Glaucoma Screening using Simple Fusion Features

Panaree Chaipayom, Somying Thainimit

Abstract—Glaucoma is the second most common cause of blindness. It is caused by high intraocular pressure within the eyes, resulting in an injury to the optic nerve. Currently, there is no cure for glaucoma. However, early detection and treatment can prevent disease progression. Thus, the use of automatic glaucoma screening system can help workload of healthcare professionals in early detection and also solve cost issues. This study proposes a method for identifying glaucoma from fundus images by using a fusion three features to find glaucoma's significant by using wavelet decomposition and texture such as Discrete Wavelet Transform (DWT), Principal Components Analysis (PCA), and Local Binary Patterns (LBP). Support vector machine (SVM) is used to classify the glaucoma condition. The experimental results yield high accuracy at 95% by using tenfold cross-validation with HRF Database and using fusion three feature as DWT, PCA, and LBP.

Keywords—Glaucoma, Fundus Image, Data Mining, Feature Extraction, Feature Ranking, Classification

I. Introduction

According to World Health Organization (WHO), Glaucoma is consider the 2nd most common diseases that causes blindness [1]. Kingman [2] reported that from all 70 Million Glaucoma patients worldwide, 6.7 million already lost their sight. In Thailand, there are 17,687 glaucoma patents recorded by Thailand's health ministry on 2012. Statistic also shows that the number Glaucoma patient is increasing every year. However, Glaucoma can't be completely cured. Present treatments can only slow down to delay blindness. To prevent glaucoma and accompany vision loss, early detection and treatment are essential. Thus, development of automatic glaucoma detection and screening system that can quantitative assessments of glaucoma signs is increasingly important.

In automatic ocular image analysis, digital eye fundus image provides a great potential. One of the frequent technique used to detect glaucoma is Discrete Wavelet Transform (DWT). In 2012, Dua et al. [3] used DWT to extract energy signatures. These signatures was subjected to 4 different feature ranking algorithm and select a subset of features to 4 Consistency Subset Evaluation (CSE) strategies. The best accuracy of 93.33% was obtained using Sequential Minimal Optimization (SMO) classifier. Additionally, the use of feature ranking and CSE has small impact on the obtained accuracy using SMO, Support Vector Machine (SVM) and Naive Bayes. Maheshwari et al. [4] extended Dua's work to identify glaucoma and also other eye diseases such as diabetes retinopathy, fatty liver disease, thyroid cancer, ovarian cancer, etc. The Empirical Wavelet Transform (EWT) was utilized for feature extraction on fundus eye images. The features was ranked and normalized,

then classified using Least Squares Support Vector Machine (LS-SVM). The obtained accuracies are 98.33% and 96.67% using threefold and tenfold cross-validation, respectively. Xiong et al. [5] detected glaucoma using Principal Components Analysis (PCA) and Bayes classifier. The success rate of Glaucoma detection is 78%. Mookiah et al. [6] used Higher Order Spectra (HOS) and DWT to extract features using fundus eye images, The feature was fed to SVM classifier and Radial Basis Function (RBF) to select the best kernel function for identifying Glaucoma. The accuracy of 95%, sensitivity of 93.33% and specificity of 96.67% were reported. Koh et al. [7] used Continuous Wavelet Transform (CWT) to extract energy and entropies of fundus eye images. The obtained features were ranking using Particle Swarm Optimization (PSO) and then fed to Random Forest classifier. The proposed method is evaluated using tenfold cross-validation. The experimental results indicated 92.48% of accuracy, of 89.37% sensitivity and 95.58%.

This paper present an automatic approach for glaucoma classification aiming to use in mass screening glaucoma suspects. The proposed approach is a non-segmentation based approach in which there are no requirement on segmenting retinal structures. Retinal features are extracted from the input image using DWT, PCA, and LBP. In this work, different sets of fused features and classifiers are investigated. The proposed method is validated using three different retinal databases. The proposed method is described in section II. Section III presents experimental results and conclusions are in Section IV.

II. Methodology

The proposed methodology has three main parts. First, the fundus images are preprocessed and then extracted features by using DWT, PCA, and LBP, and Fusion Features. After that, All features are fusion together and normalize features, then fed into SVM , Naive Bayes (NB) and Multi-layer Perceptron (MLP) Classifier.

A. Preprocessing

Quality of input images influences performance of glaucoma screen system. In first stage, fundus eye images are resized and enhanced for improving intensity distribution of the images. This work exploited Contrast Limited Adaptive Histogram Equalization (CLAHE) [8] for contrast enhancement. The CLAHE is often used in medical images due to its enhancement performance [8, 9] over global enhancement and ordinary adaptive histogram enhancement.

The CLAHE is a variant of adaptive histogram equalization technique. In this method, an image is divided into small blocks called 'tiles'. Each block is enhanced using histogram equalization with histogram contrast limiting. If any histogram bin is above the pre-defined contrast value, those pixels are clipped and distributed to other bins before applying histogram

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equalization. By limiting and redistributing intensity values, over amplification of noisy regions in images is addressed [9, 10].

B. *Feature Extraction*

(a). 2-D Discrete Wavelet Transform (DWT)

DWT is a spatial-frequency multi-resolution image analysis technique. The wavelet analysis procedure decomposes input images by passing the input image through a series of chosen wavelet function (ψ) and scaling function (φ). The scaling function is a lowpass filter (h_φ) whilst the wavelet is a highpass filters (h_ψ). The filtering decomposes the image into a set of four coefficient bands: a lowpass (A), horizontal (H), vertical and diagonal bands as shown in Figure. 1. The successive decomposition can be performed in the same way by filtering the A band at the next scale. In this paper, a four-level wavelet decomposition is applied. Image features are extracted using four different wavelet functions which are daubechies (db3), symlets (sym3), and biorthogonal (bio3.3, bio3.5, and bio3.7) wavelet filters. At each level, average, energy and entropy of the horizontal band are computed and constructed as feature vector. The mathematic expressions of computing average, energy and entropy are defined by (1)- (3), respectively.
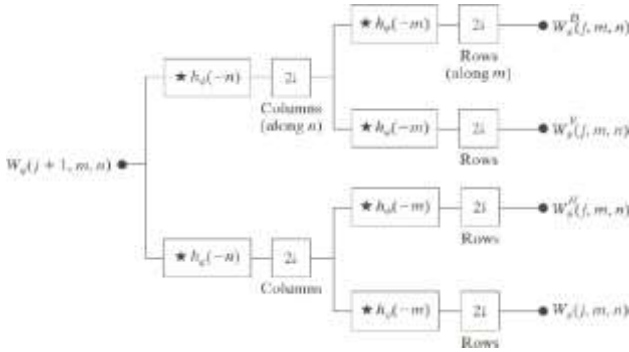

Figure 1. 2-D Discrete Wavelet Transform decomposition [11].

$$Average = \frac{1}{p \times q} \sum_{x=\{p\}} \sum_{y=\{q\}} |Dh1(x,y)| \qquad (1)$$

$$Entropy = -\sum p_i \log_2 p_i \qquad (2)$$

$$Energy = \frac{1}{p^2 \times q^2} \sum_{x=\{p\}} \sum_{y=\{q\}} (Dh1(x,y))^2 \qquad (3)$$

(b) Principal Component Analysis (PCA)

PCA is a common method to extract global characteristics of scientific data. This technique finds that the eigenvectors of the maximum covariance matrix and use these data as a new set of data. The PCA reduces the number of features by creating a small number of new variables that capture the important part of the data found in the original feature [5, 12, 13]. In our study, PCA finds 29 import features from fundus images.

(c) Local binary patterns (LBP)

The LBP extracts texture features of an image by comparing pixel intensity of the central pixels with intensity of its neighbors. If intensity of the neighbor is greater than intensity of the central pixel, the corresponding LBP binary pixel is set to 1, otherwise 0. With 8 neighbors, each pixel can be represented by converting the obtained 8-bit binary into one decimal number. The obtained LBP value ranges from 0 to 255. Next histogram of the obtained LBP codes is constructed and used as our image feature descriptor. In this study, the LBP descriptor is implemented using circular neighborhood with radius 5, resulting in 5×8 points [14]. The LBP feature vector has a length of 40.

C. *Feature Normalization and Fusion*

Studies [15] reported that the combination of features extracted from the same pattern improves pattern classification result. Sets of features obtained using the proposed feature extraction methods described in section B are concatenated into a single feature vector. Various feature combinations are investigated in this paper. Prior to feature fusion, the Z-score normalization denoted by (4) is performed to standardize the range of feature values. The Z-score normalization converts a set of features to have zero mean and standard deviation of one [3].

$$y_{old} = \frac{y_{new} - mean}{std} \qquad (4)$$

where yy_{oooooo} is the original value, yy_{nnnnnn} is the normalized value and the *mean* and *std* are the mean and standard deviation of the original data range, respectively.

D. *Classification*

This study used three classifiers to compare the performance of each classifier and select the best classifier that could be classified as accurate and fast. The selected classifiers are Support vector machines (SVM) , Naive Bayes (NB) and Multi-layer Perceptron (MLP) classifier.

(a) Support Vector Machines (SVM) classifier

SVM is a supervised learning algorithm used for both classification or regression with constructing hyper-plane in n-dimensional space. This algorithm finds the optimal hyper-plane to classify the class of data. Classification depends on the distribution of data, and the selected kernel function to provide. We experimented using the RBP and linear kernel in measuring effectiveness in analyzing different data. From our experimental results, the linear kernel provides better results and its results is indicated in the next section.

(b) Naive Bayes (NB) classifier

NB is an effective and simple supervised learning algorithm used to creating predictive modeling [16]. NB is used to calculate probability in order use in data analysis.

$$P(c|x) = \frac{P(x|c)P(c)}{P(x)} \tag{5}$$

where $P(c\,x)$ is the posterior probability of class (target) given predictor (attribute) , $P(c)$ is the prior probability of class, $P(c)$ is the likelihood, which is the probability of predictor given class , $P(x)$ is the prior probability of predictor.

(c) Multi-layer Perceptron (MLP) classifier

MLP is a class of artificial neural network composed of at least 3 nodes. Except the input node, each node is a neural cell, which uses linear stimulation [17]. MLP uses the backpropagation to learn to analyze data by using the least squared error between output values and targets. These error values are used to calculate the weight that represents the learning of neural networks [11].

III. Experiments

A. Database

Three public retinal fundus images databases are used in this study. The databases are HRF, Drishti-GS1 and RIM-ONE. Descriptions of the database are as follows:

HRF (High-Resolution Fundus Image Database) This database provides 30 images consisted of 15 normal and 15 glaucoma images [18]. All the images were taken with a resolution of 3504 × 2336 pixels.

Drishti-GS1: This database provides 101 images consist of 31 normal and 70 glaucoma images . All the images were taken with a resolution of 2049 × 1762 pixels. Ground truth was collected from four glaucoma experts [19].

RIM-One: This database is a public database focused mainly on Optic Nerve head (ONH) region. The database contains 255 healthy and 200 Glaucomatous ONH images [20]. The resolution of the image is 394 × 380 pixels.

TABLE I. DETAIL OF THREE DATABASE

Database	Std.	Mean
HRF	79.1393	9.8665
Drishti-GS1	53.6142	9.61132
RIM-ONE	98.8926	7.9320

B. Results

This study has the idea to use simple techniques of image processing in detecting features from fundus images, which can be implemented in many ways using extract energy, entropy and average features from 2D- DWT and detected identify patterns of images with LBP. Then use z-score normalization to normalize features and rank feature using T-Test then send to classify with SVM which uses linear kernel, NB, and MLP.

Glaucoma detection in this paper used three databases which are HRF, RIM-One and DRISHTI-GS1 in testing result. Results from analyzing Glaucoma by using feature ranking shows that fused features yield higher than analyzing using a single feature. The results obtained using the single feature and fused featues are shown in Table II - IV. The results show that the fused features improve detectionperformance. From the results of the experiment, it was found that by extracting the feature obtained from the full image can be used to analyze glaucoma. The results obtained using full image analysis (HRF and DRISHTI-GS1) are near the results obtained using OD image analysis from RIM-One dataset. Table V. shows the improvement of fusing feature, which help increasing accuracy by 3-5%. The results of experiment are different because of standard imaging and modeling of different cameras that affect accuracy. The strengths of this proposed method are as follows:

- This method doesn't require doing image segmentation.

- This method is easy to operate and doesn't require extensive computation. Thus, it is suitable to integrate into a mobile based eye screening system [21] for quick eye condition scanning. Further recommended hospital visit can be weighted using the detected score.

The drawback of the proposed method is that it requires larger eye image database to improve predicted efficiency. With the larger size image database, an automatic multiple diseases screening algorithm should be further investigated.

IV. Conclusions

In this study, we have developed a method to identify Glaucoma by using global algorithm such as DWT, LBP and PCA to extract features of fundus eye image. We run experiments by creating a new feature using features collected from the 3 methods. The developed method is validated using 3 different databases. Our experimental results show that fusion features can increase the accuracy rate in analyzing data. The screening performance using the whole eye images is comparable with one using only optic nerve eye images. In overall, the SVM classifier provides the best accuracy, following by the MLP and NB, respectively. In the future, we plan to develop an automatic glaucoma screening on the mobile application.

Acknowledgment

TABLE II. RESULTS OF CLASSIFICATION FOR HRF DATABASE.

	Classifier	DWT	PCA	LBP	DWT&PCA	DWT&LBP	PCA&LBP	DWT&PCA&LBP
Accuracy	SVM	88.33	65.83	78.33	86.67	95	78.33	95
	NB	66.67	75.83	83.33	68.33	70	90.83	70
	MLP	93.33	65	85	86.67	96.67	82.5	90
Specificity	SVM	92.59	70.37	81.48	85.15	96.29	85.18	92.59
	NB	70.37	70.37	74.07	70.37	74.07	81.48	74.07
	MLP	85.18	70.37	85.48	81.48	92.59	81.48	88.88
Sensitivity	SVM	85.18	66.67	74.07	88.88	92.59	74.07	96.29
	NB	62.96	77.78	92.59	66.67	66.67	92.59	70.37
	MLP	92.59	55.56	88.89	81.48	88.88	74.07	88.88

TABLE III. RESULTS OF CLASSIFICATION FOR RIM-ONE DATABASE.

	Classifier	DWT	PCA	LBP	DWT&PCA	DWT&LBP	PCA&LBP	DWT&PCA&LBP
Accuracy	SVM	74.38	82.15	74.05	79.93	75.54	80.93	76.97
	NB	67.5	78.27	71.68	68.48	68.48	73.61	69.2
	MLP	74.62	84.62	76.53	82.89	78	86.57	81.19
Specificity	SVM	71.82	76.24	68.51	77.9	70.71	79	75.13
	NB	34.81	72.93	62.98	37.01	38.67	67.95	40.33
	MLP	71.27	82.32	74.58	80.11	73.48	78.45	81.76
Sensitivity	SVM	76.31	85.52	78.51	80.7	79.38	84.21	80.26
	NB	93.42	82.45	78.51	93.42	92.1	78.5	92.1
	MLP	77.19	89.91	80.7	83.77	81.14	89.47	82.01

TABLE IV. RESULTS OF CLASSIFICATION FOR DRISHTI-GS1 DATABASE.

	Classifier	DWT	PCA	LBP	DWT&PCA	DWT&LBP	PCA&LBP	DWT&PCA&LBP
Accuracy	SVM	68.28	79.14	78.61	72.5	76.64	80.33	78.36
	NB	60.36	74.11	65.64	60.36	63.47	67.64	64.58
	MLP	68.03	79.58	74.25	72.25	79.11	78.83	78
Specificity	SVM	69.84	87.3	88.88	80.95	82.53	84.43	84.13
	NB	66.67	87.3	61.9	66.67	69.84	68.25	71.43
	MLP	82.54	88.88	80.95	80.95	90.48	87.3	87.3
Sensitivity	SVM	62.96	66.67	55.56	62.96	92.59	62.96	70.37
	NB	44.44	44.44	74.07	48.15	66.67	70.37	48.14
	MLP	44.44	55.56	51.85	51.85	88.88	59.26	59.26

TABLE V. ENHANCED PERFORMANCE OF SINGLE FEATURES AND FUSION FEATURES

Dataset	DWT and fusion feature	PCA and fusion feature	LBP and fusion feature
HRF	3.01	23.73	5.76
Drishti-GS1	6.48	-5.11	1.93
RIM-ONE	3.64	-4.33	4.63

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