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Automated Glaucoma detection using Convolutional Neural Network

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Glaucoma, fundus images, Drishti- GS, Convolutional Neural Network, Accuracy, Precision and Sensitivity

ABSTRACT

Glaucoma is one of the major causes for blindness with a high rate of unreported cases. The early detection and categorization of glaucoma will enable patients to obtain proper treatment and assistance from their eye surgeons, which will improve their quality of life. Automated methods that use fundus images have become a potential tool to help physicians diagnose patients more accurately and quickly. This paper presents Automated Glaucoma detection using Convolutional Neural Network (CNN). Drishti- GS (Glaucoma Segmentation) dataset with 151 fundus images are used to train the model. CNNs are highly effective, automated tools for glaucoma detection, analyzing retinal fundus images. Accuracy, specificity, precision and sensitivity are used parameters for performance evaluation of described model. Obtained percentage values for described model are Accuracy as 96%, Sensitivity as 97%, Precision as 98% and Specificity as 97%. The quantitative results and comparative study indicate the ability of the developed method

I. INTRODUCTION

Glaucoma is a leading cause of irreversible blindness, and the manifestation of glaucoma is unknown until it reaches the advanced stage. Hence, periodic eye checkup is the sole way of detecting the disease and preventing further blindness. Glaucoma is defined as a progressive optic neuropathy that damages the structural appearance of optic nerve head also known as optic disk (OD) [1]. The major cause of glaucoma is a decrease in outflow of the intra-ocular fluid called as aqueous humor in the eye.

As claimed by the World Health Organization, glaucoma is a permanent eye disease representing the second cause of blindness around the world. One of the main reasons for which approximately 90% of people remain undiagnosed, even in the developed countries is that glaucoma remains asymptomatic until severe. Although glaucoma cannot be cured, its progression can be slowed down by treatment [2].

Early detection of glaucoma based on effective images is highly needed. Glaucoma is produced by an increased level of intraocular pressure (IOP) which produces the decreasing of the blood flow and the damage the optic nerve. Because IOP was proven not to be very relevant for glaucoma diagnosis (many patients with glaucoma have a low level of IOP at the time of diagnosis while non-glaucoma patients have a high level of IOP) a complex eye procedure is recommended by the American Academy of Ophthalmology for an accurate diagnosis of glaucoma.

Digital Fundus Image (DFI) is one of the main and popular modalities to diagnose glaucoma [3]. Since it is possible to acquire DFIs in a noninvasive manner which is suitable for large scale screening, 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.

The CDR is one of the most important physiological features for diagnosing and treating eye illness and is therefore taken into consideration throughout the assessment process [4]. When two optic nerves have the same CDR but differing neuroretina rim width, the asymmetries of cup-to-disc may be induced by a variety of illnesses and are more susceptible to restrictions with inter individual variability than when two optic nerves have the same CDR but unequal neuroretina rim width.

Artificial Intelligence (AI) is a field of computer science dedicated to the creation of algorithms capable of simulating human intelligence. In the diagnosis of glaucoma, AI serves as a valuable aid in detecting changes in optical coherence tomography scans, visual field tests, and especially fundus images. Fundus images are widely used due to their high availability, good image quality, and cost effectiveness [5]. The emergence of deep learning has transformed this field by enabling the development of algorithms capable of identifying subtle patterns in retinal images associated with glaucoma. This paper presents Automated Glaucoma detection using CNN. Drishti- GS dataset contain 151 fundus images are used to train the model.

The paper is organized as follows. Section II relates the Literature survey, Section III introduces the described methodology of Automated Glaucoma detection using CNN, Section IV explains results and discussions and finally paper concludes with Section V.

II. LITERATURE SURVEY

In [6], the transfer-learning based web-app for glaucoma detection utilizing low-cost ophthalmoscopic cameras is presented in this paper. Fundus evaluation is an important part of an eye exam that helps the web-app provide vital diagnostic information to both ophthalmologists and non-ophthalmologists. In this paper, an effective embedded based eye testing architecture is presented.

In [7] present a computational tool for automatic glaucoma detection. We report improvements for disc segmentation in comparison with other works on the literature, a novel method to segment the cup by thresholding and a new measure between the size of the cup and the size of the disc. Results were obtained from a set of fundus images in collaboration with the Center of Prevention and Attention of Glaucoma in Bucaramanga, Colombia, where the percentage of success of glaucoma detection was of 88.5%. In [8] stated that the image processing for glaucoma detection can be done by using the fundus images. They have presented a deciding parameter for the detection of glaucoma. The work proposed by them performed well, and their presented mechanism has achieved an accuracy of 93.57%.

In [9], a Cup-to-Disc ratio based detection system is proposed where active contouring is used to detect optic cup and disc boundaries with some usage of filters for edge sharpening. Some morphological operations have also been used for boundary smoothening. However 94.2% accuracy is achieved working with a dataset of total 119 retinal fundus images. In [10] proposes a method for disc segmentation using edges detection. This method has problems if the eye has peripapillary atrophy which is a disease that alterates the edges of the disc. For segmenting the cup it uses as threshold one third of the highest grayscale intensity, however, the distance between the disc pixels and the cup pixels is not always the same, which makes difficult the segmentation among images taken from different persons. Another problem is to detect the cup edges when it is starting to grow in the early stages of the disease.

In [11] Sdis used and analysed that Glaucoma is an ocular disorder and its identification includes measuring the shapes and also the optic cup sizes. Pre-processing of data is then clustered using K-means clustering, which is used for segmenting the optic curves. It is again executed to find its various dimension. Since the fractional dimension is used to determining the various dimension of non-regular identities, the authors presented a new method for detection of glaucoma using method of the perimeter for the fractional analysis. The outcome reveals the new approach is accurate in detecting glaucoma.

III. Automated Glaucoma detection using CNN

Figure 1 shows the workflow of Automated Glaucoma detection using Convolutional Neural Network.

Drishti- GS (Glaucoma Segmentation) dataset contain 151 fundus images are used to train the model. It is organized into 50 training and 51 testing images, with manual segmentations of the optic disk and cup annotated by four experts. It includes structural labels and clinical assessments regarding the presence of glaucoma and notching, thereby facilitating tasks related to OD and cup segmentation and glaucoma diagnosis.

To improve image quality and enhance the generalizability of the models, a series of preprocessing techniques were applied. These steps were crucial for ensuring that the models could effectively learn relevant features across diverse patient samples and imaging conditions. One key preprocessing method employed was Contrast Limited Adaptive Histogram Equalization (CLAHE), a sophisticated contrast enhancement technique widely used in medical imaging.

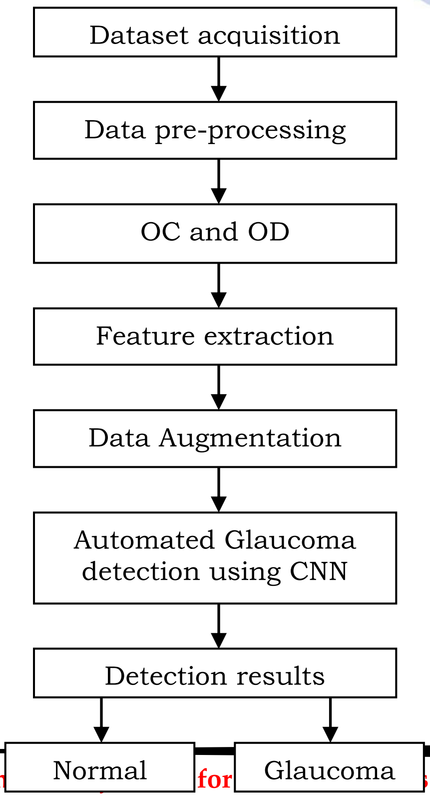

Figure 1. Workflow of Automated Glaucoma detection using CNN

The pre-processed image is used for segmentation of OD (optic disk) and OC (optic cup). The OD appears to be more prominent in the red channel of the RGB image. The red channel is considered, and statistical feature, namely absolute mean, is computed from the red channel and is subtracted in an iterative manner. A circle finder operation is performed to determine all the possible circles. For this purpose, the minimum radius of OD considered is 2.5 mm which is 9.5 pixel in terms of pixel distance. The images are overlapped with their corresponding binary mask, and the mean intensity values of the background and the region of interest (OD) are obtained. For OC segmentation, the green channel is considered because the OC appears to be more prominent in the green channel. In order to reduce background variation, in the green channel successive computation and subtraction of absolute mean are performed in an iterative manner. The number of iterations considered is three, and the resulting image shows the pixels having high intensity that belongs to OD and OC regions.

Using the segmented binary mask of OD and OC, clinical features, namely CDR (cup-to-disk ratio) and NRR (Neuro-Retinal Rim) area, are obtained. From the fundus image, features, namely: gray-level co-occurrence matrix (GLCM)-based features, texture directionality feature extracted from N + 1 directional difference of Gaussian filters, Gabor features, Hu-invariant moments and color features, are extracted.

Data augmentation was performed by random vertical and horizontal flip, rotation, and contrast adjustment. This augmentation technique has the potential to enhance the detection of glaucomatous optic neuropathy and improve the training efficacy of CNN models by preventing overfitting and minimizing sensitivity to image alignment.

Convolutional Neural Networks (CNNs) have demonstrated remarkable success in medical image classification tasks, particularly due to their ability to capture and learn hierarchical spatial features. CNNs are highly effective, automated tools for glaucoma detection, analyzing retinal fundus images. The architecture of a CNN, with its distinctive layers and operations, is well-suited for handling the complexity of medical image analysis. Finally, digital fundus images are classified into normal and abnormal (glaucoma). Accuracy, specificity, precision and sensitivity are used parameters for performance evaluation of described model.

IV. Result Analysis

This section presents performance analysis of described Automated Glaucoma detection using Convolutional Neural Network. Drishti- GS (Glaucoma Segmentation) dataset with 151 fundus images are used to train the model. Performance measures for described architecture are evaluated using metrics such as accuracy, specificity, precision and sensitivity. The following equations provide the mathematical expressions of these parameters:

Accuracy indicates the proportion of total correct pre dictions, offering a general sense of how well the model per forms across all classes. Equation 1 represents the Accuracy parameter.

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} \quad (1)$$

Precision measures the ability of the model to correctly identify only relevant instances. In the glaucoma detection context, it reflects the proportion of cases predicted as glaucoma that are actually glaucoma, helping to reduce false positives. Precision parameter is represented in below equation 2.

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

Recall (or sensitivity) evaluates how effectively the model captures true positive cases. Representation of Recall sensitivity parameter is shown below equation 3.

$$Sensitivity = \frac{TP}{TP + FN} \quad (3)$$

Specificity measures a test's ability to correctly identify negative cases (those without the disease). It is calculated as the proportion of true negatives (TN) divided by the sum of true negatives and false positives (FP). Equation 4 shows Specificity parameter.

$$Specificity = \frac{TN}{TN + FP} \quad (4)$$

Where,

Where, True positive (TP) is the condition when a test result is positive and individual can detect the glaucoma. True negative (TN) is the condition when the result is negative and individual is not diagnosed with the glaucoma. False positive (FP) is the case when a test result is positive but individual is negative. False negative (FN) is the case when a test result is negative but individual is positive.

The comparative performance analysis of described Automated Glaucoma detection using Convolutional Neural Network (CNN) with other models of Glaucoma detection using Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) is represented in below Table 1.

Table 1: Comparative Performance Analysis

Detection model	Accuracy	Precision	Sensitivity	Specificity
SVM	90	90	91	89
KNN	89	88	88	90
CNN	96	98	97	97

Figure 2 represents the Accuracy parameter comparative analysis for described Automated Glaucoma detection using CNN, SVM and KNN. X-axis represents the classification models and Y-axis represents percentage of parameter value. From figure 2 it is clear that accuracy of described model is high compared to other models.

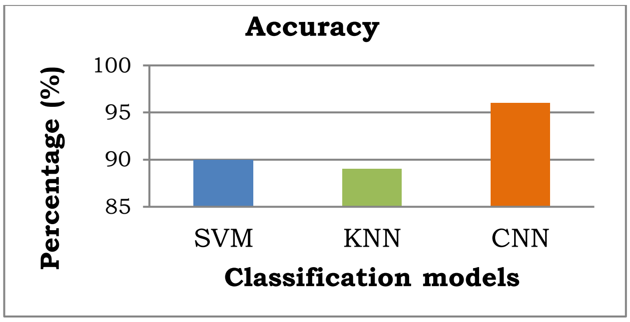

Figure 2. Comparative analysis for Accuracy parameter

Comparative performance analysis of Precision parameter for described Automated Glaucoma detection using CNN, SVM and KNN is represented in below Figure 3, in which Y-axis shows the percentage value and X-axis denotes classification models. Precision parameter of DT model is high than other models.

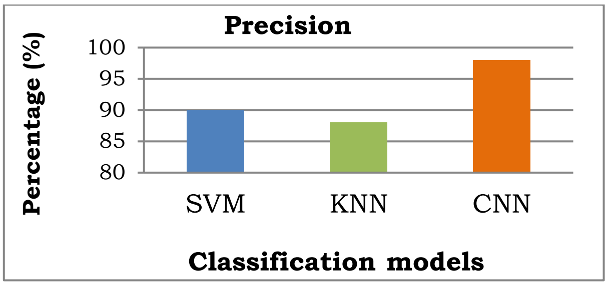

Figure 3. Comparative analysis in terms of Precision parameter

Sensitivity parameter comparative analysis graphical representation is shown in Figure 4. X-axis represents the classification models and Y-axis represents percentage value. CNN model achieves high sensitivity value than other two models.

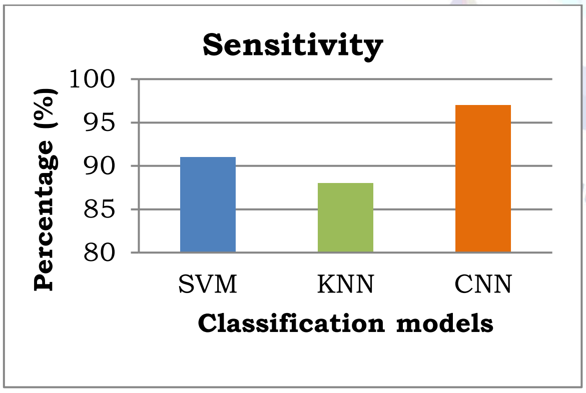

Figure 4. Sensitivity parameter Comparative analysis

Figure 5 shows the graphical representation of specificity parameter in which models are declared in X-axis and Y-axis denotes the percentage of parameter value. Specificity value of described CNN is high compared to other models.

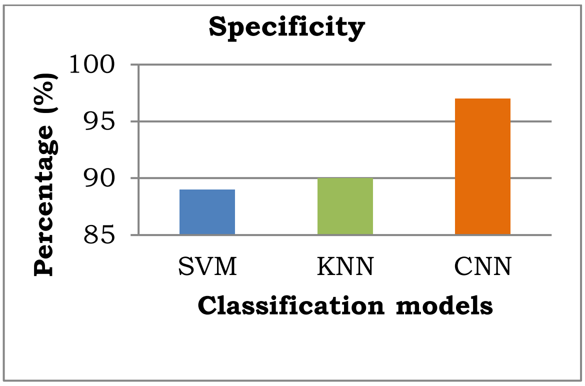

Figure 5. Specificity parameter Comparative analysis

Therefore from overall results, described Automated Glaucoma detection using Convolutional Neural Network is efficient in terms of Accuracy (96%), Precision (98%), Sensitivity (97%) and Specificity (97%) than other models.

V. CONCLUSION

In this paper, Automated Glaucoma detection using Convolutional Neural Network is described. Glaucoma is one of the primary concern for the human eye. The glaucoma is a significant defect that may result in blindness if pre-stage detection is not done. The early detection and categorization of glaucoma will enable patients to obtain proper treatment and assistance from their eye surgeons, which will improve their quality of life. **Drishti- GS (Glaucoma Segmentation**) dataset with 151 fundus images are used to train the model. CNNs are highly effective, automated tools for glaucoma detection, analyzing retinal fundus images. Accuracy, specificity, precision and sensitivity are used parameters for performance evaluation of described model. Therefore from overall results, described Automated Glaucoma detection using Convolutional Neural Network is efficient in terms of Accuracy (96%), Precision (98%), Sensitivity (97%) and Specificity (97%) than other models.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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