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Dual Machine-Learning System to Ensemble Algorithm for Glaucoma Diagnosis Using Support Vector Machine

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Abstract

A disease can affect the vision, causes optic nerve damage, which ends with vision loss is Glaucoma which is a degenerative disease. The conventional detection techniques have changed dramatically since machine learning made its way into fundus imaging. An ensemble learning algorithm is proposed for the detection of Glaucoma from fundus images. Texture-based and Sketch-based are two independent feature sets which are extracted from eye fundus images. A diagnostic aid tool is designed, trained, and then tested in this paper for the Glaucoma detection from eye fundus images. This system contains two subsystems, which was trained and tested independently, to improve the Glaucoma detection, these two results are combined. Each feature set is built with 3 basic learning models; they are Decision Tree (DT), back propagation neural network (BPNN) and Support vector machine (SVM). These three base learning models are combined for the detection of glaucoma by employing the method of stacking and majority voting of ensemble learning. This ensemble learning combines results of three learning models for the improved detection and classification accuracy of glaucoma. This system can achieve higher classification rate than previous systems. A real-world dataset includes fundus image samples which are used for testing and training. At 98.02% the system exhibits good performance results and detection accuracy.

Key Words:

Back Propagation Neural Network (BPNN), Support vector machine (SVM), Fundus images, Glaucoma detection, Decision tree (DT)

1. Introduction

The Glaucoma causes blindness, to save the patients from temporary or permanent blindness early stage of disease discovery and analysis is required. So many research projects have been developed in existing systems using different data mining methods for the detection of Glaucoma. The accuracy of glaucoma disease detection using traditional techniques is not sufficient. The presences of Glaucoma disease n input fundus image requires more time for detection [1]. Therefore, there is a requirement of system which can perform effective Glaucoma disease detection [2]. Like blood pressure the eye has intraocular pressure. The optical nerve gets damaged if such IOP increased for certain level. Due to this peripheral vision decreases and finally causes blindness.

Physical analysis on eye images consumes time and the measurements of parameters accuracy differ from one expert to another expert. This increases the requirement fan automatic technique [3].Automatic Computerized examination of retina pictures is turning into a significant screening. Instrument now a days. This strategy identifies different sort of dangers and illness of eyes. Essentially two kinds of glaucoma's are there, one is open point or interminable glaucoma and second one is shut edge or intense glaucoma, these are answerable for expanding the intraocular pressure. Mostly there have indications or signs for patients at the earlier time of glaucoma [4].Reasons for losing the vision may affect because of increasing progress in illness and also the patients may experience the ill effects of limited focus (being just ready to see halfway).Thus early identification of this disease is basic to anticipate the changeless visual deficiency. Glaucoma disease happens when Intraocular Pressure increases. To prevent the interminable blindness early detection of disease is indispensable. From past few years the Glaucoma screenings are performed based on the retina digital images. So many methods for differentiate the abnormality of retina according to the glaucoma are used. The major part of this paper in detecting and classifying glaucoma is depends on the machine learning technique and the classification techniques of Glaucoma detection are measuring and comparing the fundus images of normal patients and affected

Glaucoma patients [5]. The machine learning task of inferring a function from labeled training data is said to be supervised learning. Set of training examples are part of training data. Input objects are including in every pair of example along with the desired output under the supervised learning [6].

The algorithm of supervised learning is used for analyzing the training data that produces an inferred function which is used for examples of mapping. Great effort has been done from last few decades for automation & detection and prediction of Glaucoma using different Machine Learning. Techniques are Decision tree based on ID3 algorithms, Naïve Bayes classifier, vector support machine,k-nearest neighbor, canny edge detector, active contour model, Fuzzy min-max neural network, linear regression and Neural networks has been achieved the Automated Glaucoma detection [7]. Automated prediction of Glaucoma in our proposed system is ensemble by 3 machine learning techniques using Back Propagation Neural Network (BPNN), Decision Tree (DT), Support Vector Machine (SVM) classifiers [8].

II. Types of Glaucoma And Ml Algorithms For Its Detection

2.1 Glaucoma types

1. Chronic Glaucoma/Open Angle: The open angle between cornea and iris is said to be wide in open angle. It can be cured easily, and symptoms also easily identified. The general Glaucoma causes slow clogging on eye. Basically, it is a wide-spread affecting disease and for old ages people mainly [9].

2. Angle-closure glaucoma:

A highly dangerous and very rare Glaucoma is Angle-closure Glaucoma/ closed Angle Glaucoma, which shows impact of sudden blindness. Intraocular Pressure rise is the main reason for this Glaucoma, and retina blockage occurs for affected person. A narrow angle between cornea and iris is said to be Angle-Closure Glaucoma [10].

3. Normal Tension Glaucoma:

The eye disorder with complete features of conventional Glaucoma that is related with the blood circulation except elevation IOP is known as Normal Tension Glaucoma. The optic nerve excavation and head bulges lead so many causes which are referred as ONH.

4. Ocular Hypertension:

A visual loss or a damage of optic nerve can be caused by the IOP.10 mmHg - 21mmHg is the normal IOP range.

5. Secondary Glaucoma

It is a disease related to eye cornea which can transform from one eye to another eye disease; it leads to secondary Glaucoma when the patient takes treatment or therapy.

6. Congenital Glaucoma:

It is a very rare disease, this Glaucoma symptoms are occurred frequently, affects the children. Best method for prevention is surgery. Medicines, drugs are not helpful. The optic nerve head (ONH) is measured in hospitals considering 4 region sides such as superior, inferior, nasal &ONH temporal. Compared to these four ONH regions in observing the damage of optic nerve ONH has a little significant. The Glaucoma Atrophy characteristic features have the optic nerve head (ONH) appearance that include with optic disc excavation or cupping, with neuro-retinal rim loss seen as optic Cup-to-Disc Ratio (CDR) enlargement. By using this CDR measurement of Glaucoma clinical diagnosis can be done which is defined as optic disc vertical height ratio to the optic cup vertical height. Cupping of ONH increment corresponds to increased cell death of ganglion & so that the CDR is used to measure the developing disease probability [11].

2.2 ML Learning Algorithms for Glaucoma Detection

In interior segment imaging selection effective features performs major role for determining the technique involved in Glaucoma an Angle closure type. The main focus of the research is on redundant features use for diagnosis of complex diseases, anterior segment optical coherence tomography images using ACG. Different ACG mechanisms are cross-examined with both MRMR (Minimum Redundancy Maximum Relevance)of supervised based and L-score (Laplacian score) of unsupervised based feature selection algorithms.ACG regarding different classes say pupil block, plateau iris, iris roll are classified by using the Ada Boost machine learning classifier and for both feature selection modes no mechanism is used.

The system of Glaucoma is based on prediction of multi class and the progression. The investigation of research paper uses Fractal Analysis (FA).The pseudo-2D images are applied to FA and are converted from 1-Dretinal nerve fiber layer is obtained data from normal subjects of eye and with non-progressive & progressive subjects of Glaucoma. By using multi fractional Brownian motion method and box counting method are obtained from the features of FA and incorporate with multi resolution and texture analysis, Gaussian kernel-based multiclass classification uses these both features. Computed FA features are specificity, sensitivity, and area under receiver operating characteristic curve (AUROC). The Wavelet Fourier Analysis (WFA), Fast-Fourier analysis (FFA)are used to obtain the matrix. This proposed FA achieves better performance with less complexity and few features than FFA &WFA [12].

Glaucoma is 2nd leading reason for blindness in world wide. Due to this disease fluid pressure increases continuously in the eye, which in turn causes vision loss and optic nerve damage. Early detection of Glaucoma requires support systems like computational decision devices to reduce the complexity [13]. By utilizing scanning laser polarimetry, and Heidelberg retina tomography scanning methods optical coherence tomography, assess of optic nerve retinal fiber layer can be done [14]. The system Glaucoma detection is designed with combination texture of higher order spectra (HOS) features from digital fundus images. To perform supervised classification sequential minimal optimization, naive Bayesian, Support vector machine, and random-forest classifiers are used [15].

III. GLAUCOMA DISEASE DETECTION BASED ON CNN

The dataset used for Machine learning system training is represented in the below section. The implementation of Global Architecture for Glaucoma Diagnosis is shown in below figure (1).

In our approach two subsystems are used, and the results are combined at final stage to produce a report on diagnosis assistance to the ophthalmologist. The 1st subsystem is a feature of extraction post-processing stage and it is based on two generalized U-Net base stages to segment the cup plus and disc. The 2nd subsystem is used for classification of direct fundus image and it is based on a Mobile Net V2 network. Final fusion stage is also there to produce the blended report as a result to assist his/her diagnosis report by the ophthalmologist (divide the text into two columns).

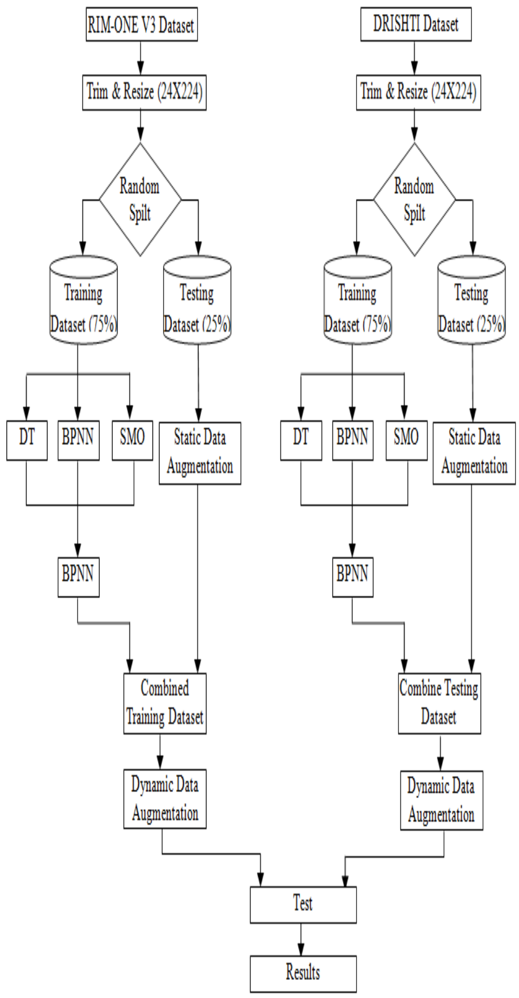

Fig.1. Architecture of Dual Machine Learning System for Glaucoma Diagnosis

3.1 Dataset

DRISHTI&RIM-One V3 are the two publicly available datasets are combined by database which is important because to compare the obtained results of present work with previous results. If the patient he /she has Glaucoma or not is provided by datasets through label indication of corresponding images of a patient. The dataset samples are labeled by supervised evaluation which is done by professionals in the field. The professional certifies that the patient with Glaucoma or healthy patient by taking each image of patient from dataset. The ophthalmologists also require the work performance of cup and disc segmentation to perform segmentation manually and also provides label images for indication of cup area and discs ground truth. The DRISTI-GS dataset made 101 fundus color images and are labeled for both cup and disc; The RIM-ONE dataset is composed 151 images, also labeled for cup and disc from the University of La Laguna. The system uses 75% of images for training from each dataset, for validating the results 25% of images are used. The system Architecture is included with dynamic (online) and static (offline) augmentation stages, so this the training and testing requires much higher images than the images in original datasets.

3.2 Pre-processing

The process of images in classification subsystem able to use the dataset images is like segmentation subsystem process. Only difference is image resizes to 224x224 for classification subsystem.

3.3 ML Classification Techniques

In order to detect the glaucoma 3 fundamental ML algorithms are used such as decision tree (DT), back propagation neural network (BPNN), and support vector machine (SVM) for each set of features.

1) Back Propagation Neural Network (BPNN)

An exclusive intelligence tool is used for simulation of human brain to generate results and for analysis. This BPNN algorithm is a multilayer neural network, has excellent features in non-linear mapping, self organization, generalization. This algorithm gives reasonable solutions when presented with inputs, which was unseen in neural networks. There is a possible way because of generalization property that made a network to be train on a representative set of input-output pairs. Then by training such network for all input-output pairs good results can obtain.

2) Decision Tree (DT)

One of the mostly used classification techniques under machine learning for real time applications is Decision tree. To obtain the underlying patterns, which are established as a root with an attribute, and as extended branches where leaf nodes categories are expressed as a concept,

named as intuitive cognition of things. The attributes rationality is key for decision tree comprehensibility. Statistical bias exists in decision tree induction which causes difficulties in attributes selection. Decision tree employs heuristic measures in traditional induction based on attributes perspective space for the selection of an attribute optimal split to partition the decision node for obtaining the improved tree.

3) Support Vector Machine (SVM):

The SVM is a machine learning algorithm which is based on kernel algorithm. To build classification and regression techniques in diverse technological fields includes discipline remote sensing and for pattern recognition problem solving purpose SVM leaning theory is developed. The SVM is based on decision surface concept, which separates the classes to maximize the margins between classes, and the surface is known as optimal hyper plane. The closed points in optimal hyper plane are known as support vectors. The critical elements in training sample set creation are sample vectors. To solve the two-class pattern recognition problem, sequential minimal optimization was introduced. The aim is to build a hyper plane which separates the negative and positive examples for smallest margin maximization. This SMO has important merits; i) For parameter tuning no effort is required, ii) No need of feature selection.

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3.4 Static Data Augmentation

For system training, static data augmentation is performed on the combined data set training fraction. This method has capability to produce images with contrast parameters or brightness modification and the process is similar to segmentation subsystem.

3.5 Dynamic Data Augmentation

For Dynamic augmentation no improvement is needed. The static augmentation is sufficient to enable DDA.

IV. RESULT

The Google Collaboratory Python development environment is used for designing the system. In Google cloud this environment provides good support for keras for implementation and networks training on GPUs. For training testing this system uses 120 image batches. For 15 epochs training requires 150 training steps and 30 testing steps per one epoch. Coming in to datasets the system utilizes DRISHTI and RIM-ONE v3 datasets which are available public. RIM-ONE v3contains 159 fundus images for cup and disc are labeled by expert ophthalmologists. DRISHTIGS consists of 101 fundus images also labeled for optic disc and cup.

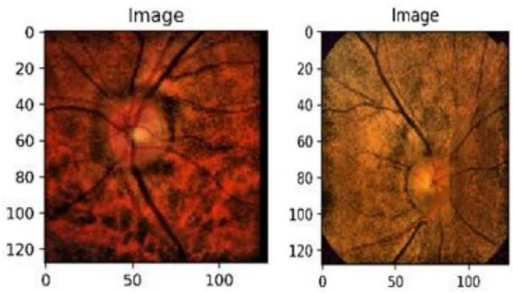

Fig. 2: Images from Rim and Drishti Datasets

The 75% of DRISHTI dataset for training and for validation remaining DRISHTI, RIM ONE is used. Train using 75% of data with RIM-ONE dataset and validation with remaining RIM-ONE with DRISTHI is carried out for validation of dataset. Performance of the classifiers can be tested and evaluated by the following parameters:

Accuracy rate $= \frac{Correctly classified samples}{Classified samples}$

Sensitivity is defined as the proportion of patients with Glaucoma positive test result, which is defined in medical field. Specificity is defined as proportion of patients with Glaucoma negative test result. These two parameters are calculated from true negative (TN), true positive (TP),false negative (FN),false positive (FP) are defined as

$$Sensitivity = \frac{TP}{TP + TN}$$

$$Specificity = \frac{TN}{FP + TN}$$

In this work, after cross validation the trained proposed dual ML based ensemble classifier has better accuracy rate of

98.02% as shown in figure (4) compared to the other individual classifier methods like DT, BPNN and SVM.

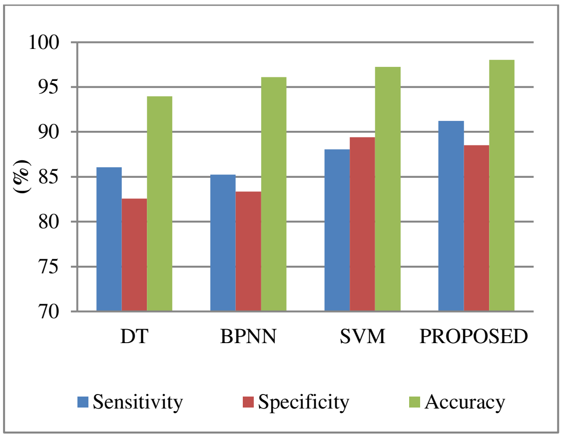

Fig. 3: Result of Performance Analysis

Table 1: Results For Glaucoma Detection On Machine Learning Models

Classifiers	Sensitivity	Specificity	Accuracy
DT	86.08%	82.56%	93.98%
BPNN	85.24%	83.35%	96.12%
SVM	88.04%	89.42%	97.25%
Proposed Dual ML technique	91.23%	88.58%	98.02%

DT classifier results are shown in above table 1.The accuracy rate is 93.98% for DT, 96.12% for BPNN, 97.25% for SVM. This proposed ensemble classifier has accuracy of 98.02% which yielded good results on the base learning models in classifying and detecting of glaucoma.

V. Conclusion

Glaucoma diagnosis and detection method using dual machine learning system with support vector machine classifier is presented in this system. For extracting the features of fundus images, sketch-based and texture-based techniques are used. For Glaucoma detection 2 ensemble machine learning algorithms are used. This system is implemented in an embedded system as a lightweight tool which can produce results at same level of other tools which needs much higher computing performance. This system tool uses completely different technologies based on ensemble of two subsystems. The reporting tool is very important part of the system and combines the output of two subsystems and provides required data to physician for understanding the diagnosis. Adequate usage of system is based on her/his own decision.

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