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Computer Aided Hierarchal Lesion Classification for Diabetic Retinopathy Abnormalities

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Abstract: ***Vision loss from Diabetic Retinopathy (DR) abnormalities can be prevented by employing timely treatment and continuous monitoring of disease progress. Early diagnosis can effectively expedite the success rate of disease curability. Automated computer aided diagnostic systems can aid the ophthalmologists and prevent their tedious and time consuming efforts using manual lesion detection approaches. Computer Aided Hierarchal Lesion (CAHL) classification approach is proposed in this paper utilizing optimal classifiers with optimal feature set for early and efficient DR diagnosis. Exhaustive statistical investigation of extracted shape and intensity features resulted in prominent features which were used for abnormality classification employing SVM, kNN and NN classifiers. The proposed CAHL approach achieved best classification performance for NN classifier in terms of four statistical indices: accuracy, sensitivity, specificity, positive prediction value of 100% for both normal and abnormal stage classification as well as DR abnormality classification. A trade-off between run-time and high cost of manual computation is maintained using NN classifier based mechanism for DR classification. The proposed method outperforms the state of the art techniques when compared to the recently published methods for DR screening. Critical DR problems like neovascularisation and blood vessel bleeding will be addressed in the future part of the research.***

Index Terms: ***Diabetic Retinopathy, Computer Aided Diagnostic System, Support Vector Machine, k- Nearest Neighbours, Neural Network, DR Abnormality Classification.***

I. INTRODUCTION

Visual impairments are caused due to various retinal disorders like Diabetic Retinopathy (DR), Glaucoma, Age-related Macular Degeneration (AMD), etc. and the best way to diagnose these disorders is with the help of ophthalmic-image processing. DR is the most severe complication arising with the incessant increase in the blood glucose level in diabetic patients ultimately leading to rupturing of tiny blood vessels of retina. Diabetic mellitus patients require regular screening to check the development of DR stages for proper diagnosis of the problem.

Intra and inter-image variability in fundus images due to poor illumination, retinal lesion's subtle appearance compared to other features in the fundus images and bad quality of image, it becomes a challenging task detect and track small retinal changes [1]. DR is a progressive disease and its arises the non-proliferative DR (NPDR) symptoms like Microaneurysms (MAs), Hemorrhages (HEMs), Exudates (EXs) and cotton wools. MAs and HEMs falls under the category of red lesions and EXs and cotton wools are categorized as yellow lesions due to their similar intensity range. Proliferative diabetic retinopathy (PDR) is another classification of DR which can be characterized by NPDR symptoms along with neo-vascularization. This is the most sensitive case of retinopathy which can lead to complete vision loss if not taken care at the right time [2]. Thus automated detection of retinal lesions present in fundus images plays a vital role in the development of reliable Computer aided screening systems for DR diagnosis.

Several approaches were adopted by the researchers for DR lesion detection and some of which are discussed in the literature below. An automatic DR detection method is proposed in [3] which utilized the well known approaches of Fuzzy-C-Means clustering and morphological image processing using for Support Vector Machine (SVM) classification achieving accuracy, sensitivity and specificity of 96.67%, 100% and 95.83% respectively. A hybrid, easy and reliable solution is proposed in [4] for retinal feature extraction using a hybrid of morphology combined with scanning window analysis is applied for feature extraction. A novel unsupervised classification approach based on sparse posterior cerebral artery was proposed in [5] to identify the earliest clinical lesions in diabetic retinopathy: MAs. A new framework of multiple instance learning is developed in [6] to use the image information present in medical expert's annotations for better representation of pathological images. The major contribution in this work is joint optimization utilized in encoding and image classification stages to achieve comparable results. An integrated approach for automated MA detection was proposed in [7] for candidate objects by employing dark object filtering process. A feature set of different statistical features was given to k-nearest neighbor (kNN) classifier for the extraction of MAs and non-MAs.

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The deep feature analysis method used by Sadek et al. [8] in this work performs better than classical bag-of words approach providing accuracy between 91.23% and 92.00% with appreciable improvement of the traditional state of the art methods. Three classification models Probabilistic Neural network (PNN), Bayesian Classification and SVM were investigated by the authors in [9] for the detection of NPDR symptoms hemorrhages and exudates. The experimental results revealed that SVM performs better and yields the accuracy of 95.38%. Paing, et al. [10] proposed an Artificial Neural Network (ANN) based DR classification system which was tested on publically available DIARETDB1dataset and other local databases. A deep learning based detection approach was presented by Yalcin, et al. which yields 98.5% success rate over other methods [11]. A computer aided diagnosis system employing SVM and Naïve Bayes classifier which provides 97.13% and 95.13% of accuracy for dark and bright lesion detection respectively utilizing optimal feature set [12].

The literature survey highlights some of the limitations in the existing lesion detection techniques and provides a way to explore new possibilities to mitigate these limitations. The major limitation in existing lesion detection approaches lies in poor discrimination between actual lesions, background noise and other anatomical structures like blood vessels and Optical Disc (OD). The other limitation lies in the optimal choice of features as well as classifiers. Traditional classification strategies are not able to maintain a trade-off between run-time and high cost of manual computation. Thus, this paper aims at addressing these limitations of the existing techniques for enhancing lesion detection and classification method.

In this paper, authors proposed a Computer Aided Hierarchal Lesion (CAHL) classification approach which comprises two stage hierarchal classifications. Normal and abnormal fundus images are classified at the first stage which is followed by abnormality Classification into Red and Yellow DR Lesions. Each lesion candidate is classified using shape and intensity based feature vector which depends upon the accuracy of lesion segmentation step. The novelty of this work lies in exhaustive statistical analysis performed on extracted feature set for selection of prominent optimal features. The major contribution of this paper lies in investigating multiple classifiers to come up with an improved lesion classification scheme which provides better accuracy and least run-time complexity.

Organization of this article is as follows: Section 2 comprises detailed discussion of datasets, attributes, classifiers, performance indices employed for the work and proposed methodology. The discussion regarding experimental results obtained along with their comparison with the existing lesion classification techniques is done in Section 3. Conclusion and future scope of the work are rationalized in section 4.

II. MATERIAL AND METHODS

The main objective behind developing the proposed CAHL classification approach is to facilitate mass screening of DR diagnosis by faster and accurate detection of DR abnormalities providing least runtime complexity. MATLAB2018b environment is used for system implementation equipped with Intel Core i5 processor, 3GHz clock speed and 8GB RAM. A detailed description of the dataset utilized and the proposed methodology is given in the following sections.

A. Dataset Description

Two benchmark datasets Structured Analysis of Retina (STARE) [13] and DIARETDB1 [14] are utilized for this research work and both of these dataset consists of varying number of fundus images with different Field of View (FOV) and resolutions. STARE dataset comprises 400 raw fundus images of size 605×700 pixels at FOV of 35 degrees captured using TopCon TRV-50 specialized fundus camera. STARE dataset was founded by US National Institute of Health. DIARETDB1 dataset was originally founded by Kuopio University Hospital, Finland. These images were captures using digital fundus camera at 50 degree FOV with varying imaging controlled system.

B. Proposed Methodology

The proposed CAHL diagnostic system for detecting DR abnormalities in retinal images is a four folds and the schematic diagram describing the process is depicted in Fig. 1. Image processing steps involved to segment background objects OD and blood vessels from the original fundus image and foreground lesion detection are used in the first step. Second step comprises shape and intensity feature extraction followed by statistical analysis of the feature set using Statistical Package for Social Sciences (SPSS) package in the third step. Fundus image classification for discrimination of DR lesions using multiple classifiers is the last step of the proposed methodology.

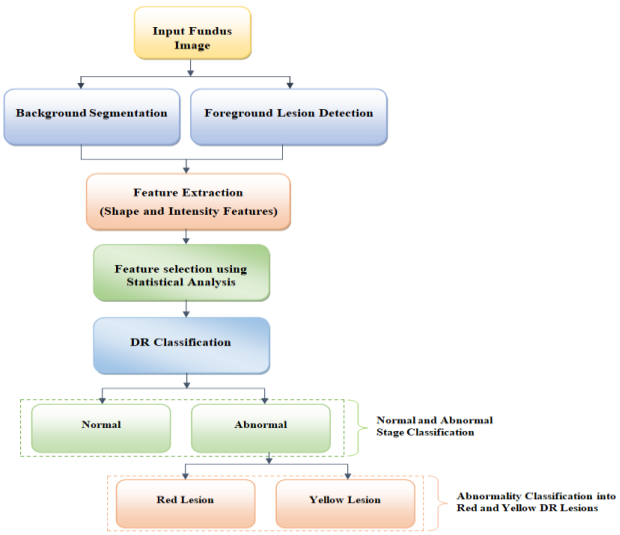


Fig. 1. Schematic Diagram of step involved in the proposed CAHL approach

Image pre-processing techniques are applied on raw fundus images acquired from the datasets and lesion candidates are identified using morphology-based detection algorithm. Image variation attenuation for the removal of inter and intra image variability, green channel extraction to obtain maximum contrast channel and contrast limited adaptive histogram enhancement (CLAHE) are the pre-processing steps [15].

Background segmentation is accomplished using boundary localization and morphological closing and OD is localized as the largest circular region in the intensity plane [16, 17]. For estimating vascular structures and vessel and non-vessel pixels morphological closing followed by global thresholding method is employed, depending upon 8-connectivity [18].

The detailed description of the proposed model is given in the pseudo code:

Pseudo-code of Proposed Model
Input: Fundus Image (I)
Output: Abnormality Classification into red and yellow lesions (I_{lesion})

Step 1: Convert the original fundus image (I) to Green channel version (I_G) of fundus image.
Step 2: Obtain the denoised image (I_{den}).
Step 3: Segment OD and blood vessel background portions to obtain final pre-processed image ($I_{pre\text{-}process}$).
Step 4: Apply morphological reconstruction (I_{MR}) for background estimation.
Step 5: Subtract the morphological reconstructed image from the original image to obtain the background removed fundus image (I_{BR}).
Step 7: Obtain a morphologically closed image (I_{cl}) by considering the minimum response over all the angles between 0º to 180º.
Step 8: Obtain the foreground potential lesion candidates by applying hard thresholding technique and empirically choosing the optimal threshold value.
Step 9: Extract feature attributes exploiting shape and intensity features of potential lesion candidates.
Step 10: Perform Statistical analysis of derived feature set for optimal feature selection.
Step 11: Classify the abnormalities using MLP for red and yellow lesions.

1) Foreground Lesion Detection: The lesion detection approach aims at providing assistance to the ophthalmologists for mass screening of DR abnormalities. Morphological operations are applied to obtain red and yellow lesion candidates. Morphological closing operation is applied on the background removed by considering the minimum response over the angles between 0º -180º. Red lesion candidates are obtained by subtracting morphologically closed image from the original fundus image. Hard thresholding is applied to extract yellow lesion candidates by choosing the optimal threshold value empirically. The tiny candidates are to be discarded and not considered as pathological regions, however, there exist some false candidates as scars, bleeding or some branching cross over points of blood vessels in the patient's clinical history [19]. Foreground lesions detected are subjected to feature extraction utilizing most relevant features for our research work based on exhaustive literature survey. The extracted attributes are described in the following section.

2) Attributes Description: This research work comprises 20 unique feature attributes describing shape and intensity based properties of DR lesions. Geometric properties are exploited by 11 shape features including lesion area, perimeter, major and minor axis length, equivalent diameter, convex area, eccentricity, orientation, solidity, extent and compactness [20]. These shape features are useful in determining the geometric properties of extracted lesions and they can be used for exact classification of lesions and non-lesions. 9 pixel based intensity features were exploited to make a clear distinction between the pixels of red and yellow lesions for abnormality classification. Intensity features used in this paper comprises minimum intensity, maximum intensity, mean intensity, median intensity, Mean Absolute Difference (MAD) intensity, Standard Deviation (SD) intensity, Inter-Quartile Range (IQR), skewness and kurtosis [21]. These set of features are used as shape feature are primitive for image content description and intensity features provide significant pixel based variations in image regions. Extracted set of features are subjected to exhaustive statistical analysis using various statistical tests. Levene's test, *t*-test and ANOVA (Analysis of Variance) statistical tools provides parametric and inferential significance of the extracted features by analyzing means and variances for different DR lesions. Design of experiment application of SPSS package is utilized for statistical evaluation of extracted features [22]. These test aided in the statistical analysis for the optimal feature selection for hierarchal classification.

3) Classifiers: Multiple classifiers available in the literature are exploited for our research work to achieve higher accuracy for classification with least complexity [23, 24].

Support Vector Machine (SVM) Classifier: Labeled training data is used in SVM supervised learning method to create a hyperplane and optimally categorize the testing data for two class as well as multi-class pattern recognition problem [25]. SVM classification accuracy and its better performance for non- linear classification rely on two tuning parameters regularization parameter (C) and kernel coefficient (γ). Regularization parameter helps in avoiding misclassification of each training example and kernel coefficient is responsible for determining each training example's influence in the classification process. The error function for SVM classifier in terms of C and γ is expressed by Eq. (1).

$$C\sum_{i=1}^{L}(\gamma_i^+ + \gamma_i^-) + \frac{1}{2}\|w\|^2 \quad (1)$$

This error function is needed to be minimized depending upon regularization parameter C and error metric γ subject to minimization constraint, $\gamma^+ \geq 0$, $\gamma^- < 0$. Here w indicates weight vector. SVM classifier with linear kernel is used for DR classification problem as it classifies each test sample belonging to the majority class.

k- Nearest Neighbour (kNN) Classifier: kNN classifier classifies the data samples depending upon the Euclidean distance of k- nearest neighbours. For a dataset consisting of '*n*' total samples consisting '*f*' feature vectors, the Euclidean distance between sample y_i and y_j is expressed by Eq. (2).

$$d(y_i, y_j) = \sqrt{(y_{i1} - y_{j1})^2 + (y_{i2} - y_{j2})^2 + \cdots + (y_{if} - y_{jf})^2} \quad (2)$$

Test data is assigned the most frequently occurring class by analyzing the Euclidean distance between k- nearest training data points [26]. kNN is preferred for DR classification by various researchers as it decides its class label depending upon its immediate neighbors, therefore, providing robust classification. For this research work, 3 nearest neighbors are taken into consideration for determining the class of test feature.

Neural Network (NN) Classifier: Network performance is determined by the weight updation, propagation function and the learning rule. Let $Y_i(t)$ indicates the output of the preceding neuron then input to the j^{th} neuron is determined by propagation function expressed in Eq. (3).

$$P_j(t) = \sum_i Y_i(t) \times w_{ij} + b \quad (3)$$

where $P_j(t)$ is the propagation function, $Y_i(t)$ is the output of the preceding neuron, w_{ij} is the weight and b is bias.

The neural network parameters are modified by the learning rule such that the favorable network outcome is obtained [25]. NN is the appropriate choice for DR diagnosis as the weights associated determines the input feature ability belonging to a particular class and these weights are adjustable.

Performance Indices

Performance indices which can be derived from true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN) are used for evaluating classification performance of SVM, kNN and NN classifiers. The indices include Positive Prediction Value (PPV), Sensitivity (Sen.), Specificity (Sp.), Accuracy and Area Under the Receiver Operating Characteristics (ROC) curve (AUC). Overall classification performance is indicated by AUC as more area under the curve depicts better classification as each point on the ROC curve shows the cut-off points between true positive and false positive rate. Visual results obtained from foreground lesion detection, findings of statistical analysis and performance evaluation outcomes using multiple classifiers are discussed in the results and discussions section.

III. RESULTS AND DISCUSSION

Visual outcomes of background segmentation, foreground identification and lesion detection are depicted in Fig. 2. Optical disc has intensity much closer to yellow lesion intensity and can be misclassified as lesions so it has to be located and removed from the fundus images. Similarly, blood vascular structures have similar intensity as those of microaneurysms and haemorrhage and they can hamper the classification of red lesions, therefore removed as background portion. The proposed technique uses morphological operations for removal of background portions and the segmentations obtained are compared to the ground truth vessel segmentations provided by professional experts.

Table 1. t-test, ANOVA and Levene's test for Shape and Intensity features

Features	Shape Features					Features	Intensity (Int.) Features				
	t-test		ANOVA	Levene's Test			*t*-test		ANOVA	Levene's Test	
	t-value	Sign. (2-tail)	Significant p-value	F	Sig.		*t*-value	Sig. (2-tail)	Significant p-value	F	Sig.
Area	3.544	0.001	0.001	24.975	0.000	**Min. Int.**	50.182	0.000	0.000	5.113	0.029
Perimeter	3.604	0.001	0.001	15.545	0.000	**Max. Int.**	40.205	0.000	0.000	32.031	0.000
Major_Axis_Length	4.518	0.000	0.000	23.674	0.000	**Mean Int.**	51.693	0.000	0.000	13.705	0.001
Minor_Axis_Length	5.211	0.000	0.000	14.255	0.001	**Median Int.**	51.472	0.000	0.000	12.524	0.001
Eccentricity	1.107	0.275	0.275	0.691	0.411	**MAD Int.**	4.700	0.000	0.000	18.631	0.000
Convex_Area	2.836	0.007	0.007	16.643	0.000	**SD Int.**	4.853	0.000	0.000	20.291	0.000
Orientation	0.458	0.650	0.650	0.348	0.559	**IQR**	4.507	0.000	0.000	15.541	0.000
Equiv_dia	5.884	0.000	0.000	28.710	0.000	**Skewness**	2.594	0.013	0.013	2.911	0.048

Solidity	6.700	0.000	0.000	9.362	0.004	**Kurtosis**	2.944	0.005	0.005	3.833	0.026
Extent	3.721	0.001	0.001	4.619	0.038						
Compactness	10.504	0.000	0.000	5.867	0.020						

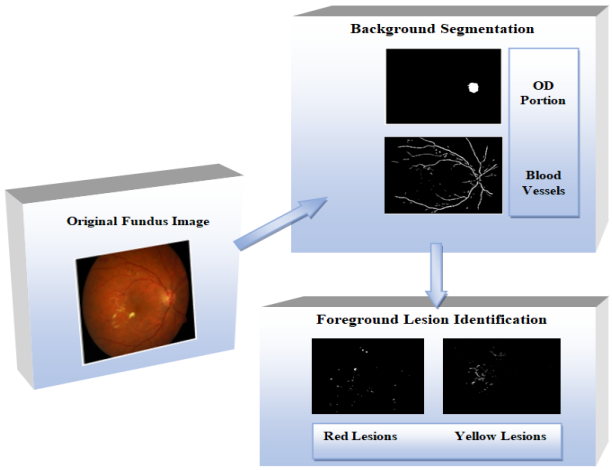


Fig. 2. Visual results for background segmentation, foreground portion and lesion identification from original fundus image

After background segmentation the region of interest are the foreground lesions and relevant features are to be extracted for discrimination of diseased and normal fundus images. The statistical feature analysis is employed to obtain optimal feature set for accurate classification.

A. Statistical feature Analysis

The lesion grading into feature set consisting of 11 shape features and 9 intensity features is justified using statistical feature analysis of the derived feature set. A totality of 20 features is considered for SPSS statistical analysis and their outcomes are discussed in terms of set hypothesis. Equality of variance (σ) is determined by employing Levene's test and equality of means (μ) is inferred from the outcomes obtained using *t*-test and ANOVA for the two classes of lesions. Hypothesis statements for *t*-test and ANOVA are expressed by Eq. (4) and Eq. (5) and for Levene's test are expressed by Eq. (6) and Eq. (7).

(Null Hypothesis): H_0: $\mu_0 = \mu_1$ The means of two data sets are equal. (4)

(Null Hypothesis Rejection): H_1: $\mu_0 \neq \mu_1$ The means of two data sets are unequal. (5)

(Null Hypothesis): H'_0: $\sigma_0 = \sigma_1$ The variances of two data sets are equal. (6)

(Null Hypothesis Rejection): H'_1: $\sigma_0 \neq \sigma_1$ The variances of two data sets are unequal. (7)

The statement of null hypothesis (H_0) for *t*-test and ANOVA have no significant difference between the means of red and yellow lesion features and its rejection (H_1) states that there exists significant difference between their means. Similarly for Levene's test, null hypothesis (H'_0) has no significant difference between the variance of red and yellow lesion features is considered and the rejection (H'_1) is stated by significant difference between the variance of features. The null hypothesis statements are rejected if the significant p-values obtained from the test are less than 0.05 otherwise it is accepted. The results of *t*-test, ANOVA and Levene's test are summarized in Table 1 for both the feature sets.

Tabular representation of *t*-test, ANOVA and Levene's test done in Table 1 reveals that significance (p-values) are less than 0.05 for all the feature attributes except two shape features *eccentricity* and *orientation*. This indicates that all the intensity features and 9 shape features (except

eccentricity and *orientation*) are statistically significant and rejects the null hypothesis of their means or variance being equal for red lesion and yellow lesions. The outcomes infer that there exist significant difference between the means and variances of both the DR abnormality features. Among 20 features extracted, 18 prominent features are selected after statistical analysis and 2 features are proved insignificant for DR classification problem. Therefore *eccentricity* and *orientation* features are not considered in further computation for DR classification.

B. Classification Analysis of Proposed CAHL system

Reduced feature set comprising 18 features after descriptive statistical analysis are used for DR abnormality classification. SVM, kNN and NN classifiers are utilized in this paper as exhaustive literature survey revealed that these classifiers perform well for DR classification. This paper classifies the DR problem in two hierarchal steps: normal/abnormal fundus image classification and abnormality classification (red and yellow lesions). SVM, kNN and NN classification uses 10 fold cross-validation scheme with 70% training and 30% testing criteria for classification.

On the basis of Performance indices: The results for both normal/abnormal stage classification and abnormality classification using SVM, kNN and NN classifiers are tabulated in Table 2.

Table 2. Performance Indices for DR Classification System using SVM, kNN and NN Classifiers

Classifier / Indices	SVM Classifier		kNN Classifier		NN Classifier	
	Normal and Abnormal Stage Classification	Abnormality Classification (Red and Yellow Lesions)	Normal and Abnormal Stage Classification	Abnormality Classification (Red and Yellow Lesions)	Normal and Abnormal Stage Classification	Abnormality Classification (Red and Yellow Lesions)
Sen.	100%	100%	92.31%	100%	100%	100%
Sp.	83.33%	70.00%	100%	95.24%	100%	100%
PPV	86.67%	100%	100%	95.24%	100%	100%
Acc.	92.00%	85.40%	96.00%	97.60%	100%	100%

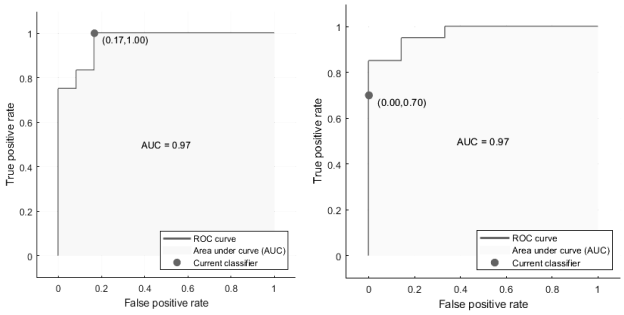
The tabular representation reveals that SVM classifier outcomes for normal and abnormal stage classification in terms of four performance indices are: sensitivity, 100%; specificity, 83.33%; positive prediction value, 86.67% and accuracy, 92%. Abnormality classification employing SVM classifier provides 100% results for sensitivity and PPV; however the specificity and accuracy are reduced to 70% and 85.40% respectively. The outcomes obtained reveals that SVM performs well for linear classification problem as it separates the input feature space into two respective classes by finding the hyperplane with largest margin.

The performance outcomes for kNN classifiers shown in Table 2 provide overall accuracy of 96% for normal/abnormal stage classification problem. The other performance indices sensitivity, specificity and positive prediction value yields the values of 92.31%, 100% and 100% respectively. kNN provides 97.60% accuracy, 100% sensitivity and specificity as well as PPV value of 95.24% for abnormality classification into red and yellow pathological

lesions. kNN classifier achieves better classification performance for both normal/abnormal stage classification and red/yellow abnormality classification as compared to SVM classifier due to its robustness for binary classification problem and its principle depends upon the Euclidean distance of k-nearest neighbours. The neural network classifier uses sigmoid activation function and 10 neurons in the hidden layer and the output neurons uses softmax activation function. The network is trained using scaled conjugate gradient backpropogation algorithm and NN classifier performance is observed in terms of four performance metrics in Table 2. 100% sensitivity, specificity, accuracy and positive prediction values are observed for both normal and abnormal stage classification and abnormality classification using NN classifier.

It is revealed that feature set reduction plays an important role in optimal classification and best performance is provided by NN classifier due to weight adjustment flexibility of NN classifier as per application requirement.

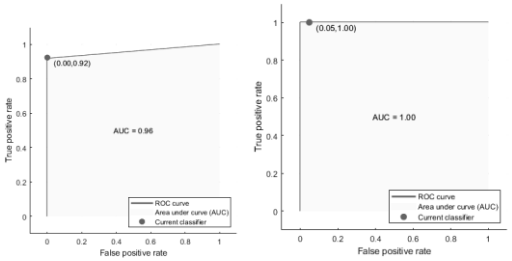
On the basis of ROC curves: The ROC curves for normal/abnormal stage classification and abnormality classification the classification results using SVM, kNN and NN classifiers are depicted in Fig. 3, Fig. 4 and Fig. 5 respectively.



(a) **(b)**

Fig. 3. ROC Curve obtained for SVM Classifier results (a) Normal and Abnormal Stage Classification, (b) Abnormality Classification into Red and Yellow Lesions

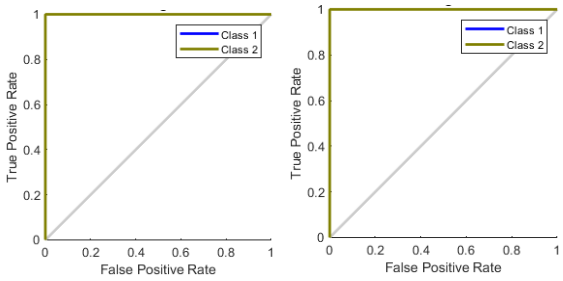
ROC curves for SVM classification depicted in Fig. 3. reveals the rate of true positives and false positives and AUC distinguishes classifier capability to distinguish between the normal/abnormal classes and different abnormality classes. SVM achieves 0.97 AUC for both the classification scenarios, however their cut off points vary for both cases.



(a) **(b)**

Fig. 4. ROC Curve obtained for kNN Classifier results (a) Normal and Abnormal Stage Classification, (b) Abnormality Classification into Red and Yellow Lesions

The true positive and false positive rate cut off points depicted by the ROC curves obtained for kNN classifier are shown in Fig. 4. Area under the curve measures the overall classification quality of kNN classifier to distinguish between normal/abnormal class and abnormality classes. kNN classifier achieves 0.96 AUC with cut-off points (0,0.92) for normal/abnormal classification and AUC of 1 with cut-off points (0.05,1) for abnormality classification into red/yellow lesions.



(a) **(b)**

Fig. 5. ROC Curve obtained for NN Classifier results (a) Normal and Abnormal Stage Classification, (b) Abnormality Classification into Red and Yellow Lesions

The ROC curves for normal/abnormal classification and red/yellow lesion classification using NN classifier are depicted in Fig. 5. It shows perfect classification outcomes with no misclassification as the cut-off point are aligned at the top left corner of the ROC plot. It provides AUC of 1 for classification performed using the derived feature set after feature selection. A comparative analysis of proposed CAHL approach for abnormality classification with the existing approaches is represented in Table 3.

Table 3. Comparison table for existing DR classification techniques with the proposed CAHL technique

Technique	Specificity	Sensitivity	Accuracy
Harangi *et al*. (2014) [27]	92%	68%	82%
Liu *et al*. (2017) [28]	83%	75%	79%
Fraz *et al*. (2017) [29]	92.42%	81.25%	87.72%
Kusakunniran *et al*. (2018) [30]	89.1%	99.7%	96.2%
CAHL Approach	**100%**	**100%**	**100%**

The comparative study reveals that our system for separating DR abnormalities provides 100% accuracy using NN classifier, which is maximum among the existing methods reported in the literature using same dataset. The system proposed is less complex in terms of run-time (10 seconds) providing highly accurate cost-effective screening solution for the detection of diabetic retinopathy. In this work, best attempts to address the limitations of existing literatures for DR abnormality classification achieving better accuracies with low complexity is made. The feature set reliability highly depends upon accuracy of segmentation steps, thus these features are analysed statistically to obtain better outcomes. The results obtained from proposed CAHL classification technique demonstrate its feasibility for analysis and classification of computer aided lesion detection in DR cases.

IV. CONCLUSION

This paper proposes a computer aided DR screening system for abnormality classification using multiple classifiers after exhaustive statistical investigation of extracted shape and intensity features. The proposed system is evaluated visually as well as statistically for critical analysis of fundus images obtained from two benchmark datasets: STARE and DIARETDB1. Optimal features are selected using SPSS tool which resulted in rejection of two shape based features, *eccentricity* and *Orientation*. The proposed system achieves overall accuracies of 92.00%, 96% and 100% for normal and abnormal stage classification employing SVM, kNN and NN classifiers respectively. Abnormality Classification into Red and Yellow Lesions utilizing SVM, kNN and NN classifiers yields 85.40%, 97.6% and 100% accuracies respectively. The multiple classifier approach used in this paper provides a robust alternative solution for DR screening and the best performance is achieved using NN classifier. Although this approach possess limited application for various other anatomical and pathological regions, but for DR based abnormalities the proposed CAHL is a good option which assist the ophthalmologist to substantiate his analysis.

Future implications of this research work are its application for neovascularisation and blood vessel bleeding problems which are not addressed in this part of the research. Deep learning techniques will also be explored for DR screening and diagnosis in the future.

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