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Automated Binary and Multiclass Classification of Diabetic Retinopathy Using Haralick and Multiresolution Features

S. GAYATHRI, ADITHYA K. KRISHNA, VARUN P. GOPI, (Member, IEEE), AND P. PALANISAMY, (Member, IEEE)

Department of Electronics and Communication Engineering, National Institute of Technology at Tiruchirappalli, Tiruchirappalli 620015, India

Corresponding author: S. Gayathri (gsgayathriunnithan@gmail.com)

ABSTRACT Diabetic Retinopathy (DR) is considered as the complication of Diabetes Mellitus that damages the blood vessels in the retina. This is characterized as a serious vision-threatening problem in most of the diabetic subjects. Effective automatic classification of diabetic retinopathy is a challenging task in the medical field. The feature extraction plays an eminent role in the effective classification of disease. The proposed work focuses on the extraction of Haralick and Anisotropic Dual-Tree Complex Wavelet Transform (ADTCWT) features that can perform reliable DR classification from retinal fundus images. The Haralick features are based on second-order statistics and ADTCWT reliably extracts the directional features in images. The proposed work concentrates on both binary classification as well as multiclass classification of DR. The system is evaluated across various classifiers such as Support Vector Machine (SVM), Random Forest, Random Tree, J48 classifiers by giving input image features extracted from the MESSIDOR, KAGGLE and DIARETDB0 databases. The performances of the classifiers are analyzed by comparing specificity, precision, recall, False Positive Rate (FPR) and accuracy values for each classifier. The evaluation results show that by applying the proposed feature extraction method, Random Forest outperforms all the other classifiers with an average accuracy of 99.7% and 99.82% for binary and multiclass classification respectively.

INDEX TERMS DR binary classification, DR multiclass classification, retinal fundus images, HARALICK, ADTCWT, 10-fold cross validation.

I. INTRODUCTION

Diabetic Retinopathy (DR) is considered as the complication of diabetes mellites. The cause of the disease is that for a subject with the history of diabetes mellites, their blood vessels in the retina gradually gets damaged. DR occurs when these tiny blood vessels leak blood and other fluids. It is considered one of the serious vision-threatening issue in the case of a subject that having diabetes. DR is a clearly defined marker of coronary diseases [1]. The early detection of DR may help to reduce the risk of coronary diseases and can be used as a biomarker for many chronic diseases. Not only the detection of DR but also its grading is also an important factor to treat it in a proper way. The major classes of DR are NPDR (Non-Proliferative DR) and PDR (Proliferative DR). The DR stages are determined based on the severity of the lesions in the retina. The major lesions [2] that we are considering for grading are (1) MicroAneurysms (MA) (2) Blood vessels (3) Haemorrhage (4) Exudates. If any of these conditions persist, then it is considered that the subject has DR. MA is a small swelling form in the wall of tiny blood vessels. In patients with DR, these minute swelling MAs are considered the earliest visible symptom of DR. They appear as small red dots in the retina [1]. As the disease progress, it's size increases. Retinal hemorrhage is another disorder in the retina which is caused by DR. If they are very small, then it resembles MAs. When there are lipid and protein residues in the leaked blood from the damaged capillaries, it forms yellow flicks in the retina called exudates. One of the major issues with DR detection is, it is difficult to identify the symptoms at its earlier stage. If it goes to the advanced stage which will completely lead to vision loss. There are many

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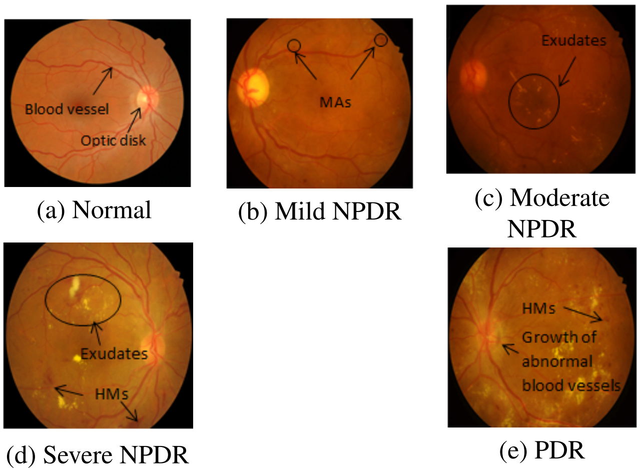
methods developed for its earlier detection still the detection of DR and its severity grading standing as a challenging task. So in order to meet this issue, many techniques were developed to detect the problem in its early stages. It is very important to make the techniques robust, accurate and cost-effective. This work deals with framing the best technique to detect DR and further classify it according to its severity. The structure of a normal retina and different grades of DR are demonstrated in FIGURE 1. The DR is categorized as Non-proliferative DR (NPDR) and Proliferative DR (PDR). From the diagrams, the changes in the retina are clearly visible. If any of these conditions persist, then it is considered that the subject has DR. Generally, ophthalmologists are considering the mentioned lesions for the DR detection and to know about its severity.



(a) Normal (b) Mild NPDR (c) Moderate NPDR (d) Severe NPDR (e) PDR

FIGURE 1. Different stages of DR in fundus images.

Many research works are progressing in the field of DR detection and grading the severity of the disease. Reference [3] explains the Anisotropic Dual-Tree Discrete Wavelet Transform (ADTDWT) for improved Trabecular bone classification. In their study, they used anisotropic textures and the real part of Complex Wavelet Transform (CWT) which is termed as Discrete Dual-Tree Wavelet Transform (DDTWT). The methods of feature extraction using the Grey Level Co-occurrence Matrix (GLCM) is reviewed in [4]. In [5], the DR classification is performed based on the extracted Haralick features. While using the SVM classifier, the system produced an accuracy of 86% with High-Resolution Fundus (HRF) images and 84% with DIARETDB0 datasets. The glaucoma detection and its classification from retinal images by combining clinical and multi-resolution features are described in [6]. The glaucoma identification is performed by extracting features using the ADTCWT method. A decision support system for early detection of DR is introduced in [7]. The system was developed with Gabor and Discrete Fourier Transform (DFT) attributes. Then spectral regression discriminant analysis is used to perform the dimensionality reduction. Random forest and logistic regression classifiers are used for the classification. For bright lesion detection, feature extraction using SIFT is applied in [8]. Then the dimensionality reduction is carried out by using Laplacian Eigen (LE) maps. Local features of retinal images are extracted using Local Binary Patterns (LBP) in [9]. Then it is evaluated across Artificial Neural Network (ANN), Random Forest and SVM for the detection task. DR classification is performed using an adaptive, rotationally invariant method for categorizing input images into normal and NPDR class is illustrated in [10]. The overall accuracy obtained for the system was 90.50%. A system for diabetic maculopathy detection using the vascular structure and optic disc location is implemented in [11]. The GMM (Gaussian Mixture Model) classifier is used and the accuracy of 97.3% is achieved. The data fusion method with a meta-SVM classifier for DR detection is implemented in [12]. An automatic method to detect MAs from retinal images using the C4.5 algorithm is implemented in [13]. Computer-aided diagnosis based on MCMF(Multi-Channel Multi-Feature) method is implemented for red lesion detection and bright lesion detection is carried out using the superpixel method in [14] for DR grading. In [15], a scanning window analysis (SWA) and the hybrid method of morphology is applied for retinal feature extraction. Principal Component Analysis (PCA) is adapted to locate the optic disc for retinal feature extraction in [16]. Also, to detect the disk boundary, a modified active shape model (ASM) is proposed. The severity analysis of macular edema using the random tree classifier is carried out in [17]. In [18], the Dual-Tree Complex Wavelet Transform (DTCWT) is utilized for retinal image enhancement. In that work, the DTCWT is implemented to decompose the grey retinal image in order to obtain high-pass and low-pass sub-bands.

In the case of DR classification, the first task is DR screening and then grade to learn about its state of severity. If the condition of the subject can be identified at the right time, it will help treat the disease in a timely manner and can also reduce the risk. Also, it might be helpful to predict the chance for other diseases. In this context, highly efficient feature extraction techniques are required to extract all required salient features from the fundus images that can differentiate normal images as well as all stages of DR images. Reliable feature extraction is an important criterion for improving classification efficiency since the extracted features are the basement of DR detection. Thus the proposed work aims to implement an automated system that can perform binary classification(DR or normal classification) as well as multiclass classification (mild DR, moderate DR or severe DR) of DR from retinal fundus images for better disease diagnosis. In order to achieve the goal, a new combined feature extraction technique is implemented using Haralick and ADTCWT methods. The Haralick features are based on second-order statistics that extract the overall average for the degree of correlation between pairs of pixels in different aspects. ADTCWT reliably extracts the directional features in images [19]. Thus the combination of two methods anticipates a good feature extractor for DR classification.

II. METHODOLOGY

The methodology for the classification and grading of DR in the proposed work combines two feature extraction techniques for extracting different features from retinal fundus images. Then the extracted features are given to the classifier for detecting DR and for grading its severity. The performance of the system is analyzed using the k- fold cross-validation method with the proposed features extraction technique for different classifiers. The workflow is illustrated in FIGURE 2.

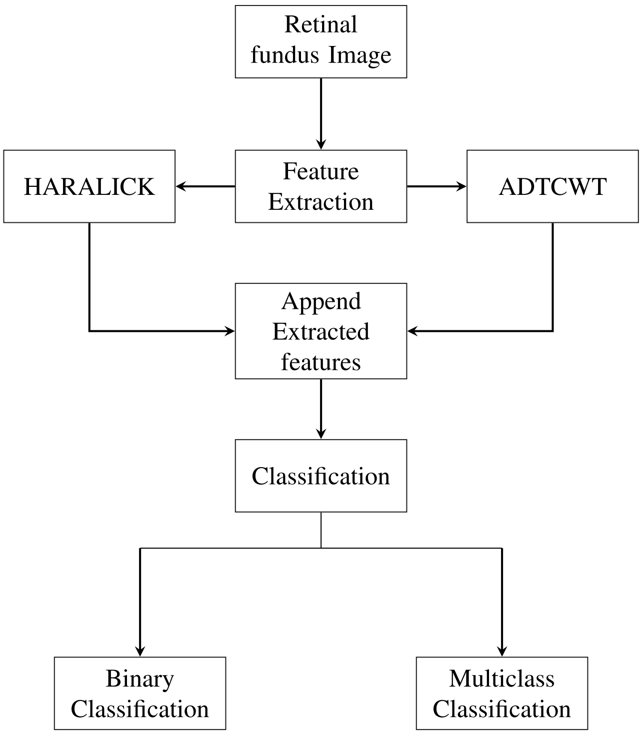


FIGURE 2. Proposed method.

A. FEATURE EXTRACTION TECHNIQUES

Feature extraction is one of the important tasks that increase the efficiency of the whole system. The feature explains some computable property of the given input image. In this work, Haralick and Anisotropic Dual-Tree Complex Wavelet Transform (ADTCWT) features are utilized for binary and multiclass DR classification

1) HARALICK FEATURES

These are 13 textural features [20] derived by Haralick from the symmetric Grey Level Co-occurrence Matrix (GLCM). These features narrate the intensity correlation between two pixels in an image at a particular distance d in the assigned direction. GLCM offers not only inter-pixel relationship but also the spatial grey level dependencies and periodicity. In the proposed work, 13 Haralick features for each GLCM is extracted [21]. GLCM is defined in four directions ($0^0, 45^0, 90^0, 135^0$) which in turn produces 4×13 features for each image. The algorithm for the generation of Haralick features is explained in Algorithm 1.

Algorithm 1 Haralick Feature Extraction

Require: Load I with input images

START:

1) consider each image in I with pixel r_k location (s, t)
2) **Do for**:
3) compute the GLCM $G^k_{s,t}$ of current pixel r_k in a neighborhood of size $m \times m$
4) Extract Haralick features for each $G^k_{s,t}$
5) **end for**

Output: Haralick features for each GLCM

2) ANISOTROPIC DUAL TREE COMPLEX WAVELET TRANSFORM (ADTCWT) FEATURES

The texture features of the image in the time domain are not sufficient for DR classification as it contains hidden frequency information. The wavelet transform uses both spatial and frequency information. In the proposed work, the wavelet features are extracted by applying ADTCWT on fundus images. In anisotropic decomposition, the sub-bands are decomposed into vertically or horizontally only [6]. The DTCWT sub-bands are directional. By adding anisotropic decomposition into the DTCWT (ADTCWT) will produce both directional and anisotropic basis functions. In this work, 10 subbands of ADTCWT are used for feature extraction and it is shown in FIGURE 3. The first order texture feature homogeneity (H) and second-order texture feature energy (E) are extracted from these 10 sub-bands for classification. Since GLCM is a powerful tool for texture analysis, and ADTCWT provides the benefit of multidirectionality and shift invariance, this hybrid feature extraction method outputs all the required features from the input images.

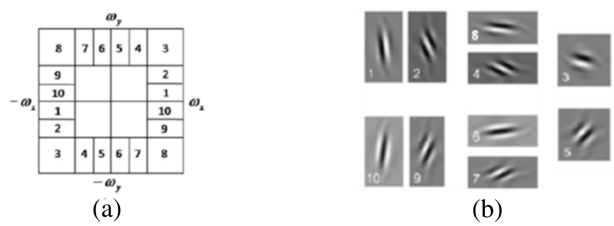


FIGURE 3. (a) Frequency-domain partition obtained from two level 2D ADTCWT decomposition; (b) Basis functions of 2-D ADT-CWT.

B. CLASSIFIER

Clinical based disease detection has its own limitations. The things become different if a machine is trained for a classification task. By giving proper instructions related to the classification to the machine, it will be able to work automatically and can provide better classification results. In this work, four classifiers are selected for performance analysis to know which one will classify and categorize the disease more accurately for the proposed feature extraction technique.

1) SUPPORT VECTOR Machine(SVM) CLASSIFIER

Support vector machines [22] are supervised learning methods with associated learning algorithms. If the vectors are non linearly separable in a space, then the SVM helps to make it linearly separable in a higher-dimensional space. In this work the SVM is implemented using a Radial basis function (RBF) kernel with gamma value selected as the reciprocal of the product of the total number of features and the variance and the algorithm used for pseudo-code generation is taken from [23].

2) RANDOM FOREST CLASSIFIER

Random Forest [24] is an ensemble model classifier, in which group of trees are developed together with each has independent random vector. ie, the K^{th} tree generates a random vector Φ_K which is independent from previously generated random vectors($\Phi_1, \Phi_2, \ldots, \Phi_{K-1}$) but have same distribution [25]. In this work, the number of trees used in random forest classifier is 100 [25].

3) RANDOM TREE

Random trees are supervised learning classifier which is constructed as a combination of single model trees and Random forest algorithms. Considerably huge sets of random trees with uniform distribution will be able to produce accurate models. The random tree is a group of tree predictors. In this work 100 trees are assigned to build the model [17].

4) J48 CLASSIFIER

This is the open-source java implementation of C4.5 [26] Decision tree. This is a decision tree algorithm mainly designed for data mining. In this, the information gain ratio is evaluated to select each node test feature. This procedure is termed as feature selection. While performing the operation, the attribute with the largest information gain will be selected as the test feature for the present node. Let us assume that F is a set of input feature vectors given to the classifier which contains $F_1, F_2, \ldots, F_n$ instances. Suppose there are t distinct values for t distinct classes $C_i(where, i = 1, 2, \ldots, n)$. Then the gain ratio G_A of sub-attribute A in each attribute can be calculated using equation (1).

$$G_A = G(A)/S_A(F) \tag{1}$$

where, $G(A)$ is the information gain of attribute A which can be obtained by taking the difference between total information $I(D)$ and the attribute information $I_A(D)$

$$G(A) = I(D) - I_A(D) \tag{2}$$

If P_i is the distinct class probability, then $I(D)$ and $I_A(D)$ can be calculated using equations (3) and (4) respectively.

$$I(D) = \Sigma P_i log_2(P_i) \tag{3}$$

$$I_A(D) = -\Sigma \frac{|F_J|}{|F|} I(F_j) \tag{4}$$

The split information value $S_A(F)$ of attribute can be formulates as:

$$S_A(F) = -\Sigma \frac{|F_j|}{|F|} log\Big(\frac{|F_j|}{|F|}\Big) \tag{5}$$

Actually, the fraction $\frac{|F_j|}{|F|}$ acts as the j^{th} partition weight. By utilizing all these equations the C4.5 decision tree can be developed which forms appropriate conditions that can be used for classification. Then during testing, it will classify the input feature vector according to the conditions.

C. PERFORMANCE ANALYSIS AND EVALUATION

The performance of the system is evaluated using MESSIDOR [27], KAGGLE [28] and DIARETDB0 [29] databases. It consists of a total of 1200 images. For binary classification 654 DR images (considering all stages as DR) and 546 normal images are used. For severity grading each stage in 654 DR images are considered individually. Among 654 images, there are 153 mild, 247 moderate and 254 severe DR images. KAGGLE database consists of a total of 35126 images of which 25810 are under the normal category, 2443 mild NPDR, 5292 are moderate NPDR, 873 are severe NPDR and 708 are PDR. The DIARETDB0 database consists of 130 retina images of which 20 are normal and 110 are DR images. These datasets are used for proposed system evaluation and analyzed via 10-fold cross-validation [30] for binary classification and multi-class classification separately. In this evaluation technique, during the training itself, the entire available dataset is split into 10-sub sections. Then each subsection is treated as a validation set for each iteration. The 13 features obtained from the Haralick method and 2 features from the ADTCWT method are given to learn the classifier.

The performance of the system is evaluated by generating a confusion matrix [31]. The matrix is generated with the number of True Positives, True Negatives, False Positives and False Negatives obtained during cross-validation. The performance of the system is assessed by calculating accuracy, False Positive Rate(FPR), Precision, Recall, F1- score and specificity from the confusion matrix using basic equations in [32]. In order to summarize the performance of the system, the weighted average of each class performance measures is required. If P_1 and P_2 denotes the performance measures obtained for class 1 (C_1) and class 2 (C_2) respectively then the weighted average of performance measure W_{PM} can be calculated using the equation (6):

$$W_{PM} = \frac{(P_1 * |C_1|) + (P_2 * |C_2|)}{|C_1| + |C_2|} \tag{6}$$

1) CLASSIFIER ASSESSMENT FOR BINARY CLASSIFICATION

The performance of the classifiers are measured from the corresponding confusion matrices. The weighted average values of each performance measure is depicted in Table 1 for MESSIDOR, in Table 2 for KAGGLE and in Table 3 for DIARETDB0 database. While analyzing the details in Table 1, it can be seen that for random forest classifiers the

TABLE 1. Weighted average values of performance measures for binary classification using MESSIDOR Database.

Classifier	FPR	Speci-ficity	Preci-sion	Recall	F1-Score
SVM	0.002	0.998	0.998	0.998	0.998
Random Tree	0.006	0.994	0.994	0.994	0.994
J48	0.003	0.997	0.996	0.996	0.996
Random Forest	**0.001**	**0.999**	**0.999**	**0.999**	**0.999**

TABLE 2. Weighted average values of performance measures for binary classification using KAGGLE Database.

Classifier	FPR	Speci-ficity	Preci-sion	Recall	F1-Score
SVM	0.001	0.999	0.996	0.997	0.997
Random Tree	0.001	0.999	0.998	0.998	0.998
J48	0.001	0.999	0.998	0.998	0.998
Random Forest	**0.00**	**1.00**	**1.00**	**1.00**	**1.00**

TABLE 3. Weighted average values of performance measures for binary classification using DIARETDB0 Database.

Classifier	FPR	Speci-ficity	Preci-sion	Recall	F1-Score
SVM	0.127	0.873	0.978	0.977	0.976
Random Tree	0.045	0.955	0.978	0.977	0.977
J48	0.001	0.999	0.998	0.998	0.998
Random Forest	**0.042**	**0.958**	**0.992**	**0.992**	**0.992**

DR class specificity and precision values are higher than the others. When the random forest classifier is compared with the random tree, the FPR in the random tree is more than the random forest classifier. The F1- score that determines model accuracy is less in the random tree. There's a similar situation for the other datasets, too. That means the random forest works better than the random tree. Among all the classifiers, random forest classifier shows least FPR, highest specificity, precision, recall, and F1- Score. The accuracy measures obtained for each classifier in the case of binary classification using MESSIDOR, KAGGLE and DIARETDB0 are illustrated in Table 4, Table 5, Table 6.

TABLE 4. Validation accuracy of each classifier for binary classification using HARALICK+ADTCWT extracted features from MESSIDOR Database images.

Classifier	Correctly classified instances	Accuracy(%)
SVM	1198	99.83
Random Tree	1193	99.41
J48	1195	99.58
Random Forest	**1199**	**99.92**

TABLE 5. Validation accuracy of each classifier for binary classification using HARALICK+ADTCWT extracted features from KAGGLE Database images.

Classifier	Correctly classified instances	Accuracy(%)
SVM	35006	99.66
Random Tree	35052	99.79
J48	35050	99.78
Random Forest	**35124**	**99.99**

TABLE 6. Validation accuracy of each classifier for binary classification using HARALICK+ADTCWT extracted features from DIARETDB0 Database images.

Classifier	Correctly classified instances	Accuracy(%)
SVM	127	97.6
Random Tree	127	97.6
J48	128	98.4
Random Forest	**129**	**99.2**

TABLE 7. Weighted average values calculated for each measures for multiclass classification using MESSIDOR database.

Classifier	FP rate	Speci-ficity	Preci-sion	Recall	F1 Score
SVM	0.006	0.994	0.975	0.974	0.974
Random Tree	0.006	0.994	0.970	0.969	0.969
J48	0.006	0.994	0.970	0.969	0.969
Random Forest	**0.001**	**0.999**	**0.998**	**0.998**	**0.998**

2) CLASSIFIER ASSESSMENT FOR MULTICLASS CLASSIFICATION

For multiclass classification the classifiers are assessed across MESSIDOR [27] and KAGGLE [28] databases. The weighted average values of performance measures are listed in Table 7 for MESSIDOR and in Table 8 for KAGGLE. For the MESSIDOR database, the FPR for Random Forest classifier is very less with a value of 0.001 and also the other performance measures give a better classification efficiency of Random Forest classifier with the proposed feature extraction. From the assessment using the KAGGLE database, the Random forest classifier provides better accuracy than other classifiers, which can be judged from Table 9 and 10. The accuracy obtained for Random Forest classifier with Haralick and ADTCWT features are 99.75% for MESSIDOR and 99.9% for KAGGLE database.

TABLE 8. Weighted average values calculated for each measures for multiclass classification using KAGGLE database.

Classifier	FP rate	Speci-ficity	Preci-sion	Recall	F1 Score
SVM	0.006	0.994	0.943	0.952	0.939
Random Tree	0.002	0.998	0.982	0.982	0.982
J48	0.05	0.95	0.992	0.992	0.992
Random Forest	**0.00**	**1.00**	**0.99**	**0.99**	**0.99**

TABLE 9. Validation accuracy of each classifier for multiclass classification using HARALICK+ADTCWT extracted features from MESSIDOR database images.

Classifier	Correctly classified instances	Accuracy(%)
SVM	1169	97.42
Random Tree	1129	94.08
J48	1163	96.92
Random Forest	**1197**	**99.75**

TABLE 10. Validation accuracy of each classifier for multiclass classification using HARALICK+ADTCWT extracted features from KAGGLE database images.

Classifier	Correctly classified instances	Accuracy(%)
SVM	33432	95.17
Random Tree	34495	98.2
J48	34862	99.2
Random Forest	**35106**	**99.9**

By analyzing all the evaluation results of both binary and multiclass classification it can be summarized that the Random Forest classifier performs well for both classification mechanisms by using the proposed hybrid feature extraction technique. Random forest classifier has the capability to decorrelate the trees with random feature splitting subsets. A classifier's effectiveness relies heavily on the input features we are given to it. The proposed technique of feature extraction has successfully extracted all minute features of the input images which are useful in distinguishing each stage of DR. In [5] the haralick feature extraction alone with SVM classifier produced an accuracy of 84% for DIARETDB0 database and 86% for HRF images, while the combination of haralick and ADTCWT feature extraction with SVM classifier in the proposed method offers a promising DR classification system with an average accuracy of 98.625% and the proposed system works best using random forest classifier with an accuracy of 99.84%. According to the dataset size, the variation in the accuracy of the system is also noticeable in each case. The comparison of existing methods for DR classification using the MESSIDOR dataset with the proposed method is tabulated in Table 11, which shows the impressive efficiency of the proposed system for DR classification than the existing methods. From the inferences, it can be concluded that the proposed feature extraction shows a wonderful improvement in DR detection and grading.

TABLE 11. Comparison of proposed work with existing methods.

Dataset	Methods	Speci-ficity	Recall	Preci-sion	Accur-acy (%)
Messidor [28]	sai prasad et. al [8]	1.00	0.928	−−	96.6
	Tariq et.al [11]	0.98	−−	0.95	97.3
	Wei Zhou et. al [14]	−−	−−	−−	94.33
	Proposed Method	**0.999**	**0.998**	**0.998**	**99.835**
DIARETDB0 [30]	Reshma et. al. [5]	−−	−−	−−	84.00
	Proposed Method (Binary)	**0.958**	**0.992**	**0.992**	**99.2**

III. CONCLUSION

An automated approach for classifying DR is proposed in this work by integrating the features extracted using Haralick and ADTCWT. The extracted features using the proposed method made the classification task smoother. For performance analysis, the extracted features are given to four classifiers (SVM, Random Forest, Random Tree, J48) and evaluated the performance. According to the performance analysis, the Random Forest classifier with the proposed feature extraction outperforms all the other classifiers for the MESSIDOR, KAGGLE and DIARETDB0 databases. Thus the average accuracy of the system for binary classification is 99.70% and for multiclass classification is 99.84. The weighted average measures of accuracy, recall, F1 score indicates the efficiency of the classifier. Besides the other classifiers, the weighted average FPR is lower for the Random Forest classifier which shows the marked efficiency of the system. Thus it can be concluded that the proposed method with Random Forest classifier is clinically significant for binary as well as multiclass classification of DR than the existing methods. In the future, the proposed system with modifications can be used to automatically detect other retinal disorders that will benefit the medical sector.

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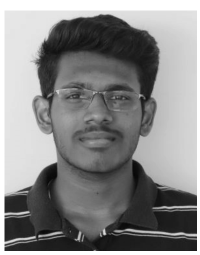
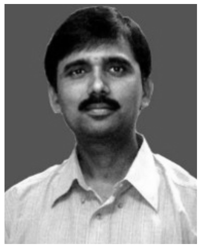
S. GAYATHRI received the B.Tech. degree in electronics and communication engineering from the Vivekandha College of Engineering, under Anna university, Chennai, in 2012, and the M.Tech. degree in advanced communication and information systems from the Rajiv Gandhi Institute of Technology, under Mahatma Gandhi University, Kottayam, in 2014. She is currently pursuing the Ph.D. degree in biomedical image processing with the National Institute of Technology at Tiruchirappalli, Tiruchirappalli, India. Her research interests include bio medical signal and image processing, machine learning, and deep learning.



ADITHYA K. KRISHNA is currently pursuing the B.Tech. degree in electronics and communication engineering with the National Institute of Technology at Tiruchirappalli, Tiruchirappalli, India. His research interests include signal processing, bio medical image processing, machine learning, and deep learning.

VARUN P. GOPI (Member, IEEE) received the B.Tech. degree in electronics and communication engineering from the Amal Jyothi College of Engineering, Kanjirappally, India, affiliated to Mahatma Gandhi University, Kottayam, India, in 2007, the M.Tech. degree in signal processing from the College of Engineering Trivandrum, affiliated to Kerala University, Thiruvananthapuram, India, in 2009, and the Ph.D. degree in medical image processing from the Department of Electronics and Communication Engineering, National Institute of Technology at Tiruchirappalli (NIT), Tiruchirappalli, India, in 2014. He is currently an Assistant Professor with the Department of Electronics and Communication Engineering, NIT Tiruchirappalli. His research interests include medical image processing, signal processing, computer vision, and compressed sensing. He was a recipient of the Canadian Commonwealth Scholarship Award under the Graduate Student Exchange Program, Department of Electrical and Computer Engineering, University of Saskatchewan, Saskatoon, SK, Canada, in 2012.



P. PALANISAMY (Member, IEEE) received the B.E. degree in electronics and communication Engineering from Bharathiar University, Coimbatore, and the M.E. degree (Hons.) in communication systems from the National Institute of Technology at Tiruchirappalli (NIT), Tiruchirappalli, where he is currently pursuing the Ph.D. degree. He is currently working as a Professor with the Department of Electronics and Communication Engineering, NIT. His research interests include array signal processing: detection and bearing estimation and frequency estimation, image processing: medical image analysis, medical image reconstruction, wireless/mobile communication, and channel estimation.