Glaucoma Detection from Ophthalmic Fundus Image Using Image Processing

NIKIL P LAL[1], SRINIVASAN S[2], VARUNALINGHAM H[3]

ABSTRACT:

Glaucoma is a degenerative disease that affects vision, causing damage to the optic nerve that ends in vision loss. In our project glaucoma is classified by extracting two features using retinal ophthalmic fundus images - Cup to Disc Ratio (CDR), and Ratio of Neuro retinal Rim in inferior, superior, temporal and nasal quadrants.In our work we were using two machine learning algorithms ➐ Random Forest Algorithm, ➐ SVM and one deep learning algorithm ➐ CNN for getting more accurate result. Here we will get separate result for all three algorithms and final conclusion will took based on the accuracy given by three algorithms. The algorithms were tested using the RIGA dataset.

Key Words: Fundus images, Glaucoma, Optic Disc, Cup & Disc, Random Forest, SVM(Support Vector Machine), CNN(Convolutional Neural Network).

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INDEX TERMS:

Artificial Intelligence, Deep Learning, Machine Learning, Artificial Neural Networks, Multi-Layer Neural Network, Neural Networks.

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1. INTRODUCTION:

Glaucoma Detection from Ophthalmic Fundus Image Using Image Processing is one of the most trending research areas. As the world's population has drastically increased, the number of people suffering from glaucoma, or those suspected to have glaucoma, has increased too.

Glaucoma is a leading cause of irreversible blindness worldwide. It affects more than 2.7 million individuals age 40 or older in the United States — approximately 1.9 percent of this population. Glaucoma is the second-leading cause of blindness among blacks, after cataract, and the third-leading cause of blindness in whites, after age-related macular degeneration and cataract.

Therefore, there is an even greater need for proper diagnosis and effective control of glaucoma. Accurate diagnosis of glaucoma requires three different sets of examinations: (1) Evaluation of the intraocular pressure (IOP), (2)Evaluation of the visual field, and (3)Evaluation of the optic nerve head Since both elevated-tension glaucoma and normal-tension glaucoma may or may not increase the IOP, the IOP by itself is not a sufficient screening or diagnosis method [2]. On the other hand, visual field examination requires special equipment which is usually available only in tertiary care hospitals equipped with a fundus camera, parametric instrumentation, and possibly an optical coherence tomography [2]. The optic nerve head examination (cup to disc ratio) is a valuable method for diagnosing glaucoma structurally [3]. Primary open angle glaucoma is causing a progressive optic neuropathy and its development is associated with loss of tissue in the neuroretinal rim of the optic disc and that will lead to increase in the size of the optic cup. The pattern of neuroretinal rim loss and cup enlargement may take the form of focal or diffuse change, or both in combination. Focal change, with the loss of the physiological shape of the neuroretinal rim, is identified by careful clinical examination. Diffuse change, with maintenance of the physiological rim shape, is much more difficult to identify. It is in these cases that quantification of the neuroretinal rim area or cup size is useful. Methods have been described to estimate the area of the neuroretinal rim during Ophthalmoscopy examination, but several measurements and calculations or additional equipment are required. The estimation of the size of the cup is usually made by comparison with the size of the disc and given as the ratio of the vertical and horizontal diameter of the cup to the vertical and horizontal diameter of the disc based on Garway-Heath et al. [4]. Thus, an automatic system for examination of optic nerve head is very useful. In a recent paper, Almazroa et al. [5] critically review the literature on glaucoma image processing.

Recently Dhumane and Patil [6] have developed an algorithm for calculating the cup to disc ratio. In this algorithm superpixel segmentation was used to extract disc and boundaries. Thirty-seven images were used to test the algorithm and it successfully segmented 33 images. Guerre et al. [7] introduced a technique based on Otsu's adaptive thresholding and a support vector machines classifier with linear kernel. The algorithm was tested on two datasets (29 and 26 images), and the accuracies of the cup to disc ratio were 89% and 59%, respectively.

[8] proposed a novel convolutional neural network based method for optic cup and disc segmentation. To reduce computational complexity, an entropy based sampling technique was introduced. The algorithm was tested using 10 images and the overlap was 89.5% between the segmented disc and ground truth, and 86.4% between the segmented cup and ground truth. Issac et al. [9] introduced a technique based on adaptive thresholding using features from the image such as mean and standard deviation. The algorithm was tested on 63 images and the accuracy was 92.06%. Alghmdi et al. [10] developed an automatic system to measure the cup to disc ratio based on superpixels clustering algorithm using simple linear iterative clustering and a feed-forward neural network classifier. The algorithm was tested using 60 images and the mean nonoverlapping error was 11% for the disc and 29% for the cup.

This paper gives the results from calculations of the horizontal and vertical cup to disc ratios using our previously introduced optic disc [11] and cup [12] algorithms. The algorithms were tested using the RIGA dataset.

2. Methodology

2.1. Dataset.

RIGA dataset was collected in order to facilitate research on computer-aided diagnoses of glaucoma. The dataset consists of 750 colour fundus images obtained from three different resources: (1) 1460 images from MESSIDOR images dataset [13] with two images of sizes 2240 × 1488 pixels and 1440 × 960 pixels, (2) 195 images from Bin Rushed Ophthalmic centrein Riyadh, Saudi Arabia. They were acquired in 2014 using a Canon CR2 Non-mydriatic digital retinal camera (less resolution images). The images sizes are 2376 × 1584 pixels. An additional 95 images were obtained from Magrabi Eye Center in Riyadh, Saudi Arabia. The images were acquired between 2012 and 2014 using

Dataset	Messidor
Normal	YES
Glaucomatous	YES
Camera Quality	Non-mydriatic camera (lower quality)
Image Size	2240*1488 1440*960
Number of training images	200
Number of testing Images	260
Total Images	460

Table 1: Dataset Table

a TOPCON TRC 50DX mydriatic retinal camera (more resolution images). The images sizes are 2743 × 1936 pixels. The images were notated manually by 6 ophthalmologists individually. Each one notated the disc and cup boundaries manually using a precise pen for Microsoft surface pro 3 with 12 inches high resolution screen (2160 × 1440 pixels).

Six parameters were calculated for the manual marking in order to be used to evaluate the algorithms, namely, disc area, disc centroid, cup area, cup centroid, vertical cup to disc ratio, and horizontal cup to disc ratio. The 3 datasets contain both normal and glaucomatous fundus images. The dataset was divided into two sets: training set with 200 images and testing set with 550 images for the training and testing purpose for the developed algorithms (Table 1).

2.2. Optic Disc and Cup Segmentation:

Briefly, the optic nerve head was localized using the procedures explained by Almazroa et al. [14] and Burman et al. [15] and optic disc segmentation was introduced by Almazroa et al. [11] based on inpainting the blood vessels and level set method. A fast digital image inpainting technique [16] was applied. The blood vessels were extracted; thus the extracted blood vessels are utilized to be the mask which identifies the area that wants to be inpainted. Blood vessels were extracted using a top-hat transform on the G-channel of the fundus image. In the second step, the segmentation process represented by the active contour model implemented by the level set [17] was applied. Based on the quality of the image, one of the two paths was considered for applying the level set (Figure 1).

From the three sets of images in RIGA dataset, Bin Rushed images are low quality and need a double level set.

After applying the first level set, the contour was considered as a second optic disc localization in order to restrict the variations from the center that cause the problems. Then the second localization was split into two to apply the level set again in order to obtain a more accurate segmentation. On the other hand, the cup segmentation was introduced by Almazroa et al. [12].The blood vessels were extracted using the same approach as that used for optic disc segmentation. Image thresholding was applied using an Interval Type-II fuzzy entropy based thresholding scheme with Differential. The training images were the keys for developing this algorithm.

2.3. Optic nerve cupping:

The optic nerve carries impulses for sight from the retina in the eye to the brain. It is composed of millions of retinal nerve fibers that bundle together and exit to the brain through the optic disc located at the back of the eye [6]. The optic disc has a center portion called the "cup" which is normally quite small in comparison to the entire optic disc.

2.4. Cup to disk ratio:

Both people with and without optic nerve damage have optic nerve cupping, although those with **glaucoma** tend to have a greater **cup-to-disc ratio**. A **cup to disc ratio** greater than six-tenths is generally considered to be suspicious for **glaucoma [6]**.

Classification:

Classification is a process of categorizing a given set of data into classes, It can be performed on both structured or unstructured data. The process starts with predicting the class of given data points. The classes are often referred to as target, label or categories. The classification predictive modeling is the task of approximating the mapping function from input variables to discrete output variables. The main goal is to identify which class/category the new data will fall into.

2.6. Convolutional Neural Network:

A **Convolutional Neural Network (CNN)** is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, CNN has the ability to learn these filters/characteristics[18].

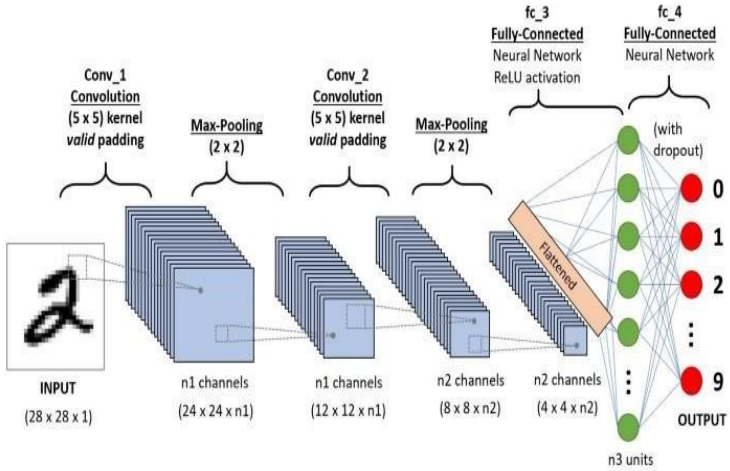

Figure 2.6.Working picture of Convolutional Network Network

The role of the ConvNet is to reduce the images into a form which is easier to process, without losing features which are critical for getting a good prediction.

2.7. Random Forest:

A random forest is a **data construct applied to machine learning** that develops large numbers of random decision trees analyzing sets of variables. This type of algorithm helps to enhance the ways that technologies analyze complex data. In general, decision trees are popular for machine learning tasks [19].

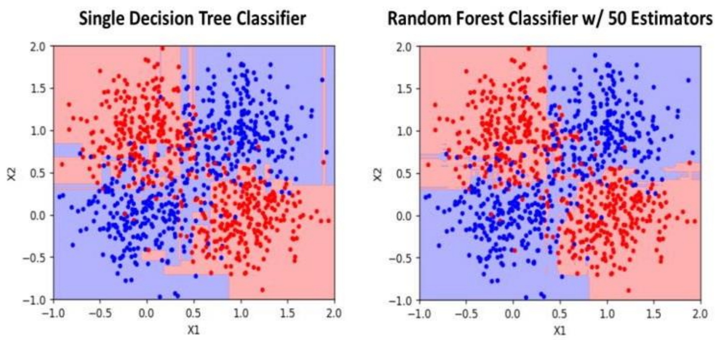

Figure 2.7. Differentiation of Single Decision Tree Classifier and Random Forest Classifier

2.8 Support Vector Machine(SVM):

A support vector machine (SVM) is a non-probabilistic binary linear classifier. The non-probabilistic aspect is its key strength. This aspect is in contrast with probabilistic classifiers such as the Naïve Bayes. That is, an SVM separates data across a decision boundary (plane) determined by only a small subset of the data (feature vectors). The data subset that supports the decision boundary are aptly called the support vectors [20]. The remaining feature vectors of the dataset do not have any influence in determining the position of the decision boundary in the feature space. In contrast with SVMs, probabilistic classifiers develop a model that best explains the data by considering all of the data versus just a small subset. Subsequently, probabilistic classifiers likely require more computing resources. The binary and linear aspects, however, are two SVM limitations. Recent advances using a “Kernel Trick” have addressed the linearity restriction on the decision boundary.

However, the inability to classify data into more than two classes is still an area of ongoing research. Methods so far involve creating multiple SVMs that compare data objects among themselves in a variety of ways, such as one-versus-all (OVA) or all-versus-all (AVA. The latter is also called one-versus-one (OVO) [20].

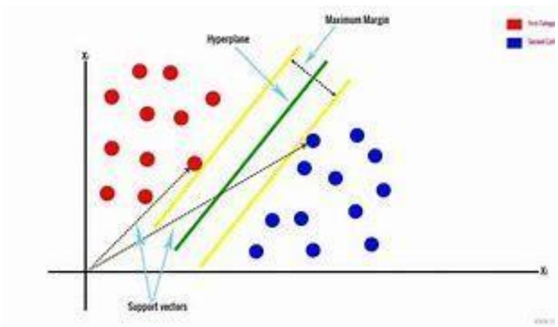

Figure 2.8Support Vector Machine (SVM)

2.9 Ophthalmic Fundus Images:

Fundus photography involves photographing the rear of an eye; also known as the fundus. Specialized fundus cameras consisting of an intricate microscope attached to a flash enabled camera are used in fundus photography. The main structures that can be visualized on a fundus photo are the central and peripheral retina, optic disc and macula. Fundus photography can be performed with colored filters, or with specialized dyes including fluorescein and indocyanine green.

Figure 2.9Ophthalmic Fundus Images

3.10 EXPERIMENTAL RESULT AND DISCUSSION / IMPLEMENTATION:

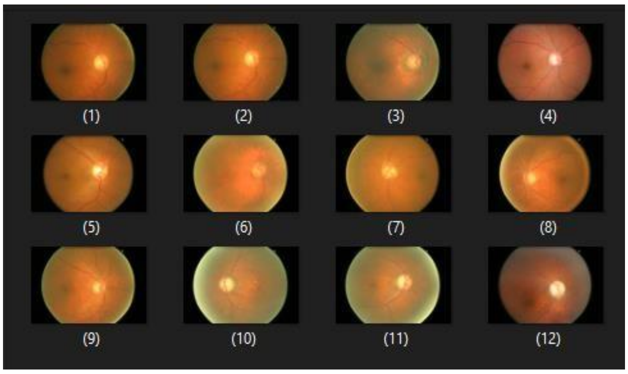

Figure 3.1 Datasets

At this stage the user asks to select the image which is to be given as input.

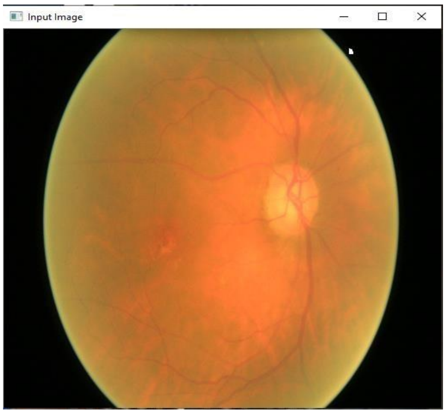

Figure 3.2 Input Image

The proposed deep convolutional neural network architecture, Our Project was evaluated from the dataset in order to reveal its efficiency. Before training the proposed deep convolutional neural network, all the images in the dataset were cropped in order to remove the redundant parts of images such as background. Here the noise is removed using Gaussian Filtering technique.

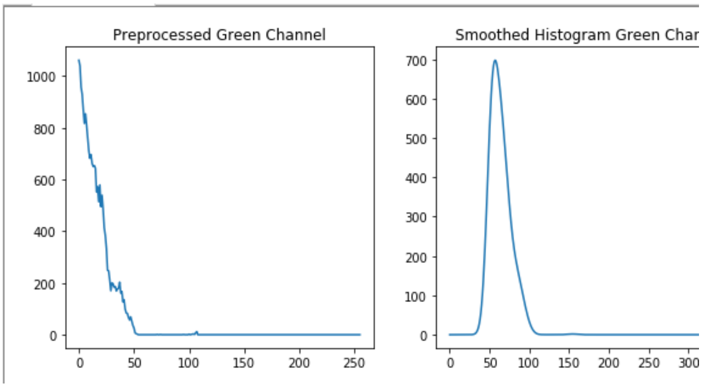

Figure 3.3 Pre-processing

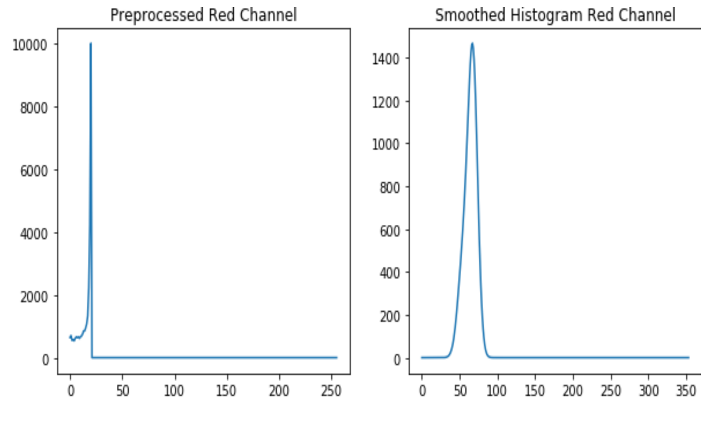

Figure 3.4 Pre-Processing

Segmentation:

At this stage the input image will get segmented into 2 part 1) Optic Disc, 2) Optic cup the glaucoma will present only at optic cup.

Figure 3.5Optic Disk

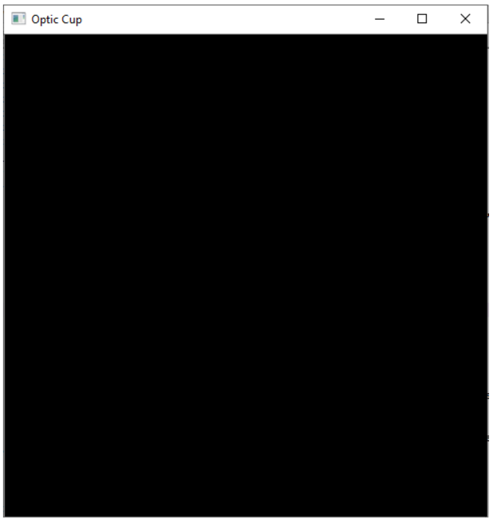

Figure 3.6Optic Cup

Since the above optic cup image is simply blank for the chosen patient the glaucoma is negative.

Figure 3.7Optic Cup

In the above image we can able to see the white region which is the glaucoma affected region.

Random Forest Accuracy: 93.5

SVM Accuracy: 74.3589

CNN Accuracy: 93.83

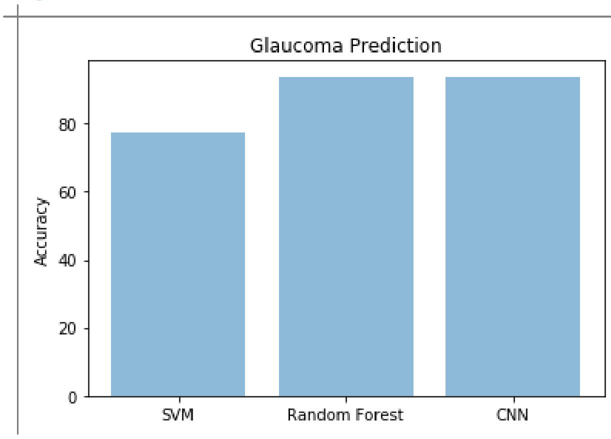

Figure 3.8 Comparison Between SVM, Random Forest,CNN.

The above pie chart is showing the accuracy of the algorithms which we have been using in this work.

4. Conclusion:

Although there existed several algorithms such a K-nearest node, U-Net there were some neglection in the classification areas. So as a team united we have developed an idea of involving two Machine Learning algorithms such as Random forest and Support Vector Machine. The intrusion of ML in the detection of Glaucoma was a boon to the field of Opthamology. The Deep learning method CNN was a plus which helped in layer and layer detection. Our project has an efficacy of 90% where the other methods have only 85%. In future more algorithms can be added.

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