Glaucoma Detection System on the Basis Combining NB and RF Classifiers

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A group of vision-impairing eye conditions known as glaucoma damages the optic nerve, which is essential for clear vision. Frequently, the result is abnormally high ocular pressure. One of the leading causes of blindness in adults over 60 is glaucoma. However, it is more prevalent in older persons of all ages. Glaucoma must be diagnosed as soon as possible. This paper presents the Glaucoma Detection System (GDS), which combines classifiers. For the purpose of glaucoma detection, the GAD system employs the Naive Bayes (NB) and Random Forest (RF) classifiers. The major function of the optic disc and cup is to find anomalies in fundus pictures. The optic cup and optic disc are first extracted from the input fundus pictures, and a region of interest (ROI) is then found.

Keywords: Glaucoma Detection, Fundus Image, Combining Classifiers, Optic Cup, Optic Disc

Introduction

Funduscopic images-based glaucoma detection is discussed in [1]. Initially, the input images are separated by green and red channels. Then the image is converted in to gray scale. The median filter is applied to grayscale image to remove noise. The average histogram analysis and maximum grey level values are identified. The identified range of pixels is extracted. Glaucoma classification using discrete orthogonal stock well transform is described in [2]. Initial input images are preprocessed and converted into grayscale image. The discrete orthogonal stock well transform is used for feature extraction and RF classifier is used for classification.

The cup and disc ratio are identified. Glaucoma detection using fundus images is described in [3]. The image is enhanced at the initial stage. Then the optic disc is segmented and smoothed. Then the ellipse is filled and detected. Finally, the ratio is identified. Blood vessels and optic cup to disc ratio for glaucoma screening is described in [4]. The input images are preprocessed by contrast improvement noise reduction and color conversion. Then the optic disc is segmented using multiclass SVM classifier. Then the disease is detected.

Glaucoma diagnosis based on complex texture features and support vector machine classifier is presented in [5]. Initially, the optical density is detected, and then the Gray Level Co-Occurrence Matrix (GLCM) like energy, correlation and contrast features are extracted. Lastly, support vector machine classifier is used for classification. Retinal fundus images-based glaucoma detection is discussed in [6]. The input image is preprocessed and region of interest is extracted and the image is resized. Then the optic cup and disc are extracted. The neuroretinal rim is extracted. The classification of glaucoma is made by some erode and disc features.

Glaucoma detection using expectation maximization algorithm is discussed in [7]. The glaucoma detection is made by using estimation maximization algorithm. Firstly, the preprocessing is made by using anisotropic diffusion filter. Then the optic disc and cup segmented by region of interest. Then fuzzy clustering means is used for the segmentation.

Digital fundus image-based glaucoma detection is described in [8]. The optic disc is segmented by using hill climbing algorithm and k-means clustering. Finally, the region of interest is detected. Glaucoma classification using fundus images based on Empirical Wavelet Transform (EWT) and GLCM is discussed in [9]. The initial fundus images are given to EWT then GLCM features are extracted. Finally, neural network classifier is used for classification.

In this study, the architecture && performance of glaucoma detection system using combination of classifiers is presented. The paper is organized as follows: Section-2 describes the methods and materials used in the glaucoma detection system. The results and discussion of glaucoma detection system is described in section 3. The last section concludes the glaucoma detection system.

Methods and Materials

The GDS workflow is shown in figure 1. Initially, the input fundus images are separated into optic cup and disc to identify the anomaly. Then the ROI region is extracted from the optic cup and disc. From the extracted ROI region, the energy feature extraction is made and stored in database. Finally, the NB classifier and RF classifier are combined for the prediction.
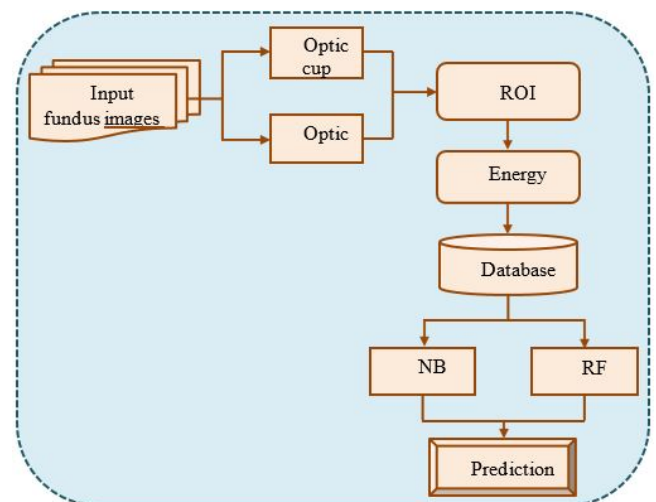

Figure 1: GDS using combining classifiers

ROI Extraction

ROI is samples identified for a specific purpose within a data set. In many applications, the concept of an ROI is widely used. For example, the borders of a tumor can be calculated in medical imaging on an image or in a volume to calculate its size.

For the purpose of cardiac function evaluation, an end-systole and end-diastole can be identified on an image in various phases of the cardiac cycle, with example. The common ROI extraction for an image is shown in figure 2.

A ROI can literally be taken as a polygonal array from a 2D map in geographical information systems. The ROI determines the boundaries of an object to be found in computer vision and optical character recognition. Symbolic labels (text) are applied to a ROI in many applications to compactly define the material. Specific points of interest can lie within a ROI. In this study, the GDS for ROI extraction is made for a glaucoma image for optic cup and optic disc segmentation to identify the abnormalities in the fundus image.
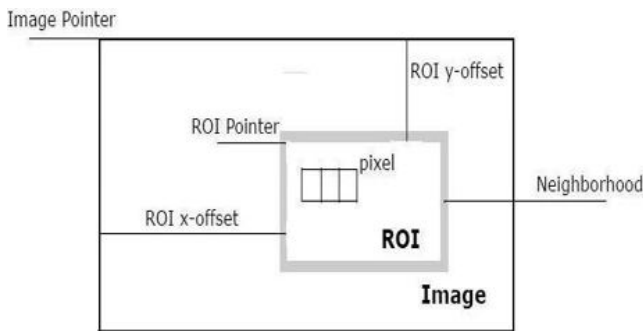

Figure 2: ROI for an image

Energy Feature Extraction: The energy of the wavelet is the square of the precise transforming factor. Depending on the signal input, the energy of the wavelet is varied over different scales. The c(t) coefficient energy of the wavelet can be defined accordingly,

$$G(y(n)) = \sum_{i=1}^{n} ce^2$$

where ej for the cj coefficient obtained from the corresponding image y(n) with the necessary scaling coefficients. In this study, the energy feature is used to extract the ROI image.

Classification Using Combining Classifiers

The machine learning, the naive classifications in Bayes are a family of basic "probabilistic classifications" based upon the application of the Bayes theorem with strict – naïve - independence

Assumptions. It's not a single algorithm but an algorithm family in which they are all common and each couple is autonomous of features labeled. In short, Bayes is a conditional likelihood: given an instance of question to be categorized and a vector is represented by R= r1 ,..., rn) It gives this instance the probability to represent some n features (independent variables).

$$p(G_m / r_1 \ldots \ldots r_2)$$

where G is a possible9 outcomes or classes Gm. The problem of the above formulation is that it is difficult to base such a model on probability tables if the number of features n is high or if a function will accept large numbers of values. The dependent probability can be broken down as per Bayes theorem is defined by.

$$p(G_m / r) = \frac{p(G_m) p(r / G_m)}{p(r)}$$

The random forest training algorithm applies to tree learners the overall technique of mixing or bagging bootstrap. Consider the training set S = s1,…,sn with responses T = t1,…,tn bagging repeatedly (B times) picks an altered sample and removes the training package. The RF is defined by,

$$k = \frac{1}{L} \sum_{l=1}^{L} k_l(s')$$

In case of classification trees, or by taking the majority vote. Random forests are a whole classification learning method, a regression system that operates by constructing a multitude of decision-making trees during the training season and delivering the class mode - classification or mean prediction - regression of each tree. The forest is an ensemble learning method. Random decision forests are right to overfit their training habit for decision-making trees.

In this study, the NB and RF classifiers are used to prediction of GDS. The optic cup and disc are used to identify the anomaly in the fundus images. The NB classifier and RF classifier classified separately and combined at the last stage for the prediction of final output.

Results and Discussion

The experimental results and discussion are explained in this section. The 50 images with both normal and abnormal categories are used for performance evaluation. From these images the optic cup and optic disc are extracted to detect the ROI region. Then the detected ROI area is extracted by using energy features. Finally, the NB and RF classifiers are used for classification. These classifiers are combined to form the output prediction. The Receiver Operating Characteristics (ROC) curve for NB classifier, RF classifier and combining classifier (NB + RF) is shown in figure 3.
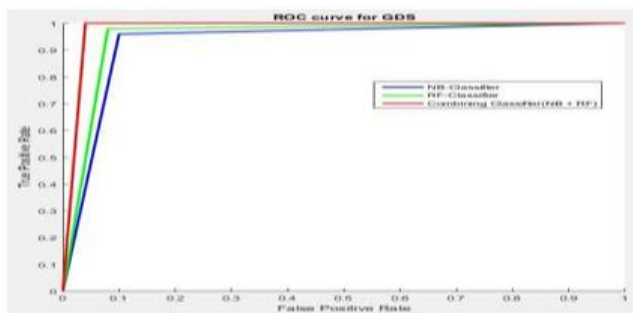

Figure 3: ROC curve for NB classifier, RF classifier and combining classifier (NB + RF)

From the above figure it is observed that the maximum area under the curve is 0.98 by using the combing classifier. The minimum area of the curve is 0.93 is obtained by using NB classifier. The graphical representation of GDS is shown in figure 4.
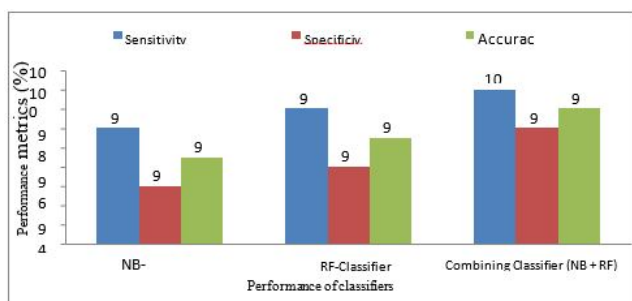

Figure 4: Graphical representation of GDS

From figure 4 it is clearly observed that the combining classifier (NB + RF) produces the higher classification accuracy of 98% using

Energy features and its sensitivity and specificity are 96% and 100%. Also RF classifiers produce the 95 % accuracy and 92% sensitivity and 98% specificity and NB classifier produces 93 % classification accuracy and 96% specificity and 90% sensitivity.

Conclusion

The method for architecture & performance of GDS on the basis combining classifiers is discussed in this study. At first, the ROI region is extracted from the fundus image, and then the energy feature is used for feature extraction and stored in the feature database. Finally, the classifiers like NB and RF classifier is combined to form the final output prediction. The GDS system yields the classification accuracy of 98% obtained by using the combining classifiers (NB and RF) and its sensitivity and specificity are 96% and 100%. The NB and RF classifiers separately produce the classification accuracy of 93% and 95% by using the energy features.

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