Automated Glaucoma Detection Using Variational Mode Decomposition from Fundus Images

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Abstract

Glaucoma is a chronic eye disorder and one of the major causes of vision loss. Increased intraocular pressure damaged the optic nurves and hence blindness. Available methods on glaucoma image classification are expensive and slow. Therefore fast and low cost methods are needed. In this paper, glaucoma image classification using two dimensional variational mode decomposition and support vector machine from fundus images is proposed. The variational mode decomposition is used to decompose the glaucoma and normal images. Features are extracted from decomposed sub band images. Selected and reduced features are used to classify images in glaucoma or normal by support vector machine. The obtained accuracy, sensitivity, specificity are 94.17 %, 95 %, and 95 %, respectively for tenfold cross validation technique. Obtained results confirm that proposed method is adequate and improved over the state-of-the-art methods.

Keywords: *Glaucoma, pre-processing, variational mode decomposition, feature extraction and normalization, singular value decomposition, support vector machine*.

Introduction

Glaucoma is a dangerous disorder within the eye and has become a second main reason of vision loss over the world.(1) About 64.3 million glaucoma cases reported in the year of 2013 and it may reach to 111.8 million by the year 2040.(2) Glaucoma is of two kind, open angle and angle closure.(3) Generally, former type of glaucoma is mainly responsible for vision loss due to increase intraocular pressure within the eye. Open angle glaucoma is also known as silent destroyer of the optic nerves of the eye because it grows gradually with continuing destroyed the optic nerves.(4) There is no heal for glaucoma, it can be stop to further damage of optic nerves if it is detected at early stage .(5)

At present computer aided diagnosis is increasing research area in glaucoma detection. (6) There are several research papers on glaucoma detection. Kolar(7) extracted fractal dimensions (FD) and power spectral features. The support vector machine (SVM) yielded an accuracy of 74%. Bock(1) extracted features from fast Fourier transform (FFT) and B-spline coefficients and fed to SVM which yielded accuracy, specificity and sensitivity of 80%, 85% and 73% respectively. Acharya(8) extracted texture and higher order spectra (HOS) features and classified by SVM. They reported an accuracy of 91%. Dua(9) extracted energy features using discrete wavelet transform (DWT) and classified by SVM. They reported an accuracy of 93%. Yadav(10) extracted texture feature with artificial neural network (ANN) and reported an accuracy of 72%. Raja(11) used wavelet packet decomposition (WPD). They extracted entropy and energy features and fed to ANN which yielded accuracy of 85%. Gajbhiye(12) proposed a method for glaucoma detection using WPD and moment features. Extracted features were normalized and fed to SVM. They reported an accuracy of 86.57%. Ghosh(13) extracted grid colour moment features and BPNN. The reported accuracy, sensitivity and specificity are 87.47 %, 88 % and 87.45 % respectively for tenfold cross validation. Maheshwari(14) proposed glaucoma diagnosis method. They extracted correntropy features using two dimensional empirical wavelet transform (2DEWT). The features are classified using SVM. They reported an accuracy of 80.66 %. Kirar(15) proposed a new glaucoma diagnosis approach using third level 2dimensional discrete wavelet transform (2D DWT). Six histogram features namely mean, variance, skewness, kurtosis,

energy and entropy were extracted and fed to LS-SVM. They reported an accuracy of 88.3 %.

State of the art methods explained above are less accurate because these methods are limited to dyadic scale and required predefined basis function. In higher level of decomposition only low frequency sub band is used for next level of decomposition. It creates interference from other nearby frequencies in every sub band. All the above explained methods are not adaptive. 2DEWT is adaptive but it suffered from interference and redundancy due to improper segmentation of image spectrum and design of wavelet filter bank. In this adaptive filter bank sub band images varies. Hence the conventional methods are less accurate.

This paper presents an automated glaucoma detection using variational mode decomposition from fundus images. 2dimensional variational mode decomposition (2DVMD) decomposes the input images in to sub band images. Concatenated sub band images (SBI) are used to extracted features. The proposed method also uses singular value decomposition (SVD) and SVM classifier to classify images in glaucoma and normal. The obtained accuracy is more than the existing methods. Hence the proposed method is better than the state of art methods. The obtained performances are validated and compared with the existing methods for tenfold cross validation. The proposed method is better because it decomposes images in to sub band images which are centered around a specific frequency and with no interference, no boundary distortion and mod mixing problem.

The remaining part of the article is organized as follows: Section materials and method explains the glaucoma image data and presents the proposed method. At last results and their discussion are presented followed by conclusion and references.

Materials and Method

In this paper 15 normal and 15 glaucoma fundus images have been used from publically available image database RIM-1 Medical Image Analysis Group (MIAG).[16] The proposed methodology contains a number of stages, which are presented in the Fig. 1.

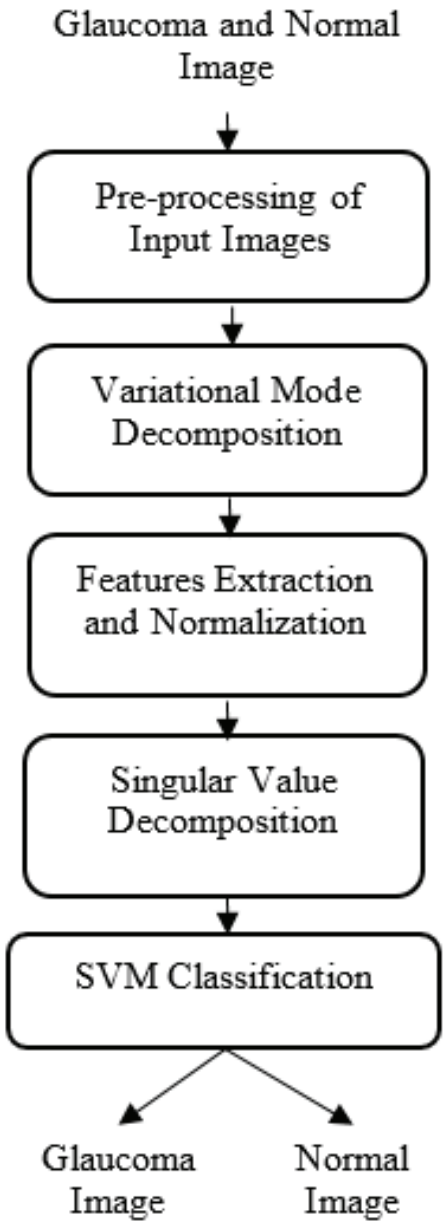

Fig.1. Block diagram of proposed method

Preprocessing: It is used to remove irrelevant variations. In this, images are resized to make all input images of same dimensions. Only green channel image is used because it contains more amount of information [1]. Contrast limited adaptive histogram equalization (CLAHE) is applied on green channel to improve the image quality.[17] The noise is reduced using median filter (MF).[18]

Variational Mode Decomposition: In this paper 2dimensional variational mode decomposition (2DVMD) is used. 2DVMD[19] is non-recursive, non stationary and fully adaptive decomposition technique for analysis of images. It overcomes the limitations of

conventional methods. In this paper decomposed sub band images are band limited and centered around a specific frequency. The bandwidth of a band limited sub band images are calculated as follows.[19]

Constrained variational problem for VMD is expressed as follows:

$$\min_{\psi_p \omega_p} \left\{ \sum_p \left\| dt \left[\left(\delta(t) + \frac{i}{\pi t} \right) * \psi_p(t) \right] e^{-i\omega_t} \right\|^2 \right\} \quad (1)$$

Such that $\sum_p \psi_p = S$

where S is a signal. ψ_p and ω_p are the p^{th} VMD component and centre frequency respectively. The above equation can be written as:

$$\mathcal{L}(\psi_p, \omega_p, \beta) = \alpha \sum_p \left\| dt \left[\left(\delta(t) + \frac{i}{\pi t} \right) * \psi_p(t) \right] e^{-i\omega_p t} \right\|_2^2 + \left\| s(t) - \sum_p \psi_p(t) \right\|_2^2 + \langle \beta(t), s(t) - \sum_p u_p(t) \rangle \quad (2)$$

The estimate of the p^{th} mode is given as follow:

$$\hat{\psi}_p^{m+1}(\omega) = \frac{\hat{S}(\omega) - \sum_{f \neq p} \hat{\psi}_f(\omega) + \frac{\hat{\beta}(\omega)}{2}}{1 + 2\alpha(\omega - \omega_p)^2} \quad (3)$$

where α is balancing parameter. The center frequency can be expressed as:

$$\omega_p^{m+1} = \frac{\int_0^\infty \omega |\hat{\psi}_p(\omega)|^2 d\omega}{\int_0^\infty |\hat{\psi}_p(\omega)|^2 d\omega} \quad (4)$$

[19,20]well explained the complete algorithm of 2DVMD. The 2DVMD sub band images for normal and glaucoma images are used to extract features.

Feature Extraction Normalization and Reduction: After decomposition, sub band images are concatenated and 77[21-29] features are extracted. Extracted features are normalized using z- score and selected using reliefF method.[30] 45 features have been selected and fed to singular value decomposition (SVD) [31] which reduces the dimensionality (r) of the dataset from 45 to 9. This part removes the redundant features while retaining important features.

Support Vector Machine: This paper used least squares support vector machine (LS-SVM) [32] with RBF kernel.[33] It is a supervised widely used method to classify two or more classes in the field of medical image classification.

The performance parameters (in %), namely accuracy, sensitivity, specificity are calculated as: [34]

$$\text{Accuracy (ACC)} = \frac{TP + TN}{TP + FP + TN + FN} \times 100 \quad (5)$$

$$\text{Sensitivity (SEN)} = \frac{TP}{FN + TP} \times 100 \quad (6)$$

$$\text{Specificity (SPE)} = \frac{TN}{FP + TN} \times 100 \quad (7)$$

where, FP, FN, TP and TN represents false positive, false negative, true positive and true negative.

Results and Discussion

Results: This paper represents a new method for glaucoma detection using 2DVMD from fundus images. The performances of proposed method using LS-SVM with RBF kernel and tenfold cross validation are listed in Table 1. The obtained specificity, sensitivity and accuracy are 95%, 95% and 94.17% respectively for tenfold cross validation.

Table 1: Performance of proposed method

(CV) Cross Validation	ACC (%)	SEN (%)	SPE (%)
3 folds	93.33	93.33	93.33
5 folds	93.33	86.67	100
10 folds	94.17	95.00	95.00

The radial basis function (RBF) kernel parameter is taken from one to ten with a uniform step size of one. Fig.2 shows performance versus cross validations

The highest accuracy is achieved for kernel parameter value = 3 and tenfold cross validation. Therefore kernel parameter = 3 and tenfold cross validation has been chosen. Fig. 2(d) has the highest value.

The cross validation technique is taken from two to eleven with a uniform step size of one. The plot of performance versus cross validation for kernel parameter = 3 and 9 features is depicted in Fig. 3. Tenfold cross validation technique yielded highest glaucoma detection accuracy. Therefore tenfold cross validation is better and selected for the proposed method.

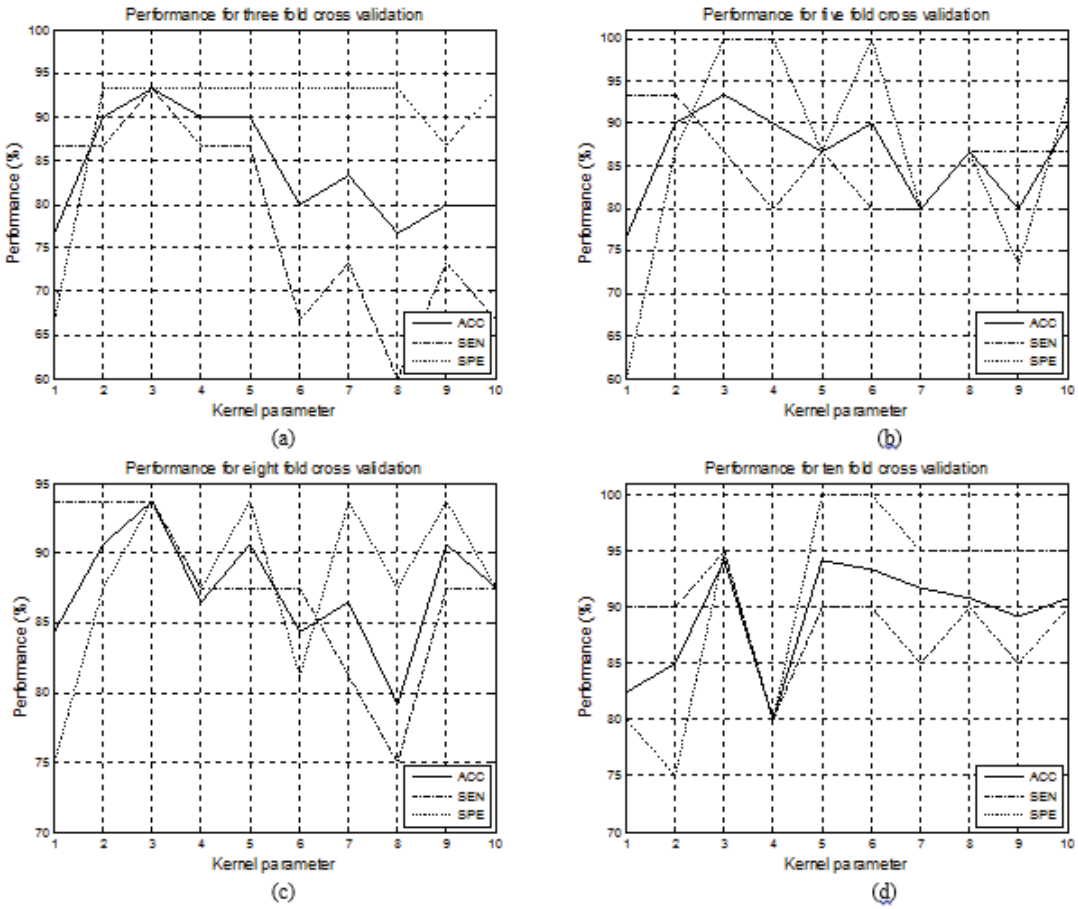

Fig.2: Plot of performance versus kernel parameter for cross validation (a) Three, (b) Five, (c) Eight and (d) Ten

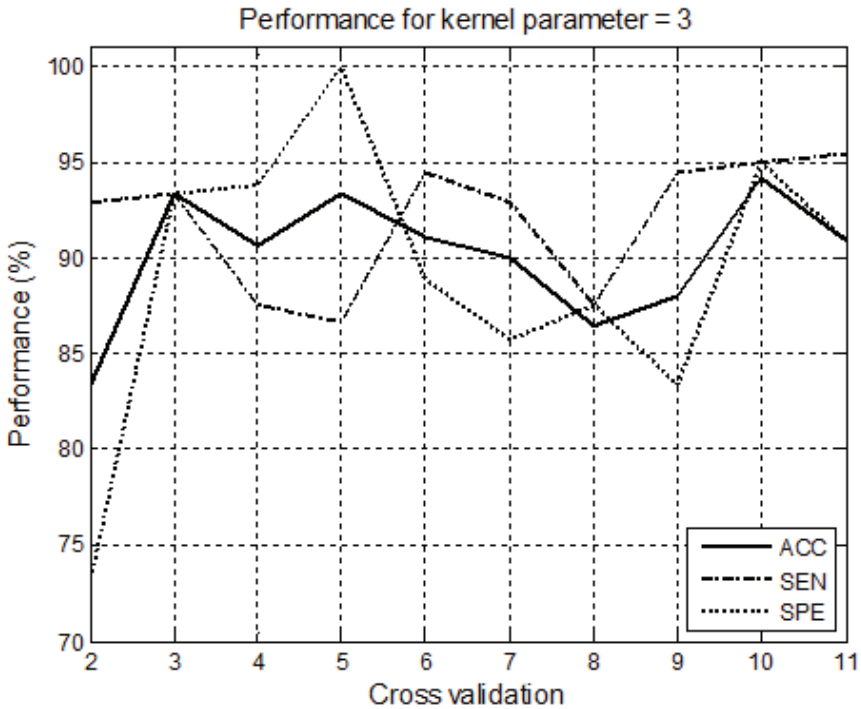

Fig.3: Plot of performance versus cross validation using proposed methodology

The extracted features also fed to different types of classifiers using weka soft-ware to compare the performance of the proposed methodology. It is clear from the Table 2 that the selected SVM classifier for the proposed methodology is found suitable.

Table 2: Performance using different classifiers

Comparison	**Accuracy (%)**		
Classifiers	3 FCV	5 FCV	10 FCV
Naive Bayes	73.33	76.67	76.67
Random Forest	76.67	80	80
Logistic Regression	73.33	83.33	83
OneR	73.33	73.33	83
Multilayer Perceptron	66.66	83,33	90
Support Vector Machine	93.33	93.33	94.17

FCV-Folds cross validation

Discussion

Glaucoma detection using 2DVMD from fundus images is presented in this paper. The obtained performances have been validated and compared with the existing methods for tenfold cross validation using public image database.[16] A comparison has been given in Table 3.

Kolar[7] extracted FD and power spectral features with SVM and obtained an accuracy of 74%. Bock[1] extracted features from FFT and B-spline coefficients and fed to SVM obtained accuracy, specificity and sensitivity of 80%, 85% and 73% respectively. Acharya[8] extracted new types of texture and HOS features and classified by SVM. They reported an accuracy of 91%. It was a good accuracy. Dua[9] extracted energy features using DWT and classified by SVM. They reported an accuracy of 93%. Yadav[10] extracted texture feature with ANN and reported an accuracy of 72%. Raja[11] used WPD. They extracted entropy and energy features and fed to ANN which yielded accuracy of 85%. Gajbhiye[12] proposed a method for glaucoma detection using WPD and moment features. Extracted features were normalized and fed to SVM. They reported an accuracy of 86.57%. Ghosh[13] extracted grid colour moment features and BPNN. The reported accuracy, sensitivity and specificity are 87.47 %, 88 % and 87.45 % respectively for tenfold cross validation. Maheshwari[14] proposed glaucoma diagnosis method. They extracted correntropy features using 2DEWT. The features are classified using SVM. They reported an accuracy of 80.66 % form 505 images. Kirar[15] proposed a new glaucoma diagnosis approach using third level 2D DWT. Six histogram features namely mean, variance, skewness, kurtosis, energy and entropy were extracted and fed to LS-SVM. They reported an accuracy of 88.3 %.

State of the art methods explained and listed in Table 3 are less accurate due to interference, distortion and redundancy.

Table 3: Comparison of methods based on accuracy (%) for tenfold cross validation

Authors / Ref.	Methods description	ACC
Yadav,[10]	Texture feature & ANN	72
Kolar,[7]	Power spectral features & SVM	74.00
Bock,[1]	FFT, PCA & SVM	80.00
Maheshwari,[14]	2DEWT, correntropy & LS-SVM	80.66
Raja,[11]	WPD, entropy, energy & ANN	85
Gajbhiye,[12]	WPD, moment feature & SVM	86.57
Gosh,[13]	Color moment features & BPNN	87.47
Kirar,[15]	2D-DWT & histogram features	88.30
Acharya,[8]	HOS features & RF	91.00
Dua,[9]	DWT, texture features & SVM	93.00
Proposed method	2DVMD, hybrid features, SVD and LS-SVM	94.17

This paper presented a novel variational computer based glaucoma detection using 2DVMD from fundus images.

Our proposed method yielded accuracies of 93.33%, 93.33%, and 94.17% for 3, 5 and 10 fold cross validation respectively.

The obtained results found better than the existing and compared methods as depicted in Table 3. This shows that our method detects glaucoma more accurately and hence it out performed over state of art methods.

Conclusion

This paper presented a novel approach of glaucoma detection using 2DVMD from fundus images. The green channel image is extracted from the fundus images and decomposed using 2DVMD. LS-SVM classifier with RBF kernel used to classify images. The obtained accuracies are 93.33%, 93.33%, and 94.17% for 3, 5 and 10 fold cross validation respectively. The obtained glaucoma detection accuracy is better for tenfold cross validation with kernel parameter = 3 and 9 features.

Glaucoma, serious eye disorder worldwide may be treated if detected at an early stage. The presented method is effective for glaucoma detection. Obtained results have been listed in Table 1 and Table 3 confirmed that this approach is better than state of-the-art methods.

The proposed methodology requires testing for huge image database. In upcoming research it is planned to implement it on other disease like diabetes and retinopathy with deep learning.

Conflict of Interest: Nil

Source of Funding: Self

Ethical Clearance: None (because method is implemented on publically available dataset)

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