# Automated Diagnostic System for Grading of Diabetic Retinopathy Stages from Fundus Images Using Texture Features

Dr. M. Ponni Bala
Department of Electronics and Instrumentation Engineering
Kongu Engineering College
Perundurai, Erode, Tamilnadu, India.
*e-Mail: ponnibalakumar@gmail.com*

Dr. M. Sivachitra
Department of Electrical and Electronics Engineering
Kongu Engineering College
Perundurai, Erode, Tamilnadu, India.
*e-Mail: sivachitra@kongu.ac.in*

***Abstract***— Computational methodologies and medical imaging are become an important part of real time applications. These techniques transform medicine by providing effective health care diagnosis in all major disease areas. This will allow the clinicians to understand life-saving information using less invasive techniques. Diabetes is a rapidly increasing worldwide disease that occurs when the body is unable to metabolize glucose. It increases the risk of a range of eye diseases, but the main cause of blindness associated with diabetes is Diabetic retinopathy (DR). A new feature based automated technique for diagnosis and grading of normal, Nonproliferative diabetic retinopathy (NPDR) and Proliferative diabetic retinopathy (PDR) is proposed in this paper. This method involves preprocessing of retinal images, detection of lesions, extraction of blood vessels and extraction of texture features such as local binary pattern, Laws texture energy and Fractal Dimension. These features were used for classification of DR stages by means of supervised classifiers namely Support vector machine (SVM) and Extreme Learning Machine (ELM). In this work, in addition to morphological features, statistically significant texture features were also used for classification. It was found that the average classification accuracy of 98.88%, sensitivity and specificity of 100% respectively achieved using ELM classifier with texture features. The results were validated by comparing with expert ophthalmologists. This proposed automated diagnostic system reduces the work of professionals during mass screening of DR stages.

***Keywords*** *- Diabetic Retinopathy; Local Binary Pattern; Laws Texture Energy; Fractal Dimension; Support Vector Machine; Extreme Learning Machine.*

*****

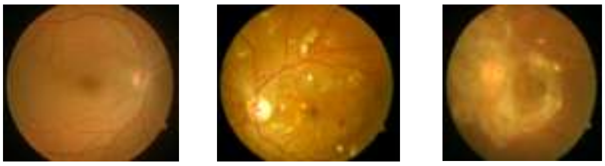
## I. INTRODUCTION

Diabetic retinopathy is the popular ocular symptom of diabetes, and diabetics are at a risk of loss of eyesight due to DR. It leads to new cases of blindness and normally occurs among people aged 20 to74 years. DR damages blood vessels inside the retina, at the back of the eye. Poorly controlled blood sugar, high blood pressure and high cholesterol increase the risk of developing DR. According to WHO (World Health Organisation) it is reported that, more than 75% of people affected with diabetes for more than 20 years will have some form of DR[1]. The occurrence of retinopathy is minimal during the first 5 years in younger patients (below 30 years of age) but increases to greater than 95% after 15 years of diabetes [2]. Hence regular screening for retinopathy and timely treatment by laser surgery can extensively reduce the incidence of blindness.

The need for screening methods of diabetic retinopathy will increase as the number of diabetes affected people is increasing worldwide. The high cost of examining retinal images and the shortage of ophthalmologists in rural areas are the important factors that delay diabetic patients from getting regular examinations [3]. Hence an automated retinal image diagnosis system is developed to analyse the initial set of retinal images. The images with lesions alone can be directed to ophthalmologists for further analysis. This could allow more patients to be examined in a short period of time by the ophthalmologists and reduce their workload. So that they can spend more amount of time for the patients who are actually in need.

Diabetic retinopathy is a general term for all disorders of the retina caused by diabetes. The main stages of DR are Non-proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR) depending on the presence of clinical features such as microaneurysms, exudates, haemorrhages and neovascularisation. There are four stages of diabetic retinopathy depending on the presence of specific features of DR; the stages can be classified as mild, moderate, severe and proliferative. The stages are progressive and medical treatment at this stage can only stop the growth of the disease and reduce its progress. Hence it is essential for early diagnosis and regular eye screening for diabetics. Screening to detect retinopathy disease can lead to successful treatments in preventing visual loss. In this paper, an automatic screening system for the detection of normal and DR stages have been presented which assist ophthalmologists by providing second opinion for accurate detection of DR.

Microaneurysms (MAs) are one of the first clinical sign of NPDR and are caused by focal dilatations of thin blood vessels. MAs appear as small red dots almost round in shape on fundus images. In some cases small blood vessels break and leak blood into the retina causing hemorrhages. The incidence of blindness can be reduced by detecting microaneurysms at an earlier stage. In the second stage of NPDR, the damaged blood vessels leak extra fluid and small amount of blood into the eye. This condition leads to the formation of exudates in the retina. As the disease progresses the amount of exudates also increases. In PDR, the blood vessels in the retina close and prevent blood flow in the eye. This condition leads to the formation of new blood vessels in order to supply blood to the blocked area and is called as neovascularisation. These vessels have a greater risk of rupturing and causing large hemorrhages than normal vessels. Figures 1 (a), (b) and (c) show the different stages of retinal images such as normal, NPDR and PDR. DR can progress from NPDR to PDR. Detection of diabetic retinopathy through regular screening in an early stage is important to prevent vision loss. Computer aided diagnosis and digital retinal imaging will help to support the large scale screening of individuals having diabetes.



(a) (b) (c)

Figure 1. Stages of Retinal Images (a) Normal Retinal Image (b) NPDR image (c) PDR image

## II. LITERATURE REVIEW

Automated grading of DR was done by many researchers. M.R.K.Mookiah et al [4] have presented an automatic screening system for the detection of DR stages such as normal, NPDR and PDR. This involves extraction of blood vessels, exudates, texture and entropies. They have used Probabilistic neural network, Decision tree and Support vector machine classifiers for DR diagnosis. It was found that the accuracy of 96.15%, sensitivity of 97.27% and specificity of 96.08% with PNN classifiers. Jagadish Nayak et al [5] have proposed a computer based approach for the detection of diabetic retinopathy stage using fundus images. The features are detected using Image preprocessing, morphological processing techniques and texture analysis methods. The extracted features such as area of hard exudates, area of the blood vessels and the contrast are then used as an input to the artificial neural network (ANN) for an automatic classification. It showed a classification accuracy of 93%, sensitivity of 90% and specificity of 100%.

M. Ponni Bala et al [6] have proposed an automated DR detection system expending mathematical morphology and connected component analysis method. Sequential learning algorithms such as SRAN and McNN are adopted for classifying the retinal images as exudates and their severity and non-exudates. The sensitivity, specificity and accuracy reported performance levels of 97.05%, 100 % and 97.61% respectively. Ponni Bala et al [7] also presented a method for early detection and screening of DR based on microaneurysms. The features are extracted using morphology based segmentation technique and a supervised classifier namely Meta-cognitive Neural Network (McNN) was employed for classification. They reported that the McNN classifier produces good classification accuracy compared to other classifiers.

Acharya et al [8] presented a DR detection system such as NPDR and PDR stages by applying higher order spectra for extraction of features and SVM classifier was used to get the reasonable accuracy. Song Ke-Chen et al [9] showed the principle of local binary pattern (LBP) method, which mainly analyses the threshold operation, the uniform pattern and rotation invariant pattern in this method. LBP method is relatively simple and of low computation complexity. It also has a rotational invariance, gray scale invariance and other significant advantages. Therefore, LBP has obtained fruitful results and is widely used in image matching, pedestrian and car target detection and tracking, as well as biological and medical image analysis.

A new approach for detection of Proliferative Diabetic Retinopathy Using Brownian Motion Features was developed by Wong Li Yun et al [10]. Here Fractal dimensions and Hurst coefficient features were extracted from normal and proliferative diabetic retinopathy images. And these features were given as input to five classifiers namely, Support Vector Machine (SVM), Probabilistic Neural Network (PNN), Decision Tree (DT), K-Nearest Neighbour (KNN) and Fuzzy Sugeno (FS) to select the best classifier. They reported that the FS classifier yielded the highest average accuracy of 94%, sensitivity of 92% and specificity of 96%. Acharya et al [11] improvised a method for automated detection of DR by making use of texture features and it reported an accuracy of 85.2%, sensitivity of 98.9% and specificity of 88%. In the literature, the researchers used different classifiers for diagnosis of DR stages and have a slower training speed.

The important challenge in the above mentioned methods is the identification of microaneurysms and separating it from other lesions and background noise. The size of microaneurysms varies from images and lead to inaccurate detection of MAs. Hence the traditional image segmentation methods are not effective for early detection and diagnosis of NPDR in fundus images. In this work, diabetic retinopathy stages are classified without segmentation of lesions. Initially the retinal images are preprocessed using Contrast Limited Adaptive Histogram Equalisation (CLAHE) to enhance the contrast of an image. Further various texture features such as Local Binary Pattern (LBP), Laws Texture Energy (LTE) and Fractal Dimension (FD) are extracted from the preprocessed images and the features are selected using one-way ANOVA test. Finally the selected features are given to the supervised classifiers namely Support Vector Machine (SVM) and Extreme Learning Machine (ELM) for classification of DR. The training time of ELM classifier is lower compared to that of the SVM classifier.

This paper introduces a new method for automatically classifying the different stages of DR as normal, NPDR and PRD fundus images by extracting the texture features. The approach is based on: (a) Preprocessing by CLAHE (b) extraction of texture features and (c) classification of DR stages by employing SVM and ELM classifier. The experimental results are encouraging and clearly highlight that the new texture features used for classification provide a better performance accuracy than the results reported in the literature.

## III. MATERIALS AND METHODS

### A. *Methodology*

The major objective of this work is to classify the fundus image into normal, nonproliferative diabetic retinopathy and proliferative diabetic retinopathy stages. The fundus image used for this work is subjected to the preprocessing steps such as green channel extraction and histogram equalization. The fundus images used for this work are collected from Lotus Eye Care Hospital, Coimbatore. The images form a dataset of 198 colour fundus images of which 22 are of those patients with normal, 148 contain lesions such as microaneurysms, haemorrhages and exudate patches and 28 contain neovascularisation of different stages of abnormality. The images collected for this study with an age group of 28 to 75 years. Images were captured with 90 degree field-of-view digital fundus Cannon non-mydriatic ZEISS FF450plus camera. Each image was captured using 24 bit per pixel at a resolution of 774×893 pixels in JPEG format. In addition to the private dataset, publicly available dataset DIARETDB0 are also used to test the performance of the proposed retinal image diagnosis system. The block diagram of the proposed method is shown in Fig. 2.

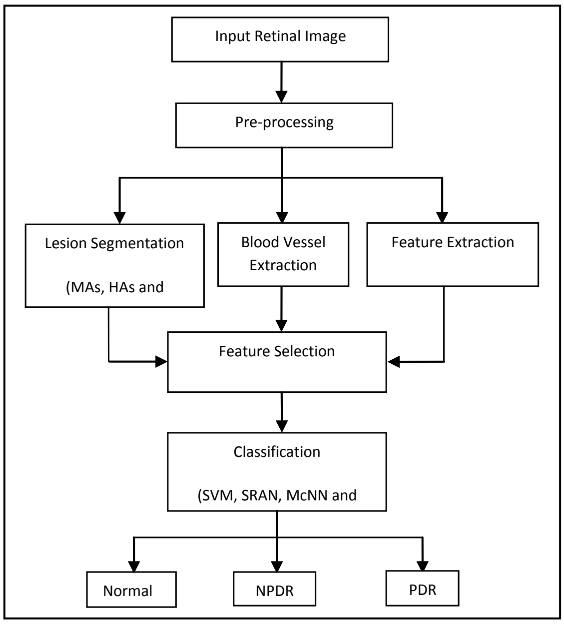



Figure 2 Block Diagram of the Computer-aided Retinal Image Diagnosis System

## B. *Preprocessing*

The green channel of the colour fundus image is subjected to contrast enhancement using Contrast-Limited Adaptive Histogram Equalization (CLAHE). This method separates the images into blocks and performs histogram equalization on the separated blocks by considering pixels in the adjacent area. Unlike histogram equalization, it operates on small data regions called as tiles rather than the entire image. Each tile's contrast is enhanced so that the histogram of each output region approximately matches the specified histogram.

## C. *Feature Extraction*

Feature extraction, is a special form of dimensionality reduction. The features set will extract the related information from the input image in order to perform the desired task. In this work different techniques are used to extract the features from retinal images. It is clinically understood that when the disease progress from NPDR to PDR, there may be some textural changes. The texture features such as Local Binary Pattern (LBP), Laws Texture Energy (LTE) and Fractal Dimension (FD) are extracted from the preprocessed images. Depending on the abnormal stages of DR, the retinal image has many granular structures which are self similar patterns at different scales called 'texture'. This refers to the properties in respect to the smoothness, roughness and regularity of any structure [12]. The extracted feature values of different ranges are normalized in an acceptable range for classification. From these features, the most useful features are applied for classification. The features are selected using one -way ANOVA (Analysis Of Variance) test. The features which have p-value < 0.0001 are selected, when a probability (p-value) is less than a threshold (significance level) justifies the rejection of the null hypothesis [13].

### L *Local Binary Pattern (LBP):*

The Local Binary Pattern is a very powerful and fine scale texture descriptor and was introduced by Ojala et al [14]. $LBP_{8,1}$ type is applied and is used for capturing the micropatterns. Label is allocated to all pixel of an image by thresholding the neighbourhood of each pixel with the center pixel value [15]. The LBP operator detects microstructures such as edges, lines, spots and flat areas whose underlying distribution is estimated by the histogram. Then, the histogram of the labels can be used as a texture descriptor. The illustration of the basic LBP operator is shown in Fig. 3. When all the pixels have been labelled with the corresponding LBP codes, the histogram of the labels is computed and used as a texture descriptor.

| | | |
|---|---|---|
| 145 | 132 | 120 |
| 130 | 123 | 124 |
| 116 | 126 | 121 |

Image

| | | |
|---|---|---|
| 1 | 1 | 0 |
| 1 | 0 | 1 |
| 0 | 1 | 0 |

Threshold

| | | |
|---|---|---|
| 1 | 2 | 4 |
| 128 | | 8 |
| 64 | 32 | 16 |

Weights

Binary=10101011
LBP code
=1+2+8+32+128
= 171

Figure 3 Illustration of basic LBP operator

The LBP operator provides a unified approach to the traditionally divergent statistical and structural model of texture analysis [16]. A total of nine LBP based features were extracted from the retinal image.

### *Laws Texture Energy (LTE):*

The texture energy measures developed by K. I. Laws [17] have been used for many diverse applications. Laws texture energy measure is calculated by applying small convolution kernels to a digital image initialy, and then performing a non-linear windowing operation. It is an additional approach of detecting various types of textures with local masks. Laws masks represented image features not considering to the frequency domain. All the masks were derived from one dimensional (1-D) vectors of five pixels length L5, E5, S5, R5, W5 describe the following features.

L5 = Level detection
E5 = Edge detection
S5 = Spot detection
R5 = Ripple detection
W5 = Wave detection

Mutual Multiplying of these vectors, considering the first term as a column vector and the second term as row vector, results in 5×5 Matrix known as Law's Masks. By convoluting the Law's Mask with Texture image and calculating energy statistics, a feature vector is derived that can be used for texture description [18]. By convoluting any vertical one dimensional vector with a horizontal one, twenty five two dimensional filters of size 5×5 are generated. The two dimensional masks are created by convolution of a vertical vector with a horizontal vector. It can be seen that a vector of size N can give rise to $N^2$ different masks. Each mask represents a characteristic feature that can be detected such as Level, Edge, Spot, Wave, Ripple, Undulation and Oscillation. Laws determined that the variance or standard deviation was the best single transform to extract texture information from the filtered images [19]. The application of the Laws' masks requires no image pre-processing. This point constitutes one of the advantages of this technique.

*Fractal Dimension:*

Fractal Dimension is one of the measures to perform texture analysis. PDR is the result of severe vascular complication and is visible as neovascularisation of retina. Automatic detection of such new vessels would be useful for the severity grading of DR, and it is an important part of screening process to identify DR patients who need insistent treatment. Fractals are geometric objects which resemble exactly or statistically the whole object under magnification. The concept of fractal was introduced by Benoit Mandelbrot in 1975 [20]. According to him, fractals objects have three important properties, (1) Self similarity (2) Iterative formation and (3) Fractional dimension. Fractal Dimension (FD) reflects the structure's convoluteness and it allows one to measure the complexity of an object. FD is a real number used to characterise the geometric complexity of *A*. A bounded set *A* in Euclidean *n*- space is self similar if *A* is the union of $N_r$ non-overlapping copies of itself scaled up or down by a factor of *r*. The fractal dimension *D* of *A* is given by,

$$1 = N_r r^D \tag{1}$$

$$D = \frac{\log_r(N)}{\log\left(\frac{1}{r}\right)} \tag{2}$$

Here modified differential box counting with sequential algorithm is used for evaluation. The algorithm considers the grid size as power of 2 which is used for efficient computation. By considering the minimum and maximum grey scale difference, *N* and *r* can be calculated [21].

## IV. CLASSIFICATION

Efficient classification algorithms help in reducing the screening time and can be used a tool to assist clinicians. To classify the retinal images, supervised learning algorithms called Support Vector Machine (SVM) and Extreme Learning Machine (ELM) is put to use. Extracted features from the retinal images are used for classification. The classifier arrays the images into Normal, NPDR and PDR stages automatically.

### *A. Support Vector Machine (SVM) classifier*

Support vector machine is a supervised learning process applied for analyzing the training data to find an optimal way to classify the diabetic retinopathy images into their respective classes namely Normal, PDR and NPDR. SVM is a robust method used for data classification and regression invented by Vapnik [22]. SVM models construct a hyper plane for separating the given data linearly into separate classes. Support vector machine method is used to distinguish between the various classes. The training data should be statistically sufficient. The classification parameters are formed according to the calculated features using the SVM algorithm by Chih-Wei Hsu et al [23]. These classification parameters are used for classifying the images.

Whenever a dataset is linearly separable, i.e., there exists a hyper plane that correctly classifies all data points, there exist many such separating hyper planes. Choosing hyper plane is very important such that not only the training data but also future examples unseen by the classifier at training data are correctly classified. Hyper plane classifiers will work better if the hyper plane not only separates the examples correctly, but does so with a larger margin. Here the margin of a linear classifier is defined as the distance of the closest example to the decision boundary.

The contents of the images are distinguished into various classes according to the designed SVM classifier. For nonlinear classification of the given data, SVM uses a non-linear kernel function to map the given data into a high dimensional feature space where the given data can't be linearly classified. Kernel function *K*(*x*, y) represents the inner product $\langle\phi(x),\phi(y)\rangle$ in feature space. In this case, RBF kernel function is used as,

$$K(x,x') = \exp\left\{-\frac{\|x-x'\|^2}{2\sigma^2}\right\} \tag{3}$$

where *x* and *x*' are the training vectors, where σ is the parameter that controls the width of the Gaussian. The output can be one of the three categories namely normal, NPDR and PDR fundus images.

### *B. Extreme Learning Machine (ELM) Classifier*

ELM is a single hidden layer feedforward neural network where the input weights are chosen randomly and the output weights are calculated analytically [24]. The weights of the input layer and the hidden layer biases of Single-hidden Layer Feed forward Neural network (SLFN) can be randomly assigned for this extreme learning machine network if the activation functions in the hidden layer are infinitely differentiable. After the weights and the hidden layer biases are selected randomly, SLFNs can be simply considered as a linear system and the output weights of SLFNs can be analytically determined. The analytical determination is through the simple generalized inverse operation of the output matrices of the hidden layer. Based on this, it proposes a simple learning algorithm for SLFNs called Extreme Learning Machine (ELM) whose learning speed, faster than conventional feed forward network learning algorithms like back-propagation (BP) algorithm, which have better generalization performance.

Extreme Learning Machine is a three-step algorithm which doesn't have tuning mechanism. The learning speed of ELM is extremely fast and it can be used as a classifier. ELMs were originally developed for the SLFNs and then extended to the "generalized" SLFNs. ELM not only tends to reach the smallest training error but also the smallest norms of output weights [25].

Comparing ELM with conventional learning methods, ELM could generate the hidden node parameters before training data is fed to them. It is a network which contains only one hidden layer. The input layer to hidden layer weights can be chosen randomly and hidden layer to output layer weights can be calculated analytically. Unlike traditional gradient-based learning algorithms which only work for differentiable activation functions, ELM can be able to work for all bounded non constant activation functions [26].

ELM tends to reach the solutions in a straightforward way where the traditional gradient-based learning algorithms faces issues like local minima and improper learning rate. This learning algorithm is much simpler than other learning algorithms and needs very less time for training compared to popular Back Propagation (BP) algorithm. ELM does not require tuning and implementation is easier than BP and SVM algorithms. The classification accuracy of ELM is also better than BP and tough classification applications.

## V. RESULTS AND DISCUSSION

The retinal image dataset is subjected to pre-processing and features are extracted. From the pre-processed retinal image, GLCM features, LBP features LTE features and Fractal Dimension were extracted. Depending on the presence of features on the retina said above, the stages of DR can be identified. Among all the twenty two GLCM features, seven features such as energy, entropy, contrast, correlation, homogeneity and cluster prominence were selected using ANOVA test which are statistically significant ($p<0.0001$) and used for evaluation. Grading of retinal images can be done using these features and classified by Support Vector Machine classifier initially.

To improve the classification accuracy of the automated system, new features like Local binary pattern (LBP), Laws texture energy (LTE) and Fractal Dimension are availed for classification. The selected seven GLCM features, nine LBP feature, Fractal Dimension, LTE energy and LTE entropy are provided as inputs to the classifier and are used to capture the variations in the pixels of normal, NPDR and PDR images.

In this work, training and testing set was formed by 65% and 35% samples respectively. The implementation of this technique is carried out using MATLAB. Here the supervised classifiers SVM and ELM are applied to evaluate the screening system using 18 features. The performances of both SVM and ELM classifiers are studied using 3 fold cross validation of training and testing data to get a good efficiency. The performance of the proposed system is measured using sensitivity, specificity and accuracy to assess the accuracy of the algorithms.

Testing classification accuracies for each of the texture features and in different combinations are shown in Table 1. The classification accuracy would increase above the highest value, when selectively combining certain texture features.

TABLE I. CLASSIFICATION ACCURACIES OF EXTRACTED TEXTURE FEATURES IN DIFFERENT COMBINATIONS

| Features used | Sensitivity | Specificity | Accuracy |
|---|---|---|---|
| | % | % | % |
| GLCM | 100 | 90.90 | 50 |
| GLCM +LBP | 100 | 100 | 33.33 |
| GLCM +LTE | 100 | 90.90 | 50 |
| GLCM +FD | 100 | 90.90 | 50 |
| LBP+LTE | 100 | 95 | 86.66 |
| LBP+FD | 100 | 100 | 91.66 |
| LTE+FD | 97.43 | 90.47 | 95 |
| GLCM +LBP+LTE | 100 | 100 | 90 |
| GLCM + LTE+FD | 100 | 100 | 95 |
| GLCM +LBP+FD | 100 | 95 | 48.33 |
| LBP+LTE+FD | 100 | 95 | 95 |
| GLCM +LBP+LTE+FD | 100 | 50 | 66.66 |

From the above results it is observed that when the GLCM features alone are used for classification, it produces 50% accuracy for 3-class classification. But when combining texture features with GLCM features and in all possible combinations, some combination improved the overall accuracy upto 95%. Here, grouping GLCM features with Laws Texture Energy and Fractal Dimension improved the accuracy of 95% for classification of Normal, NPDR and PDR images using SVM classifier. The results of classification procedure, sensitivity, specificity and percentage of accuracy for the three classes, normal, NPDR and PDR stages of retinal images exerting the different classifiers namely SVM and ELM are given in Table 2. It is observed that certain texture properties would represent a better pattern than others based on the frequency of occurrence and noise in the images. The combination of more than two texture measures would not give a better accuracy even with the removal of highly correlated features. This will lead to complexity in features and hence having a negative effect on the classifiers performance. The combination of GLCM, LTE and FD features are the best for classifying three stages of DR and these three measures perform better than the other measures in this study.

TABLE II. RESULTS OF SENSITIVITY, SPECIFICITY AND ACCURACY VALUES OF DIFFERENT CLASSIFIERS

| Features | Sensitivity % | Specificity % | Accuracy % |
|---|---|---|---|
| | ***SVM Classifier*** | | |
| GLCM | 100 | 90.90 | 50 |
| GLCM +LTE+FD | 100 | 100 | 95 |
| | ***ELM Classifier*** | | |
| GLCM | 100 | 100 | 95.71 |
| GLCM + LTE+FD | 100 | 100 | 98.88 |

The sensitivity, specificity and accuracy obtained for SVM classifier with GLCM feature alone are 100%, 90.90% and 50% and for combination of LTE, FD and GLCM features, they are 100%, 100% and 95% respectively. The best overall performance (98.88%) is obtained with 3-fold cross validation using ELM classifier. From the above results, it is found that the best performance is obtained with combination of GLCM, LTE and FD features using ELM classifier.

## VI. CONCLUSION

The novel approach proposed in this paper proved that the Extreme Learning Machine classifier produces an improvement in classification accuracy to the problem of computer aided diagnosis of digital fundus images for grading

DR. The algorithm used here classified images into Normal, NPDR and PDR. Initially the retinal image is preprocessed using CLAHE, and then the texture features such as Local Binary Pattern, Laws Texture Energy and Fractal Dimension are extracted and classified using SVM and ELM classifiers. ELM produces good class separability between different stages of DR for selected texture feature combination. ELM classifier performs a highly efficient classification with an average accuracy of 98.88%, corresponding sensitivity and specificity of 100% respectively. Thus the work has established a successful automated DR grading method which helps to diagnose the disease and reduces the work of ophthalmologists during the mass screening of fundus images.

## ACKNOWLEDGMENT

The authors are grateful to Lotus Eye Care Hospital, Coimbatore for providing the photographic database of retinal images and also to Dr. R. J. Madhusudanan DO, for his valuable suggestions on this work.

## REFERENCES

[1] M. Reema, and R. Pradeepa, "Diabetic retinopathy: An Indian perspective", Indian Journal of Medical Research, 2007, 125(3), pp. 297-310.

[2] D. M. Abramoff, M. Niemeijer, Suttorp-Schulten, A. M. Viergever, R. S. Russell and B. Van Ginneken, "Evaluation of a system for automatic detection of diabetic retinopathy from color fundus photographs in a large population of patients with diabetes", Diabetes Care, 2008, 31(2), pp.193-198.

[3] M.R.K. Mookiah, U. R. Acharya, R. J. Martis, C.K.Chua, C. M Lim, E.Y.K.Ng, "Evolutionary algorithm based classifier parameter tuning for automatic diabetic retinopathy grading: A hybrid feature extraction approach", Knowledge- Based Systems, 2012, 39, pp. 9-22.

[4] J. Nayak, P. Bhat, U.R.Acharya , C.M. Lim and Manjunath Kagathi, "Automated identification of diabetic retinopathy stages using digital fundus images", J. Med. Syst. 2008, 32, pp.107–115.

[5] M. Ponni Bala and S. Vijayachitra, "A sequential learning method for detection and classification of exudates in retinal images to assess Diabetic Retinopathy", Journal of Biological Systems, 2014, 22(3), pp. 413-428.

[6] M. Ponni Bala and S. Vijayachitra, "Early detection and classification of microaneurysms in retinal fundus images using sequential learning methods", International Journal of Biomedical Engineering and Technology, 2014, 15(2), pp.128-143.

[7] U.R.Acharya, Chua Kuang Chua, E. Y. K. Ng, W. Yu and C. Chee, "Application of Higher Order Spectra for the Identification of Diabetes Retinopathy Stages", J Med Syst, 2008, 32, pp.481–488.

[8] Song Ke-Chen, Yan Yun-Hui, Chen Wen-Hui and Znang Xu, "Research and Perspective on Local Binary Pattern", Acta Automatica Sinica, 2013, 9(6), pp.730-744.

[9] Wong Li Yun, Muthu Rama Krishnan Mookiah, and Joel E W Koh, "Automated Detection of Proliferative Diabetic Retinopathy Using Brownian Motion Features", Journal of Medical Imaging and Health Informatics, 2014, 4, pp.1–5.

[10] U.Rajendra Acharya, E. Y. K. Ng, Jen-Hong Tan, S. Vinitha Sree and Kwan-Hoong Ng, "An Integrated Index for the Identification of Diabetic Retinopathy Stages Using Texture Parameters", J Med Syst, 2012, 36, pp.2011–2020.

[11] M.M.R.Krishnan, A. Choudhary and C. Chakraborty, "Texture based segmentation of epithelial layer from oral histological images", Micron, 2011, 42, pp.632–641.

[12] A. M. Gun, M. K. Gupta and B. Dasgupta,"An Outline of Statistical Theory", third ed., The World Press Private Ltd., Kolkata, India, 2005.

[13] T. Ojala, M. Pietikainen and T. Maenpaa, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns", IEEE Transactions on Pattern Analysis and Machine Intelligence, 2002, 24, pp. 971–987.

[14] M. Pietikainen, G. Zhao, A. Hadid and T. Ahonen, "Computer Vision Using Local Binary Patterns, Computational Imaging and Vision", 40, Springer-Verlag London Limited, 2011.

[15] Pradeep Chowriappa, Sumeet Dua, U. Rajendra Acharya and M.M.R.Krishnan, "Ensemble selection for feature- based classification of diabetic maculopathy images", Computers in Biology and Medicine, 2013, 43, pp.2156–2162.

[16] K. Laws, "Textured image segmentation", Ph.D. dissertation, University of Southern California, 1980.

[17] G. N. Srinivasan and G. Shobha, "Statistical Texture Analysis", Proceedings of World Academy of Science, Engineering And Technology, 36, 2008.

[18] D. E. Harris, "Texture analysis of skin cancer images". PhD thesis Doctorate in Electrical Engineering Dissertation. University of Missouri-Rolla, 1994.

[19] B. B. Mandelbrot, "The Fractal Geometry of Nature", edited by WH Freeman, New York, 1982.

[20] M. K. Biswas, T. Ghose, S. Guha and P. K. Biswas,v"Fractal dimension estimation for texture images: A parallel approach", Pattern Recognition Letters, 1998, 19, 309.

[21] V. Vapnik, "Statistical learning theory", Wiley, New York, 1998.

[22] Chih-Wei Hsu and Chih-Jen Lin, "A Comparison of Methods for Multiclass Support Vector Machines", IEEE Transactions on Neural Networks, 2002, 13(2), pp. 415-425.

[23] Guang-Bin Huang, Qin-Yu Zhu and Chee-Kheong Siew, "Extreme learning machine Theory and Applications", Neurocomputing, 2006, 70: pp.89–501.

[24] Guang-Bin Huang, M. Li, L. Chen, C. K. Siew, "Incremental extreme learning machine with fully complex hidden nodes", Neurocomputing, 2008, 71, (4–6), pp.576–583.

[25] S. Suresh, B. VenkateshBabu, H. J. Kim, "No-reference Quality Assessment using Modified Extreme Learning Machine Classifier", Applied Soft Computing, 2009, 9(2), pp. 541-552.

[26] Runxuan Zhang, Guang-Bin Huang, Narasimhan Sundararajan and P. Saratchandran, "Multicategory Classification Using an Extreme Learning Machine for Microarray Gene Expression Cancer Diagnosis", IEEE/ACM Transactions on Computational Biology And Bioinformatics, 2007, vol.4, no.3, pp.485-495.