IJCTA, 9(7), 2016, pp. 3135-3145 ISSN: 0974-5572

Automatic Diabetic Assessment for Diabetic Retinopathy Using Support Vector Machines

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ABSTRACT

Diabetic retinopathy become the common disease in most of the countries. Many classifiers are used to classify the extracted features to identify the presence of normal and abnormal retinal images. Microanuerysms, Hemorrhages and exudates are the major symptoms for detecting the proliferative and non-proliferative diabetic retinopathy. In this proposed work, an automated assessment system has been developed for the diabetic retinopathy using the classifier support vector machine which gives the higher accuracy in detecting the micro aneurysms (MAs), hemorrhages (HA) and exudates. In this work, the combination of Support Vector Machine with the Bayesian, probabilistic neural network, clustering, Artificial neural network has been discussed which improves the overall accuracy of the classification.

Keywords: *Microanuerysms, Hemorrhages; exudates; Support Vector Machine.*

1. INTRODUCTION

Diabetic retinopathy is the one of the most common medical challenge in the society. Diabetic retinopathy leads to vision loss due the growth of new blood vessels in the retina because of the imbalanced blood glucose level. These new blood vessels are not normal which grows like a network or loop like structure. Diabetic retinopathy is classified as mild nonproliferative, moderate nonproliferative, severe nonproliferative and proliferative. In the mild non proliferative stage, microanuerysms began to develop at this stage which appears as dark lesions.

At the next stage of moderate non proliferative, retinal vessels are getting blocked. In the severe nonproliferative stage, several vessels reaching the retina gets blocked and in the proliferative stage of diabetic retinopathy new vessel growth began to develop which has thin fragile wall, in the advanced stage, vessel leaks blood leads to vision loss and blindness. This may damage the optic disc which takes the signal to brain. This diabetic retinopathy needs to be detected and screened at an earlier stage.

In earlier stage, it was very tedious and takes long time to detect the diabetic retinopathy. The proposed automated assessment system helps ophthalmologist to easily detect the diabetic retinopathy. As the first stage of detection, preprocessing is performed to reduce the noise, filtering is used to extract the features to classify. Several classifications methods are used to classify the features extracted to detect microaneurysms, hemorrhages. Support Vector machine performs well to classify the abnormalities from the normal retinal images. SVM is statistical learning method. Support Vector Machine associated with clustering improves the accuracy. SVM consists of hyperplane at high dimensional space improves the classification, regressions. SVM reduces the need for labelled training instances. In most of the cases, Laser marks are also extracted by the classifier support vector machine. SVM has proven to be the best classifier and also easier than the neural network. The goal of SVM is to produce a model on the training data which predicts the target value.

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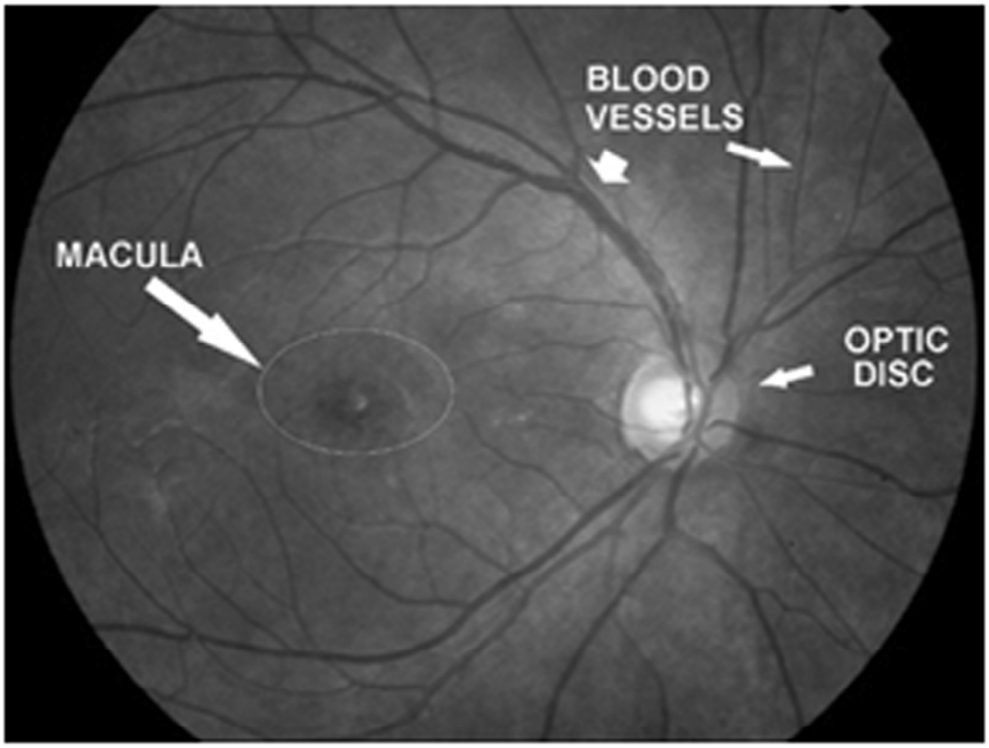

Figure 1: Retinal Image [35].

As a result, for classifying a retinal image taken from any publicly available database, it is necessary to perform preprocessing to reduce the illumination variation, noise reduction and to enhance the contrast by any histogram equalization method. The features to be examined are extracted using segmentation and extracted features for classifying exudates, Microaneurysms, cotton wool spots, hemorrhages like shapes, length, area, color, texture features like contrast, homogeneity, energy and correlation.

2. AUTOMATIC ASSESSMENT OF SUPPORT VECTOR MACHINE

S. Saranya Rubini et al. [1] investigated on eigen values of the Hessian matrix. Semi-automated hessian based candidate selection algorithm (SHCS) followed by thresholding to detect MAs and HMA. Automated approach used hessian based candidate selection algorithm (AHCS) followed by feature extraction and feature selection.

Semi-automated algorithm reduces noises and disturbances. Threshold values detected the true Mas and HMAs. Automated detection starts with preprocessing by extracting Mas and HMAs. The final result is obtained from SVM classifiers. The images for analyses were taken from hospital laboratory. The performances are based on the false positive and true positive values with resultant probability of $p < 0.005$. Jyotiprava Dash et al. [2] investigated the blood vessel detection methodologies in retinal images. This work proposes a novel method for segmenting the retinal blood to overcome variations in contrast. 2D Gabor wavelet is used for vascular pattern enhancement. Star networked pixel tracking algorithm is used to eliminate noise in the vessel format which is the best vessel detection method with the accuracy of 95.83%. Thresholding, tracking method and machine trained classifiers are the segmentation methods. Fragments from feature extraction are support vector machine. Bálint Antal et al.[3] proposed an for screening system of diabetic retinopathy with ensemble feature extraction model in which features are extracted from several retinal images. The algorithms like image level, lesion specific, anatomical are used as the components of image extraction. The decisions are taken by the ensemble of machine learning classifier. The database MESSIDOR produces 90% sensitivity, 91% specificity and 90 % accuracy. The image level algorithms are

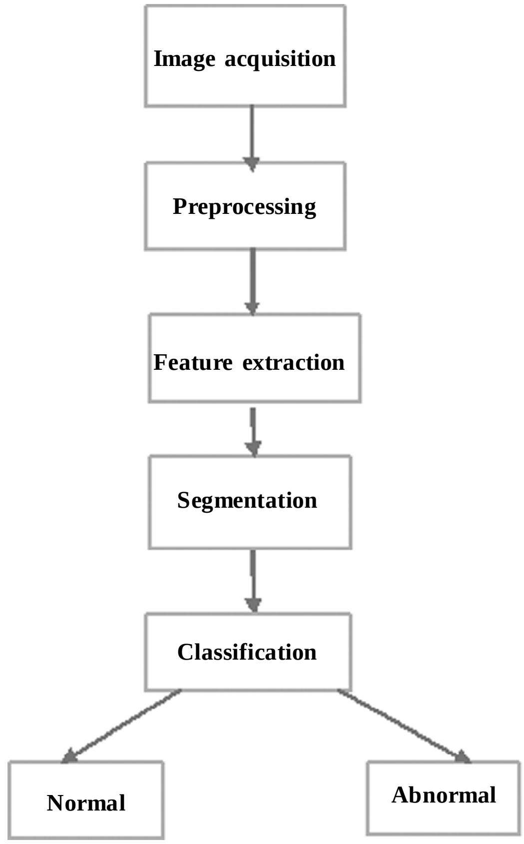

Figure 2: Detection process of abnormality

used for quality assessment, preprocessing and AM/FM. Lesion based algorithms are used to extract the features of microanuerysms and exudates. The anatomical algorithms are used for macula and optic disc. An optimal ensemble is selected for the diabetic retinopathy classification. Classifiers used are alternating decision tree, KNN, Adaboost, Multilayer perceptron, Naïve Bayes, random forest, SVM and pattern classifiers.Adeel M. Syed et al. [4] investigated the automated laser mark segmentation from colored retinal images. In the preprocessing stage the background is separated and contrast is enhanced for detecting laser marks on the retina. In preprocessing, thresholding technique converts grey scale image to binary image. The feature extraction have made based on the color, texture and shape. Laser marks are extracted by the classifier support vector machine. Jośe Tońas Arenas-Cavalli et al. [5] investigated the web based platform for automated diabetic retinopathy screening. The dataset is collected and prepared from the patients through the health care center. Patient details are registered and given to the automated diabetic retinopathy screening. Blood vessel localization. Optic disc localization, bright lesion detection, red lesion detection techniques are used. The overall system performance is 91% with 89% sensitivity, 65.24 % specificity.T.Ruba et al. [6] identified and segmented exudates using SVM classifier by resizing the retinal images and are filtered using median filter. The resulting filter images are classified as normal and exudates using SVM. Once the exudates are found out it is segmented using thresholding and morphological operations. Using Gabor, GLCM (Grey Level Co-occurrence Matrix) features such as contrast, correlation, cluster prominence, cluster shade, dissimilarity, energy entropy, homogeneity, maximum probability, sum of squares and auto correlation are extracted. The three steps of exudate segmentation are blood vessel detection, optic disc detection, exudate detection with the accuracy of 99.35%.Vijay M Mane et al. [7] proposed a system for detecting red lesions in diabetic retinopathy in retinal fundus images. This work proposed matched filtering for extraction of retinal vasculature and detection of candidate lesions. Features of candidate lesions like area, aspect ratio, perimeter, eccentricity, mean intensity, standard derivation, major axis length, minor axis length, compactness, equivalent diameter and roundness of object are extracted using classifier support vector machine. SVM extracts lesions and non-lesions in the database DIARETDB1 with the sensitivity 96.42%, specificity 100% and accuracy 96.62 %. Mohammad Aloudat and Miad Faezipour [8] presented a model by analyzing histograms for detecting blood vessels automatically as a first step of intraocular pressure (IOP). Simulation of the analysis was made by MATLAB. 50 images were taken as an input, for each image face selection, iris detection and eye segmentation were made. Iris was detected by Circular Hough Transform (CHT). Blood vessels are detected by adaptive histogram which finds the width of the vessel. The fragments of the images are classified using Support vector machine. Dr. Jaykurnar Lachure et al. [9] proposed a method for detecting diabetic retinopathy using morphological operations and machine learning. Microaneurysms and exudates are detected using SVM and KNN. Features are extracted using GLCM and structural features of classifications. SVM achieves greatest accuracy than KNN. Hybrid median filter improves the quality of the image and reduces noise. The CLACHE method is used to enhance the contrast. For the classification, the features to be extracted are entropy, contrast and homogeneity. The specificity and sensitivity is 100 % and 90% respectively. The database used for the evaluation is MESSIDOR. Aditya Kunwar et al. [10] proposed an algorithm for the detection of risk maculae edema using texture feature and classification using SVM. In this method segmentation, technique disk diameter around the macula center was extracted out. The combination of texture feature extraction for the region of interest around the macula and grading is done using SVM. The sensitivity, specificity and accuracy for the database MESSIDOR is 91%, 75% and 86% respectively. GLCM is used for texture analysis from co-occurrence matrix. The SVM classifies Normal and abnormal features. G. Mahendran et al. [11] investigated the severity level of diabetic retinopathy by detecting the lesion exudates. A SVM (support vector machine) and PNN (probabilistic neural network) are used to investigate the severity and the results are compared with the segmentation technique. In preprocessing, color space conversion, filtering, contrast enhancement are done along with the median filter to reduce noise, CLAHE is used to enhance contrast. Edge detection is done to identify the discontinuities. Kirsch operator is used to identify the edges and the direction of edges. SVM and PNN are used to classify the normal and abnormal images. With MESSIDOR database it gives 97.89% and 94.76% of accuracy respectively in SVM and PNN. R.A. Welikala et al. [12] proposed genetic algorithm associated with feature selection and dual classification for detecting the proliferative diabetic retinopathy. Two vessel segmentation methods like line operator and modified line operator are used which generates two binary vessel maps using SVM. Independent classifications are made and the combinations of the result gives the final decision. Feature are selected using genetic algorithm which observes the chromosomes providing the optimal solution. MESSIDOR database achieves the sensitivity of 0.91 and specificity of 0.96. Williamson et al. [13] observed the detection of diabetic retinopathy in the proliferative stage using a modified line operator and dual classification for vessel segmentation. The performance of Support vector machine is independent for each feature set. In preprocessing step, median filter is used to reduce noises. The feature sets includes number of vessel pixels, number of vessel segments, number of vessel orientations and vessel density. Sreeja K.A. et al. [14] reviewed the recent studies on Microaneurysm (MA) detection by using Microanuerysms candidate extraction and classification. The features extracted are color, brightness using artificial neural network (ANN), Support Vector Machine (SVM).The classification results categorizes the features into MA candidates and Non MA candidates. Meindert Niemeijer et al. [15] investigated the information fusion for diabetic retinopathy CAD in digital color fundus photographs which detected all relevant images using a CAD algorithms. This CAD technique is applicable in automatic screening problem. The feature extraction is based on the pixel classification. The preprocessing step is making difference in the field of view. SVM is achieved best performance. U. Rajendra Acharya et al. [16] proposed a model for identifying the stages of diabetic retinopathy using integrated index with texture parameters. Texture features such as homogeneity, correlation, short run emphasis, long run emphasis and run percentage. These features are given to support vector machine. This system is used to identify he unknown class with an accuracy of 85.2%, sensitivity 98.9 % and specificity 89.5%, and AUC of 0.972. M. Usman Akram et al. [17] proposed an algorithm for the identifying the microaneurysms and classifying them in the early stages of diabetic retinopathy. This works proposes a three stage filter banks. For classification, features extracted like shape color, intensity and statistics. A hybrid classifier is used by combining Gaussian mixture model, support vector machine and extension of multimodal median based approach to enhance the accuracy. A publicly available database is used. Karthikeyan Ganesan et al. [18] proposed the diabetic retinopathy detection algorithm using trace transforms on digital fundus images. In this work, a trace transform is used to model a human visual system. Features are extracted using Support Vector machine, probabilistic neural network and genetic algorithm. Features are extracted using the measurement of Mahanobolis distance. Using the MESSIDOR database the classification accuracy of SVM and PNN-GA is 99.44%, 99.12% respectively. Meindert Niemeijer et al. [19] investigated the image structure clustering for image verification of color retinal images in diabetic retinopathy screening. This work automatically determines the quality of the retinal images. A cluster filter bank has been used for the compact representation of the image structure. Statistical classifier is used to differentiate the normal images and low quality images. The feature sets are classified using Support Vector machine providing a ROC of 0.9968. Atul Kumar et al. [20]proposed a segmentation based approach for detecting exudates from retinal fundus image in which morphological preprocessing, image boundary tracing, and adoptive threshold using Otsu methodology. Features are extracted using 2DPCA (2 Dimensional Principal Component Analysis) and the classification is done using support vector machine. The database used is DRIVE. In the preprocessing stage, color space conversion, image normalization, adoptive median filtering, adoptive histogram equalization are performed. In the image boundary tracing stage edge detection, adoptive thresholding, optic localization, and vessel extraction are performed. The sensitive of the classification is 97.1% and the specificity is 98.3%. Désiré Sidibé et al. [21] observed the discrimination of retinal images containing bright lesions using sparse coded features and Support vector machine in which the retinal lesions such as micro aneurysms, exudates and drusen are detected. The proposed work shows that the sparse coded features with SVM is more effective in classifying the images when compared with the bag of visual word technique. The features extracted are color features, histogram of oriented gradient and local binary patterns. The retinal images from various sources are collected and achieves the specificity of 96.50% and sensitivity of 97.70%, then of 99.10% and 100% for drusen class, the exudates sensitivity 97.40% and 98.20%. Lili Xu et al. [22] proposed the support vector machine based method for identifying hard exudates in retinal images.Stationary wavelet transform (SWT) and GLCM are used for candidate extraction. SVM with Gaussian radial basis function is used as the classifier. In SWT high pass filter and low pass filters are given to the vectors in which a new sequence same length as the original is obtained. The classification accuracy, sensitivity and specificity is 84%, 88% and 80% respectively. Muhammad Nadeem Ashraf et al. [23] proposed the texture feature analysis of digital fundus images for early detection of diabetic retinopathy.For detecting the hemorrhages and micro aneurysms, the texture micro patterns of the region of interest is analyzed using a local binary pattern. Support Vector machine is used to identify the presence of Hemorrhages and Micro aneurysms by classifying the ROI as healthy and non-healthy. The texture features include basic, uniform, rotation invariant uniform.10 fold cross validation is used for SVM. The specificity, sensitivity and accuracy of the classifications are 85.99%,87.48% and 86.15% respectively. K.Narasimhan et al. [24] proposed an efficient automated system for detection of diabetic retinopathy from retinal fundus images using support vector machine and Bayesian classifier. The features extracted for detecting microaneurysms, hemorrhages and exudates are based on filtering, morphological transformation and region growing techniques. The segmentation of hard and soft exudates are performed using color histogram based clustering and the normal, abnormal blood vessels are classified using support vector machine and Bayesian network. Median filtering is used to remove noises and the effect of the intensity variation. Region growing partitions the image into number of regions in which the pixels closer to the grey values are extracted. With the DIARETDB0 database the classification accuracy is 95% using SVM and 90% using 95%. Pavle Prentasic et al. [25] proposed weighted ensemble automatic system for detecting exudates in fundus retinal images with associated preprocessing and candidate extraction algorithms. Simulated annealing is computing the weights for combining the results of the ensembled algorithms. Exudate regions are detected using the machine learning based classification algorithms. In the preprocessing stage, green channel extraction, CLAHE, gray world normalization, illumination correction, white top hat transformation and contrast enhancement are performed. SVM and clustering is used to classify the exudate region. Anum Abdul Salam et al. [26] proposed the optic disc localization using local based features and support vector machines which detects optic disc region and extracts the vessel based and intensity based features of the retinal images using blob detection algorithm. Finally, these extracted features are fed into support vector machine as optic disc bright lesions and non-optic disc bright lesions. Vessels are segmented using 2D Gabor Wavelets. If more optic disc regions are located Manhattan distance is calculated with mean value of the training feature matrix for optic disc is computed. The databases used are DRIVE, STARE, MESSIDOR and DIARETDB1achieves an accuracy of 97.5%, 97.5%, 99.6% and 100% respectively. B. Ramasubramanian et al. [27] presented a novel approach for automated detection of exudates using retinal image processing in which preprocessing is performed using CLAHE and Gaussian filter. The images are segmented soft clustering algorithm. The features are extracted using Scale invariant Feature transformation (SIFT) algorithm, Active support vector machine effectively classifies the image as exudates and nonexudates with larger datasets. SIFT is three dimensional spatial histogram which is very sensitive to noise. The database used is MESSIDOR which achieves a specificity and sensitivity of 99.6% and 99.96% respectively. Jiayi Wu et al. [28] proposed new hierarchical approach for Microanerysms Detection with Matched Filter and Machine Learning in which microanurysms are detected using multi scale and multi oriented sum of matched filter (MMMF). The machine learning classifier such as k nearest neighbor (KNN), local linear discrimination analysis (LLDA) and Support Vector Machine (SVM).The feature are based on maximum, minimum and average of MMMF response. SVM has given the higher sensitivity than other classifiers.Mohd Fazli Hashim et al. [29] investigated the detection of diabetic retinopathy lesions with the help of region based methodology. In this work, feature extractions are performed using two classifiers and Harlick features of textures.CLAHE is used for enhancing the contrast and the two classifiers are Support Vector Machine and Multilayer perceptron. The main contribution of the work is that all operations are performed as region by region. Features extracted are contrast, correlation, sum entropy etc. The databases used are DRIVE, DIARETDB1, and STARE. Comparing with multilayer perceptron, Support Vector Machine is providing greater sensitivity, specificity and accuracy as 82.39%, 62.42% and 71.94% respectively.Adarsh. P. et al. [30] proposed a multiclass based Support Vector Machine for the detection of diabetic retinopathy. In the proposed work, blood vessels, pathologies like exudates, Microanuerysms are identified using their texture features.A multiclass SVM is used to classify the abnormalities as mild, normal, moderate and severe.The databases used are DIARETDB1 and DIARETDB0.The average sensitivity of the two databases are sensitivity, specificity and accuracy are 90.6%,93.65% and 95.3% respectively.Xiaohui Zhang et al. [31] proposed a model using Support Vector Machine for the diagnoses of diabetic retinopathy by finding the abnormality hemorrhages in which the features are extracted by 2 Dimensional Principal Component Analysis (2DPCA). PCA is used for regulating the dimensions of the input space which gives better accuracy if there is moderate sample size of data. In this proposed work, top down support vector machine is used for the detection of hemorrhages. The hemorrhages are located first in a small window size and its boundary is segmented out accordingly with the window size. The transformation invariances used in the proposed work are illumination invariance and rotation invariance. The true positive value of SVM is 93.2%.Anam Tariq et al. [32]proposed observed a computer aided system for grading of diabetic retinopathy for the detection of microanuerysms, hard exudates, soft exudates, hemorrhages and cotton wool spots using the classifier Support Vector Machine.All candidate lesion are extracted using filter bank. The extracted features are shape, color, statistical and grey level filter. The filter bank values are calculated using different orientations. SVM is able to separate different regions in its hyperplane if they are linearly separable. The databases used are DIARETDB0 and DIARETDB1. The proposed method gives the accuracy of 98.16%, specificity of 98.36 and the sensitivity of 97.81% for the detection of red lesions. For the Bright lesions, the accuracy is 97.69 %, specificity

98.42% and the sensitivity is 95.15%. Handayani Tjandrasa et al. [33] investigated the non-proliferative diabetic retinopathy for detecting hard exudates using Support vector Machine with Soft Margin. The main contribution of the support vector machine is to find the optimum hyperplane which classifies the features in the largest margin. Hard exudates are segmented using morphological operations mathematically. Soft Margin Support Vector Machine is used to find the severity grading of the non-proliferative diabetic retinopathy. The feature vectors are area, perimeter and number centroids. Quadratic programming is used for finding the best hyperplane for Soft Margin Support Vector Machine. The accuracy of the proposed SVM is 90.54%. Balazs Harangi et al. [34] proposed the Morkovian model of segmentation in the detection of exudates in retinal images in which the identification of the exudates are performed using their shape and size. The Extraction of the features are done using grey scale morphology and the shapes are identified using Morkovian segmentation method with the inclusion of edge information In the Morkovian segmentation model Morkov Random Field (MRF) is used to identify the exact boundary of the hard exudates by decreasing the energy function. CLAHE is used to enhance the contrast while extracting the features of RGB fundus image.Finally SVM is used to classify the candidates as normal and abnormal in terms of true and false.The database used is DIARETDB1.The sensitivity of the proposed method is 0.73.

3. DISCUSSION

In table 1.the literature review of the support vector machine is presented in the form of survey table. Support Vector Machine can be both linear and non-linear. The support vector machine is well suitable for segmenting out and classifying the features like texture, entropy, rotation variation, color, shape size, contrast etc. Since Support vector machine is providing a greater probability of accuracy in all kind of databases like DIARETDB, MESSIDOR, DIA-RECT. Support Vector Machine is a non-probabilistic linear classifier which can easily analyze the data used for classification and regression analysis. SVM can be combined with other classifiers like artificial neural network, K-means clustering, probabilistic neural network etc. for the detection of diabetic retinopathy in the digital fundus image of retina. SVM classifier makes the ophthalmologists to detect the abnormalities much easier. SVM shows greater performance with the combination of clustering. In SVM, the original finite dimensional space can be mapped with the higher dimensional space. Infinite dimensional space of SVM which is a construction of set of hyper planes are very much associated with the classification and regression. SVM is broadly used in several medical applications. In most of the cases support vector machine can also be used for grading severity of the risk as well as the abnormalities of diabetic retinopathy. Binary Support Vector Machine is used for identifying very thin vessels from the fragments. Thus using Support Vector Machine with associated ensemble preprocessing techniques outperforms in the overall classification of the medical images.SVM separates different regions of each other in its maximum probability by the use of separating hyper planes if they are easily and linearly separable. Several Support Vector Machine has been used for the detection and classification utilization, namely, multiclass Support Vector machine, binary Support Vector Machine, Soft Margin Support Vector Machine etc. Support vector machine is highly capable of classifying the interested fragments which significantly differentiating the noises from the extracted features.

In this discussion, the preprocessing stage which is prior to the classification is performed with several filtering methodologies, contrast enhancement methodologies, Extraction of the features from the region of interest, segmentation process are the vital part of classification with greater performance measures. Multi-classifiers and ensemble classifiers makes the classification more effective with less computation. Support Vector machine with Bayesianclassifiers, Support Vector Machine with Radial Basis Function (RBF) can also be used for identifying the healthy and non -healthy features of the fundus images. All data processing enhancement is done with the support of Support Vector machine. If the data is linearly separable, then the there is a feasibility of optimization problem. Active Support Vector Machine performs effectively in the larger dataset. Support vector machine is capable of mapping implicitly its input values to highly

Table 1
The performance analysis on automatic Diabetic Assessment for Diabetic Retinopathy Using Support Vector Machines

Authors Name	*Feature Extraction*	*Merits*	*Demerits*	*Performance*	*Database*
S. Saranya Rubini et al. [1]	Intensity values	Can be used for all real world retinal images	Can make it fully automated.	Probability <0.005	–
Jyotiprava Dash et al. [2]	Vessel orientation	Tested with all available DRIVE databases.	Accuracy is not up to the level.	Accuracy 93.2%	DRIVE
Balint Antal et al. [3]	Backward search method	Can be extended with more components and classifiers		Sensitivity 90% Specificity 91% Accuracy 90%	MESSIDOR
Adeel M. Syed et al. [4]	Texture, shape, colour	Extracted all possible regions	Tested with small database	Sensitivity 94% Specificity 97% Accuracy 96%	–
Jos´e Tom´as Arenas-Cavalli et al. [5]	–	Fully operational	Action buttons and display are not available	Sensitivity 91.9% Specificity 65.2%	Health center
T. Ruba et al. [6]	Contrast, Energy, Entropy, Correlation	Effectively works even in a poor computing system	Can be tested with multi classifiers.	Sensitivity 78.57% Specificity 86.36% Accuracy 99.35%	MESSISOR
Vijay M Mane et al. [7]	Area, aspect ratio, perimeter, eccentricity, compactness, perimeter, standard deviation	Easily identifies lesions and non-lesions	Not automated	Sensitivity 96.42% Specificity 100% Accuracy 96.62%	DIARETDB1
Mohammed Aloudat [8]	Features of Eye, Iris, Face	Can get clear and Exact view of veins.	Programmed division is not immaculate	–	From Hospitals
Dr. Jaykurnar Lachure et al. [9]	Energy, Contrast, Entropy, Homogeneity and Area.	Severity grading can be decided	Inverted image is used	Specificity 100% Sensitivity is more 100%	MESSIDORDB-Rect
Aditya Kunwar et al. [10]	Disc diameter	Reduces computational time	Immediate change around 1disc diameter	Sensitivity 91% Specificity 75% Accuracy 86%	–
G. Mahendran et al. [11]	Contrast, cluster shade, energy, entropy, Homogeneity.	Does not affect the vision of the patients.	Severity has not been calculated using the distance of the fovea	Accuracy 97.89% for SVM and 94.76%	MESSIDOR
R.A. Welikala et al. [12]	Number of pixels, vessel segmentation, vessel orientation and vessel density	Dual classification	Risk of causing overfitting	Sensitivity 91.38% Specificity 96%	MESSIDOR
R.A. Welikala et al. [13]	Number of vessel pixels, Vessel segments, Vessel orientation, vessel density	Provides per Patch basis analysis	New vessel delineation has not been evaluated	Sensitivity 86.2% Specificity 94.4%	MESSIDOR
Sreeja K.A. et al. [14]	Colour, brightness	Different automated detections are examined	Few images are manually labelled	–	–

(*contd...*)

(*Table 1 contd...*)

Authors Name	*Feature Extraction*	*Merits*	*Demerits*	*Performance*	*Database*
Meindert Niemeijer et al. [15]	Lesion features	Diagnosed multiple scales of multiple types of abnormal-ities	Eye level informat-ion fusion is not possible here	ROC 0.881	–
U. Rajendra Acharya et al. [16]	Homogeneity, Correlation, short run emphasis	Only one integrated index to check normal.	Tested with limited images	Accuracy 100%	MESSIDOR
M. Usman Akram et al. [17]	Shape color, intensity statistics	Combined classifiers	Databases are used only at the lesion level	–	DIARETDB1 DIARETDB0
Karthikeyan Ganesan et al. [18]	Texture	Multiple classifiers increases the per-formance	No difference of lesions and other diseases	Accuracy 99.12%	MESSIDOR
Atul Kumar et al. [20]	–	Combination of classifiers improves the performance	Success rate can be improved.	Sensitivity 97.1% Specificity 98.3%	DRIVE
Désiré Sidibé et al. [21]	Color, SIFT, HOG, LPB	Does not require preprocessing.	Size and location of lesion are not identified	Sensitivity of exudates 97.40% Specificity 98.20%	–
Lili Xu et al. [22]	Textures	Optimal parameter combination incre-ases the accuracy	Tested with small database	Accuracy 84% Sensitivity 88% Specificity 80%	Hospital laboratory
Muhammad Nadeem Ashraf et al. [23]	Basic texture, uniform texture, rotation invariant texture.	Reduced preprocessing	Energy and entropy are not used as feature	Sensitivity 87.48% Specificity 85.99%	–
K. Narasimhan et al. [24]	Area, circularity, aspect ratio	Flexible and simple. Fixed protocol is used	Heterogeneous database can be used	AUC 0.95	DIARETDB0
Pavle Prentasic et al. [25]	Size, shape, location	Combined preprocessing	Can improve the sensitivity	Sensitivity 0.75 F-score 0.76	DRiDB
Anum Abdul Salam et al. [26]	Vessel density, vessel orientation, intensity	–	–	97.5% 97.5% 100% 99.6%	STARE DRIVE DIARETDB1 MESSIDOR
B. Ramasubramanian et al. [27]	Texture features like entropy, energy, contrast, correlation	Does not require ant retraining	Training is done only once.	Sensitivity 99.96% Specificity 96.6%	MESSIDOR UTHSC SA
Jiayi Wu et al. [28]	–	Identifies all possible features	Tested with limited dataset	–	–
Mohd Fazli Hashim et al. [29]	Contrast, correlation, sum Entropy tec.	No normal segmentation and normal structure removal is needed	Accuracy can be improved	Sensitivity 82.39%, Specificity 62.42% Accuracy 71.94%	DRIVE DIARETDB1 STARE
Adarsh. P et al. [30]	Texture features and area of vessels and exudates	Tested with Large database	Computation is not simple	Sensitivity 90.6%, Specificity 93.65% Accuracy 95.3%	DIARETDB1 DIARETDB0

(*contd...*)

(*Table 1 contd...*)

Authors Name	*Feature Extraction*	*Merits*	*Demerits*	*Performance*	*Database*
Xiaohui Zhang et al. [31]	Rotation invariance Illumination invariance	Post processing is used for segmenting the boundary	Accuracy is not up to the mark	True positive 93.2%	From Health Center
Anam Tariq et al. [32]	Shape, Statistical, grey level, color	Fully Automated	Grading the severity is not performed	Accuracy Of Red Lesions 98.16	DIARETDB1 DIARETDB0
Handayani Tjandrasa et al. [33]	Area, perimeter, centroid	Quadratic programming is used	Accuracy can be improved	Accuracy 90.54%	–
Balazs Harangi et al. [34]	Shape, size and grey level values.	Segmentation is done with edge information	Sensitivity is very less	Sensitivity 0.73	DIARETDB1

dimensioned feature spaces. If the data is notlabeled supervised learning is not applicable for classification and in such cases unsupervised learning is used.

4. CONCLUSION

In this survey paper,, an automatic assessment system of diabetic retinopathy using Support Vector Machine has been discussed with various preprocessing techniques including post filtration followed by the extraction of several features such as color, shape, intensity, entropy, energy, texture etc. Classification of abnormalities from normal fundus retinal images can be performed with various classifiers. From observation, Support vector Machine is the best classifier for extracting and classifying the abnormalities in retina like microanuerysms, hard exudates, soft exudates, neovascularization, and macular edema in an effective manner. Support vector machine classifier achieves a greater accuracy in detection of diabetic retinopathy which makes the diagnosis and screening of retinal images for the ophthalmologists in an easier way.

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