 shows that the general retinal image diabetic retinopathy. There is no vision problems and symptoms in the early stage of the disease, and it can cause blindness ultimately. The initial clinical indication of DR is the recognition of microaneurysmswhich are occurred due to the outflow of blood from capillary. Microaneurysms are the small and red dots which spread on the lightweight retinal layers (Paing et al., 2016). When the walls of microaneurysm get broken, the hemorrhages happen which is also small dots. The fragment of hemorrhages which occur in the lightweight nerve fiber layer known as flame-shaped hemorrhages. The more outflow of blood from injured capillaries can lead to exudates that are normally in yellow color lipid and unequal-shaped on the retina. The exudates differ from the microaneurysms and hemorrhages in terms of brightness. Microaneurysms and hemorrhages are dark injuries and the exudates are bright (Akram et al., 2014). Cotton wool spots abnormal area of the retina of the eye which appears as white patches on the retina.

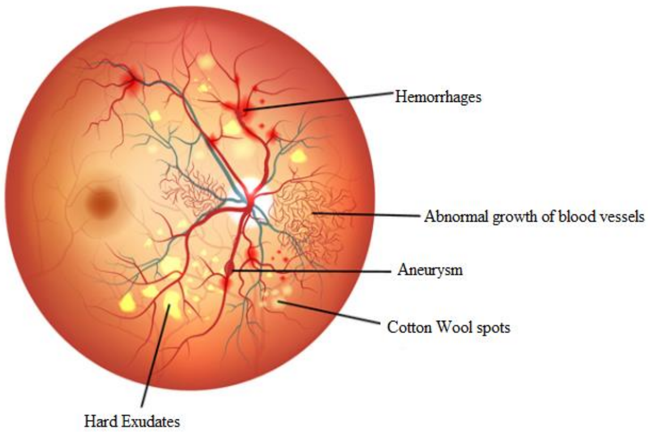


Fig 1.A general Retinal Image of Diabetic Retinopathy.

Medical image diagnosis in image processing plays a vital role in healthcare applications. Verma et al., (2011) proposed a technique for detection and classification of DR based on retinal images. The technique is used to identify blood vessel, hemorrhages and categorize the various stages of DR from normal retinal images. Harini&Sheela, (2016) proposed the morphological image processing and fuzzy c-means clustering technique for DR detection. ManojKumar&Sheshadri, (2016) proposed a retina image segmentation technique using pillar k-means algorithm that provides more accurate and faster segmentation. Rajput &Patil, (2014) proposed the detection and classification of exudates in color retinal images based on k-means clustering. Kumar et al., (2013) proposed an automatic detection of exudates based on histogram analysis of retinal images in DR. Ravishankar et al., (2009) developed an early detection of DR in fundus images using morphological operations and learning techniques.

In this paper, a novel DR detection is proposed using Gray-Level Co-occurrence Matrix (GLCM) based feature extraction and Fuzzy Naïve Bayesian (FNB) model for classification of retinal images. Also, Discrete Wavelet Transform (DWT) based noise removing method is applied in the pre-processing stage in order to improve the quality of the retinal images. Section 2 deals with the review of the literature. Section 3 describes the detailed process of the proposed work. Section 4 discusses simulation results and performance evaluation. Finally, section 6 concludes the paper.

## II. LITERATURE REVIEW

Antal&Hajdu, (2012) proposed an enhanced ensemble-based method for the detection of microaneurysm. This approach integrates the internal elements such as pre-processing techniques and candidate extractors of microaneurysm detectors. The method classified DR and non-DR based on the presence or absence of the microaneurysms. Welikala et al., (2015) proposed a dual classification method based on an ensemble system of bagged decision trees. Also, two vessel segmentation algorithms are employed to form two individual binary vessel maps which include essential information. From this, local morphology, gradient, and intensity features are extracted which is used for classification purpose.

Welikala et al., (2014) presented an automated approach for the detection of vessels in retinal images. The segmentation is attained based on a standard line and a novel modified line operator. The two individual feature sets are extracted from each binary vessel using local morphology. The separate classification is applied for each feature set using a Support Vector Machine (SVM) classifier. The final decision is achieved by integrating these two individual classification results. Further improve this technique, Welikala et al., (2015) proposed an automated detection approach of vessels from retinal images. In this, Genetic Algorithm (GA) is used for the feature selection from the two extracted feature vectors which improve the classification performance.

Roychowdhury et al., (2014) proposed a computer-aided system based on diabetic retinopathy using Machine Learning (ML) techniques. This method analyses the fundus images with fluctuating illumination and generates a severity grade. Besides, a two-step hierarchical classification algorithm is presented in which the non-lesions images are rejected. Then, the bright lesions are classified into hard exudates and cotton wool spots, and the red lesions are classified into hemorrhages and microaneurysms. AdaBoost is used to reduce the feature vectors, and it is feed to the classification techniques such as Gaussian Mixture Model (GMM), k-nearest neighbor (kNN) and SVM using the Dempster-Shafer theory. From these, the SVM classifier produces more classification error than the GMM and kNN classifiers.

Saha et al., (2016) proposed an early diagnosis of DR for detection and classification of the bright and dark lesions of fundus retinal images using ML techniques. In this, the segmentation of the retinal images is achieved through the Fuzzy C-Means (FCM) clustering technique. The classification of the bright and dark lesions are classified using Naive Bayes and SVM classifiers respectively. The simulation results demonstrate that the 97% of bright lesion classification accuracy is obtained by using Naive Bayes classifier and 89% of dark lesion classification accuracy is achieved through SVM classifier.

Otálora et al., (2017) proposed a label-efficient Convolutional Neural Networks (CNN) model for the automatic classification of DR. This method considered the expected gradient length, selection of most informative patches using an active learning algorithm and a local optimum scheme. So, this technique used for the detection and segmentation of DR. Gargeya&Leng, (2017) developed a deep learning algorithm for automatic diagnosis of DR which is processed a color fundus retinal images. The simulation results show that the method achieves the more accuracy, specificity, and sensitivity based on 5-fold cross-validation. Doshi et al., (2016) proposed the design of deep CNN for diagnosing and classify retinal images into five different stages of DR. Also, to improve the accuracy the developed model based on deep CNN with quadratic weighted kappa metric is presented.

Ganesan et al., (2014) proposed a new automatic detection and classification of DR using trace transforms. This method presented two types of classification techniques with its accuracy such as SVM with quadratic kernels (99.12%) and Probabilistic Neural Network (PNN) with GA (99.41%). Bhatia et al., (2016) presented various machine learning classification algorithms which are applied to feature extracted from the retinal images. Akram et al., (2013) proposed a three-stage system for early detection of microaneurysms using filter banks. Initially, it extracts all candidate regions for microaneurysms present in a retinal image. From this, to extract the feature vector based on shape, color, intensity, and statistics. Finally, the classification is done using the integration of Gaussian mixture model (GMM) with SVM to improve the accuracy. Tang et al., (2013) proposed a splat feature classification approach for retinal hemorrhage detection in fundus images using splats, and shape and texture features.

## III. PROPOSED METHODOLOGY

The block diagram of proposed Diabetic Retinopathy (DR) diagnosis process is shown in Fig.1. In this proposed model consisted of four main stages, 1) In pre-processing, Bayes

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Shrink method using Discrete Wavelet Transform (DWT) is used to reduce noise and enhance the quality of image, 2) To segment the abnormal area of retinal image is achieved byusingactive contour with Fuzzy C-Means based segmentation, 3) Texture-based feature extraction namely is used to extract the important features from the segmented imageGray-Level Co-occurrence Matrix (GLCM), and 4) Finally, the classification of four retinal abnormalities such as Hordeolum, Seborrheic keratosis, Xanthelasma and squamous cell carcinoma are classified using Fuzzy Naive Bayesian (FNB) classifier.

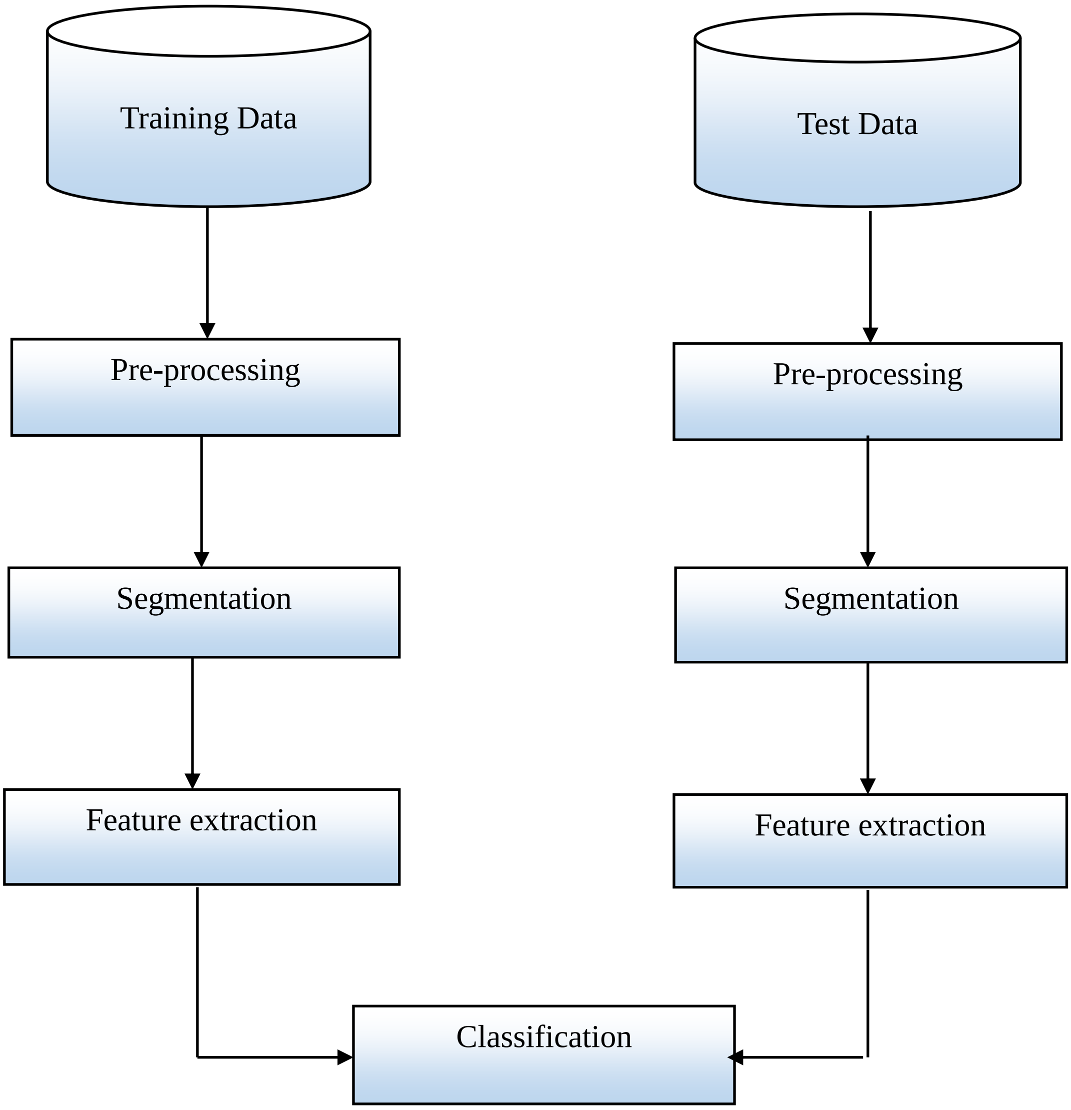


Fig.1 Block Diagram Of Diabetic Retinopathy (DR) Diagnosis Process.

*A. Image pre-processing*

The raw retinal images gathered from the websites, or the scan centre are not appropriate for direct diagnosis processing due to the several noises present in these images. Hence, the image pre-processing is an important stage in an automatic diagnosis of Diabetic Retinopathy (DR).In the preprocessing stage,the raw retinal images are necessary to enhance the quality and make the segmentation, feature extraction and classificationstages are more reliable. This paper presented Bayes Shrink method based on Discrete Wavelet Transform (DWT) for reducing the noise and improving the quality of the images. DWT-based image decomposition is performed on the noisy raw retinal image to transform noisy image data into wavelet domain. Then, 2D-DWT is employed to generate four sub-images. Thresholding technique is developedbased on BayesShrink method to produce superior image quality. Based on this method, shrinking the wavelet transform is performed to eliminate the low amplitude noise or undesired signal in wavelet domain of the image. Now, determine the threshold that reduces the Bayesian risk. At last, estimate the Inverse Discrete Wavelet Transform (IDWT) to obtain the denoised image. Fig.2 shows that the block diagram of noise removing from the retinal image based on the DWT-based thresholding.

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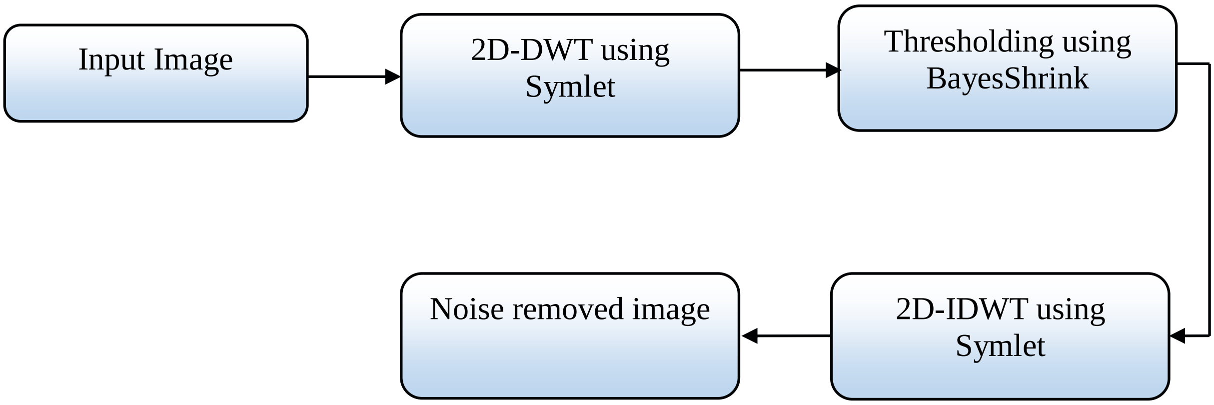


Fig.2 Noise Removal Using DWT-based Thresholding.

Let, W and $W^{-1}$represent the 2D-DWT and its inverse respectively, and G = W(s) denotes the matrix of wavelet coefficients of (s) which has four sub-bands namely LL, LH, HL and HH. Then, threshold estimation criteria called Bayes Shrink estimation used (Portilla et al., 2003). Bayes Shrinkconsiders generalized Gaussian distribution for the wavelet coefficients in each detail of sub-band and uses a Bayesian mathematical model to compute the best threshold that minimizes the Bayesian risk, defined as,

$$\sigma_B = \frac{\lambda_{noise}^2}{\lambda_{signal}^2} = \frac{\lambda_{noise}^2}{\sqrt{\max(\lambda_G^2 - \lambda_{noise}^2)}} \qquad (1)$$

Where, $\lambda_G^2 = \frac{1}{P_s}\sum_{x,y=1}^{N_s} V_{xy}^2$

Ps denotes the number of wavelet factors$V_{xy}$on the sub-band. The estimation of noise variance uses the median absolute value of the wavelet factorsthat is impervious to isolated outliers of possibly high amplitude,expressed as

$$\lambda_{noise} = \frac{\text{meadian}(|V_{xy}|)}{0.6745}, V_{xy} \text{ subband HH} \qquad (2)$$

Where,$V_{xy}$ is HH wavelet coefficients which creates the finest decomposition levels.

*B. Image Segmentation*

In image segmentation, the active contour model plays an important role in accurate segmentation. In this, various initial conditions development will give different segmented region. The attainedoutcomes will not be satisfactory. This insufficientoutcome is the minimization problem of the active contour. Hence, energy minimization is trapped into a local minimum. An algorithm is used to compute the global minimization which is to adjust the Region of Features (ROF) energy is defined as (Bresson et al., 2007),

$$E_R(v,\lambda) = \int_\Omega |\nabla v| + \frac{\lambda}{2}\int_\Omega |v-f|^2 \qquad (3)$$

The variation ($L_1$) is changed by weighted variation ($L_2$)shifting the measure based on a fidelity (f) from the square of $L_2$ to the $L_1$.

$$E(v,\lambda) = \int_\Omega g(f)|\nabla v| + \lambda\int_\Omega |v-f|^2 \qquad (4)$$

Where, $g(f) = \frac{1}{1+\beta|\nabla v|^2}$

If v is the typical function of a set with boundary indicated by the curve $C$ the energy value$E_2$ is the similar as the energy valve of the active contour occurred,

$$E_C = \int_\Omega g(f)ds \qquad (5)$$

Where, $f$ approximated ($L_1$) by a binary function of a region

*C*. Statistically, the minimization is a convex problem. Therefore, the fusion of images which is to be enhanced for flattening the contour level in images the Gaussian filter is employed.The global minimization of active contourmitigates the uncertainty disturbances, thus FCM with spatial initialization is employed as clusters.

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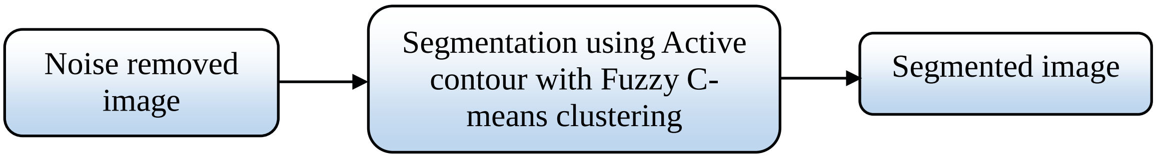


Fig.3 Hybrid retinal image segmentation.

The Fig.3demonstrates the block diagram of hybrid retinal image segmentation method. The concept is to minimize the energy that gives a quality image which is produced.The optimization characteristics of FCM is enhanced when it is combined with Fuzzy C-Means (FCM) .

Fuzzy C-Means (FCM) begins with the middle point of the cluster which is not precise; thus FCM considers membership rank for each cluster at each point. It moves the cluster to the exact place iteratively within the image. The iteration is used to minimizing the objective function that denotes the distance from any specified data point (Chuang et al., 2006). To normalized the datapointappeared in the images a gradient function using FCM is clustered when pixels are near to the centroid of pixels considered as 0,1 which optimize the function as,

$$C=\sum_{p=1}^{M}\sum_{q=1}^{N}R_{pq}^{t}\left\|y_p-x_q\right\|^2 \qquad (6)$$

Where,$R_{pq}$denotes the membership of pixel $y_p$in the $p^{th}$cluster and $v_i$is the $q^{th}$cluster center,$\|.\|$ denotes a norm metric and t is the constant. The function is minimized when pixels are near to the centroid of their clusters which areconsidered by membership values (0,1).Low membership values are considered to the pixels with data remote from the centroid. The probability denotes the membership function is a pixel that related to a particular cluster. This probability is dependent only on the distance between the pixel and each distinct cluster dependent based on the image.

$$R_{pq}=\frac{1}{\sum_{r=1}^{t}\left(\frac{y_q-x_p}{y_q-x_r}\right)^{2/t-1}} \qquad (7)$$

Where, $$x_p=\frac{\sum_{q=1}^{M}R_{pq}^{t}y_p}{\sum_{q=1}^{M}R_{pq}^{t}}$$

Starting with a point for each cluster, the FCM converges to destination point $v_i$, denoting the cost function. When the images are highly unified with the neighbouring pixels, that illustrates the feature values which is related to the similar group a spatial function is represented as:

$$h_{ij}=\sum_{F=S(x_j)}M_{ik} \qquad (8)$$

Where,S($x_j$) denotes the square window centered on pixel x which is in the spatial domain. The spatial function $g_{ij}$denotes the probability and $p_i$related to the cluster. The spatial function of a pixel for a cluster is huge if the majority of its neighborhood related to the same cluster. The spatial function is fused into membership function as,

$$M_{ij}=\frac{h_{ij}^{p}M_{ij}^{q}}{\sum_{k=1}^{C}h_{kj}^{p}M_{kj}^{q}} \qquad (9)$$

Where, p and q are metrics to operate the functions that reinforce the membership when the clustering fallouts remain unchanged. The clustering is a two-stage scheme at each iteration that is the spectral domain is estimatedbased on membership function. Then, the membership information of every pixel is mapped to the spatial domain.The FCM iteration keeps with the new membership which is combined with the spatial function. The iteration is haltedwhen the maximum difference between two cluster centers is lesser than the threshold. After the convergence, defuzzification is employed to considered each pixel to a particular cluster for the membership is maximal.

*C. Feature Extraction Using Glcm*

The use of feature extraction is to minimize the original data set by computingthe features that discriminate one input pattern from another pattern. The extracted feature provides the properties of the input type to the classifier by permitting the description of the related properties of the image into a feature space. But, these features are computed in a different way for the classification. Then, image classification is performed between images based on the computed features from the entire image. In this paper, texture based features are extracted using Gray-Level Co-occurrence Matrix (GLCM).

GLCM is used to compute the spatial dependence of gray levels in an image. GLCM consists of the number of rows and columns are equal to the number of gray levels in an image (Tang et al., 2013). Co-occurrence matrices are derived in four spatial orientations such as 0°, 45°, 90° and 135°. Additional matrix is constructed as the average of previous matrices. Let, the co-occurrence matrix is $P_{i,j}$ and the size of the matrix is N x N. Every element (i,j) denotes the frequency where the pixel with gray level i is spatially related to the pixel with gray level j. GLCM expresses the relation between reference pixel (i) and neighbour pixel (j) in different orientation. The relation between the pixels are estimated horizontally towards the right (0º). At first, the value of each elements in GLCM is considered as zero. Then, the value of each elements in GLCM (i,j) is zero. Besides, the value of each element is updated based on the occurrence of pixels together. In this, texture features such as entropy, sum average, variance, homogeneity or Angular Second Moment (ASM) and maximum probability are extracted using GLCM. These features are estimated the different textural features which can be used to train the classifier.

*a) Entropy*

Entropy is computed to characterize the randomness of the textural image and is defined as,

$$\text{Entropy}=-\sum_{i=0}^{G-1}\sum_{j=1}^{G-1}P(i,j)\times\log(P(i,j)) \quad (10)$$

*b) Sum average*

Sum average is defined as the sum of all values and divided by the total number of values.

$$\text{Sum Average}=\sum_{i=0}^{2G-2} iP_{x+y}(i) \quad (11)$$

*c) Variance*

$$\text{Variance}=\sum_{i=0}^{G-1}\sum_{j=1}^{G-1}(i-\mu)^2P(i,j) \quad (12)$$

*d) Homogeneity (or) Angular Second Moment (ASM)*

Homogeneity measures the similarity of pixels. A diagonal GLCM gives homogeneity of 1. It becomes large if local textures only have minimal changes.

$$\text{ASM}=\sum_{i=0}^{G-1}\sum_{j=1}^{G-1}\{P(i,j)\}^2 \quad (13)$$

e) *Maximum probability*

f) $$\text{Maximum probability}=\max(P(i,j)) \quad (14)$$

*C. Fuzzy Naive Bayesian (FNB) classifier*

The Naive Bayes classifier is constructed based on the theorem of Bayes' probability (Jang & Park, 2016). In the Bayes' theorem, the conditional probability which is an event related to a class that isestimated from the conditional probabilities of determining the particular events and also the unconditional probability of the event in each class. For given data $x \in X$ and $C$ classes, in which $X$ represents a random variable, the conditional probability of an event $x$ related to a class $k$ is estimated by using the below expression,

$$P(C_k|x)=P(C_k)\frac{P(x|C_k)}{P(x)} \quad (15)$$

The computation of $P(C_k|x)$ is a pattern classification problem as it predicts the probability for the given data related to class.Then, select the optimum class by selecting the class with the maximum probability among all possible classes ($C$), thatreduce the classification error. In this, $P(x|C_k)$ is calculated by using following equation,

$$P(x|C_k)=\prod_{i=0}^{n}P(x|C_k) \quad (16)$$

Where, $x$ is an n-dimensional vector $x=(x_1,x_2,...,x_n)$.

Based on equation (16), the Naive Bayes classifier considers thateach feature is statistically independent. This considerationproduces a simpler computation cost and efficient data processing. The Naive Bayes classifier is estimated by combining equation (15) and equation (16) as the following equation,

$$k=\arg\max_k P(C_k)\prod_{i=0}^{n}P(x_i|C_k) \quad (17)$$

In this, the denominator $P(x)$ is neglected since the value is the similar to all class. In general, the Naive Bayes classifier is known as the maximum a posteriori (MAP) decision rule.

## IV. RESULTS AND DISCUSSION

The experimentation of Diabetic Retinopathy (DR) detectionisconducted on the processor Intel (R) Core (TM) i3 Lenovo platform with 3GHz main a processor speed and 8 GB memory. The algorithm is developed in Matlab 2016b.The datasets consist of 80abnormalretinal images and 20 retinal images from each category.Each image size is 868×922 which are downloaded from the standard diabetic retinopathydatabase(http://www.it.lut.fi/project/imageret/diaretdb1/).

In the pre-processing stage, each input retinal images are resized to 400×400 uniform size. Then, the colour image is converted into the gray-scale image and it is fed to the noise removal and quality enhancement process using DWT-based thresholding technique. Fig.4 shows that the wavelet packet object structure of DWT that uses the symlet wavelet and Shannon entropy.

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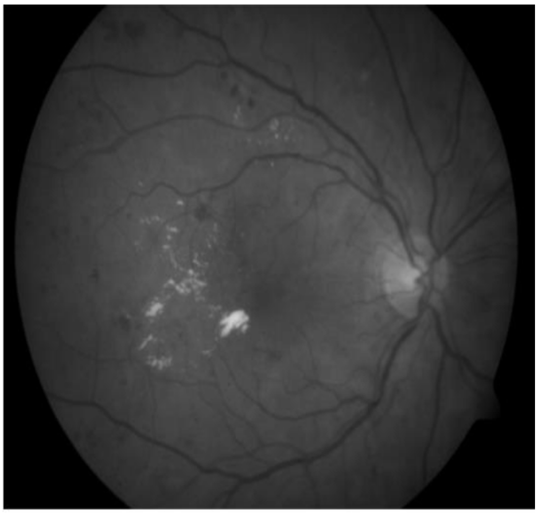
```
Wavelet Packet Object Structure
=================== =========
Size of initial data :   [4     00]
Order              :    4
Depth              :    2
Terminal nodes     :   [5 6 7 8 2 3 4]
-------------------------------------------
Wavelet Name              :sym2
Low Decomposition filter  :[-0.1294   0.2241   0.8365    0.483]
High Decomposition filter :[ -0.483   0.8365  -0.2241  -0.1294]
Low Reconstruction filter :[ 0.483    0.8365   0.2241  -0.1294]
High Reconstruction filter :[-0.1294  -0.2241   0.8365   -0.483]
-------------------------------------------
Entropy Name           :shannon
Entropy Parameter        :0
-------------------------------------------
```

Fig.4 Result of DWT based filtering.

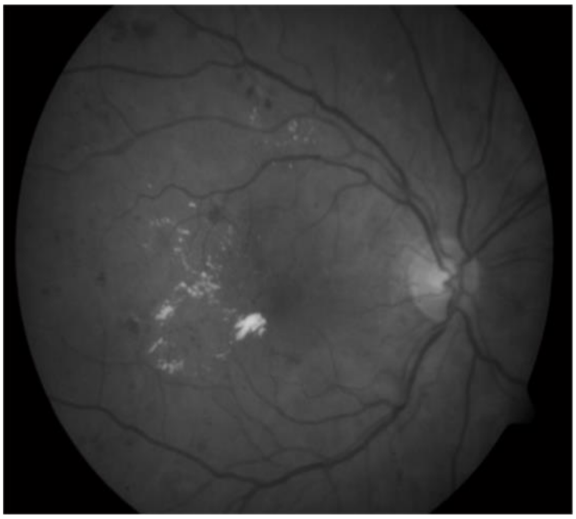
These noise removed is used for further processing such as segmentation and feature extraction. In the segmentation stage, the abnormal area of retinal image is accurately segmented using active contour with fuzzy c-means algorithm. Fig.5 shows that the results of the pre-processing stage where (a) shows the raw input image with the noise of size 868×922, (b) demonstrates that the input image is resized into 400×400, (c) shows that the grayscale resized image, and (d) shows the noised removed image.

(a)

(b)



(c)



(d)

Fig.5 Results of Pre-Processing Stage. (A) Input Retinal Image, (B) Resized Image, (C) Grayscale Image and (D) Noise Removed Image.

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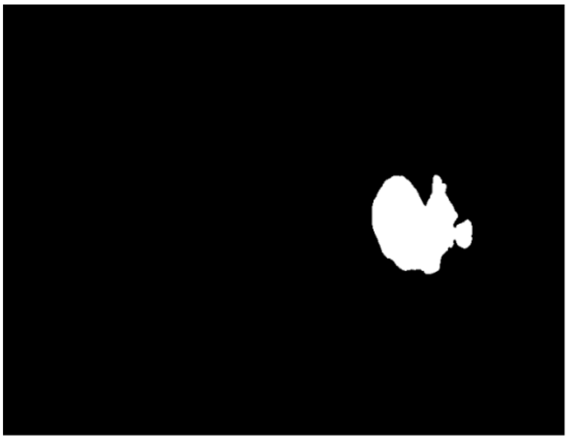
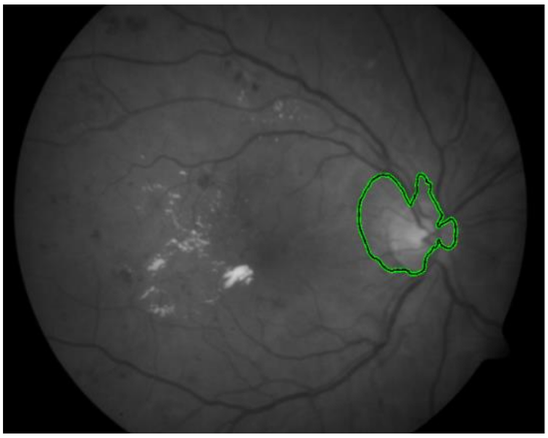
In the segmentation stage, the proposed method applied hybrid retinal image segmentation method to segment the region of the abnormal area. Also, the optimization segmentation is enhancedthrough combining it with Fuzzy C-Means (FCM). The accurate segmentation is achieved by the iteration value is kept 300.Fig.6demonstrate that the results of segmentation stage in which (a) shows that the segmented binary image, (b) depicts the segmented image with Region-of-Interest (ROI) and (c) shows that the final segmented image.

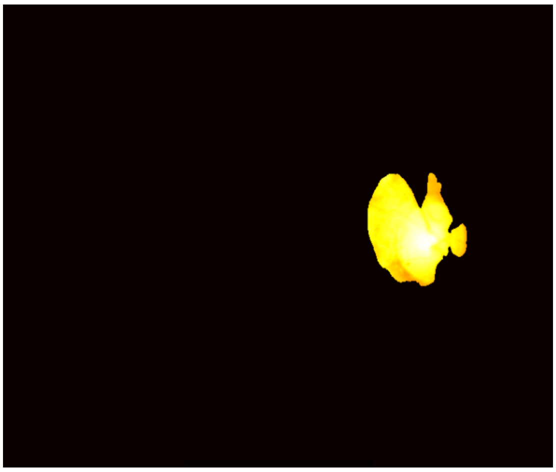
From the segmented image, the important texture-based features variance, homogeneity, maximum probability, sum rate and entropy are extracted using GLCM. To train these feature values and it is used to classification stage. The classification is achieved through the FNB classifier which classify the input image is as retinal abnormalities such asHordeolum, Seborrheic keratosis, Xanthelasma and squamous Cell Carcinoma.



(a)



(b)



(c)

Fig.6 Results of Segmentation. (A) Segmented Binary Image, (B) Segmented Image With ROI, and (C) Final Segmented Image

Fig.7demonstrates that the FNB classifier performance based on thetraining state, error histogram and the overall confusion matrix. In the performance plot, the cross-entropy error is maximum at the starting of training. For the proposed system, the best validation performance is at epoch 95, and at this point the cross-entropy error is very close to zero. In the training performance plot, the maximum validation check 6 at epoch 11 and MSE is going down towards the best results is expected. The error histogram plot depicts that the error of this proposed method is very close to zero. An overall confusion matrix is three sets of merged confusion matrices which are the training confusion matrix, validation confusion matrix, and testing confusion matrix.

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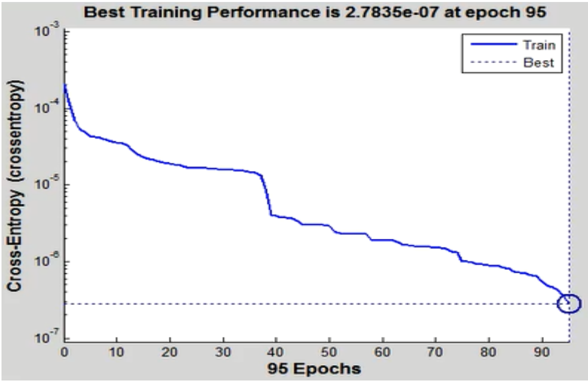
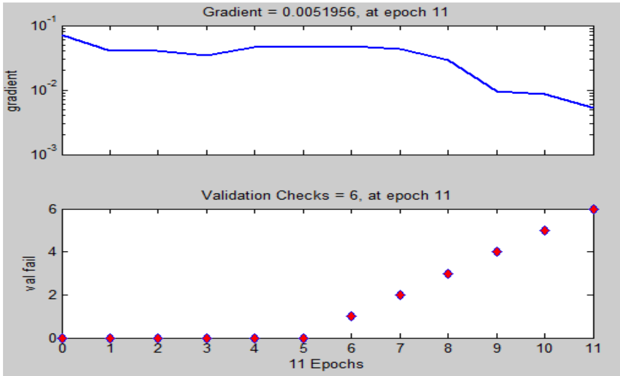
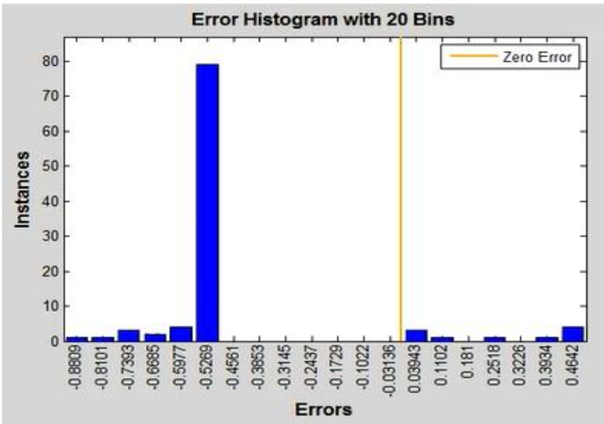


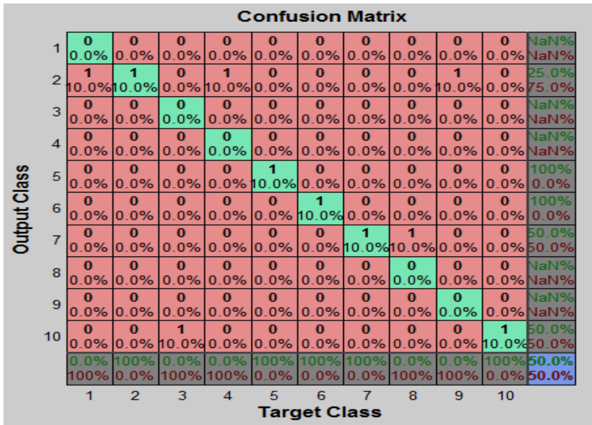

(a)




(b)




(c)




(d)

Fig.7Performance analysis.(a) Training State, (b) Error Histogram, (c) and (d) Overall Confusion Matrix

ROC curve of the proposed method which shows the true positive rate versus false positive rate at several threshold settings. Fig.7 demonstrates that the ROC curve of the method.

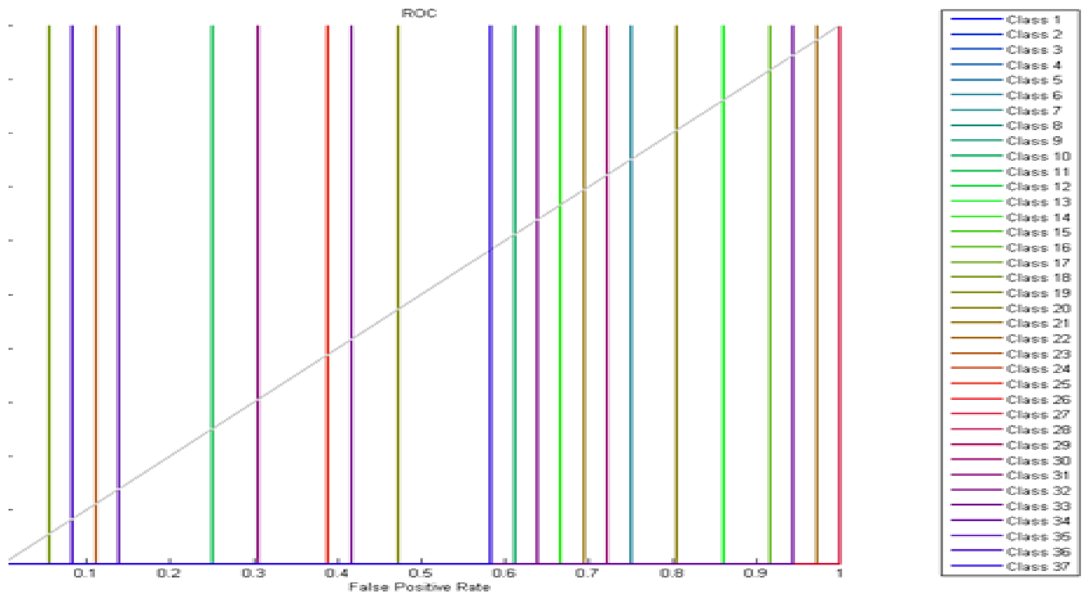



Fig.7 Receiver Operating Characteristic (ROC)Curve

The performance of diagnosis is examined by evaluating the performance of sensitivity, specificity and accuracy. It is measured based on the true positive (TP), true negative (TN), false positive (FP) and false negative (FN). In this, TP and TN defines the classifier obtaining right classification outcomes and FP and FN defines the classifier attaining wrong classification results.

$$\text{Sensitivity}=\frac{\text{Number of true positive assessment}}{\text{Number of all positive assessment}}=\frac{TP}{TP+FN} \tag{18}$$

$$\text{Specificity}=\frac{\text{Number of true negative assessment}}{\text{Number of all negative assessment}}=\frac{TN}{TN+FP} \tag{19}$$

$$\text{Accuracy}=\frac{\text{Number of correct assessment}}{\text{Number of all assessment}}=\frac{TN+TP}{TN+TP+FN+FP} \tag{20}$$

Table: I Performance comparison of proposed DR detection with existing techniques.

| Reference | Sensitivity | Specificity | Accuracy |
|---|---|---|---|
| Akram et al., (2014) | 96.1% | 94.7% | 94.81% |
| Jahiruzzaman&Hossain, (2015) | 98.2% | 89.8% | 92.3% |
| Proposed method | 98.2% | 96% | 98.7% |

The comparison of proposed DR detection method is compared with existing techniques in terms of sensitivity, specificity and accuracy which is shown in Table I. The proposed method achieve the better sensitivity, accuracy, and specificity than the existing techniques.

## V. CONCLUSION

In this paper, a Fuzzy Naive Bayesian (FNB) classifier is proposed to classify the Diabetic Retinopathy (DR) abnormalities. Initially, DWT-based Bayes Shrink thresholding method used to eliminate noise from the image. Then, based on active contour with FCM algorithm, the abnormal area of the image has been segmented. By applying GLCM to the segmented image for extracting texture features and which is fed to the FNB model to classify abnormalities of the retinal image. The simulation results of the proposed classifier obtained the accuracy of 98.7%, sensitivity of 98.2%, and specificity of 96%. Also, it is verified that the performance of the proposed method is better than the existing methods.

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