Glaucoma Detection Using Fundus Images Through Deep Learning.

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Abstract - *Glaucoma is a chronic eye condition which is may lead to permanent vision loss within a few years. It is known to damage the eye's optic nerve which sends images to your brain. Glaucoma tends to get worse overtime which is linked to the pressure buildup in the eye known as the intraocular pressure which maybe caused due to heavy stress. The chronic part about the disease is that once if a person loses vision due to glaucoma it can't be bought back and glaucoma is the second leading cause for blindness word wide, But with early detection and lowering the eye pressure can help keep the sight they have without deteriorating any further. Hence it is very important to detect it in earlier stages. People who have glaucoma have no early signs of pains or any symptoms regarding glaucoma, hence people must visit the doctor regularly in order to diagnose and treat glaucoma before it leads to vision loss. The medical procedure for the detection is a complex process and also said to be tedious, time consuming and requires human intervention. The medical systems have targeted the parameter cup to disc ratio (CDR) for detection but that may not be the efficient approach. This paper makes use of manual feature crafting with deep learning to make an improved and accurate diagnosis of glaucoma through automated techniques.*

***Key Words*: Glaucoma, Deep Learning, Disease identification, Convolutional Neural Network, Feature extraction, Fundus images.**

1. INTRODUCTION

Glaucoma is expected to have reached an alarming rate of 76 million by 2020 and around 111 million on 2040 [1]. It is believed to have caused by high intraocular pressure which causes degeneration of ganglion cells (the projection neurons of the vertebrate retina, which conveys information from the eye to the brain) of the optic nerve. In account of glaucoma blindness being irreversible, an early detection is most crucial at the moment. The manual assessment of optic nerve by medical field is not only time consuming but also costly. Hence a automated means for detection is required. Glaucoma detection using automated means is performed by extracting feature through convention image processing namely fundus photography. The optic nerve head examination is performed for this method which involves measurement of cup-to-disc ratio. Prediction of cup-to-disc ratio requires segmentation of optic disc and optic cup. It is based on deep learning, which is the modification of U-Net convolution neural network. For both optic disc and cup segmentation, this method achieves accurate prediction time.

In this paper the means of glaucoma detection using fundus images is discussed in the following manner. Section II defines the literature survey for this paper. Section III explains about the propose system. Section IV points out the experiments and evaluations used for the detection process. Section V concludes the paper.

2. Literature Survey

Annu, N., and Judith Justin et al., [2] in 2013 brought up a novel method for detection using DWT based textural energy features. Wavelet features are generated using five filters as specified in the paper. This system boosts of achieving 95% accuracy for detection.

In [3] Abhishek Pal et al., in 2018, proposed G-EYENET named auto encoding system which consists of two model system frame in which the ROI which is region of interest comprising of OD is obtained from fundus images. It was obtained with the help of modified u-net CNN comprising of binary map.

In 2015, [4] Xiangyu Chen et al., proposed 6 layered CNN for glaucoma detection. Over fitting was a major problem which was taken care of by using response-normalization and with pooling layers. The system was known to use dropout and data augmentation strategies to improve performance.

In [5] Alan Carlos de Moura Lima, et al., in 2018, a comparison study is made between various CNNs to find out the best. A large number of features were extracted by each of CNN architecture since per image forming five datasets for each image.

In [6] U. Raghavendra et al., in 2015, used the source of energy spectrum for glaucoma detection. At first optic disc localization was performed by a search window based method. After that Radon transformation (RT) was performed followed by modified census transformation (MCT). SVM the classifier used. This method was known to claim the accuracy of ninety seven percent.

In [7] S. Maheshwari et al., in 2017 proposed a method for glaucoma diagnosis. At first EWT was used to image breakdown into various frequency bands. After that correntropy features were obtained. Then feature ranking was done on the value of t value feature selection algorithm. Least squares support vector machine classifier was used to classify the image to find the image with and without glaucoma. This approach boosts of 98.33% accuracy.

In [8], 2017 authors formulated a glaucoma diagnosis using texton and local configuration pattern based features. Initially, adaptive histogram equalization was performed by them, followed by convolution operation of images with various filter banks, resulting in generation of textons. Further, Local configuration pattern (LCP) was generated which referred to distinctive pattern which was found in the image the system accuracy was 95.8%.

3. PROPOSED SYSTEM

3.1. IMAGE ACQUISITION

Initially, input images are collected from dataset of size 256x256 which is given as the input for data augmentation.

3.2. IMAGE PREPROCESSING

The major problem which causes blurred non clarity images are rectified in preprocessing. Color space conversion, image restoration and also image enhancement are the stages that take place in this process. A grayscale image has value of each pixel as a single sample. They are composed of gray shades, such as black being the weakest intensity and white being the strongest as shown in Figure 3.1. Grayscale is often mistaken for black and white images which in context of computer imaging have only two colors black and white.

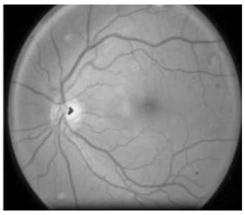


Figure 3.1: Gray Scale fundus image

3.3. DATA AUGUMENTATION

Data augmentation is used to create new data with different orientations. It plays a vital role in the balance of 2 classes in glaucoma. Horizontal flip operation is performed to balance those classes. The two classes are

1. Class 0(No Glaucoma)
2. Class1(Glaucoma)

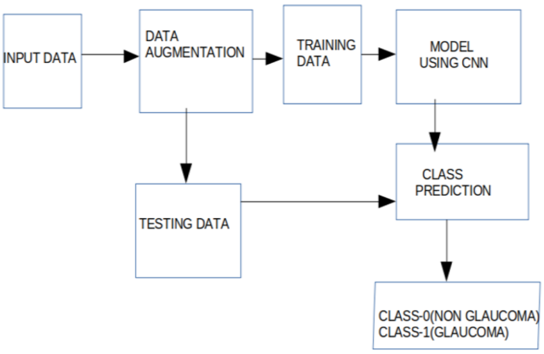


Figure 3.2: System Architecture

3.4. ARCHITECTURE

The convolution layer accepts image input of the pixels 256x256. The first layer of the CNN filters the image into 32 filters of size 3x3. Then a pooling layer of filters size 2x2 is used. The max-pooling operation has the maximum value among the filtered value chosen. The second layer also consists of 32 filters of size 3x3. The output is again fed into a pooling layer which now has filters of size 2x2. The rectified Layer Unit which is called ReLU rectifies the negative pixel values. Then the fully connected layer classifies into the two classes. Then the CNN is trained to classify the images into these two classes.

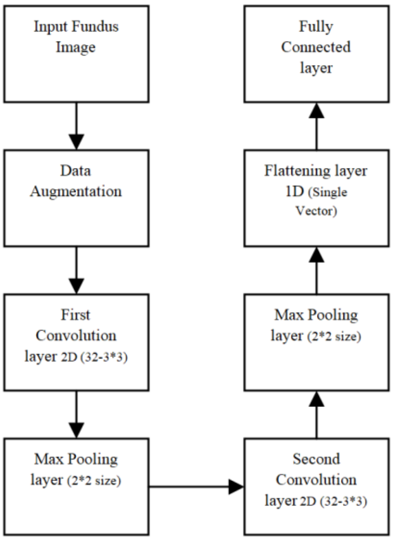
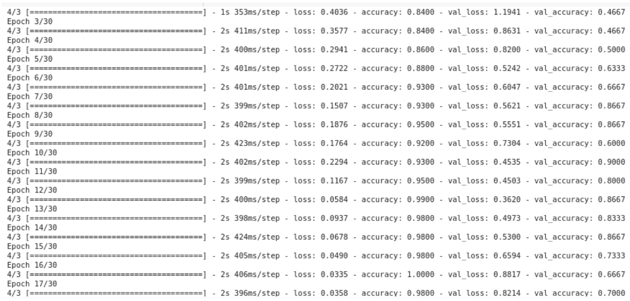


Figure 3.3: Network Architecture

4. EXPERIMENTS AND EVALUATION

The model is trained and the training data is shown in Figure 4.1.



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4/3 [==============================] - 1s 353ms/step - loss: 0.4036 - accuracy: 0.8400 - val_loss: 1.1941 - val_accuracy: 0.4667
Epoch 3/30
4/3 [==============================] - 2s 411ms/step - loss: 0.3577 - accuracy: 0.8400 - val_loss: 0.8631 - val_accuracy: 0.4667
Epoch 4/30
4/3 [==============================] - 2s 400ms/step - loss: 0.2941 - accuracy: 0.8600 - val_loss: 0.8200 - val_accuracy: 0.5000
Epoch 5/30
4/3 [==============================] - 2s 401ms/step - loss: 0.2722 - accuracy: 0.8800 - val_loss: 0.5242 - val_accuracy: 0.6333
Epoch 6/30
4/3 [==============================] - 2s 401ms/step - loss: 0.2021 - accuracy: 0.9300 - val_loss: 0.6047 - val_accuracy: 0.6667
Epoch 7/30
4/3 [==============================] - 2s 399ms/step - loss: 0.1507 - accuracy: 0.9300 - val_loss: 0.5621 - val_accuracy: 0.8667
Epoch 8/30
4/3 [==============================] - 2s 402ms/step - loss: 0.1876 - accuracy: 0.9500 - val_loss: 0.5551 - val_accuracy: 0.8667
Epoch 9/30
4/3 [==============================] - 2s 423ms/step - loss: 0.1764 - accuracy: 0.9200 - val_loss: 0.7304 - val_accuracy: 0.6000
Epoch 10/30
4/3 [==============================] - 2s 402ms/step - loss: 0.2294 - accuracy: 0.9300 - val_loss: 0.4535 - val_accuracy: 0.9000
Epoch 11/30
4/3 [==============================] - 2s 399ms/step - loss: 0.1167 - accuracy: 0.9500 - val_loss: 0.4503 - val_accuracy: 0.8000
Epoch 12/30
4/3 [==============================] - 2s 400ms/step - loss: 0.0584 - accuracy: 0.9900 - val_loss: 0.3620 - val_accuracy: 0.8667
Epoch 13/30
4/3 [==============================] - 2s 398ms/step - loss: 0.0937 - accuracy: 0.9800 - val_loss: 0.4973 - val_accuracy: 0.8333
Epoch 14/30
4/3 [==============================] - 2s 424ms/step - loss: 0.0678 - accuracy: 0.9800 - val_loss: 0.5300 - val_accuracy: 0.8667
Epoch 15/30
4/3 [==============================] - 2s 405ms/step - loss: 0.0490 - accuracy: 0.9800 - val_loss: 0.6594 - val_accuracy: 0.7333
Epoch 16/30
4/3 [==============================] - 2s 406ms/step - loss: 0.0335 - accuracy: 1.0000 - val_loss: 0.8817 - val_accuracy: 0.6667
Epoch 17/30
4/3 [==============================] - 2s 396ms/step - loss: 0.0358 - accuracy: 0.9800 - val_loss: 0.8214 - val_accuracy: 0.7000
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Figure 4.1: Training Model

Among 851 testing images the overall accuracy is predicted as 94%.

Total: 351

Loss: 0.267507028579712

Accuracy: 0.9486769856743874

5. CONCLUSION

This paper is implemented by using neural networks and deep learning for the detection of glaucoma. The testing accuracy is 94% and it is successfully predicted into respective classes. The testing accuracy can be increased by increasing the convolution layers and the number of images.

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