Diabetic Retinopathy Lesion Discriminative Diagnostic System for Retinal Fundus Images

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Abstract
Diabetic retinopathy (DR) is the main cause of retinal damage due to fluid leakage from blood vessels. Automated diagnostic systems assist the ophthalmologists practice manual lesion detection techniques which are tedious and time-consuming. A Diabetic Retinopathy Lesion Discrimination (DRLD) model is proposed for abnormality identification followed by DR lesion detection based on identification of DR pathological symptoms. Shape, intensity and gray-level co-occurrence matrix (GLCM) features are extracted from the identified lesions, and exhaustive statistical analysis is performed for optimal feature selection. Overall accuracies of 97.9% and 91.5% are obtained using multi-layer perceptron neural network (MLPNN) and support vector machine (SVM) classifiers, respectively, for non-diseased versus diseased fundus image discrimination. MLPNN provides better performance for the fundus image discrimination approach, and further accuracy of 98.9% is obtained for DR lesion detection. When compared with other state-of-the-art techniques, the proposed approach provides better performance with significantly less computational complexity. A maximum accuracy improvement of 20.13% in fundus image discrimination and 5.90% in lesion categorization is achieved.

Keywords: Diabetic Retinopathy, Lesion Discrimination, Support Vector Machine, Multi-Layer Perceptron Neural Network.

Adv Biomed Eng. 9: pp. 71–82, 2020.

1. Introduction
Diabetic retinopathy (DR) is a serious complication of diabetes and a leading cause of acute blindness. Patients suffering from diabetes are 25 times more expected to develop severe blindness as compared to people without diabetes [1]. It is the most common severe diabetic complication characterized by prolonged deterioration of retinal blood vessels. DR is a silently progressing disease and its symptoms are visible to the patients only when the disease has reached its severe stage. Severe DR condition occurs due to swelling of retinal blood vessels, leakage of blood and fluids from blood vessels or growth of abnormal blood vessel.

DR can be characterized by increased glucose level in the blood which damages the capillaries and leaks blood and fluid into the retina. This leakage may appear in the form of lesions such as microaneurysms (MAs), hemorrhages (HMs), hard exudates (EXs), and cotton wool (CWs) spots [2]. MAs and HMs fall under the category of red or dark lesions, and EXs and cotton woolls are characterized as yellow or bright lesions. The broad classification of DR falls into two categories; non-proliferative DR (NPDR) and proliferative DR (PDR) due to the presence of specific lesions. The earliest mild stage of DR causing lesions such as MAs results in swelling in the walls of small blood vessels. In the moderate stage, rupturing of these MAs leads to retinal HMs, which is identified as dark red spots of blood on the retinal surface. EXs, which are lipids or fat deposits leaking into the retina, also appear in moderate NPDR stage. They are reflective yellow lesions that appears bright, unlike HMs which are red lesions and appear dark in the image of infected eye. Increased level of retinopathy causing blood vessel blockage in the retinal areas is termed severe NPDR. In this stage, the blood vessels become blocked causing lack of blood supply and oxygen into the retina. Proliferative DR occurs when retinal blood vessels do not supply enough blood flow to the retinal areas. The retina responds by growing new blood vessels which are weak, fragile and leaky, causing blood leakage into the retinal surface. This stage leads to bifurcated pattern of abnormally grown new blood vessels. This stage is a more severe stage of DR and may even lead to retinal detachment causing severe vision loss [3]. The labeled image of an abnormal fundus image is depicted in Fig. 1.

Automated DR diagnostic system has emerged as an important tool worldwide for disease identification, pathology detection and prognosis. In the field of medical
sciences, automated pathology detection plays a vital role to assist disease interpretation by automatically analyzing the disease severity level, helping the patients in receiving timely treatment and follow-ups. DR can be controlled at the initial stages of the disease by effective treatment; therefore, early detection via regular screening plays a vital role in preventing DR complications.

Various attempts have been made by researchers to devise DR detection methods for fundus image discrimination and abnormality detection at the initial stage. Inbarath et al. [3] proposed a hemorrhage detection approach for automated DR screening utilizing Splat and gray-level co-occurrence matrix (GLCM) features, which were classified using support vector machine (SVM) classifier. Experimentations were performed on MESSIDOR dataset to yield improved classification accuracy compared to other methods. A MA and EX detection technique using SVM and k-nearest neighbor (kNN) classifiers was introduced previously [4] employing the MESSIDOR dataset. Structural and GLCM features were provided to SVM classifier to yield better classification performance. A computer-aided diagnosis system (CAD) for DR severity grading was proposed using an ensemble of classifiers such as SVM, kNN and Gaussian mixer model (GMM) [5]. A reduced feature set was used for lesion detection and hierarchal classification to firstly classify lesions and non-lesions, and then yellow lesions were categorized as EXs and cotton wools and red lesions as MAs and HMs. A CAD system for digital processing of retinal images to help early-stage DR detection was proposed by Carrera et al. [6]. The authors graded NPDR retinal images by isolating various features of blood vessels, exudates, and microaneurysms, which were further provided to SVM classifier. The approach provided maximum sensitivity of 95% and predictive capacity of 94% with robustness to change in parameters. A retinal health detection system differentiating between non-diseased and diseased fundus images has been developed by Koh et al. [7], which uses correlated features from pyramid histogram of oriented gradients as well as speeded-up robust features (SURF) to be provided to kNN classifier, with an average accuracy of 96.21% using the 10-fold cross-validation scheme. An efficient scheme utilizing SVM parameters along with glowworm swarm optimization (GSO) and genetic algorithm (GA) for DR disease classification was proposed by Karthiyayan and Ali [8]. The approach lags in computational complexity; thus future implications of this work will focus on applying meta-heuristic approaches. Reza and Eswaran [9] proposed a rule-based classification scheme for non-diseased and diseased classes considering only bright fundus image lesions. The system achieves better accuracy for bright lesion detection, although dark lesions should also be considered for more accurate DR classification. The above literature review presents various state-of-the-art techniques for DR classification and reveals that there exist manifold possibilities in improving lesion discrimination approach for DR detection.

Human interventions involved in manual DR diagnostic systems are subjective, laborious and require human expertise. Also the major limitation for lesion discrimination lies in the lack of distinction ability between actual lesions and background noise or other anatomical structures. To overcome the limitations of the currently used diagnostic systems, this paper proposes a Diabetic Retinopathy Lesion Discrimination (DRLD) model for identification of abnormalities. A fundus image discrimination strategy along with lesion categorization is proposed in this article employing image feature vector based on shape, intensity and textural properties of DR lesions. A feature set reduction strategy is applied for optimal feature selection in the DR abnormality detection stage. The major contribution of this work lies in devising a reliable DR lesion detection scheme employing machine learning algorithms and achieving a trade-off between classification accuracy and computational complexity. The proposed system outperforms the other state-of-the-art techniques when tested on the same benchmark dataset.

The organization of the paper is as follows: Material and methods are detailed in section 2 describing the dataset and proposed methodology. Experimental results are summarized in section 3 followed by discussion in section 4. Section 5 highlights the conclusion and future scope of the proposed approach.

2. Materials and Methods

The proposed system is implemented using MATLAB2019b environment on a system equipped with the Intel Core i5 processor and 8 GB RAM. The following subsections describe the dataset used in this paper followed by discussion of the proposed methodology and performance metrics.
2.1 Materials
The datasets comprise a varying number of images captured using different cameras with different resolutions and field of view (FOV). Structured Analysis of Retina (STARE) and DIARETDB1 are the two datasets utilized in this work.

The STARE [10] dataset is suitable for structural analysis of the retina. It comprises 400 fundus images of 605 × 700 pixels captured using TopCon TRV-50 at 35 degree FOV. The DIARETDB1 [11] dataset was originally obtained from Kuopio University Hospital, Finland. This dataset comprises 89 fundus images and provides the position and detailed labelling of retinal abnormalities. Out of these 89 fundus images, 84 images contain NPDR symptoms and the other five non-diseased fundus images. These images are 1500 × 1152 and 1936 × 1296 pixels with 50 degree FOV captured using digital camera.

2.2 Methodology
The four-step implementation strategy is carried out for fundus image discrimination and DR lesion detection. Pre-processing of fundus images by background removal and foreground identification is followed by detection of diseased and non-diseased retinal fundus images. From the diseased retinal fundus images, red and yellow lesion abnormalities are detected by applying a proposed DRLD algorithm. Shape, intensity and textural features from diseased and non-diseased fundus images are extracted, subjected to statistical analysis to select the optimal features. DR lesion detection is the final step of the proposed methodology, which involves fundus image discrimination into diseased and non-diseased followed by discrimination of disease pathology into red and yellow lesions. The following subsections detail the step by step descriptions as shown in Fig. 2.

2.2.1 Background Removal and Foreground Identification
The foremost steps to pre-process the acquired fundus images are background removal and foreground identification.

Optical Disc (OD) is the undesirable physiological structure for DR diagnosis as it has similar intensity value to that of yellow lesion. OD boundary localization is accomplished using morphological closing operation, and the largest circular region is identified as the OD portion [12, 13].

Blood vessel is another background object that is identified employing morphological reconstruction followed by global thresholding technique, considering the absolute difference between the original and estimated

Fig. 2 Schematic diagram of DR Lesion Detection Approach.
fundus image background. Further, to filter out some of the isolated regions that do not belong to vascular regions, connected component analysis is used. Eight connected pixel connectivity is used to distinguish between the vessel and non-vessel pixels [14]. The background elimination step including OD localization and blood vessel removal using morphological reconstruction ($I_{M_{rph}}$) is expressed by Eq. (1).

$$I_{BC} = I - I_{M_{rph}}$$

where $I$ is the original fundus image, $I_{M_{rph}}$ is morphologically reconstructed image and $I_{BC}$ is the background removed fundus image.

The identified background is subtracted from the original fundus image to obtain the foreground region. After background removal, non-diseased fundus image does not possess any foreground lesion portion. For diseased fundus images, intensity-based foreground region discrimination is further done to discriminate lesions into red lesions including MAs and HMs and yellow lesions comprising EXs and CWs. Background region and foreground identified portions for one of the images are depicted in Fig. 3.

Lesion discrimination for foreground region is accomplished using the proposed DRLD approach.

### 2.2.2 Proposed Diabetic Retinopathy Lesion Discrimination (DRLD) Approach

The main aim of our proposed DRLD approach is to provide a computer-assisted DR lesion detection scheme to ophthalmologists for efficient diagnosis as detailed in Fig. 4.

#### Lesion Identification

After background removal from the retinal fundus image, the diseased foreground comprises of two types of lesions (red and yellow) that are extracted using morphological operations. To extract red lesions, morphologically closed image is subtracted from the original image by considering minimum angular response. Yellow lesions are extracted using hard thresholding operation by empirically choosing the optimal threshold value [15]. Lesion histogram properties are also considered for threshold selection to identify the candidate lesions [16, 17].

Lesion discrimination step is followed by feature attribute extraction and optimal feature selection utilizing statistical analysis. The final stage of the proposed DRLD scheme involves classification of diseased and non-diseased fundus images followed by DR lesion detection.

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**Fig. 3** Representation of background and foreground identification.

**Fig. 4** Proposed Diabetic Retinopathy Lesion Discrimination (DRLD) algorithm.
employing machine learning techniques, utilizing optimally selected features after exhaustive statistical analysis to obtain better performance.

**Feature Attribute Extraction**

After exhaustive literature review, 34 unique features were chosen for this work, exploiting the shape, intensity and textural properties of the lesions. Eleven shape features exploring the geometric properties of lesions comprise area, perimeter, convex area, major and minor axis lengths, eccentricity, orientation, diameter, solidity, extent, and compactness [18]. Pixel-based properties consider nine intensity features; maximum intensity, minimum intensity, mean, median, standard deviation (SD), inter-quartile range (IQR), mean absolute difference (MAD), skewness and kurtosis [19, 20]. GLCM textural features are used to exploit properties considering the spatial relationships of pixels. It comprises 14 unique features; autocorrelation, correlation, contrast, energy, entropy, homogeneity, dissimilarity, cluster shade, cluster prominence, maximum probability, inverse difference normalized, inverse different moment normalized, information measure of correlation1 (InfoCorr1) and information measure of correlation2 (InfoCorr2) [19, 20].

**Tables 1, 2 and 3** respectively tabulate the shape, intensity and textural feature sets utilized in the DRLD system.

**Statistical Analysis for Optimal Feature Selection**

Dimensionality reduction significantly improves the system performance in terms of computation time and storage. In this work, the extracted features are reduced using t-test and analysis of variance (ANOVA) [21, 22] to find their statistical significance for classification. The most prominent features are selected from the extracted feature vector using the significant p-value indicating the significance of a particular feature, and is expressed in Eq. (2).

\[
p = \begin{cases} 
  p \leq 0.05 & \text{indicates Strong Significance} \\
  0.01 < p \leq 0.05 & \text{indicates Moderate Significance} \\
  p > 0.05 & \text{indicates Weak Significance} 
\end{cases}
\]

where \( p \) is the significance value.

These tests compare the means and variances of normally distributed data sets by analyzing its p-value, which should be less than 0.05 to reject the hypothesis, and select the most significant features for classification.

**Machine Learning Techniques**

Several classifiers are used in the literature for fundus image discrimination. For this research work, different machine learning techniques including SVM classifier and multi-layer perceptron neural network (MLPNN) classifier are employed for lesion detection.

**Support Vector Machine (SVM) Classifier:** SVM is a supervised discrimination method that creates a supervised model using labeled data, thereby categorizing the test data utilizing that trained model [23]. SVM model creates a decision boundary/ hyper plane using training data points that best separates the class labels. Maximal margin hyper plane is selected whose distance to the nearest data point of each class label is largest. A clear pictorial representation of SVM hyper plane is given in Fig. 5.

For a given set of input data denoted by \( \mathbf{x} \) with weight vector \( \mathbf{w} \) and bias \( b \), the output vector may either be 1 or \(-1\) depending on the class it belongs. Elements of class \( i_1 \) are represented by green color and elements belonging to class \( i_2 \) are denoted by red color separated using a hy-
perplane. SVM classification relies on the selection of kernels as it is able to map the non-linearly separable data into a higher dimensional space where it can be separated using a hyperplane. For this study, we have selected Gaussian radial basis function (RBF) kernel, because unlike other kernels, it is best suited for data without any prior knowledge of the class labels. RBF kernel function provides desirable results in terms of classification accuracy for fundus image discrimination problem. Eq. (3) explains the Gaussian RBF kernel.

\[
K(x, x_i) = \exp(-\gamma \times \sum \|x - x_i\|^2)
\]

where \(x\) is the input vector, \(x_i\) is the support vector and \(\gamma\) denotes the width of the Gaussian envelope.

**MLPNN Classifier:** MLP is a feed-forward NN that employs the intermediate hidden layers in which neurons are not directly connected to the output layer. MLPNN acts as interpreter and approximates the outcomes by utilizing non-linear activation function at both hidden and output layers. The layer-wise representation of MLPNN is given in Fig. 6. Input nodes are represented by green color, hidden nodes by blue color, and the two output classes \(O_1\) and \(O_2\) by red and yellow colored nodes, respectively.

The input vector is fed to the initial layer of MLPNN which are further provided to the hidden layers for intermediate processing utilizing the weight vectors and activation functions. Classification outcomes are interpreted through feature mapping and continuous training employing back propagation technique [17, 24]. Out of various activation functions, tangent hyperbolic function is used in this paper at the hidden layer, which can be ex-

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**Table 2** Set of intensity features chosen for DRLD system.

| Intensity Features            | Description                                                                 |
|------------------------------|-----------------------------------------------------------------------------|
| Minimum Intensity            | Value of the pixel with the lowest intensity in the lesion portion           |
| Maximum Intensity            | Value of the pixel with the greatest intensity in the lesion portion          |
| Mean Intensity               | Mean of all the intensity values in the lesion portion                       |
| Median Intensity             | Median of all the intensity values in the lesion portion                     |
| MAD Intensity                | Mean absolute difference of all the intensity values in the lesion portion   |
| SD Intensity                 | Standard deviation of all the intensity values in the lesion portion          |
| IQR                          | Inter-quartile range of all the intensity values in the lesion portion        |
| Skewness                     | Measure of the asymmetry of the probability distribution about the mean of lesion portion |
| Kurtosis                     | Measure of the tailedness of the probability distribution of lesion portion   |

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**Table 3** Set of textural features chosen for DRLD system.

| Textural Features            | Description                                                                 |
|------------------------------|-----------------------------------------------------------------------------|
| AutoCorrelation              | Linear dependencies of gray level pixels at a specific point with respect to itself |
| Correlation                  | Linear dependencies of gray level pixels at a specific point with respect to each other |
| Contrast                     | Measure of pixel intensities and its neighbour over the lesion portion       |
| ClusterShade                 | Measure of lack of symmetry or skewness in the lesion portion                |
| ClusterProminence            | Measure of grayscale variation in the lesion portion                         |
| Energy                       | Measure of pixel pair repetition or uniformity of lesion portion             |
| Entropy                      | Measure of randomness of lesion portion                                      |
| Homogeneity                  | Closeness of distribution of elements in the lesion portion                  |
| Inverse Difference Normalized| Difference between the neighbouring intensity values is normalized by total pixels in the lesion portion |
| Inverse Difference Moment    | Difference of local homogeneity between the neighbouring intensity values normalized by total pixels in the lesion portion |
| Dissimilarity                | Measures the mean gray level difference in distribution of pixels in the lesion portion |
| Maximum Probability          | Max probability of distribution of pixels in the lesion portion              |
| InfoCorr1                    | Measure of information correlation in terms of its mutual information which is expressed as: \(H_{xy} - H_{xy1}\) \(\max(H_{xy})\) |
| InfoCorr2                    | It is the measure of information correlation expressed as: \((1 - \exp[-2(H_{xy} - H_{xy1})^{1/2}]\) |

where \(H_{xy} = -\sum p(i,j)\log(p(i,j))\), \(H_{xy1} = -\sum p(i)\log(p(i)p(y)\)), \(H_{xy2} = -\sum p(i)p(j)\log(p(i)p(j))\), \(H_x\) and \(H_y\) are the entropies of \(p_x\) and \(p_y\).
pressed using Eq. (4).

\[
\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{4}
\]

This function improves the learning speed and enhances the separation capability of MLPNN. Output layer uses softmax activation function to derive classification outcomes, and is expressed by Eq. (5).

\[
F(x) = \frac{e^x}{\sum_{i=0}^{k} e^x}, \text{ for } i = 0, 1, 2, \ldots, k \tag{5}
\]

Softmax activation function calculates the probabilities within the range of 0 to 1 providing the classification outcomes as probabilities of each class with the highest probability value for the target class.

### 2.3 Performance Metrics

The metrics used for the performance evaluation of the classifier are derived from true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). The metrics used in this paper are positive prediction value (PPV), sensitivity, specificity and accuracy [25]. The formulas for the performance metrics utilized in this paper are tabulated in Table 4.

| Performance Metric | Formula |
|--------------------|---------|
| PPV                | \( \frac{TP}{TP + FP} \) |
| Sensitivity        | \( \frac{TP}{TP + FN} \) |
| Specificity        | \( \frac{TN}{TN + FP} \) |
| Accuracy           | \( \frac{TP + TN}{TP + FN + TN + FP} \) |

### 3. Experimental Results

The experiments are performed utilizing STARE and DIARETDB1 datasets comprising non-diseased and diseased images. The acquired fundus images from the dataset are initially subjected to image pre-processing consisting of background removal and foreground lesion detection. The visual depiction of image pre-processing, OD localization and blood vessel extraction for one of the images is given in Fig. 7.

The image pre-processing stage is employed to remove poor contrast and inadequate illumination for the enhancement of physiological and pathological regions [26]. OD has similar intensity attributes as those of yellow lesion, and therefore can be misclassified as a lesion portion. Thus, this anatomical portion requires removal initially before proceeding to lesion identification. The blood vessels may also be misclassified as red lesions (MA and HM) due to its similar intensity range to these pathological symptoms. Thus, pre-processing step is employed to remove all these fundus image artifacts and eliminate unwanted pathological regions that may
hamper DR diagnosis. The non-diseased fundus images do not contain foreground lesion portion. Thus, further lesion discrimination is applied to the diseased foreground fundus images to distinguish between red and yellow lesions. To detect the lesions, DRLD algorithm is proposed. The DRLD algorithm is used to extract red lesion and yellow lesion candidates utilizing morphological operations and thresholding function. The experimental results for red and yellow lesion extraction are depicted in Fig. 8 and Fig. 9 respectively.

Lesion discrimination is followed by feature extraction for accurate disease detection. Shape, intensity and textural feature attributes are utilized to obtain relevant pathological information for accurate disease classification. Exhaustive statistical analysis of these extracted features is done to obtain optimally selected features. ANOVA and \( t \)-test statistical tools are used in this work to provide reduced dimensional complexity along with increased accuracy rate to improve the diagnostic information. Most prominent features are selected from the entire feature vector using significance value (\( p \)-value) obtained from the statistical tests. Features providing \( p \)-value less than 0.05 are the most prominent features, and features having \( p \)-value greater than 0.05 are weakly significant and therefore discarded. The optimal features selected using descriptive statistical analysis by \( t \)-test and ANOVA are tabulated in Table 5.

The reduced feature set comprising 32 features is used for SVM and MLPNN classification to perform fundus image discrimination.

### 3.1 Fundus Image Discrimination into Non-Diseased and Diseased

The classification approach utilized for abnormality classification includes fundus image discrimination into diseased and non-diseased fundus images followed by le-

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**Table 5** Statistical analysis of extracted feature set using \( t \)-test and ANOVA.

| Shape Features       | \( t \)-test (Sig.) | ANOVA (Sig.) | Intensity Features       | \( t \)-test (Sig.) | ANOVA (Sig.) | GLCM Textural features       | \( t \)-test (Sig.) | ANOVA (Sig.) |
|----------------------|---------------------|--------------|--------------------------|---------------------|--------------|--------------------------------|---------------------|--------------|
| Area                 | 0.019               | 0.019        | Min. Int.                | 0.003               | 0.000        | Auto Correlation              | 0.001               | 0.001        |
| Perimeter            | 0.040               | 0.033        | Max. Int.                | 0.000               | 0.000        | Correlation                   | 0.000               | 0.000        |
| Major_Axis_Length    | 0.033               | 0.003        | Mean Int.                | 0.000               | 0.000        | Contrast                      | 0.000               | 0.000        |
| Minor_Axis_Length    | 0.011               | 0.005        | Med. Int.                | 0.000               | 0.000        | ClusterShade                 | 0.005               | 0.007        |
| Eccentricity         | 0.062               | 0.062        | MAD Int.                 | 0.000               | 0.000        | ClusterProminance             | 0.000               | 0.000        |
| Convex_Area          | 0.005               | 0.002        | SD Int.                  | 0.000               | 0.000        | Energy                        | 0.002               | 0.000        |
| Orientation          | 0.102               | 0.102        | IQR                      | 0.000               | 0.000        | Entropy                       | 0.001               | 0.000        |
| Equiv_dia            | 0.002               | 0.002        | Skewness                 | 0.012               | 0.015        | Homogenity                    | 0.000               | 0.000        |
| Solidity             | 0.015               | 0.007        | Kurtosis                 | 0.005               | 0.005        | InverseDiffNorm               | 0.000               | 0.000        |
| Extent               | 0.033               | 0.030        |                          |                     |              | InvDiffMoment                 | 0.007               | 0.007        |
| Compactness          | 0.002               | 0.000        |                          |                     |              | Dissimilarity                 | 0.000               | 0.000        |
|                      |                     |              |                          |                     |              | MaxProb                       | 0.000               | 0.000        |
|                      |                     |              |                          |                     |              | InfoCorr1                     | 0.002               | 0.000        |
|                      |                     |              |                          |                     |              | InfoCorr2                     | 0.005               | 0.005        |

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![Fig. 8](image1.png) Experimental results of red lesion detection: (a) original fundus image, (b) detected red lesion candidates.

![Fig. 9](image2.png) Experimental results of yellow lesion detection: (a) original fundus image, (b) detected yellow lesion candidates.
sion discrimination of diseased fundus images into red and yellow lesions.

The classification results are depicted for 100 non-diseased and 100 diseased retinal fundus images using 70%/30% training and testing criteria with 10-fold cross validation. The performance metrics for non-diseased and diseased fundus image discrimination are tabulated in Table 6.

The features determining the non-diseased and diseased fundus images provide overall accuracy of 91.50% and 97.90% employing Gaussian RBF kernel of SVM and MLPNN classifiers, respectively. The MLPNN classifier achieves better performance for non-diseased and diseased fundus image discrimination. The other performance indices for MLPNN are 96.15% sensitivity, 100% specificity, and 97.73% PPV.

After fundus image discrimination, DR lesion detection is important to aid the ophthalmologists in accurate screening and diagnosis. DR anomalies are categorized into red and yellow lesions based on the intensity properties of lesion candidates.

### 3.2 DR Lesion Detection from Diseased Fundus Images

As MLPNN provides better results for fundus image discrimination, it is also employed for DR lesion detection. Hidden layer weights are updated for every training sample and the errors are propagated backward for weight updation [22]. The shortest computational time of 2 seconds is achieved using MLPNN. Various performance indices in terms of specificity, sensitivity, accuracy and PPV are calculated to find the clinical relevance of detected lesions. Table 7 provides the classification performance metrics for DR lesion discrimination utilizing both STARE and DIARETDB1 datasets.

The proposed system achieves performance of 98.9% accuracy and computationally less complex mass screening solution for DR lesion detection.

| Table 6 | Performance metrics for fundus image discrimination. |
|---------|-----------------------------------------------------|
| Classifier | Sensitivity | Specificity | Accuracy | PPV |
| SVM | 84.61% | 100% | 91.50% | 100% |
| MLP | 96.15% | 100% | 97.90% | 100% |

| Table 7 | MLPNN classification performance for DR lesion detection. |
|---------|---------------------------------------------------------|
| Classifier | Sensitivity | Specificity | Accuracy | PPV |
| MLP | 97.8% | 100% | 98.9% | 97.73% |

### 4. Discussion

The proposed technique successfully discriminates between non-diseased and diseased fundus images and also classifies red and yellow lesions. The DRLD approach is used to extract most of the actual lesions but there exists some fallacious lesion portions because of scars or blood spots from patient’s previous medical history. It has been observed that red lesions have darker intensity histogram range and yellow lesions have brighter intensity ranges [16]. Some of the false red and yellow lesion candidates are very tiny, which are not considered as pathologic region. Fallacious red lesions can occur due to branched blood vessels, blood spots and scars [17], while false yellow lesions occur due to reflection of nerve fiber layers or some other bright structures. These fallacious segments should be discarded and are not considered as lesion candidates. After identifying the lesions of diseased and non-diseased images, various features are analyzed.

Feature attributes are extracted for abnormality identification and lesion discrimination which are further subjected to statistical analysis for optimal feature selection. Out of the 34 extracted features, 32 features have significance values less than 0.05 (with the exception of two shape features: eccentricity and orientation). Thus 32 features indicate significant differences between the mean values of non-diseased and diseased DR fundus images. These statistically selected features are utilized in the classification stage.

SVM and MLPNN-based classification approaches are used for fundus image discrimination into non-diseased and diseased classes. The SVM classifier provides accuracy of 91.50% for fundus image discrimination. To improve the classification performance, a less complex neural network-based MLPNN classifier is employed, which reduces computational time for DR classification. The MLPNN classifier provides better performance for fundus image discrimination with accuracy of 97.90%. Error function is minimized using continuous training and the weights are updated using back propagation technique.

A comparison is shown in Fig. 10 highlighting the efficiency of the proposed fundus image discrimination approach compared with other state-of-the-art research reports employing the same dataset. From Fig. 10, it is observed that the proposed approach for classification of diseased and non-diseased fundus images outperforms the other state-of-art methods in terms of accuracy, with the greatest accuracy improvement of 20.13% over that of Solkar et al. [27]. Comparison with other state-of-the-art methods reveals accuracy improvement of 4.90% over Rahim et al. [14].
and 2.10% over Pedro et al. [28]. The proposed system provides a cost-effective mass screening solution for fundus image discrimination to aid automated detection of diabetic retinopathy. After fundus image discrimination, the diseased images containing different lesions can be further classified based on the lesion intensity range. Red lesions lie to the darker intensity region of the dynamic range, whereas yellow lesions lie towards the brighter side of the dynamic range. Thus, these lesions are significant in detecting the presence of DR abnormality, reducing the burden of ophthalmologists by identifying patients requiring immediate ophthalmic care. For this work, the MLPNN classifier provides 98.90% accuracy for classifying lesions into red and yellow lesions. The ability of MLPNN to learn from experience makes this classifier flexible for image processing-based applications.

MLPNN performs well for DR lesion discrimination because, unlike other classification techniques, this approach is not restricted to the input data distribution. The generalized MLPNN classifier provides 98.9% accuracy which is significantly higher than the existing state-of-the-art approaches. The comparison of percentage accuracy improvement of the proposed approach with other methods is shown in Fig. 11.

This comparative analysis of the proposed lesion detection approach with existing techniques reveals that it outperforms other state-of-the-art methods, with the greatest accuracy improvement of 5.90% over Nayak et al. [29]. Comparison with other techniques shows accuracy improvement of 3.52%, 2.90% and 3.77% over Priya et al. [30], Paing et al. [31] and Saha et al. [32] respectively.

5. Conclusion

This paper presents a DRLD approach employing SVM and MLPNN classifiers to aid ophthalmologists in detecting the severity of DR. From a total of 34 features based on shape, intensity and texture of identified anomalies, 32 prominent features were extracted after exhaustive statistical analysis. The performance of severity classification by the proposed approach is investigated using STARE and DIARETDB1 datasets. Overall accuracies of 91.50% and 97.90% are achieved using SVM and MLPNN classifiers, respectively, for fundus image anomaly detection, and 98.9% accuracy is achieved for DR lesion discrimination. The proposed system outperforms the existing techniques, as shown by a significant accuracy improvement of 5.90% for lesion discrimination, providing a less complex and cost-effective DR screening solution. This approach will aid automated DR detection by integration of ophthalmic processing with an optimal feature set. Future work will focus on assessing the other classifier combinations for DR severity detection.

Conflicts of Interest

The authors declare no conflict of interest.

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