



A COMPARATIVE ANALYSIS OF DIFFERENT TECHNIQUES FOR DIABETIC RETINOPATHY DETECTION USING FUNDUS IMAGES

D. Ashok kumar¹, A.Sankari²

Abstract- In recent decays, diabetic retinopathy is an important eye disorder that may cause low vision if its diagnosis is late. Different feature extraction and classification methods have been studied in literature survey for the purpose of improving diabetic retinopathies accuracy in the screening test. In this paper, three hybrid types of diabetic detection approaches are analyzed namely 1) Hybrid MinIMas With Sparse Principal Component Analysis(HM: SPCA), 2).Hybrid Morphological-based Scanning Window Analysis and Hit-or-Miss Transformation (HMSWA-HMT),3.Low rank based dictionary based learning (HMSWA-HMT). To this end, in this comparative analysis of different algorithms is performed to select most appropriate method for retinopathy detection with various hybrid segmentation, feature extraction and classification method. Each technique is compared with evaluation metric of accuracy, sensitivity and specificity. Simulation results show that performance of individual procedure and can be used to decide the factor in algorithm selection for future research.

Keywords – Diabetic Retinopathy, Segmentation, Feature Extraction, Classification.

1. INTRODUCTION

In recent years, Diabetic retinopathy (DR) becomes major cause for blindness, which is also known as eye diseases [1]. Regular screening is recommended to diabetic patients for early diabetic diagnosis, which can help them to prevent loss of sight. Furthermore, a huge amount of diabetic patients are undergone screening process, which leads to increase the workload for ophthalmologists. In order to overcome this problem, an automatic DR detection is necessary to improve the diagnosis speed and accuracy of detection [2].

In first phase two key contributions are invented towards DR detection system. In this paper, a novel MinIMas overlap algorithm is proposed to initialize the OD center in low contrast fundus image. Most of the prior approaches have not been achieved successful results more than 91% on real public dataset [3]. But our segmentation approach achieves 100% accuracy in dataset DRIVE [4] and 98.68% accuracy in STARE dataset [5] for OD detection. Additionally, most existing algorithms [5] has not been robust to field of view (FOV) variation of input images. Also, some of the prior methods affect from image over-training since they follow the vessel-branch networks after extracting the blood vessels, looking for merging patterns in images that do not have a visibly bright OD, thus resulting in false detections [6]. Our segmentation algorithm is trained with varying FOV and illuminations images and thus, it does not affect from over-training. Also, the MinIMas overlap algorithm does not fail in the presence of exudates which similar to bright spot OD detection.

2. LITERATURE SURVEY

Various schemes for the segmentation of the retinal blood vessel and classification of the retinal images based on the type and severity of the diseases are developed [3-10]. Nayak et al. [7] proposed a method for the automatic classification of retinopathy based on the Artificial Neural Network (ANN) for the early detection of the DR. The existing methods enable accurate detection of DR at the early stages. However, these techniques require high computational complexity and large training to the classifiers [8]. Detection of the significant points such as terminal, intersection and bifurcation points provides information about the vascular structure and facilitates efficient diagnosis of the retinal disease [9].

Nivetha et al. [10] proposed a new method for finding the exudates patches from the retinal blood vessels during DR treatment. The GLCM features are extracted and features are processed using Probabilistic Neural Network (PNN) classifier. Morphological operations are applied to the abnormal image for extracting blood vessels and FCM is applied to detect the exudates in the blood vessels. Sisodia et al. [11] applied preprocessing and feature extraction method for the detection of DR using machine learning techniques. Totally, 14 features are extracted from the normal and diabetic retinal fundus image. Among them, seven features such as exudate area, blood vessel area, bifurcation point count, Shannon Entropy, optic distance, hemorrhage area and MA(microaneurysms) area are extracted to identify the normal and abnormal image. Saha et al. [12] proposed a new diagnosis system for the detection of bright and dark lesions using Naïve Bayes and SVM classifier. The detection of MAs and blood vessel is eliminated by using the improved machine learning algorithms. Cortés-Ancos et al.

¹ Department of Computer Science, Government Arts College, Trichirappalli-620 022, India

² Department of Computer Science, Research Scholar, Bharathidhasan University, Trichirappalli-620 022, India

[13] integrated MA extraction method and classification system for detecting the diabetic retinopathy. The methodology detected the low contrast MAs with lower false positive rates. Lachure et al. [14] proposed a system for detecting retinal micro-aneurysms and exudates for automatic screening of diabetic retinopathy using SVM and KNN classifier. The morphological operations are performed to find MA and features such as GLCM and structural features are extracted for classification of disease severity as normal, moderate and severe.

All mentioned prior approaches show different classification results, finding a perfect technique to classify the fundus image in DR screening stages. Also these approaches are having a common problem that non-Mas features vary in a wide range. To overcome these issues, Hybrid approaches are invented and compared using image segmentation, Feature extraction and classification approach. All these hybrid techniques are tested and optimized for DR detection using fundus images. To determine best technique for detection on fundus images, these hybrid techniques are compared in terms of accuracy, sensitivity and specificity. In this research DIARETDB1 dataset are used which is publically available from internet.

The remaining section of this paper is structured as follow: Section 2 explains the different hybrid methodology for segmentation, feature extraction and classification in DR systems. Performance comparisons of individual technique are discussed in Section 3 in terms of accuracy, sensitivity and specificity. Section 4 concludes the paper with best hybrid system for DR detection on fundus image.

3. DESIGN OF PROPOSED SYSTEM

Hybrid Methodology

In this section, the following three hybrid methodologies are discussed on 15 fundus images from DIARETDB1 dataset.

- 1) Hybrid MinIMas with Sparse Principal Component Analysis (HM: SPCA)
- 2) Hybrid Morphological-based Scanning Window Analysis and Hit-or-Miss Transformation (HMSWA-HMT)
- 3) Low rank sparse representation on HMSWA-HMT

3.1 HM: SPCA

The complete structure of MA detection, implementation flow is proposed HM-SPCA method in Figure 1. It contains four stages of process named as, 1) Preprocessing 2) Segmentation 3) Feature Extraction 4) Classification. Firstly, preprocessing algorithm is applied to contrast enhancement and convert an image into more suitable form for next processing stage. Next, segmentation of optical disc area is founded by MinIMas algorithm and morphological based blood vessel extraction is applied on fundus image. Furthermore, detection a foreground images consisting of subtracting the unwanted details of OD and blood vessels from background. Foreground image is consisting of red and bright lesion values. After that, all possible features are extracted from each candidates based on shape based, color and intensity based and Gaussian features. Finally, proposed HM-SPCA modal is used for feature training and classification.

3.1.1 Preprocessing Stage

In this section image preprocessing works are discussed for noise removal and contrast enhancement. In real world fundus images are affected by noise, intensity variation and low illumination. As states in [15], Green channel image are more contrast to detect MA in fundus images. So, Green channel image is extracted and adapted to contrast enhancement based on contrast limited adaptive histogram equalization (CLAHE) [16] approach in order to make hidden features are more visible. Finally, smoothing filter is applied on enhanced images with width 5 and standard deviation 1 for reducing the effects of noise on images.

3.1.2 Segmentation

In first stage of our proposed method, the back ground of all fundus images are consisting of optical disk (OD) and blood vascular arc is detected and masked out.

3.1.3 OD Detection using MinIMas overlap algorithm

Mathematically, two sub image lesion regions are extracted from image, named as red lesion and bright lesion . Then, we define an overlap function, that uses a predefined constraint (ne), such that is pixels of are located in the neighborhood of pixels in, overlapping regions (R) are identified in. Let be the l overlapping regions discovered. Now, at individual, we describe a circular mask whose center is at the centroid of and radius is the maximum major axis length of all regions in R. Then, we estimate the sum of pixel intensities of all the pixels within individual such circular mask described by a function intensity. Also, we compute the solidity of individual region by,

$$Solidity (S) = \frac{Area (R_i)}{Convex Area (R_i)} \leq 1 \quad (1)$$

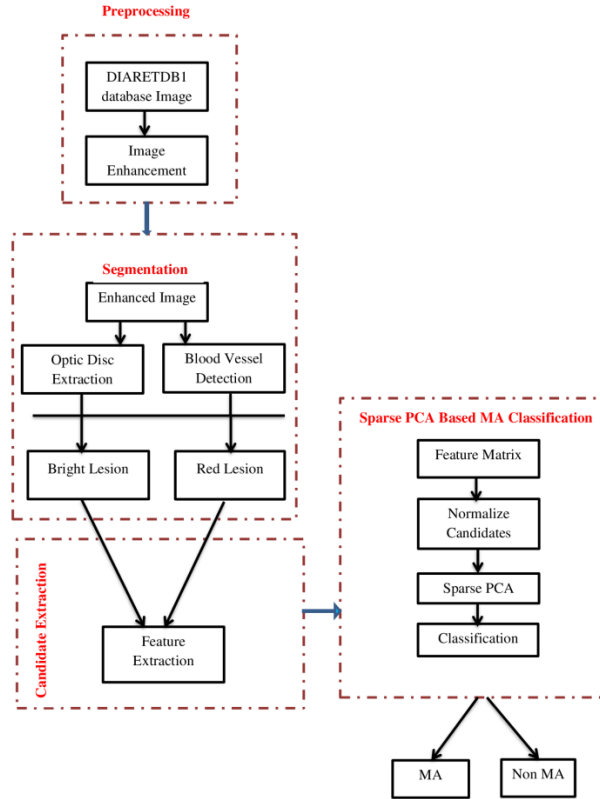


Figure -1 Proposed Method

Where convex area is states that the smallest convex polygon's area which contains the particular region of interest. The OD region will be a region with minimal intensity and maximal solidity [17]. Thus,

$$R_1 = \max_{intensity} (R_i)$$

$$R_2 = \max_{solidity} (R_i)$$

$$R_{OD} = R_1 \cup R_2$$

$$\text{such that, } R_i = \text{overlap}(I_b, I_r, ne) \quad (2)$$

3.1.4 Blood Vessel Detection

Next, Major portion of blood vessels are masked out from fundus image, since OD is extracted. For each image, median filter is applied to achieve gradient smoothed background from green channel image [18]. Shade corrected image can be estimated by subtraction of background image from green channel image [18].

$$I_{Sc} = I_{green} - I_{bg} \quad (3)$$

3.1.5 Candidate Extraction

In this section, features of all candidate regions are extracted based on shape-based, intensity and color based and Gaussian filtering based. Table 1 describes shape based features. Color and intensity based features are described in Table II. Finally, Gaussian filtering based features is defined in Table III. In summary total 36 features have been extracted in for each candidate regions.

Table 1 Shape Based Features

SS.N	Features
0	
1	Area
2	Perimeter
3	Aspect Ratio
4	Circularity
5	Compactness

Table 2 Color and Intensity Based Features

1	Total Intensity_Green Plane
2	Total Intensity_Shade Corrected image
3	Mean intensity_Green Plane
4	Mean intensity_Shade Corrected Image
5	Normalized Intensity_Green Plane
6	Normalized Intensity_Shade corrected Image
7	Normalized Mean Intensity_Green Plane
8	Normalized Mean Intensity_ Shade corrected Image
9	Mean contrast of Edge pixels
10	The mean intensity of I_{bg}
11	Standard Deviation of I_{bg}

Table 3 Gaussian Features

1	Mean and standard deviation of Gaussian filter
2	Correlation co-efficient of candidates

3.1.6 Sparse Classification

Subspace orthogonal matching pursuit (SOMP) method is used to increase the speed up the classification process, which will efficiently classify MA from Non- MA candidates. Consider N images with MX N feature matrix, our classification steps are follows:

Training matrix is constructed by extracted features for all N images.

i.e.,

Each contains features for both bright lesion and red lesions.

For each test image y, is extracted and coefficient vector is obtained by orthogonal matching pursuit algorithm.

The recognition coefficient of each candidate is related to the testing sample to calculate the residual:

$$r_i = \|y - F_y x_i\|_2, \quad i = 1, 2, \dots, N.$$

Finally, recognition result is identified by,
 $Identity(y) = argmin(r_i), i = 1, 2, \dots, N,$

This SOMP matching method is greatly decrease the size of the training sample, which makes it easy to calculate sparse coefficients. Further, reduces the number of the loop count and improve the recognition rate with minimum error rate for large size of testing sample.

The method SOMP is used to greatly decrease the size of the calculated sample, which makes it easy to calculate sparse coefficients and error results in the comparison, and reduces the number of the loop count accordingly, improving the precision level than the calculation of samples with larger size. More important, this method can significantly improve the recognition result.

3.2 H-MSWA-HMT

The images obtained from the DIARETDB1 database is applied as input to the preprocessing step. The image enhancement is applied as a preprocessing technique for eliminating the unwanted distortion present in the retinal image. A hybrid method of morphological-based Scanning Window Analysis and Hit-or-Miss Transformation (H-MSWA-HMT) is applied for the segmentation of image. After segmenting the ridge end, bifurcation points and vessel ends in the retinal image, the optimal features are extracted from the segmented image. The difference Subspace Sparse representation based Classification (DSSRC) is applied for the classification of the retinal images into normal (MA) and abnormal (non-MA) images. Due to the segmentation of the ridge end, bifurcation points and vessel ends and extraction of the optimal features, the normal and abnormal images are classified efficiently.

3.2.1 Image segmentation

Segmentation process divides the whole image into multiple subsections for analyzing the region of interest (ROI) in the image. The segmentation process is stopped, when the object of interest is found.

3.2.2 MSWA

Morphology is highly suitable for the analysis or detection of shapes in the images. Erosion and dilations are the two main morphological procedures [33]. The dilation adds the pixels to the boundary of objects in the image and erosion removes the pixels from the boundaries. The opening process is the structured removal of boundary pixels in the image region and closing is the structured filling of the boundary pixels. The objects in the image are processed based on its shape characteristics. Usually, the size of the structuring element is 3×3 . The structuring element is initially located at the center pixel and shifted over the image. The structuring elements are compared with the set of original pixels. The pixel lying below the origin of the structuring element is set to 1, based on the matching of double sets of structuring elements with the specific condition determined by the morphological operator. Otherwise, the pixel value is fixed to zero. These morphological operators are used for selecting or suppressing the features of certain shape or selecting the objects with a particular direction. The more refined operators consider zeros, ones and don't care's in the structuring element. The morphological operators can also be applied to gray level images to reduce noise or enhance the image.

3.2.3 SWA

The SWA is used to stimulate the characteristics after setting the thinned image to a single pixel [19]. Similarly, all the lines are reduced to one pixel. A 3×3 window is used for obtaining the information about the ridges and bifurcation. The thinned image is scanned from the top to bottom and left to the right by using the window. If the center pixel is found to be black, the presence of any ridges or bifurcation is detected. Hence, it is clear that only two pixels in the scanning window result in the end of the ridges. If the pixel count is greater than or equal to four, it leads to be a bifurcation. The scanning window of 70×70 is used for the localization of optical focal point. The SWA method provides better localization irrespective of the complex disorder patterns in the image. This minutiae information is used for the recognition purpose.

3.2.4 Hit-or-miss transformation (HMT)

The HMT process is applied for discriminating the exact patterns in a binary image [20]. It is applied for detecting the significant points on an image by examining the image with a set of structuring element. The structuring element comprises two elements B_FG representing the set of pixels that match with the foreground and B_BG defining the set of pixels matching with the background. Both the background and foreground structuring elements are separate sets and they share the same origin, i.e., . The HMT determines whether the origin belongs to the [35]. The HMT of a set 'X' by a complex structuring element is described as [13].

Where \bar{X} is the complement set of X.

Algorithm 1: Finding Bifurcation Point

Input: Image of the retinal skeleton 'f', circular window 'W'

Output: Binary image of the terminal points T , binary image of bifurcation points B and binary image of the crossing points C

Initialize

m-connectivity conversion;

terminal point detection;

bifurcation point detection;

crossing point detection;

Complex crossing point detection

if (f_{BP_i} is connected with f_{BP_j}) & ($loop(f_{BP_i})$)

;

end

end

end

end

crossing point detection;

3.3 Low-rank Sparse Representation

Initially, the input retinal images are preprocessed for enhancing the image quality. The HMSWA-HMT is applied for the segmentation of retinal image. The morphological operators are applied to minimize the noise or enhance the image. The SWA method provides better localization irrespective of the complex disorder patterns in the image. The HMT detects the significant points such as bifurcations points, ridge and vessel ends that are able to define the vascular skeleton. Group-based low-rank sparse representation is applied for extracting the candidate features from the segmented images. The DSSRC

method focuses on improving the distinguishability for the classes rather than the representation capability for the samples. The DSSRC is applied for the classification of the retinal images into normal and abnormal images.

3.3.1 Group-based low-rank sparse representation

In the dictionary learning algorithm, the images are denoted as a linear combination of atoms in a dictionary ‘D’. The sparse representation of the input image ‘y’ is learned through the optimization problem [21]

$$\min_x \|x\|_0 \quad (1)$$

Where $\|x\|_0$ denotes $\|x\|_0$ norm that provides the number of non-zero entries in the vector ‘x’. K-SVD algorithm is one of the methods for learning a dictionary from the training samples. K-means clustering is considered as a method for sparse representation to find the best possible codes for representing ‘y’ using the nearest neighbor method

$$\arg \min_{D,x} \|Y - DX\|_F \quad (2)$$

The sparse representation $\|x\|_0$ applies K-means algorithm to ensure one atom in the dictionary. As the K-SVD algorithm intends to achieve linear combinations of atoms, the constraint is updated in such a way that $\|x\|_0 \leq T$ and $\|x\|_1 \leq T$,

$$\arg \min_{D,x} \|Y - DX\|_F \quad (3)$$

Where x_i are sparse codes of ‘N’ input images. and T restricts the input to require less than T items in its decomposition. ‘k’ denotes the number of atoms in the learnt dictionary and ‘n’ indicates the number of samples. This equation is solved for learning both the sparse codes and dictionary alternatively and iteratively. The sparse representation of the input image is obtained as the result.

The Low Rank Representation (LRR) is used for finding the LRR of the data using a given dictionary. It can recover the data from multiple subspaces and acquire the global structure of data. The objective function of Group-based Sparse and Low-Rank (GSLR) representation is expressed as

$$\min_{D,Z} \frac{1}{2} \|X - DZ\|_F^2 + \lambda_1 \sum_{i=1}^n w_{g_i} \|z_i\|_1 \quad (4)$$

Such that

Where Z is a matrix comprising members of $\mathbb{R}^{n \times k}$. ‘Z’ and ‘D’ denote the representation matrix with the group-based sparse and low-rank regularization and the dictionary to be learned. z_i refers to the ith group of Z, D_i denotes the ith column of D, λ_1 and w_{g_i} are the parameters that balance three terms in the objective function. λ_1 represents the regularization parameter for the ith group. $\|z_i\|_1$ with spatial groups g_i . $\|D_i\|_F$ represents the ith column of D, $\| \cdot \|_F$ and $\| \cdot \|_1$ denote the Frobenius norm and the $\| \cdot \|_1$ norm of the matrix. $\| \cdot \|_*$ represents the nuclear norm of a matrix, i.e., the sum of singular values of matrix. The optimal representation matrix ‘Z’ is computed for a dictionary ‘D’ and the dictionary is solved with fixed Z.

Optimization of ‘Z’

The representation matrix ‘Z’ is solved with the current dictionary ‘D’. The optimization problem is modeled by

$$\min_{D,Z} \frac{1}{2} \|X - DZ\|_F^2 + \lambda_1 \sum_{i=1}^n w_{g_i} \|z_i\|_1 \quad (5)$$

Such that

The objective function is separable with various spatial groups g_i . Hence, Z can be solved for each independently. Without the generality loss, z_i is simply expressed as $z_i = D_i^{-1} X_i$ with $\|z_i\|_1 \leq T$. The subproblem yields

$$\min_{z_i} \frac{1}{2} \|z_i\|_1 \quad (6)$$

Such that

Where z_i derives from the group ‘g’ of X. The above equation comprises reconstruction error, low-rank representation and sparsity of z_i , λ_1 and w_{g_i} reflect the tradeoff among these three components. Two auxiliary matrices ‘E’ and ‘W’ are added. The problem is reformulated as

$$\min_{Z,E,W} \frac{1}{2} \|X - DZ\|_F^2 + \lambda_1 \sum_{i=1}^n w_{g_i} \|z_i\|_1 \quad (7)$$

Hence, the augmented Lagrangian function is expressed as

$$\mathcal{L}(Z_g, W, E, Y_1, Y_2, \mu) = \frac{1}{2} \|E\|_F^2 + \beta_1 \|Z_g\|_* + \beta_2 \|W\|_1 + Q(Z_g, W, E, Y_1, Y_2, \mu) - \frac{1}{2\mu} (\|Y_1\|_F^2 + \quad) \quad (8)$$

Where μ denotes the penalty parameter, η_1 and η_2 are matrices of Lagrangian multipliers, $\text{tr}(\cdot)$ denotes the trace of a matrix and

$$Q(Z_g, W, E, Y_1, Y_2, \mu) = \frac{\mu}{2} \left(\|X_g - DZ_g - E + \frac{Y_1}{\mu}\|_F^2 \right)$$

The Q is quadratic and approximated by its first order approximation while adding a proximal term. The above equation is unconstrained and minimized by updating the variables Z_g , W and E simultaneously. At this point, the Z_g , W and E is evaluated as

$$Z_g^{k+1} = \mathcal{D}_{\frac{\beta_1}{\mu^k \eta_1}} \left(Z_g^k + \frac{1}{\eta_1} \left[D^T \left(X_g - DZ_g^k - E^k + \frac{Y_1^k}{\mu^k} \right) \right] \right) \quad (9)$$

$$(10)$$

Where \mathcal{D} represents the partial differential of Z_g with respect to Z_g , \mathcal{S}_τ denotes singular value thresholding operator. Let $C_1 = Z_g^k + \frac{1}{\eta_1} \left[D^T \left(X_g - DZ_g^k - E^k \right) \right]$, the rank of the matrix C_1 be r . $C_1 = U \Sigma V^T$, the singular value decomposition of C_1 be

Then, Z_g^{k+1} satisfies

$$Z_g^{k+1} = \mathcal{S}_\tau \left(C_1 \right) \quad (11)$$

Where, \mathcal{S}_τ shrinkage operator is defined as

Optimization of 'D'

In the dictionary update step, Z is fixed and 'D' is optimized by solving

$$\min_D \frac{1}{2} \|X - DZ\|_F^2 \quad (12)$$

That is quadratic with respect to the dictionary. The dictionary atoms with larger than the unit norm are projected inside the non-negative than a unit ball. When the gradient of the objective function equals zero,

$$(13)$$

The above equation suffer from the computation of inverse of $Z^T Z$, the dictionary atoms are updated iteratively. Let d_i , where Z_j represents the j th row of Z in the column form. The objective function of the i th atom yields

. The objective function is rearranged as

$$\min_{d_i} \frac{1}{2} \left\| d_i - \frac{R_i Z_j^T}{\|Z_j\|_2} \right\|_2^2 \quad (14)$$

Whose solution is

$$(15)$$

Where $\mathcal{P}_{\text{non-neg}}$ denotes the projection inside the non-negative orthant of a unit ball [33].

In the dictionary learning process, Z and D are updated alternately. The iteration of the algorithm stops, when the relative error of two successive objective functions is less than the tolerance.

Input: The matrix 'X' and parameters

Output: Z and D

Step 1: Initialize Z and D

Step 2: while Convergence is not attained do

Step 3: Solve D with respect to Z

Step 4: Update Z with fixed D by solving eqn (12)

Step 5: Update 'k' by

Step 6: end while

4. EXPERIMENTATION AND RESULTS

Performance Comparison:

In this section, performance of our three hybrid DR system is analyzed in term of following metrics.

$$Sensitivity (SEN) = \frac{TP}{TP + FN}$$

$$Specificity (SPEC) = \frac{TN}{TN + FP}$$

$$Accuracy (Acc) = \frac{TP + TN}{TP + TN + FP + FN}$$

Here,

TP – True Positive

FP – False Positive

TN – True Negative

FN – False Negative

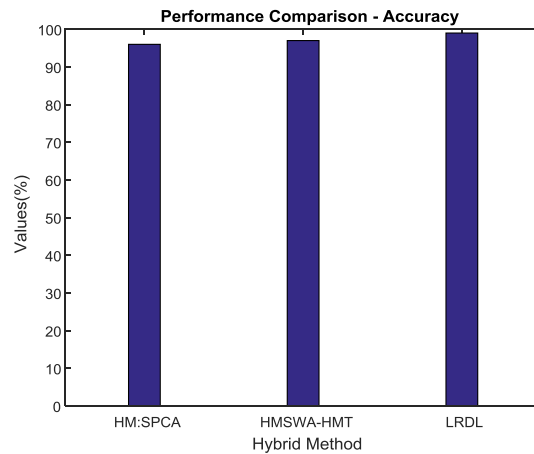


Figure 2 Accuracy comparison of hybrid method

Figure 2 depicts the comparative analysis of the accuracy for different hybrid classification methods. The third phase low rank based learning method with HMSWA-HMT approach yields maximum accuracy rate than the HM:SPCA and HMSWA-HMT hybrid methods. Due to the segmentation of the ridge end, bifurcation points and vessel ends and extraction of the optimal features, the normal and abnormal images are classified efficiently. This facilitates the efficient diagnosis of the DR.

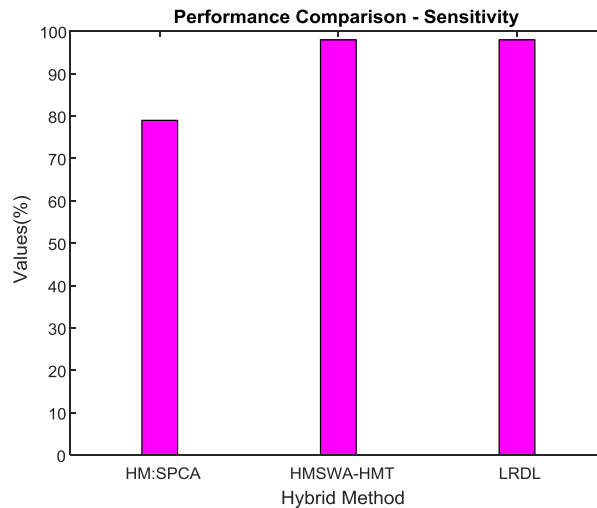


Figure 3 Sensitivity comparison of hybrid method

Figure 3 shows that the low rank based dictionary learning based DR classification yields maximum sensitivity. Due to the extraction of the optimal features, the normal and abnormal images are identified well.

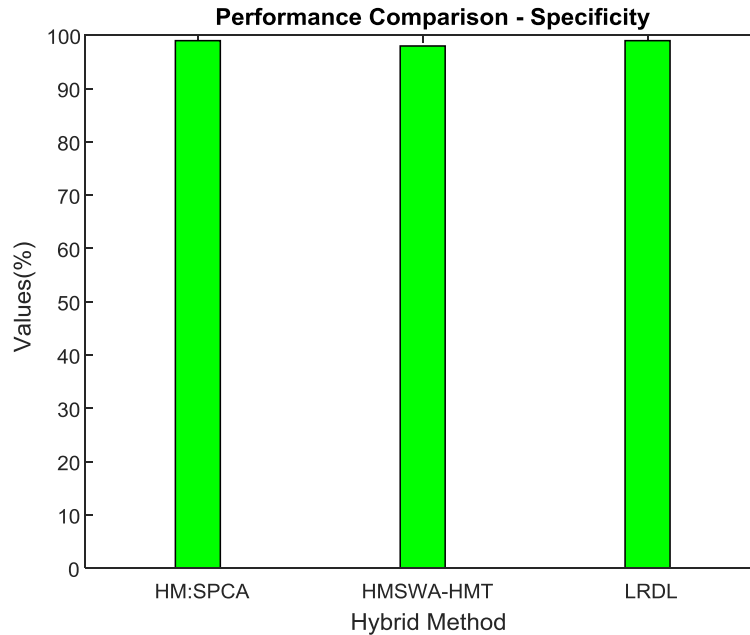


Figure 4 Specificity comparison of hybrid method

Figure 4 illustrates the specificity (99%) of LRDL with HMSWA-HMT have maximum value when compared with HM-SPCA (79%) and HMSWA-HMT (98%).

5. CONCLUSION

In this paper, three hybrid method's performance is studied in the application of retinopathy detection using fundus images. Each hybrid method is structured with suitable feature extraction and classification parameters. From this survey, we can say suitable hybrid method in DR classification for best performance. Based on the results, low rank dictionary learning with HMSWA_HMT method having acceptable performance on accuracy, sensitivity and specificity rather than other two methods.

6. REFERENCES

- [1] B. Antal, A. Hajdu, "An ensemble-based system for microaneurysm detection and diabetic retinopathy grading," *IEEE transactions on bio-medical engineering*, vol. 59, no. 6, pp. 1720-6, 2012.
- [2] D. B. Mukamel, G. H. Bresnick, J. C. Dickinson, D. R. Cole, "A screening approach to the surveillance of patients with diabetes for the presence of vision-threatening retinopathy," *Ophthalmology*, vol. 107, no. 1, pp. 19-24, 2000.
- [3] A.-H. Abdel-Razik Youssif, A. Ghalwash, and A. Abdel- RahmanGhoneim, "Optic disc detection from normalized digital fundus images by means of a vessels' direction matched filter," *IEEE Transactions on Medical Imaging*, vol. 27, no. 1, pp. 11–18, jan. 2008.
- [4] J. Staal, M. Abramoff, M. Niemeijer, M. Viergever, and B. van Ginneken, "Ridge based vessel segmentation in color images of the retina," *IEEE Transactions on Medical Imaging*, vol. 23, pp. 501–509, 2004.
- [5] A. Hoover, , and M. Gold baum, "Locating the optic nerve in retinal image using the fuzzy convergence of blood vessels," *IEEE Transactions on Medical Imaging*, vol. 22, August 2003.
- [6] F. terHaar, "Automatic localization of the optic disc in digital colour images of the human retina," M.S. Thesis in Computer Science, Utrecht University, Utrecht, 2005.
- [7] J. Nayak, P. S. Bhat, R. Acharya, C. M. Lim, and M. Kagathi, "Automated identification of diabetic retinopathy stages using digital fundus images," *Journal of medical systems*, vol. 32, pp. 107-115, 2008.
- [8] P. K. R. Yelampalli, J. Nayak, and V. H. Gaidhane, "Blood Vessel Segmentation and Classification of Diabetic Retinopathy Images using Gradient Operator and Statistical Analysis," in *Proceedings of the World Congress on Engineering and Computer Science*, 2017.
- [9] S. Morales, V. Naranjo, J. Angulo, A. Legaz-Aparicio, and R. Verdú-Monedero, "Retinal network characterization through fundus image processing: Significant point identification on vessel centerline," *Signal Processing: Image Communication*, 2017.
- [10] C. Nivetha, S. Sumathi, and M. Chandrasekaran, "Retinal blood vessels extraction and detection of exudates using wavelet transform and pnn approach for the assessment of diabetic retinopathy," in *Communication and Signal Processing (ICCSPP)*, 2017 International Conference on, 2017, pp. 1962-1966.
- [11] D. S. Sisodia, S. Nair, and P. Khobragade, "Diabetic Retinal Fundus Images: Preprocessing and Feature Extraction for Early Detection of Diabetic Retinopathy," *Biomedical and Pharmacology Journal*, vol. 10, pp. 615-626, 2017.
- [12] R. Saha, A. R. Chowdhury, and S. Banerjee, "Diabetic retinopathy related lesions detection and classification using machine learning technology," in *International Conference on Artificial Intelligence and Soft Computing*, 2016, pp. 734-745.

- [13] E. Cortés-Ancos, M. E. Gegúndez-Arias, and D. Marin, "Microaneurysm Candidate Extraction Methodology in Retinal Images for the Integration into Classification-Based Detection Systems," in International Conference on Bioinformatics and Biomedical Engineering, 2017, pp. 376-384.
- [14] J. Lachure, A. Deorankar, S. Lachure, S. Gupta, and R. Jadhav, "Diabetic Retinopathy using morphological operations and machine learning," in IEEE International Advance Computing Conference (IACC), 2015, 2015, pp. 617-622.
- [15] T. Walter, P. Massin, A. Erginay, R. Ordonez, C. Jeulin, J.C. Klein, "Automatic detection of microaneurysms in color fundus images," *Medical Image Analysis*, vol. 11, no. 6, pp. 555-566, 2007.
- [16] K. Zuiderveld, "Contrast Limited Adaptive Histogram Equalization," *Graphics Gems*, pp. 474-485, 1994.
- [17] S. Roychowdhury, D. D. Koozekanani, and K. K. Parhi, "Screening fundus images for diabetic retinopathy," in 2012 Conference Record of the Forty Sixth Asilomar Conference on Signals, systems and Computers (ASILOMAR), 2012, pp. 1641-1645.
- [18] A. Frame, P. Undrill, M. Cree, J. Olson, K. Mc Hardy, P. Sharp, and J. Forrester, "A comparison of computer based classification methods applied to the detection of microaneurysms in ophthalmic fluorescein angiograms," *Comput. Biol. Med.*, vol. 28, pp. 225-238, 1998.
- [19] P. Panchal, R. Bhojani, and T. Panchal, "An Algorithm for Retinal Feature Extraction using Hybrid Approach," *Procedia Computer Science*, vol. 79, pp. 61-68, 2016.
- [20] W. Gonzalez and R. E. Woods, "Eddins, Digital Image Processing Using MATLAB," Third New Jersey: Prentice Hall, 2004.
- [21] Z. He, L. Liu, S. Zhou, and Y. Shen, "Learning group-based sparse and low-rank representation for hyper spectral image classification," *Pattern Recognition*, vol. 60, pp. 1041-1056, 2016.