Glaucoma Detection Using Little Wood Paley Decomposition On Local Derivative Structure Of Fundus Images

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ABSTRACT
Glaucoma is the stern ailment that affects the eye and causes blindness without screening significant symptoms at early stage. Glaucoma is instigated due to unseemly draining of aqueous humour within the eye. The eye diseases such as glaucoma, diabetic retinopathy are diagnosed using the retinal features such as Optic Disc (OD) and Optic Cup (OC). In this paper, the optic disc region is segregated from the input retinal image using Local Region Recursive Segmentation (LRRS). The discriminative features are extracted from segmented optic disc using the proposed LP_LDS method. In this LP_LDS method, the micro level details of optic disc are extracted by considering the pairwise directions of vector of the referenced pixel and its neighbourhood using Local Vector Pattern (LVP). The resultant image after extraction is decomposed with 2D Little Wood Paley (LP) Empirical Wavelet Transform to obtain the detailed sub images. The sub images are disintegrated and their features are normalized using z-score normalization. Finally obtained features are classified using different classifiers. Among the four classifiers (Support vector machine classifier, K-Nearest Neighbour classifier, Random Forest Classifier, Decision tree classifier), Random Forest Classifier exhibits better performance than other classifiers. This LP_LDS method has been examined using MIAG RIMONE (Release2) database that contains 255 normal images and 200 glaucoma images. This LP_LDS method achieves a sensitivity of 89.29% in classifying glaucoma images and an overall accuracy of 89.71% using Random Forest Classifier.
Keywords: Local vector pattern, Empirical wavelet transform, Local derivative structure, Local region recursive segmentation.

1 INTRODUCTION

Glaucoma injures the nerve that is located inside the eye. It connects the retina to the brain which results in gradual vision loss. Rigorous eye soreness, queasiness, reddishness in eye, rapid vision disturbances, looking coloured rings around lights, abrupt blurred vision are few symptoms of glaucoma. If persons with glaucoma were not treated properly, they may lost their vision

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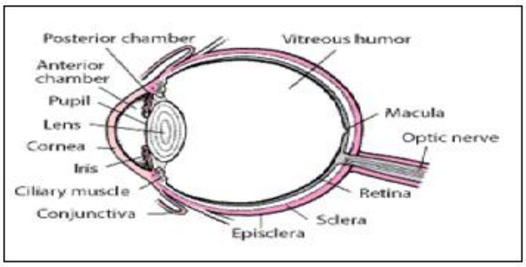

Figure 1 Structure of an eye

The optic disc is the primary portion of the optic nerve. When the person is affected by glaucoma, the fluid drains slowly which leads to rise of pressure inside the eye. When this pressure is not brought under control, it affects the optic nerve and its associated portion of the eye.

2 RELATED WORK

N. D. Salih, Marwan [1] presented a technique in which the optic disc is segmented automatically from colour fundus images. This process involves three main phases such as finding the location of OD, preprocessing and separating the OD region from fundus image. The position of OD was determined using FFT(Fast Fourier transform)starting from the initial pixel located on the optic disc. The primary pixel along with neighbouring pixels were utilized as a key for the region growing technique which ends in the process of dividing the image into segments . Artem Sevastopolsky [2] presented an global approach for automated segmentation of OD and OC. The regions of OD and OC are recognized accurately by acquiring the discriminative features using the architecture of U-Net convolutional neural network. Fengshou Yin [3] presented a numerical type technique to isolate OD and OC using Circular Hough Transform.The binary edge map was considered as an input and the shapes are recognized. A innovative adaptive method was introduced by DanielWelfer [4] using mathematical morphology for locating the OD position and OD boundary from retinograph images.

A modern system was suggested to identify the OD and optic cup (OC) by Baidaa Al-Bander [5]. The prime focus of this DenseNet CNN process was based on pixel classification. The boundaries of OD and OC are achieved and CDR ratio was computed to detect glaucoma.Jefferson Alves de Sousa [6] proposed a method to examine the structure and features of the OD region to determine glaucoma using a texture operator (Local Binary Pattern). The texture features are classified based on support vector machine.

Shishir Maheshwari [7] presented a methodology to identify glaucoma. In this method, the image and its correntrophy characteristics are extracted from EWT elements and are categorized on the basis of value feature selection process. These characteristics are utilized for classification of retinal fundus images using Least Square Support Vector Machine. M.Esmaeili [8] presented a technique to detect OD from fundus images. The magnificent candidate lesions in the image are extorted using digital curvelet transform and the curvelet coefficients of retinal images are obtained. The vivid lesions map image is constructed to distinguish between exudates and OD. Mohamed Saleh Miri [9] proposed an intermodal model to implement the additional information from retinal images and the device spectral domain optical coherence tomography to segment the OD and disc boundaries. Suraya Mohamed [10] proposed a paper for OD segmentation in retinal images based on texture dimensions.

Mailo Claro [11] presented a methodology which includes acquisition of images, OD identification, attainment of texture from different color models and classification. The texture features from OD region were obtained using GLCM in different color models. P.V. Rao [12] proposed a method in which the features related to structure and energy are pondered and examined to label the retinal fundus image as glaucomatous. The extracted texture features are implemented to neural network for efficient classification. Finally Naive Bayes classifier was utilized to classify the image. Ali Mohamed Nabil Allam [13] presented a method in which the retinograph image was changed to L*a*b colorspace in order to decompose the color quality information of the image. Based on the information of unsupervised k-means algorithm, the retinal image was split up into five separate groups. The image with brightest average intensity was chosen. The threshold value was computed using statistic based metrics. The image with relative brightness was preserved. Finally the OD was identified from the threshold image. Nataraj A. Vijapur [14] presented a method in which the energy features are extracted from retinal fundus images using discrete wavelet transform that can be used to recognize glaucoma. The OD was extracted using disc prediction method and the OC was segmented using watershed segmentation and CDR was calculated. Both techniques are utilized for the detection of glaucoma.

Many papers are presented for texture feature extraction. Timo Ahonen [15] presented a new and proficient technique for representing facial image based on Local Binary Pattern (LBP) as in [16]. Kew-chin Fan Hung 17] proposed a method in which the difference in value between the referenced pixel and the closest pixel is computed from various directions. Jenitta [18] presented a feature extraction approach in which the texture features in the retinal images are extracted using Local Pattern Descriptor(LPD) and Gray Level Co-occurence Matrix (GLCM). Local Mesh Co-occurence Pattern (LMCoP) was constructed from fusion of local mesh pattern with GLCM and Local Vector Co-occurence Pattern (LVCoP) was generated from the combination of local vector pattern along with GLCM.Local Mesh Vector Co-occurence Pattern was created by concatenating both LMCoP and LVCoP and was utilized for further feature extraction. An image processing algorithm was proposed by Loretta Ichim [19] based on adaptive local texture analysis considering different features. These features are acquired from co-occurence matrix, the fractal dimension and blood density. Retinal images are decomposed into patches using sliding box method. By applying pre processing techniques, regions with different intensities and sound are obtained. A method which is the combination of voting scheme and sorting procedure was implemented to identify the OD. Seema Tukaram Kamble [20] proposed a method to identify glaucoma in which a classifier model was utilized to find OD region.

Cheng Wan [21] proposed a technique in which the features are extracted using convolutional neural network. Several layers included in neural network are trained for the localization of optic disc region. The candidate pixels in the OD region was arranged based on threshold value. The center of gravity among the pixels are computed and the OD region was identified for the detection of glaucoma. Qaisar Abbas[22] presented an approach for the identification of glaucoma. Using multilayer and Deep belief network the deep features are acquired. The images are classified as glaucoma and non-glaucoma using softmax classifier. Marcos Vinícius Ferreira[23] proposed a technique for computerized identification of glaucoma using deep learning and texture attributes via phylogenetic diversity indexes. Andres Diaz-Pinto[24] presented a novel retinal image synthesizer and a semi-supervised learning approach to diagnose glaucoma anchored in Deep Convolutional Generative Adversarial Networks. Yunshu Qin[25] stated an innovative disc-aware ensemble network which includes deep hierarchical context of retinal fundus images and optic disc region to detect glaucoma.

3 METHODOLOGY

The image features are extracted from the segmented OD image, using local vector pattern. The local vector pattern applied image components are decomposed using Little Wood Paley in empirical wavelet transform. The correntropy features that are used to assess the dissemination of texture in the disintegrating image elements are acquired. The obtained attributes are chosen applying Student's t-Test algorithm and are synchronized using z-score normalization. Then the features are classified by K-Nearest neighbour, SVM, Decision tree and random forest classifier.

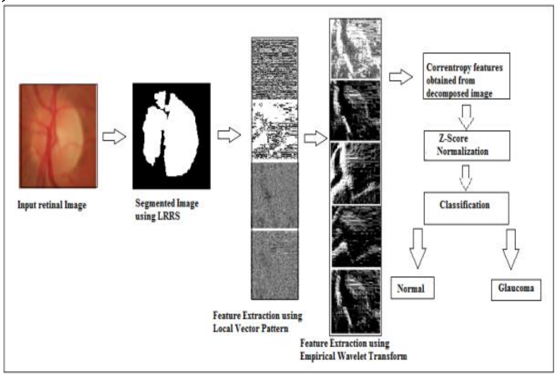

Figure 2LP_LDS Methodology

3.1 PREPROCESSING

The RGB retinal fundus image is taken as input. Among the colour RGB image, only the green channel was extracted and it is cropped using directional matched filtering to find the rough location of OD. The 9x9 template is taken in order to crop the OD region and it is resized using bilinear interpolation to sizes 241x81, 361x121, 481x161 and 601x201 to match the structure of the vessel region at different scales. The differences between the four templates were found and vessel direction map (VDM) is calculated. Thus the least accumulated difference is selected as cropped OD region. ROI Image that is needed for future diagnosis is obtained to impart the highest quality results and enhance the speed of processing. As the OD region seems to be more dissimilarity alongside the backdrop in the red channel, the red channel in the ROI figure is detached.

The Median filter was implemented on the separated red channel of ROI image. The Median filter was implemented in order to reduce noise and to preserve the edges of OD. In Median filtering, the neighbouring pixel values are sorted according to intensity and the middle value becomes the output value for the pixel under evaluation. Existence of blood vessels in the image leads to inaccurate OD boundary segmentation. To avoid such inconvenience, it is required to eliminate the blood vessels. Morphological operations such as close and open are utilized to remove blood vessels. The opening morphological operation was implemented on the image to smooth the contour of OD and to remove the blood vessels (objects) which appear too small to contain the structuring element.

LRRS Algorithm

- Consider a Region set R_p where p=1...z
- Initialize the area as N_p where p=1....k
- Calculate mean intensity for each region
- Calculate global threshold T_g
- Truncate region whose mean intensity is greater than T_g.
- Merge the remaining adjacent regions to form new region.
- Calculate the number of intensity values (V) and area A(R) for each merged region.
- Find the upper bound of the candidate region.(T_{area}).
- Check the condition whether area of merged region $A(R)>T_{area}$ and V>2.
- If the condition is true split the region into sub region using mean values and assign these regions to candidate region.
- Continue the split and merged process till there is no region satisfying the condition.

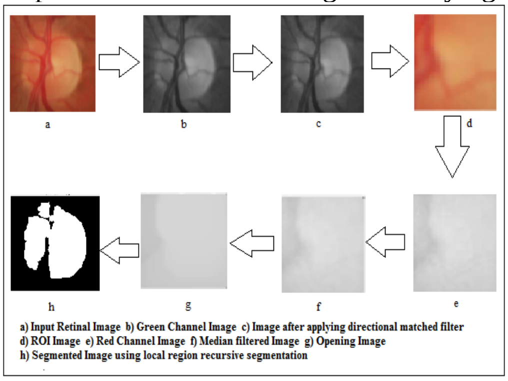

Figure 3 Local Region Recursive Segmentation

Using LRRS algorithm, the OD is deeply segmented.

3.2 FEATURE EXTRACTION

A. Local Binary Pattern

It describes the limited texture model of an image. Let us take a 3x3 pixel.

- Consider the cell 5 as centre pixel and the other eight pixels as neighbouring pixels.
- Find the variance between the value of centre pixel and the value of adjacent pixel in isolation.
- When the value of centre pixel value is greater than the value of neighbouring pixel, subsequentlymark as 0 or else mark as 1.

  Applying weights in threshold table, we get

  $=1x2^0 + 1x2^1 + 1x2^2 + 0x2^3 + 1x2^4 + 0x2^5 + 0x2^6 + 1x2^7$

  =1+2+4+0+16+0+0+128=151

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Now the value 151 is replaced with the centre pixel value. The process is repeated till all the other pixels are replaced with new value using binary threshold and weights. This gives a feature vector for the entire window. In mathematical terms

$\mathbf{LBP_{R,M}}=\sum_{p=0}^{p-1} \mathbf{s(n_p - c_p)2^p}$, (1)

Where adjacent pixels n_p in each group is limited by its middle pixel value $c_{p.}$

B. Local Vector Pattern

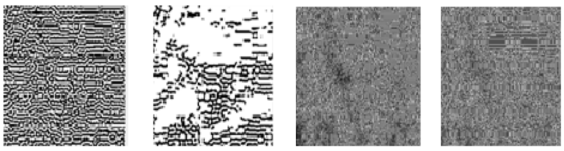
Local Binary Pattern (LBP) is a elemental operator for extorting nano patterns without the consideration of viable neighbouring relationship. Local Tetra Pattern (LTrP) [26] generates minuscule patterns from parallel and perpendicular derivative directions equally. It creates large repletion and augmenting feature length. To resolve the shortcomings that is found in present local pattern descriptors, LVP is presented which generates the microscopic patterns obtained from both the directions of vector using Comparative Space Transform (CST) to extricate individual traits.

The local vector Pattern is utilized to compute the range of value among referenced and neighbouring pixel from various directions and distances to acquire the structure and texture details. CST enables to attain contrastive attributes.

A local sub-region R and the direction value of a vector is denoted as $W_{\beta,d}(P_r)$.

Let P_c denote the referenced pixel marked with red in R, β as the index angle of the variation direction, and das the range among the referenced pixel and its neighbouring pixels with the direction of index angle. The direction value of a vector at the referenced pixel P_r can be described as

$\mathbf{W_{\beta,d}(P_r) = (R(P_{\beta,d}) - R(P_r))}$ (2)



Local vector Pattern at different angles

Figure 4 Sub bands using Local Vector Pattern

$Q_{135°,3}$			$Q_{90°,3}$			$Q_{45°,3}$
	$Q_{135°,2}$		$Q_{90°,2}$		$Q_{45°,2}$	
		$Q_{135°,1}$	$Q_{90°,1}$	$Q_{45°,1}$		
$Q_{180°,3}$	$Q_{180°,2}$	$Q_{180°,1}$	Q_c	$Q_{0°,1}$	$Q_{0°,2}$	$Q_{0°,3}$
		$Q_{225°,1}$	$Q_{270°,1}$	$Q_{315°,1}$		
	$Q_{225°,2}$		$Q_{270°,2}$		$Q_{315°,2}$	
$Q_{225°,3}$			$Q_{270°,3}$			$Q_{315°,3}$

Figure 5 Local Vector Pattern

Finally LVP, LVP_P,$R(G_c)$, at referenced pixel P_r is denoted as the combination of the four 8-bit binary patterns LVPs.

LVP_P,

$\mathbf{R(P_r) = \{LVP_{p}, R, \beta(P_r) | \beta = 0°, 45°, 90°, 135°\}}$ (3)

LVP can obtain more added texture details than the LTrP by implementing the four pairwise directions of vector. At last, the LVPs are combined to create a 32 (4 × 8)-bit binary pattern for every referenced pixel in the local sub-region.

3.3 EMPIRICAL WAVELET TRANSFORM

Empirical wavelet transform disintegrates the specified bit stream into distinct ways by constructing adaptive wavelet filter bank. The Fourier band is segregated as X closest segments and then X-1 edges are needed leaving 0 and π. With the intension of finding the edges, the position of local maxima in the spectral region are identified and arranged in reverse order. The support boundaries are taken as the central point between consecutive maxima.

Let ω_n be the support boundaries and T_n be half the length of transition phase. Let we choose $Tn = \Upsilon\ \omega_n$.

1. The input is taken as *f* and N (number of scales).
2. Consider $\tilde{f}$ be the fourier transform of *f* and compute the local maxima of $\tilde{f}$ on $[0,\pi]$ and find the set $\{\omega_n\}$.
3. Select the value of Υ where $\Upsilon < \min_n \left(\frac{\omega_{n+1}-\omega_n}{\omega_{n+1}+\omega_n}\right)$.
4. Construct the filter bank.
5. Separate the signal to obtain each component.

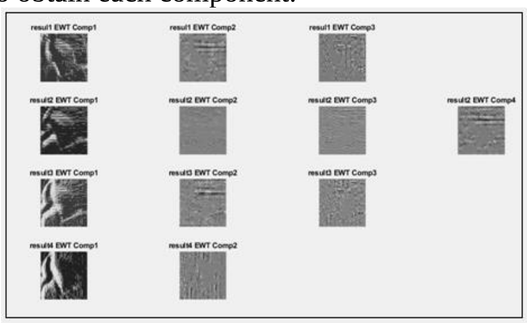


Figure 6 Empirical Wavelet Transform

A phase T_n that switch over from one state to another is denoted with thickness $2T_n$. It is positioned around each edge ω_n. For all n>0, the empirical scaling function is given as equations (1), (2) and (3) respectively.

$$\boldsymbol{\varphi\hat{}n(\omega) = 1 \text{if} |\omega| \leq (1-\gamma)\omega_n} (4)$$

$$\boldsymbol{\varphi\hat{}n(\omega) = \cos\left[\frac{\pi}{2}\beta\left(\frac{1}{2\gamma\omega_n}(|\omega|(1-\gamma)\omega_n)\right)\right]}$$

$$\boldsymbol{\text{if } (1-\gamma)\omega_n \leq |\omega| \leq (1+\gamma)\omega_n} (5)$$

$$\boldsymbol{\varphi\hat{}n(\omega) = 0 \quad \text{otherwise}} \ (6)$$

The empirical wavelets are denoted as equations (4), (5), (6) and (7) correspondingly.

$\psi\hat{}n(\omega) = 1$

$$\text{if } (1+\gamma)\omega_n \leq |\omega| \leq (1-\gamma)\omega_{n+1} \ (7)$$

$$\boldsymbol{\psi\hat{}n(\omega) = e^{-1\frac{\omega}{2}} \cos\left[\frac{\pi}{2}\beta\left(\frac{1}{2\gamma\omega_{n+1}}(|\omega|-(1-\gamma)\omega_{n+1})\right)\right]}$$

$$\boldsymbol{\text{if}(1-\gamma)\omega_{n+1} \leq |\omega| \leq (1+\gamma)\omega_{n+1}} (8)$$

$$\boldsymbol{\psi\hat{}n(\omega) = e^{-1\frac{\omega}{2}} \sin\left[\frac{\pi}{2}\beta\left(\frac{1}{2\gamma\omega_n}(|\omega|-(1-\gamma)\omega_n)\right)\right]}$$

$$\boldsymbol{\text{if } (1-\gamma)\omega_n \leq |\omega| \leq (1+\gamma)\omega_n} (9)$$

$$\boldsymbol{\psi\hat{}n(\omega) = 0 \quad \text{otherwise}} \qquad (10)$$

Correntropy Features

Correntropy is a nonlinear computation of resemblance among two arbitrary variables X and Y. Then the correntropy can be estimated as

$$\boldsymbol{C(X,Y) = \frac{1}{M}\sum_{i=1}^{M} D(X_i, Y_i)} (11)$$

For each image, four EWT components are attained and for each decomposed EWT component, three correntropy features are gained. In this way twelve correntropy features are got for each image. Based on t value, the acquired correntropy features are positioned and the extremely inequitable details are picked using student's test algorithm. The attributes are homogenized with mean value as zero and standard deviation as one (z-score normalization)

ZScore can be computed as

$$\mathbf{ZScore} = \frac{\mathbf{y-mean}}{\mathbf{sd}} \quad (12)$$

$$\mathbf{sd} = \sqrt{\frac{\sum(\mathbf{y-mean})^2}{\mathbf{num}}} \quad (13)$$

Where y is the individual feature value, mean is the average of all the feature values and sd is standard deviation and num is the sum of feature values.

3.4 CLASSIFICATION

A. SVM classifier

Support vector machine (SVMs)is a method implemented for categorization, regression and outliers detection. Support Vector Machine (SVM) is predominantly a classifier routine that analyzes the tasks by creating hyper planes in a multidimensional space that detach cases of diverse class labels

Pseudocode:

- Input the sample data
- Generate data, a two-column matrix containing length and width measurements.
- From the class vector, introduce a new column vector namely groups to categorize data into two sets: glaucoma and non glaucoma.
- Randomly choose training and test sets.
- Train an SVM classifier by means of a linear kernel function and design the categorized data.
- Apply *svmclassify* function to classify the test set.
- Calculate the efficiency of the classifier

B. Random Forest classifier

The random forest algorithm can be used for the process such as classification and the regression. It can manage the omitted values and can be applied for categorical values also.

The principle for random forest method can be divided into multiple phases.

- Random forest construction code.
- Code to make decision based on generated random forest classifier.

Principle for Random Forest construction:

1. Consider "w" be entire features and choose "r" features from whole where r is lesser than w
2. Compute the node value "a" using best split concept.
3. Split the node "a" into subnodes using the same concept.
4. Repeat the steps from1 to 3tillthe last node is reached.
5. construct forest by reiterating steps 1 to 4. for example, the steps should be repeated "n" number times to generate "n" number of trees.

Principle for Random forest prediction:

1. Initially consider the test features. Prognosticate the outcome by applying the rules of each randomly generated decision tree. Save the endresult
2. Calculate the priority for each endresult.
3. Decide the higher precedence endresult as final.

C. K Nearest Neighbour Classifier

KNN is a process based on simple principle.

Pseudo code:

- Store the records.
- Reset the value of k.

- Consider each data in dataset. evaluate the range between the test data and every line of training data. Add distance value and index value of each data to a structured collection.
- Place the calculated distance value and indices value in ascending order.
- Choose the first “k” rows among the organized data collection.
- Find the majority reappeared group of the rows and restore it.
-

D. Decision tree classifier

It is a type of supervised machine learning. It is utilized for both classification and regression. It works efficiently with non-linear data. As it uses only one feature for each node to split the data, construction of decision tree is very simple.

Root node is the initial point of a tree. The first split is done at this stage. Each internal node represents a feature that leads to the prediction of the outcome. Leaf nodes or terminating nodes indicate the final class of the outcome. Branches are connections or link between two nodes.

Pseudo code:

1. Choose the feature that classifies the dataset into expected class and allot that feature to the root node.
2. Traverse down from the root node and categorize the data at each internal node till arriving at the leaf node.
3. Repeat step1 and step2 until the input data is assigned a label class.

4 EXPERIMENTAL RESULTS AND ANALYSIS

4.1 DATA SET

This proposed LP_LDS technique was experimented on MIAG-RIM ONE(release2)database that contains 255 normal images and 200 glaucomatous images. Among this,318(70%) images are utilized for training and 137(30%)images are employed for testing. This technique was examined for MIAG-RIM ONE (release3) database that contains 85 normal images and 39 glaucomatous images. Among 124 images,93(75%) images are utilized for training and 31(25%) images are manipulated for testing.

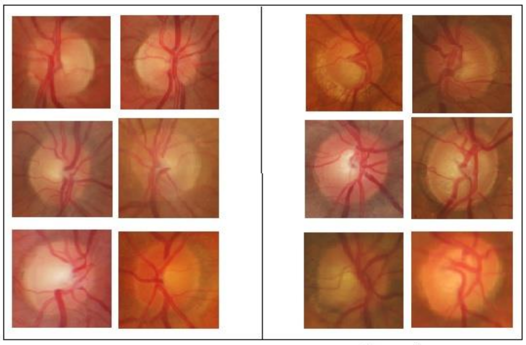


Figure 7 Experimental Images

4.2 PERFORMANCE METRICS

1. **True Positive Rate (TPR) or Sensitivity or Recall**

Sensitivity is termed as the ratio of really affected persons in the concealed population who are diagnosed as affected. It involves the percentage that the test will accurately detect the affected.

$$\mathbf{TPR} = \frac{\mathbf{TP}}{\mathbf{TP+FN}} \quad (14)$$

TP shows the count of affected image exactly identified being affected.
FN reveals the sum of affected image wrongly diagnosed as unaffected.
TN specifies the total of normal image correctly recognized as unaffected.
FP indicates the collection of normal image wrongly detected as affected.

2. **True Negative Rate (TNR) or Specificity or Selectivity**

The ratio of persons without disorder in the concealed population who are diagnosed as healthy. It implies the proportion that the test will accurately detect the normal persons.

$$\mathbf{TNR} = \frac{\mathbf{TN}}{\mathbf{TN+FP}} \quad (15)$$

When the value of sensitivity intensifies, the specificity dwindles and the same in reverse order.

3. Accuracy

The ratio of persons correctly detected as normal and glaucomatous to the total persons.

$$\mathbf{ACC} = \frac{\mathbf{TP+TN}}{\mathbf{TP+FP+TN+FN}} \qquad (16)$$

4. Precision or Positive Predictive Value

Positive Predictive value is the fraction that glaucoma is present when the analysis is positive

$$\mathrm{P} = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \qquad (17)$$

5. F1 Score

It is two times the quotient of the mathematical product of precision as well as recall and the addition of precision with recall.

$$\mathbf{F1} = \mathbf{2} * \frac{\mathbf{precision\ .recall}}{\mathbf{precision+recall}} (18)$$

For the dataset RIMONE (release2), sensitivity value using Random forest classifier shows greater performance than SVM classifier by 17.99%, KNN classifier by 19.53% and decision tree classifier by 7.79%. The Specificity value using Random forest classifier demonstrates larger performance than SVM classifier by 17.99%, KNN classifier by 19.53% and decision tree classifier by 7.79%. The value of accuracy using Random forest classifier illustrates better performance than SVM classifier by 17.65%, KNN by 19.53% and decision tree classifier by 8.09%. The Precision value using Random forest classifier reveals higher performance than SVM classifier by 18.05%, KNN classifier by 20.30% and decision tree classifier by 8.51%. The F1Score value using Random forest classifier indicates enhanced performance than SVM classifier by 18.08%, KNN by 19.87% and decision tree classifier by 8.07%.The following Table 1 shows the performance of classifiers for RIMONE release2 and release3 dataset and Figure 8 reveals the results of classifiers for both the datasets.

Table 1 Performance of classifiers using LP_LDS method

		SVM	RF	KNN	Decision Tree
Dataset RIMONE release2	**Accuracy**	0.7206	**0.8971**	0.6985	0.8162
	Sensitivity	0.713	**0.8929**	0.6976	0.815
	Specificity	0.713	**0.8929**	0.6976	0.815
Dataset RIMONE release3	**Accuracy**	0.5806	**0.6774**	0.4516	0.5806
	Sensitivity	0.481	**0.5262**	0.3595	0.481
	Specificity	0.481	**0.5262**	0.3595	0.481

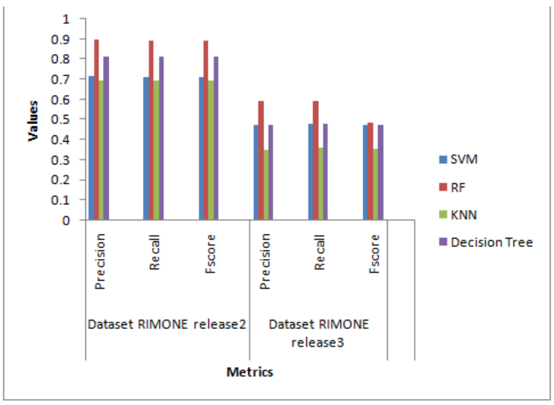


Figure 8 Performance of Classifiers using LP_LDS method

From Table 1 and Figure 8, it is shown that RF classifier performs higher than other classifiers. Due to its versatile feature and default hyper parameters of random forest, it shows good prediction result than other classifiers. Decrease in over fitting problem and reduction in variance value improves the accuracy of random forest classifier.

5. CONCLUSION

Related to the study of OD detection, the fundus image features are extorted using local vector pattern from the segmented OD region. The image components are not acquired from raw fundus images, but obtained after applying local vector pattern. These Local Vector Pattern applied image components were decomposed using Little Wood Paley Empirical Wavelet Transform. The attributes are selected after acquisition of correntropy features and were normalized using z-score normalization. The normalized features were classified using decision tree , random forest, SVM and KNN classifiers. The performance of random forest classifier was found to be higher than other classifiers.

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