An Automatic Screening Method For Detecting Glaucoma Using Multi-class Support Vector Machine

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Abstract—This paper introduces an automatic screening method for detecting the development of glaucoma using multi-class support vector machine (Multi-class SVM). Due to the high rate of blindness worldwide from glaucoma, the early detection is a must for early treatment and preserving the eye sight. Only the diagnoses of the optic cup and the optic disc from the ophthalmologists or technicians are subjective. The multi-class SVM is introduced to overcome this problem by classifying it into 3 classes; normal case, glaucoma suspect case, and glaucoma case. This research proposes 2 types of multi-class SVM; One-vs-the-rest SVM and SVM with 2-stage of decision tree. The linear and polynomial kernel functions are selected to generate the classifier. The evaluation is done by 10-fold cross validation technique which does not only focus on the high accuracy rate, but also considers the number of false negative rate. The final results show that SVM with 2-stage decision tree with polynomial kernel function provides the best performance to classify each stage of glaucoma.

Keywords—Glaucoma, Cup-to-disc ratio, image segmentation, Feature extraction, and Multi-class support vector machine.

I. INTRODUCTION

Glaucoma is recognized chronic degenerative health problem worldwide, estimated to affect over 60 million people of all ages [1]. It is asymptomatic in the early stage. The patients stay unnoticed until the vision field is lost gradually. Glaucoma can be computerized based on the peripapillary chorioretinal atrophy (PPA), Retinal nerve fiber layer defect (NFLD), vision field test, and the optic cup-to-disc ratio (CDR) [2-3]. When glaucoma damages the optic nerve or the nerve fiber layer around the optic nerve head (ONH), it cannot be cured. Therefore, the early detection could bring the early treatment to prevent the vision loss. The primary treatment is to reduce the intraocular pressure (IOP) inside the eyes by drops. The other clinical factors are ages (over 40), glaucoma in the family, diabetes mellitus [4]. Nowadays, to analyze and diagnose glaucoma, the followings are generally considered; the clinical data, optical coherence tomography (OCT) scan, and the vision field examination. However, in some rural area, the lack of ophthalmologists and effective equipment is appeared. The analyzing result of inexperienced trainee might cause some mistakes and that probably make some damages or the loss of vision to the patients. To overcome the subjective results, the learning machine is introduced to classify the data basing on the training set in the data base. The feature extraction and feature selection are applied to the input fundus image. The followings are the example of the extracted features; the size optic cup and optic disc in vertical and horizontal, the area of the optic disc and optic cup, pixel intensity values, fast Fourier (FFT) coefficients, B-spline coefficients [5-6]. The classification process consists of many kinds of algorithm and theories. Mostly it is divided into 2 types; supervised and unsupervised. In this research, the supervised learning is considered. The new data will be classified based on the training set which is already labeled to be likely or unlikely. It is widely used in the real world application such as target marketing, banking analysis, agriculture, remote sensing, and medical diagnosis. Artificial neural network (ANN) is the example of traditional supervised classifier that mostly used to classify the data in binary. Moreover, this research introduces support vector machine (SVM) which is a supervised classifier that powerful to the high dimensional data.

According to Ref. [7], SVM is applied to an screening system for the age-related macular degeneration (AMD). The training set consists of 4 different data sets of AMD; normal, drusen, micro aneurysms, and circinate. The features are extracted from EMD and DWT techniques. It is shown that the accuracy of EMD-SVM is higher than DWT-SVM. They conclude that features extracted from EMD techniques are more adaptive than the DWT technique. Therefore, feature selection process is very important. When the feature widely separates to the each other, the margin between classes will be maximized and provide well results. Referring to Ref. [8], when the data is imbalanced, SVM does not provide good performance, because of the weakness of soft-margins and imbalanced support vector ratio. This problem can be solved by sampling method, synthetic minority oversampling technique (SMOTE). In Ref. [9], it explains the idea to synthetic the data by an adaptive over-sampling technique based on data density (ASMOBD). The idea of ASMOBED is to synthetic the new data in the majority area and in the overlapping area in order to avoid the overfitting problem. For the outlier, it is considered as a noise and no synthetic data around that area.

Moreover, SVM can be used to classify the multi-class classification. Ref. [10] is analyzed by using 2-stage SVM.
The heart failure are diagnosed into 3 classes; healthy, heart failure-prone, and heart failure. SVM is combined with decision tree and set the cutoff value to tradeoff between sensitivity and specificity. The output provides high accuracy. Therefore, using SVM to classify the data more than 2 classes is affective.

In this work, the data set is considered as 3 classes; non-glaucoma, glaucoma suspect, and glaucoma case. Generally, the cup-to-disc ratio (CDR)<sub>V</sub> in vertical is the main indicator to analyze the development of glaucoma. When the CDR<sub>V</sub> is increased gradually, it also means that the size of the optic cup becomes larger. According to the ophthalmologist's suggestion and Ref. [11-12], when CDR<sub>V</sub> is higher than 0.6 is considered as glaucoma as shown in Fig. 1c. When CDR<sub>V</sub> is approximately between 0.4 and 0.6, it is in the suspect range of glaucoma as described in Fig.1b. Finally, Fig. 1 shows the comparison of CDR<sub>V</sub> in each stage.

The multi-class SVMs, one-vs-the-rest SVM and SVM with 2-stage decision tree are applied to classify those 3 cases. The evaluation is done by 10-fold cross validation technique. Finally, the results show that SVM with 2-stage decision tree performs a good outcome in both terms: high accuracy rate and less false detection.

This paper is organized as follows: In the Second Section, problem statements will be described and then the methodology is shown in the Third Section. The results will be analyzed in the Fourth Section. Finally, the Fifth Section will draw the conclusion and the future works of this research.

II. PROBLEM STATEMENT

The early detection of glaucoma is very important issue to pay an attention on because it can preserve the permanent vision loss. According to the experiments, it is found that only diagnosis of the technicians or ophthalmologists is subjective. This might cause some mistakes when the glaucoma is detected incorrectly such as false positive and false negative cases. In addition, glaucoma is asymptomatic in the early stage. The damage progresses very slowly and it has no symptoms or early warning signs until the eye sight is lost in the later stage. If it can be detected on time, the eye sight will be preserved. It is shown that treatment and regular checkups can prevent vision loss in people only with early stage. If the vision loss has already occurred, the treatment can slow down or prevent further vision loss [web1]. Therefore, the automatic screening of glaucoma is introduced to detect the glaucoma in the primary stage and also in the later stages.

III. METHODOLOGY

The fundus images are obtained from the Autofocus Fundus Camera (NIDEK AFC-230), Mettapracharak Hospital, Nakornpathom, Thailand. The total number of the data set is 170 fundus images: 60 images for normal case, 50 images for glaucoma suspect case, and the left for glaucoma case. The original fundus image is shown in Fig.3.a, with 2916 x 3166 pixels in RGB. To reduce the computational time, the original fundus image is identified the region of interest (ROI) around the observing target, the optic cup and the optic disc. The bright polar spot in the fundus image will be detected and expand the boundary of interest around it. The resolution is reduced by half to become 475 x 550 pixels.

The framework for classification is divided into 4 main steps as shown in Fig.2; preprocessing, segmentation, feature extraction, and machine learning and classification.

A. Image processing part

For the preprocessing process, the input fundus image is processed to provide the proper format. The red and green channels are selected as described in Fig.3.c-d. Assigning the interested region interest around the optic nerve head (ONH) (Fig.3.b) and removing blood vessels are help reducing the false detection in the segmentation process. The global intensity is determined to adjust the threshold level of the contour.

To extract the features, the K-mean clustering is performed to remove the unwanted noises from the background. After that the ellipse fitting is applied by detecting the maximum voting of every pixels from the edge of optic cup and disc seperately. Fig. 4 shows the example of the detected features from the fundus images.
The retinal fundus image; (a) the original fundus image, (b) extract the region of interest (ROI), (c) the ROI image in green channel (to detect the optic cup), (d) the ROI image in red channel (to detect the optic disc).

The feature extraction from the fundus image.

The expression below shows the selected features that extract from the fundus image.

\[
\text{Features} = [\text{Cup}_v, \text{Disc}_v, \text{CDR}_v, \text{Cup}_h, \text{Disc}_h, \text{CDR}_h]
\]

These feature vectors are fed to the classification process in the next step.

B. Machine learning part

Support vector machine (SVM) is widely used in binary classification. It is an effective classifier with high dimensional space that can transform the input data to a higher dimension space with the kernel function and find the maximum margin between 2 classes. To calculate the maximum margin of the support vectors, the kernel function is represented by the Euclidean inner product \(K(x,y) = x^Ty\).

The followings are the expression of 2 selected kernel functions:

Linear kernel (default)

\[
K_L(x,y) = x^T y
\]  

Polynomial kernel

\[
K_P(x,y)=(x^T y+c)^d, \ c \geq 0
\]  

where \(c, d\) are the parameter of the kernel, those can be adjusted to find the most efficient kernel function.

However, there is some limitation of SVM. Normally, SVM achieves only for binary classes. The other traditional techniques are added in order to increase the performance of SVM. In this work, the one-vs-the-rest SVM and SVM with 2-layer decision tree are introduced. The multi-class SVMs are selected to classify 3 classes of data with linear and polynomial kernel function. The comparisons of those techniques are shown in the Fourth Section.

IV. RESULTS AND ANALYSIS

In this section, the results will be analyzed and also the criteria of each stage of glaucoma will be described.

A. Ground Truth

The experiment is divided the training data into 3 main groups based on the progression of the optic cup and disc as shown in Fig.1.a-c. According to the medical knowledge and ophthalmologist’s suggestion, the followings describe the criteria of 3 classes:

Class 1: Normal case
This class provides 60 images of healthy eye. In general, the range of cup-to-disc ratio in vertical direction \(\text{CDR}_V\) is less than 0.4 as shown in Fig.1.a.

Class 2: Glaucoma suspect
This case provides 50 images that have a risk to become glaucoma. The glaucoma suspect range of \(\text{CDR}_V\) is approximately between 0.4 and 0.6 as described in Fig.1.b.

Class 3: Glaucoma case
It is consisted of 60 unhealthy eyes that have the \(\text{CDR}_V\) approximately higher than 0.6 or 0.65 as shown in Fig.1.c.

In addition, one advantage of \(\text{CDR}_V\) detection is when there are some rapid changes within a few period of time such as \(\text{CDR}_V\) is increased rapidly from 0.45 to 0.6 within a month. This can be used for evaluating the development of glaucoma as well. However, the \(\text{CDR}_V\) is not the only one considered factor to diagnosis glaucoma in nowadays. The other factors that the ophthalmologists consider are intraocular pressure (IOP), optic nerve fiber layer (RNFL), and the visual field.

B. Proposed Method

This work proposed 3 methods to distinguish 3 classes of glaucoma. Classes 1-3 are non-glaucoma, glaucoma suspect, and glaucoma respectively. The 6 selected features are the size of the optic cup and optic disc and the cup-to-disc ratio in both vertical and horizontal direction as described in Fig.4. The following shows a set of input features.
Features = \{\text{Cup}_b, \text{Disc}_g, \text{CDR}_g, \text{Cup}_h, \text{Disc}_h, \text{CDR}_h\}

When the features of training data are fed to the model, the machine learning generates the classifier model to diagnosis the real input data. The followings describe the proposed method:

a. **Method 1 : One-vs-the-rest support vector machine.**

This method consists of 3 classifiers; Class1-vs-other SVM, Class2-vs-other SVM, and Class3-vs-other SVM as shown in Fig. 5. This technique separates one class from all of the rest. The final class will be chosen by selected the highest score produced by each model.

![Fig. 5. The process of one-vs-the-rest support vector machine (Method 1).](image)

b. **Method 2 : Support vector machine with 2-stage decision tree.**

This method contains 2 classifiers; SVM-1 and SVM-2. SVM-1 is applied to identify healthy case and then SVM-2 is performed to classify class 2 and 3 as shown in Fig.6. The training set of healthy case does not undergo to the next classifier (SVM-2). Finally, 2 classes of data; glaucoma suspect and glaucoma are classified by SVM-2.

![Fig. 6. The process of support vector machine with decision tree (Method 2).](image)

c. **Method 3 : Support vector machine with 2-stage decision tree.**

This method contains 2 classifiers; SVM-1 and SVM-2. Firstly, SVM-1 is used to identify class 3 and then SVM-2 is applied to classify class 1 and 2 as described in Fig. 7. The training set for the second stage (SVM-2) is decreased by eliminating the training data from class 3 (unhealthy case) and then SVM-2 classifies the 2 classes; non-glaucoma and glaucoma suspect.

![Fig. 7. The process of support vector machine with decision tree (Method 3).](image)

C. **Evaluation**

To evaluate the performance of each method, 10-fold cross validation technique is performed. It means that the data is divided into 10 folds and repeatedly performs the classifier 10 times by randomly setting 10% of the data base as a testing set and assigning the rest (90% of the data base) as a training set. Finally, the results are accumulated and shown in confusion matrix. The 4 parameters in confusion matrix are true positive (TP), true negative (TN), false positive (FP), and false negative (FN).

The accuracy (ACC) of each class is the rate of true positive (TP) over all positive events. It can be defined as follows:

\[
ACC = \frac{TP}{TP+FP} 
\]  

(3)

Where TP indicates the case that the target class is detected correctly. FP indicates the case that the other class is detected as the target class.

The total accuracy is determined by averaging the weighted accuracies of each class. The accuracies of the 3 methods are shown in Tab.1-3. The comparisons of linear and polynomial are demonstrated and also the total accuracies of the model are pointed out in each table.

**TABLE I : THE ACCURACY AND AVERAGE TIME CONSUMING OF METHOD 1 USING ONE-VS-THE-REST SUPPORT VECTOR MACHINE.**

<table>
<thead>
<tr>
<th>KERNEL FN.</th>
<th>CLASS 1</th>
<th>CLASS 2</th>
<th>CLASS 3</th>
<th>TOT. ACC.</th>
</tr>
</thead>
<tbody>
<tr>
<td>LINEAR</td>
<td>98.3%</td>
<td>92.0%</td>
<td>86.7%</td>
<td>91.8%</td>
</tr>
<tr>
<td>POLYNOMIAL</td>
<td>100%</td>
<td>90.0%</td>
<td>98.3%</td>
<td>96.5%</td>
</tr>
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</table>

**TABLE II : THE ACCURACY AND AVERAGE TIME CONSUMING OF METHOD 2 USING SUPPORT VECTOR MACHINE WITH DECISION TREE.**

<table>
<thead>
<tr>
<th>KERNEL FN.</th>
<th>CLASS 1</th>
<th>CLASS 2</th>
<th>CLASS 3</th>
<th>TOT. ACC.</th>
</tr>
</thead>
<tbody>
<tr>
<td>LINEAR</td>
<td>98.3%</td>
<td>92.0%</td>
<td>91.7%</td>
<td>93.5%</td>
</tr>
<tr>
<td>POLYNOMIAL</td>
<td>95.3%</td>
<td>98.3%</td>
<td>95.3%</td>
<td>97.3%</td>
</tr>
</tbody>
</table>

**TABLE III : THE ACCURACY AND AVERAGE TIME CONSUMING OF METHOD 3 USING SUPPORT VECTOR MACHINE WITH DECISION TREE.**

<table>
<thead>
<tr>
<th>KERNEL FN.</th>
<th>CLASS 1</th>
<th>CLASS 2</th>
<th>CLASS 3</th>
<th>TOT. ACC.</th>
</tr>
</thead>
<tbody>
<tr>
<td>LINEAR</td>
<td>98.3%</td>
<td>98.3%</td>
<td>98.3%</td>
<td>98.3%</td>
</tr>
<tr>
<td>POLYNOMIAL</td>
<td>85.0%</td>
<td>98.0%</td>
<td>98.3%</td>
<td>98.3%</td>
</tr>
</tbody>
</table>

Finally, it is shown that the proposed method 3 (Tab.3) provides the best performance to the screening process of glaucoma suspect and glaucoma case. It is found that this
technique is robust to those classes. The number of wrong-classified case (FN) is less than 2%. The third method is better than the first method because the first method is robust to healthy and glaucoma cases. The healthy case is not the first priority target group of the screening system. The target is to perform the efficient detection of glaucoma in early or advanced stages in order to prevent the vision loss.

CONCLUSION AND FUTURE WORK

This work proposes an automatic screening method for detecting the development of glaucoma using multi-class support vector machine. The experiment compares 3 different types of multi-class support vector machine; one is one-vs-the-rest technique, others are SVM with the decision tree. The results show that the performance of SVM together with the decision tree provides a good outcome. However, to obtain more reliable, the false negative rate should be the smallest number. Based on our data base from Mettapracharak hospital, method 3 provides the best performance among the other techniques. The overall accuracy of method 3 is 94.7% and it is found that this method is robust to class 2 and class 3, which are belong to the target class of this screening process, glaucoma suspect and glaucoma cases.

In the future study, 3D reconstruction of the optic nerve head is proposed in order to help diagnosis the glaucoma with the different features such as a depth and a shape of an optic cup and disc. Moreover, to develop this system as software by creating the GUI is important. It will become a user friendly interface that is easy to use and understand.

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