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Detection of Glaucoma with Deep Learning

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ABSTRACT

Glaucoma is an ocular disorder caused due to increased uid pressure in the optic nerve. It damages the optic nerve subsequently and causes loss of vision. The available scanning methods are Heidelberg Retinal Tomography (HRT), Scanning Laser Polarimetry (SLP) and Optical Coherence Tomography (OCT). These methods are expensive and require experienced clinicians to use them. So, there is a need to diagnose glaucoma accurately with low cost. Hence, a new methodology for an automated diagnosis of glaucoma is required. Fundus images are used for the diagnosis of glaucoma. The effect of glaucoma can be reduced if we can predict glaucoma in its early stages. To predict glaucoma in its early stages a deep learning (DL) and machine learning techniques are used. with convolutional neural network and Bayesian networks. Classifiers, such as convolutional neural networks (CNNs) and Bayesian network, can infer a hierarchical representation of images to discriminate between glaucoma and non-glaucoma patterns for diagnostic decisions. These networks are compared with the parameter classification accuracy to predict which network model is best for classifying Fundus images. The features relevant for distinguishing Glaucoma patients is extracted from the fundus image. The Empirical Wavelet Transform (EWT) is employed for extracting features from fundus image . Use of wavelet transform for the feature extraction, which is faster and enables better resolution and high performance for representation and visualization of the abnormality in fundus image than other methods.

Keywords: Glaucoma, Raised Intraocular Pressure, Optic Nerve Head, Optic Cup.

I. INTRODUCTION

Glaucoma is one of the common causes of blindness, and is predicted to affect around 80 million people by 2020. It is a chronic eye disease that leads to vision loss, in which the optic nerve is progressively damaged. As the symptoms only occur when the disease is quite advanced, glaucoma is called the silent thief of sight. Although glaucoma cannot be cured, its progression can be slowed down by treatment. Early detection of glaucoma based on effective images is highly needed. Digital Fundus Image is one of the main and popular modalities to diagnose glaucoma. DFI has emerged as a preferred modality for large-scale glaucoma screening. In a glaucoma screening program, an automated system decides whether or not any signs of suspicious for glaucoma are present in an image. Only those images deemed suspect by the system will be passed to ophthalmologists for further examination. Diagnosis of glaucoma is mainly based on the Intra Ocular Pressure (IOP), medical history of patient's family, and change in optic disc structure. Glaucoma suspect will have IOP more than 21 mmHg. Different types of glaucoma are Open Angle/ Chronic Glaucoma, Acute Angle Closure Glaucoma, Normal Tension.

In normal healthy eye, the light rays enters to the eye via the cornea, pupil and lens. Those rays are fully focused onto the retina directly, then the light-sensitive tissue are lining the eye backside and retina converts those light rays into some impulses that can sent via the optic nerve to brain, at that time only they are recognized as image [1]. In glaucoma eye, blind spots are developed when the optic nerve fibers can occurred the damage and blind sports are usually unable to detect until optic nerve is damaged. The Early detection and treatment keys to preventing vision loss from glaucoma [2].

Diagnosis of glaucoma is mainly based on the Intra Ocular Pressure (IOP), medical history of patient's family [4], and change in optic disc structure [5]. Glaucoma suspect will have IOP more than 21 mmHg [6]. Other methods of monitoring glaucoma involve Optical Nerve Hypoplasia Stereo Photographs (ONHSPs), advanced imaging technology such as Optical Coherence Tomography (OCT), Scanning Laser Polarimetry (SLP), and Confocal Scanning Laser Ophthalmoscopy (CSLO) to generate reference images to study the eye and its internal structure [5]. These methods are expensive and require skilled supervision. It is suggested that combining various imaging methods will significantly improve the accuracy of glaucoma identification.

The glaucoma disease is characterized by change in the structure of nerve fibers and optic disc parameters such as diameter, volume, and area [5], [7]. Structural changes occur due to obstruction to the discharge of aqueous humor, which in turn increases IOP. This injures the optic nerve fiber and prevents the transmission of information from eye to the brain [8]. Ophthalmologists examine distinct regions to identify disease during eye inspection. Different methods have been employed to determine representative features such as irregularity of blood vessels [9]. The fundus images are used for the diagnosis of glaucoma [10], [11] and diabetic retinopathy [12]. Damage to optic nerve fibre is detected using the morphological features of fundus images . Morphological features such as cup to disc ratio, the ratio of area of blood vessels in inferior-superior side to the nasal-temporal side, and ratio of distance between the optic disc center and optic nerve head to diameter of the optic disc are used to detect glaucoma [10]. In morphological methods, choosing structural elements is difficult which may not yield high classification accuracy [1], [10]. Image segmentation based techniques have been used for glaucoma detection [10]. These segmentation have shortcomings like localization, thresholding or demarcation which may lead to unacceptable results and unavoidable errors in glaucoma diagnosis [1].

The progression of the disease can be categorized in six different stages. The first stage is the Primary Open Angle Glaucoma . It is the most common form of glaucoma. It occurs when the trabecular meshwork of the eye gradually becomes less efficient at draining fluid. The second stage is known as Normal Tension Glaucoma. Some people whose eye pressure is consistently below 21 mm Hg have this type of glaucoma . Next stage is the Ocular Hypertension - It is a condition where someone has higher eye pressure than normal, but does not have other signs of glaucoma, such as optic nerve damage or blank spots that show up in their peripheral (side) vision when tested. The forth stage is the Primary open angle glaucoma. It occurs when the drainage angle of the eye becomes blocked. Unlike open-angle glaucoma, eye pressure usually goes up very fast. Next stage is known as Secondary Glaucoma. It is glaucoma that results from another eye condition or disease. The final stage is known as Congenital Glaucoma It is a rare type of glaucoma that develops in infants and young children and can be inherited.

The objective of the proposed work is to develop a new method for automatic detection and classification of Glaucoma into two category normal and Glaucoma patient using various classifiers and wavelet feature extraction method. The Empirical Wavelet Transform (EWT) is a signal dependent decomposition technique. The working principle of EWT depends upon frequency spectrum of the signal. In this work, we are proposing a novel method for the classification of glaucoma images based on EWT and correntropy features. EWT decomposes the image into various frequency bands. Correntropy is extracted from the decomposed EWT components. The features are normalized and ranked on the basis of significant criteria. In this work, a novel approach towards the automatic detection and classification based on SVM using EWT is employed. The Convolutional Neural Network and Bayesian Network where also used as classifiers.

This paper is organized as follows: Section II describes the concept of fundus images and its relevance. The details of dataset used are also described in this section. Preprocessing of fundus data and method used for extracting features are also included in this section. Section III describes the basic concepts of classifiers i.e. support vector machine, Bayesian networks and convolutional neural network. Section IV proposes the working of the proposed systems with the three classifiers and at the end in Section V the conclusions of this research will be presented.

II. FUNDUS IMAGES

Fundus photographs are ocular documentation that record the appearance of a patient's retina. The photographs allow the clinician to study a patient's retina, detect retinal changes and review a patient's retinal findings with a coworker. Fundus photographs are routinely called upon in a wide variety of ophthalmic conditions.

Figure 1. Standard fundus images (a) normal, (b) glaucoma.

Fundus photography is used to inspect anomalies associated to diseases that affect the eye and to monitor the progression of the disease. It is vital for disease processes such as macular degeneration, retinal neoplasms, choroid disturbances and diabetic retinopathy. Additionally it aids in identifying glaucoma, multiple sclerosis, and other central nervous system abnormalities. It evaluates irregularities in the fundus, monitors the progression of a disease, management and therapeutic outcome. They are crucial to create a starting point to better understand a disease's progression. Fundus photographs may be useful if there is a new disease affecting the fundus and for the planning of additional management options.

Dataset

Fundus dataset, which is available online and includes data for both normal and glaucoma patients. The proposed method has been applied on this databases. The dataset includes 30 normal and 30 glaucoma images. These images are obtained from Kasturba Medical College, Manipal, India. The image quality and its usability have been certified by the doctors of ophthalmology department. The image is stored in 24-bit JPEG format with resolution of 560×720 pixels. Figs. 2(a) and 2(b) show the sample normal and glaucoma digital fundus images, respectively.

Feature Extraction

Feature extraction is done using Empirical wavelet transform. In feature extraction using EWT, the preprocessed signals undergo signal decomposition. In signal analysis, EWT is signal dependent method and does not use pre-defined basis functions like in Fourier and wavelet transform. EWT is an adaptive method of signal decomposition based on the information content of the signal. In EWT, the Fourier spectrum in the range 0 to π is segmented into M number of parts. Bandpass filters defined on each contiguous segment defines empirical wavelets. Littlewood-Paley and Meyer's wavelets are used as a bandpass filters with the empirical scaling function and the empirical wavelets .MATLAB enables function for performing multi-level one-dimensional wavelet analysis using a specific wavelet in its Wavelet Toolbox

III. CLASSIFFIERS

The three classification module that have been used in the proposed system are as follows:

A. *Support Vector Machine*

The entire document should be in Times New Roman or Times font. Type 3 fonts must not be used. Other font types may be used if needed for special purposes. The proposed methodology uses digital fundus image for the automated diagnosis of glaucoma which is based on Empirical Wavelet Transform (EWT).In this method an combination of EWT and SVM was used for the automated diagnosis of glaucoma. EWT aims to decompose an signal or an image on wavelet tight frames which are built adaptively. The support vector machines are supervised learning models with associated learning algorithms that analyse data used for classification and regression analysis. The SVM is used to classify the images into glaucomaus or non glaucomaus based on the features extracted. The correntropy has been used as feature in the proposed methodology. Correntropy is extracted from the decomposed components of 2D EWT. Here twelve entropy features are computed from each image. All these features are further processed using Student's *t*-test process. The features are then standardized with zero mean and unit standard deviation. The ranked features are classified using the Least Squares-Support Vector Machine (LS-SVM). LS SVM is a supervised machine learning algorithm used to discriminate two or more classes using linear or non-linear hyperplanes.

B. *Bayesian Network*

Bayesian Nework or probabilistic directed acyclic graphical model is a probabilistic graphical model (a type of statistical model) that represents a set of random variables and their conditional dependencies via a directed acyclic graph (DAG). It is used to calculate probability of an uncertain cause given some observed evidence. Bayesian networks, or alternatively graphical models, are very useful tools for dealing not only with uncertainty, but also with complexity and (even more importantly) causality. Given symptoms, the network can be used to compute the probabilities of the presence of various diseases. Depending upon the features extracted the Bayesian Network calculate the probability of an glaucomatous and non glaucomatous image.

C. *Convolution Neural Network*

An deep learning architecture which is based on CNN is proposed here. DL architectures are an evolution of multilayer neural networks (NN), involving di_erent design and training strategies to make them competitive. These strategies include spatial invariance, hierarchical feature learning and scalability. The main emphasis is given to capturing the deep features of glaucoma based on deep CNN capturing the discriminative features that better characterize the hidden patterns related to glaucoma. The adopted DL structure consists of six layers:four convolutional layers and two fully-connected layers, which infers a hierarchical representation of images to discriminate between glaucoma and non glaucoma patterns for diagnostic. decisions. In addition, to reduce the overfitting problem, we adopt responsenormalization layers and overlapping-pooling layers.

IV. PROPOSED SYSTEM

Glaucoma is a major eye disease, being the second cause of blindness worldwide. Its mechanisms are not completely known and early medication is still considered the best management available. The purpose our method is to predict future disease progression in an individual patient as accurately as possible where the prediction must be done on the basis of digital fundus datasets. The problem is that it is expensive and time consuming to obtain the digital fundus measurements. It is a critically important task to predict how rapidly the disease is progressing on the basis of a limited number of measurements obtained at an early stage. Inorder to identify the best method for the detection and prediction of glaucoma an comparison between 3 methods are done.

A significant way for identifying and analyzing Glaucoma in humans is by using fundus image. In this work fundus image will classified as normal (healthy) image or as Glaucoma images using an automated system. The proposed methodology uses digital fundus image for the automated diagnosis of glaucoma which is based on Empirical Wavelet Transform (EWT).In this method an combination of EWT and SVM was used for the automated diagnosis of glaucoma. EWT aims to decompose an signal or an image on wavelet tight frames which are built adaptively. The support vector machines are supervised learning models with associated learning algorithms that analyse data used for classification and regression analysis. The SVM is used to classify the images into glaucomaus or non glaucomaus based on the features extracted.

The pre-processing module constitute 3 steps such as Sampling, ROI Extraction and Channel Selection. The R, G, B components and grey scale of fundus images are subjected to 2D EWT. The R, G, B components of image consists of significant details in the form of variation of grey pixel intensities. The information present in R, G, B components are used to extract features for automated diagnosis of glaucoma. The EWT method is used for signal decomposition. The correntropy has been used as feature for extraction. The correntropy has been extracted from the decomposed components of 2D EWT.

Feature selection plays an important role in performance evaluation.The t-test is any statistical hypothesis test in which the test statistic follows a Student's t-distribution under the null hypothesis. The t-test discriminates two classes on the basis of population mean. The t-test assumes the normal distribution of feature sets corresponding to different classes. Features are ranked based on the t-value. The features are then standardized with zero mean and unit standard deviation. The process is known as z-score normalization. The ranked features are classified using the Least Squares Support Vector Machine (LS-SVM) classifier with kernels such as Radial Basis Function (RBF).

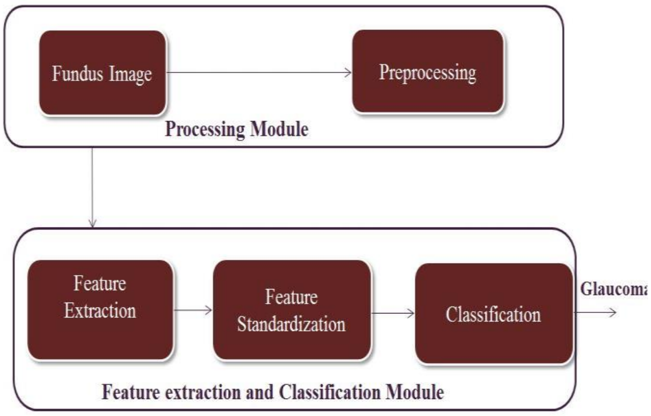

Figure 1 . System Architecture

The classification phase consists of training the neural networks and SVM with the selected features which is extracted in the previous phase and testing the neural network to classify fundus image into 2 categories (Glaucoma and Normal). Training is performed so that new incoming fundus image will be classified into Normal and Glaucoma categories. The Fundus image is classified with all the three classifies mentioned in the Section III and best accuracy obtained when classified with convolutional neural network.

V. CONCLUSION

Accurate automated Glaucoma detection remains an important challenge and a critical step in removing the uncertainty associated with when Glaucoma will occur and further the understanding of Glaucoma and its causes. In the proposed method, the Fundus images have been classified in 2 classes. A classification system for this purpose makes use of a Support Vector Machine, Bayesian Network and Convolutional Neural Network. Result shows classification with CNN will provide best accuracy when compared to BN and SVM.

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