Glaucoma Detection using Bi-Dimensional Empirical Mode Decomposition from Retinal Fundus Images

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Abstract: Eye is a precious part of human body. But in the world, glaucoma has affected the human eye as second main cause of blindness. This disease grows very slowly in the eye and without noticing it destroyed the optic verves within the eye. Traditional glaucoma detection methods are costly and time consuming. Therefore, better methods are required to detect glaucoma more accurately. Hence, a new adaptive approach for glaucoma detection using bi-dimensional empirical mode decomposition (BDEMD) from retinal images is proposed. Adaptive bi-dimensional intrinsic mode functions (BDIMFs) are obtained using very simple steps, from pre-processed and coloured decomposed images, is the main idea of the proposed method. Moment and texture features contain more information hence these are extracted from decomposed BDIMFs. These features are then normalized and classified by support vector machine (SVM) with its different kernel functions. The achieved results like, accuracy, sensitivity, and specificity are 97.02 %, 98.23 %, 95.46 %, respectively for 10-fold cross validation. Experimental analysis shows that our method outperformed over the traditional methods for glaucoma detection.

Keywords: Image, Pre-processing, Bi-dimensional empirical mode decomposition, Feature extraction and normalization, Support vector machine.

1. Introduction

Eye is a precious part of human body. But in the world, glaucoma has affected the human eye as second main cause of blindness. This disease grows very slowly in the eye and without noticing it destroyed the optic verves within the eye [1]. The main two form of glaucoma are primary open angle glaucoma (POAG) and primary angle closure glaucoma (PACG) [2].

In the year 2013, about 64.3 million people were reported because of this eye disease and it is expected to about 111.8 million by 2040 [3]. Over all 12.3% of the eye patient reported as blindness due to glaucoma in the world [4].

There are many research papers on glaucoma detection published using public image data set. Mostly, based on pre-processing, decomposition and features extraction from retinal images with various classifiers.

Raja [5-7] proposed automated glaucoma detection approach in his three different works. His first work [5] included tri-spectrum and complex wavelets transform (CWT), second work included wavelet packet decomposition (WPD), and third work optimal hyper analytic wavelets transform (OHAWT). Raja [6] decomposed converted gray images by third level of WPD with "db3" wavelet function to explore the significance of approximation and detail coefficients. Detailed coefficient sub-bands images were used in the entropy and energy feature extraction process.

Gajbhiye [8] developed new method of glaucoma screening by WPD with moment feature using SVM. Ghosh [9] used new idea, in which grid colour moment features were classified by back propagation neural network (BPNN) for screening of glaucoma.

Maheshwari [10-11] proposed automated glaucoma detection approach in his two different works. His first work [10] included empirical wavelet transform (EWT) with correntropy features and

second work included variational mode decomposition (VMD) with entropies & fractal dimensions (FD) features. In both the works the method had been performed in 5 steps, pre-processing, decomposition, feature extraction, features normalization and selection and classification by support vector machine (SVM) for tenfold cross validation.

Araujo [12] diversity indexes in their work for glaucoma detection. They used Genetic algorithm and SVM classifier. Kirar [13] proposed automated glaucoma detection approach using discrete wavelet transform (DWT) and [14] using DWT with EWT. Kirar [15] designed an automated glaucoma detection method using compact variational mode decomposition (CVMD). Robust features were found out using post-processing, and then classified by SVM. Agrawal [16] designed an automated glaucoma detection using quasi-bivariate variational mode decomposition (QB-VMD). Robust features were found out using post-processing, and then classified by SVM. Kirar [17] designed a new glaucoma detection approach using image channels and DWT from fundus images. The obtained glaucoma detection accuracy of the proposed method was reported using SVM.

Pinto [18] proposed a new glaucoma detection approach using convolutional neural networks (CNNs). Serte [19] proposed a new glaucoma detection approach using deep learning (DL) using fundus images. Claro [20] proposed a new features extraction approach with transfer learning (TL) for glaucoma classification. Elangovan [21] proposed a new approach for glaucoma detection with CNN. Kirar [22] implemented new approach for glaucoma detection using second stage QB-VMD (SS-QB-VMD) with SVM for ACRIMA database. Authors of methods [18-22] used 705 images [18].

State of the art methods are less accurate and have some limitations like; methods [5-8, 13-14, 17] are based on DWT or WPD. These are non-adaptive, limited to dyadic scale, responsible for interference and have low frequency resolution which leads nonflexible time-frequency covering. Methods [10, 14] are based on EWT, it overcomes the drawback of DWT based methods but due to having improper segmentation it leads to redundancy and interference. Methods [11, 15-16, 22] are based on VMD, it overcomes the limitations of DWT and EWT based methods, but it also suffers from boundary effects problems to perform on larger and varied data set.

Therefore, there is a requirement to increase the performance of glaucoma detection by extracting small, moderate and high frequency texture form the fundus images, which are the main discriminating characteristics of the glaucoma patient.

In this paper, a new adaptive approach for glaucoma detection using bi-dimensional empirical mode decomposition from retinal images is proposed.

The main advantage of the BDEMD is that it decomposes the fundus image in to its corresponding small, moderate and high frequency BDIMFs. BDIMFs contains pixel variations information at precise scale which helps to captures subtle pixel variations due to structural deviations in the glaucoma patient. Therefore, our main concern is to decomposes the fundus raw image in to its corresponding small, moderate and high frequency BDIMFs, so that we can easily extract various inherent most discriminating features from the raw fundus image more effectively to offer the better results.

Initially, all the images are decomposed in to different colour components. Then, BDIMFs are obtained using very simple steps, from pre-processed and colour decomposed images, it is the main idea of the proposed method. Moment and texture features contain more information hence these 17 important features are mined from decomposed BDIMFs. These features have more discriminative nature. These features are then normalized and classified using SVM with its different kernel functions. The achieved results like, accuracy, sensitivity, and specificity are reported in result section.

There are total 6 sections; remaining 5 sections are as follow: image data set is given in 2nd section. Methodology is given in 3rd section. Results are given in 4th section. Section 5th covered the discussion. Conclusion is given in 6th section.

2. Images data set

Total 705 images (396 Glaucoma+ 309 Healthy) of ACRIMA public database are used [18]. The images of ACRIMA database have dimensions from 178×178 pixels to 1420×1420 and are resized to 64×64. These are captured by Topco TRC retinal with a field of view of 35. This project was founded by the Ministerio de Econom´ıa y Competitividad of Spain. Sample images of Glaucoma (Im685_g_ACRIMA.jpeg) and healthy (Im123_ACRIMA.jpeg) are given in Fig. 1. These images have been taken from [18].

3. Proposed methodology

The steps of proposed methodology are given in Fig. 2. It includes input images, resizing of images, conversion of colour image into Red, Green, Blue and Gray images, equalization and filtering of images,

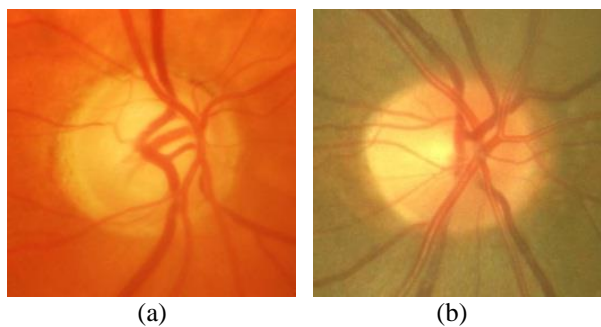251

(a)   (b)
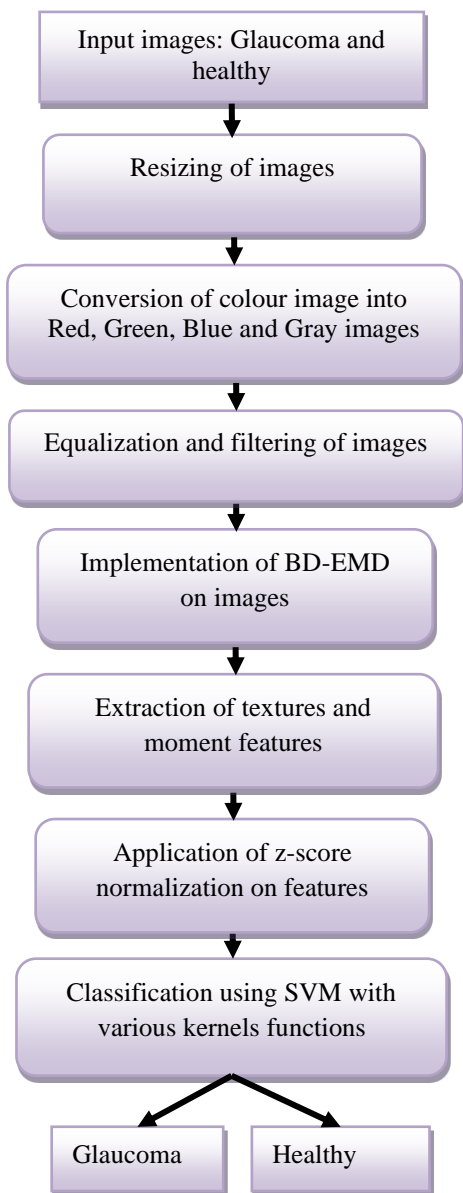Figure. 1 Images: (a) glaucoma and (b) healthy

Figure. 2 Procedure of proposed methodology

implementation of bi dimensional empirical mode decomposition (BDEMD) on images, extraction of textures and moment features from decomposed BDIMFss, application of z-score normalization on features, classification using SVM with various kernels functions.

3.1 Pre-processing

Pre-processing is performed on images to increased image quality [1]. It improves the image quality [23]. It comprises resizing of images, conversion of colour image into Red, Green, Blue and Gray images (shown in Fig. 3), and equalization [24] followed by filtering (shown in Fig. 4).
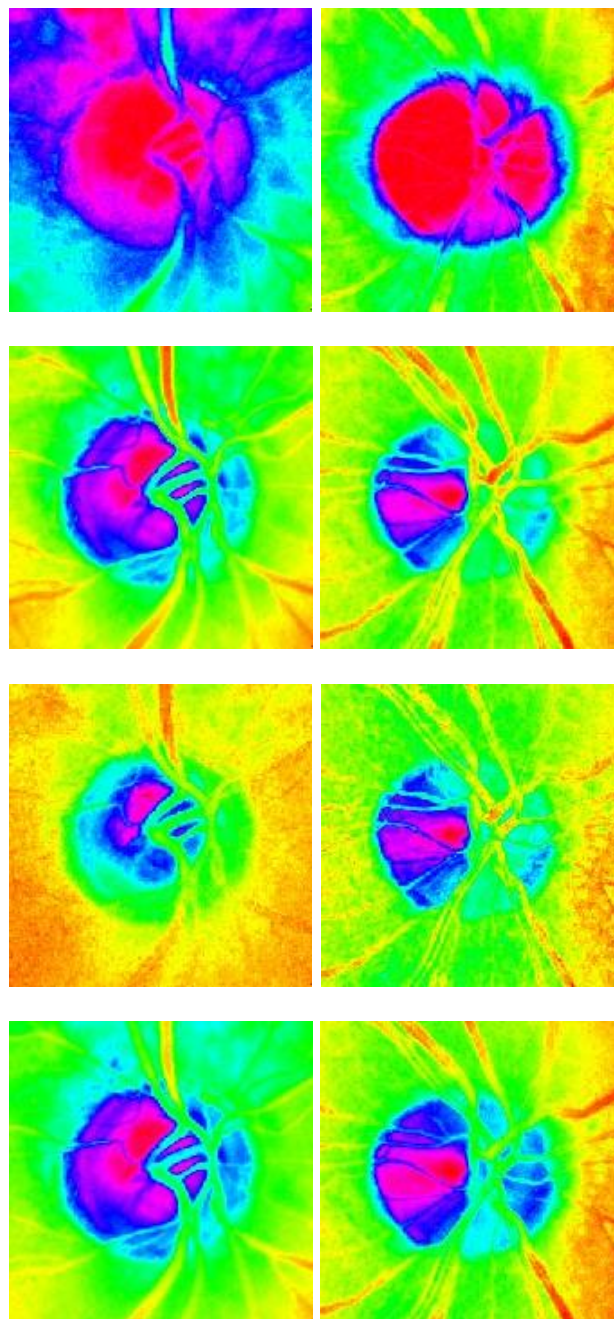

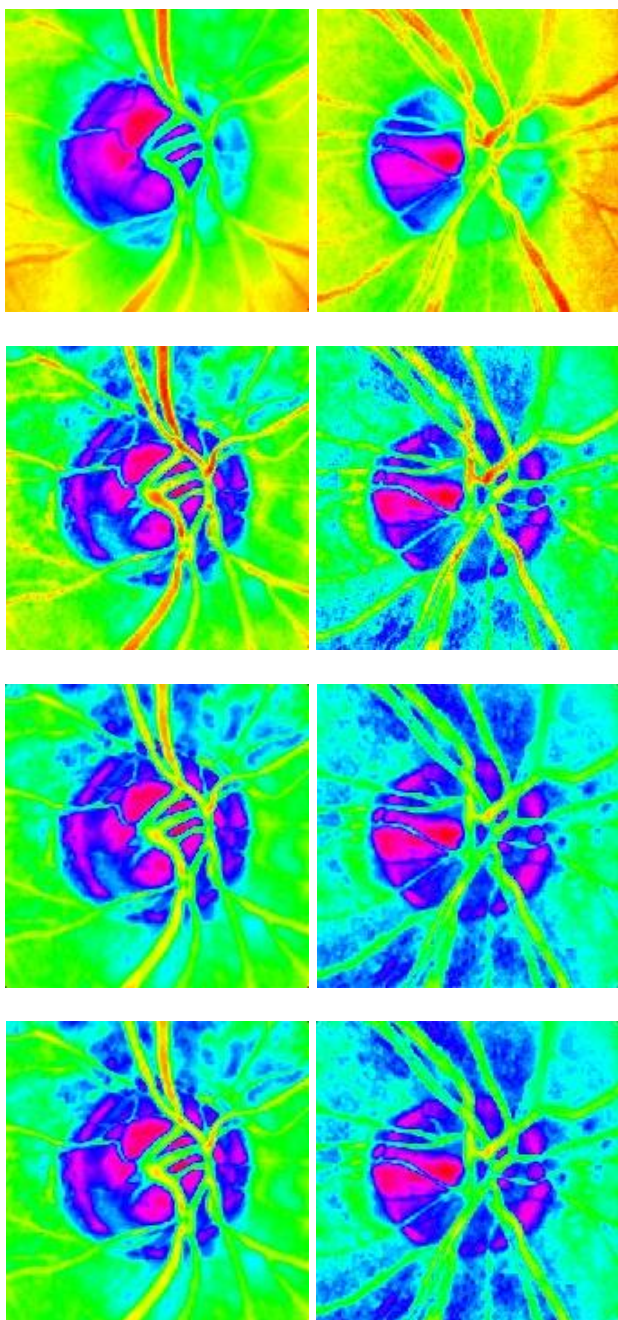Figure. 3 Red, green blue and gray converted image: for glaucoma in 1st column and for healthy in 2nd column

Figure.4 Green, equalized, filtered and pre-processed images: for glaucoma in 1st column and for healthy in 2nd column

3.2 Bi dimensional empirical mode decomposition

Empirical mode decomposition is abbreviated as EMD and developed by Huang. It is an adaptive in nature and used to decompose a signal, which is non-stationary and non-linear in time domain. It is independent to linearity and stationary property of signal.

The main advantage of the BDEMD is that it decomposes the fundus image in to its corresponding small, moderate and high frequency BDIMFs. BDIMFs contains pixel variations information at

precise scale which helps to captures subtle pixel variations due to structural deviations in the glaucoma patient.

Huang's shifting algorithm is used to extract IMF$p(z)$ from a signal $F(z)$ is given as [25-27]:

$$F(z) = \sum_{p=1}^{P} I_p(z) + R_P(z) \qquad (1)$$

Where $I_p(z)$ is the IMFs for $p = 1\ldots, P$ and R_p is the residue.

Nunes [25] extended EMD to Bi-dimensional EMD (BDEMD), its algorithm is summarized in the following steps is as follows [26-27]:

Step1: Calculate the maxima and minima the input image $I(x, y)$.

Step2: Upper and lower envelops are obtained using interpolation method.

Step3: Calculate mean m by taking average of upper and lower envelopes.

Step4: Calculate BDIMF $R = I - m$. And check for R . If it is BDIMF, then move to step5 else repeat step1 to step3 using the proto-BDIMF R is an input, and awaiting the newest proto-BDIMF turns to be BDIMF.

Standard deviation (SD) criterion for image is given as follow:

$$SDC = \sum_{x=1}^{M} \sum_{y=1}^{N} \frac{[R_p(x,y) - R_{p-1}(x,y)]^2}{R_{p-1}^2(x,y)} \qquad (2)$$

If the SD is more than the threshold ε, then repeat step1 to step4 with input $R_p(x, y)$, otherwise $R_p(x, y)$ is a BDIMF $D_p(x, y)$.

Step5: Now, take proto-BDIMF R as input for steps1 to step 4 to calculate the remaining BDIMF.

Image is decomposed using BDEMD is given as follows:

$$I(x, y) = \sum_{p=1}^{P} D_p(x, y) + R(x, y) \qquad (3)$$

Where $D_p(x, y)$ is a BDIMF and $R_P(x, y)$ is a residue. The BDEMD decomposes the input image as a sum of BDIMFs and residue. D_1 is the highest frequency of I, D_2 is the moderate frequency of I, and R_p represents the lowest frequency of I.

The decomposed BDIMFs for glaucoma and healthy images are shown in Fig. 5. The BDIMFs for glaucoma in 1st column and for healthy in 2nd column.

3.3 Feature extraction and normalization

Total 17 features, 7 moment invariance and 10 texture features have been extracted from BDIMFs. These features have more discriminative nature.

Textures features (6-chip histogram and 4-GLCM). 6-chip histogram features like kurtosis, entropy, energy, mean, variance, and skewness. 4-GLCM features are like energy, homogeneity, contrast, and correlation [13-14, 28]. In this way 17 features have been extracted from each of 4 colour components, hence over all 68 features have been extracted from one input image.

All the extracted features are normalized to improve performance of the algorithms. This research paper used z-score normalization method. It is expressed using Eq. (4) [10].

Figure. 5 BDIMFs for green image: for glaucoma in 1st column and for healthy in 2nd column

$$\hat{S} = \frac{S - m\,(S)}{std\,(S)} \qquad (4)$$

Where, std=standard deviation, m = mean, S = extracted features data.

3.4 Support vector machine

Support vector machine (SVM) is widely used supervised machine learning technique [13, 29].

The proposed method used SVM with different kernel function like, Linear (L), Quadratic (Q), Cubic (C), Fine Gaussian (FG), Medium Gaussian (MG), and Coarse Gaussian (CG). Therefore these are named as L-SVM), Q-SVM, C-SVM, FG-SVM, MG-SVM, and CG-SVM.

3.4.1. Performance measures

The following performance measures have been calculated: accuracy (acc), sensitivity (sen), and specificity (spe) using Eqs. (5-7) [14, 30].

$$acc = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \qquad (5)$$

$$sen = \frac{TP}{TP + FN} \times 100 \qquad (6)$$

$$spe = \frac{TN}{TN + FP} \times 100 \qquad (7)$$

Where, TP= TruePositive, TN= TrueNegative, FP=FalsePositive and FN=FalseNegative.

4. Results

In this paper, a new adaptive approach for glaucoma detection using bi-dimensional empirical mode decomposition from retinal images is proposed. We have implemented it on 705 images (396 glaucoma and 309 healthy) of ACRIMA public image dataset [18]. Therefore features set of 705x68 is formed normalized and classified by SVM.

A normalized data is fed to L-SVM, Q-SVM, C-SVM, FG-SVM, MG-SVM, and CG-SVM.

Table 1. Performance of proposed method for 3FCV

Classifiers	Acc(%)	Sen(%)	Spe(%)
L-SVM	95.04	96.21	93.53
Q-SVM	96.31	97.47	94.82
C-SVM	96.88	97.98	95.47
FG-SVM	86.24	99.49	69.26
MG-SVM	95.60	97.98	92.56
CG-SVM	91.77	93.43	89.64

Table 2. Performance of proposed method for 5FCV

Classifiers	Acc(%)	Sen(%)	Spe(%)
L-SVM	95.04	95.71	94.17
Q-SVM	96.88	97.98	95.47
C-SVM	96.45	97.73	94.82
FG-SVM	87.38	99.75	71.52
MG-SVM	96.17	97.47	94.50
CG-SVM	91.49	93.69	88.67

Table 3. Performance of proposed method for 10FCV

Classifiers	Acc(%)	Sen(%)	Spe(%)
L-SVM	95.46	95.45	95.47
Q-SVM	97.02	98.23	95.47
C-SVM	96.60	97.73	95.15
FG-SVM	87.80	99.49	72.82
MG-SVM	96.60	98.23	94.50
CG-SVM	92.62	95.45	89.00

We have listed the performances of our method in Tables 1-3 for 3, 5, and 10 fold cross validation, respectively. The obtained better results like acc, sen, spe, and area under curve (AUC) for the receiver operating characteristic (ROC) are 97.02 %, 98.23 %, 95.47 %, and 0.99, respectively for tenfold cross validation using Q-SVM.

The Fig. 6 has been plotted for accuracy versus SVM with various kernel functions for 3, 5, and 10 tenfold cross validation. In Fig. 6, Q-SVM, C-SVM, and MG-SVM reported better results for 3, 5, and 10 tenfold cross validation. But Q-SVM showed best accuracy among all with better sensitivity and specificity using tenfold cross validation. We have selected tenfold cross validation because it yielded better accuracy.

The obtained performance of the proposed method in term of ROC is also plotted in Fig. 7 for Q-SVM using tenfold cross validation. The AUC for the ROC is shown in Fig. 7.
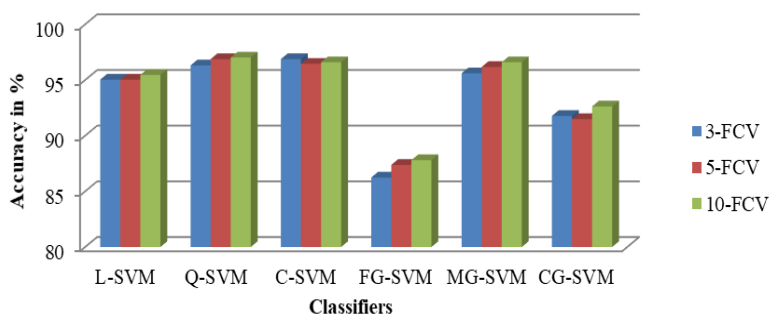

Figure. 6 Plot for accuracy versus SVM with various kernel functions for 3, 5, and 10 tenfold cross validation
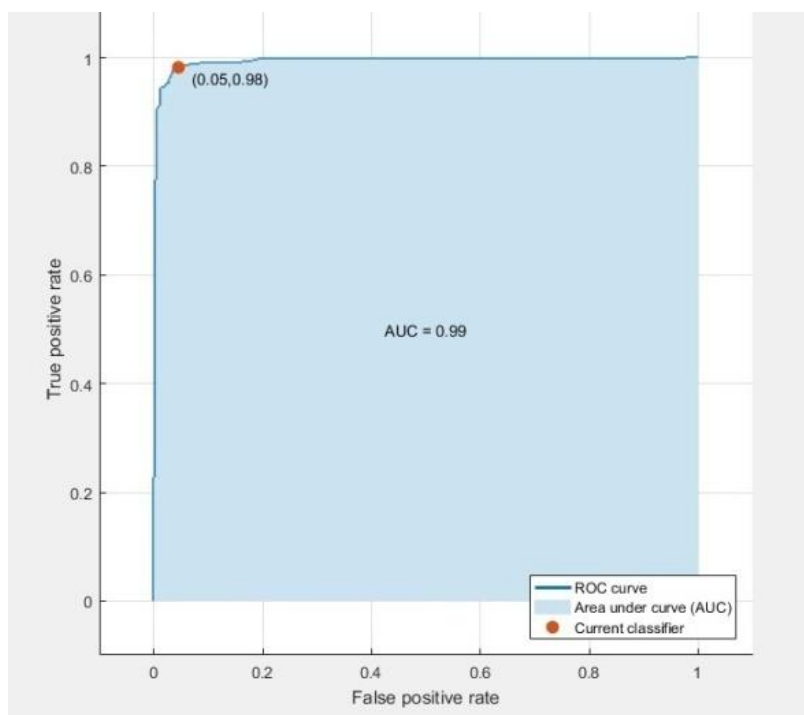

Figure. 7 ROC plot using Q-SVM for tenfold cross validation

Table 4. Comparison of methods (in %) for MIAG and ACRIMA image data set

Year & ref.	Images used	Classifiers	ACC	SEN	SPE
2017/[10]	505 (250 Glaucoma+ 255 Healthy)	SVM	80.63	76	84.25
2017/[11]	505 (250 Glaucoma+ 255 Healthy)	SVM	81.22	NR	NR
2019/[14]	505 (250 Glaucoma+ 255 Healthy)	SVM	83.57	86.4	80.8
2019/[16]	505 (250 Glaucoma+ 255 Healthy)	SVM	86.13	84.8	97.43
2020/[17]	505 (250 Glaucoma+ 255 Healthy)	SVM	84.95	86	83.85
2019/[18]	705 (396 Glaucoma+ 309 Healthy)	CNN	70.21	68.93	70.2
2019/[19]	705 (396 Glaucoma+ 309 Healthy)	GoogleNet	65	NR	87
2019/[20]	705 (396 Glaucoma+ 309 Healthy)	CNN	95.31	NR	NR
2020/[21]	705 (396 Glaucoma+ 309 Healthy)	CNN	96.64	96.07	97.39
2021/[22]	705 (396 Glaucoma+ 309 Healthy)	SVM	92.06	91.42	92.89
Our Method	705 (396 Glaucoma+ 309 Healthy)	SVM	97.02	98.23	95.46

5. Discussion

A new adaptive and computer based approach for glaucoma detection using bi-dimensional empirical mode decomposition from retinal fundus images using SVM with different kernel functions has been presented.

Raja [5-7] proposed automated glaucoma detection approach using [5] CWT, [6] WPD, and [7] OHAWT). Methods [5-7] reported an accuracy of 81 %, 85 %, and 85 % using ANN, ANN and SVM, respectively. Gajbhiye [8] reported an accuracy of 86.57 % using WPD & SVM. Ghosh [9] report an accuracy of 87.47 % using BPNN.

Maheshwari [10, 11] used EWT and VMD and reported an accuracy of 80.7 % and 81.22 % using SVM, respectively from Medical Image Analysis Group (MIAG) dataset. Araujo [12] developed genetic algorithm and SVM classifier to report an accuracy of 86.37 %.

Kirar [13] proposed DWT and [14] DWT and EWT and reported an accuracy of 88.3 % and 83.57% using SVM, respectively. Kirar [15] proposed CVMD in new work and reported an accuracy of 89.18.3% using SVM. Agrawal [16] designed an automated glaucoma detection method using QB-VMD. They reported an accuracy of 86.13.3% using SVM. Kirar [17] designed a new glaucoma detection approach using image channels and DWT from fundus images. They reported an accuracy of 84.95% using SVM. Authors of methods [10, 11, 14, 16, 17] used 505 images (250 Glaucoma + 255 Healthy) from MIAG image data set by Fumero [31]. It is publicly available at http://medimrg.webs.ull.es/.

Pinto [18] proposed CNNs. The reported accuracy was 70.21% using ACRIM image data set.

Serte [19] DL based approach and reported an accuracy of 65% using ACRIM image data set. Claro [20] proposed a new features extraction approach with TL for glaucoma classification. They reported an accuracy of 95.31% using ACRIM image data set. Elangovan [21] proposed a new approach for glaucoma detection with CNN. The reported accuracy, sensitivity, specificity were 96.64%, 96.07%, and 97.39%, respectively, for ACRIMA database. Kirar [22] proposed a new approach for glaucoma detection using SS-QB-VMD with SVM. The reported accuracy, sensitivity, specificity was 92.06%, 91.42%, and 92.89%, respectively, for ACRIMA database [18].

Above discussed state of the art methods is less accurate and have some limitations like; methods [5-8, 13, 14, 17] are based on DWT or WPD and these are non- adaptive, which also responsible for interference in the components. Methods [10, 14] are based on EWT, having improper segmentation which leads to redundancy and interference. Methods [11, 15, 16, 22] are based on VMD, it overcomes the limitations of DWT and EWT based methods, but it also suffers from boundary effects problems to perform on larger and varied data set.

However, for similar dataset [18], in this paper new adaptive approach, bi-dimensional empirical mode decomposition has been implemented on pre-processed coloured components to obtain BDIMFs and extracted textures and moment features have been classified using SVM with its different kernel functions. The achieved results like, acc, sen, and spe are 97.02 %, 98.23 %, 95.46 %, respectively for 10-fold cross validation.

Furthermore, the comparison of other methods has been listed in Table 4. Thus, Table 4 clearly

shows that the proposed method is superior to the state of art methods because it has some benefits over the existing methods. The benefits of the proposed method are:

1. It decomposes the pre-processed fundus image in to its corresponding small, moderate and high frequency BDIMFs.
2. BDIMFs easily extract various inherent most discriminating features from the raw fundus image.
3. It is efficient to capture subtle variation in pixels.
4. It is more effective to offer the better results.
5. Reported highest accuracy of 97.02% (compared to existing methods Table 4).
6. Used 10-fold cross validation for robust system.

6. Conclusion

This paper presented a new adaptive and computer based approach for glaucoma detection. The coloured image is converted in to its different colour components, like red, green, blue and gray image. These are then pre-processed and decomposed using BDEMD to get BDIMFs. The main advantage of the BDEMD is that it decomposes the fundus image in to its corresponding small, moderate and high frequency BDIMFs, further these BDIMFs easily extract various inherent most discriminating features from the pre-processed fundus image. Extracted features are normalized and classified using SVM with different kernel functions. The accuracy of our method is better for tenfold cross validation using Q-SVM. The obtained acc, sen, and spe are 97.02 %, 98.23 %, 95.46 %, respectively for 10-fold cross validation.

Furthermore, the comparison of other methods has been listed in Table 4. Thus, Table 4 and Fig. 7 clearly show that the proposed method is superior to the state of art methods.

Our method is more effective and robust to enhance the glaucoma detection performance. In future, it can be implemented on various disorders like, fatty liver, diabetes and retinopathy.

Acknowledgments

Conflicts of Interest

The authors declare no conflict of interest.

Author contributions

Conceptualization, methodology, data curation, formal analysis, writing-original draft preparation, P. Manghnani; visualization, supervision, validation, writing-review and editing, A. Moghe; all authors read and approved the final manuscript.

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