GLAUCOMA DETECTION BASED ON DEEP NEURAL NETWORKS

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Abstract. Glaucoma is a condition that affects the optic nerve which can lead to irreversible and progressive loss of vision. Glaucoma is considered to be the world's second-major cause of vision loss. The early detection of Glaucoma occurrence can be very beneficial for clinical treatment. Despite the fact that there are instruments for leading optic nerve investigation, they don't analyze this malady consequently. In recent times, deep convolutional neural networks show superior efficiency in image classification compared to previous handcrafted image classification methods based on features. This paper proposes a method that trains from a dataset of fundus digital pictures and fabricates a model. This model is utilized to anticipate Glaucoma and its severity utilizing profound CNN (Convolution Neural Networks). We built a system with CNN architecture which will be able to recognize the multifaceted features which are present in the task of classification.

Keywords: Glaucoma, Fundus image, Deep Learning, Automatic feature extraction, Classification, CNN.

1 Introduction

The human eye is considered a chief part among organs as it works as the source of the sensation for sight. The eye's retina is the most important and critical part of the human vision system. Glaucoma is a serious disease that damages the retina thereby causing blindness. As per the survey present in https://www.ncbi.nlm.nih.gov/pubmed/24974815, Glaucoma is predicted to affect a population of around 76.0 million by 2020 extending to 111.8 million by the year 2040. Until it reaches an advanced stage, Glaucoma usually does not exhibit any kind of signs or symptoms. By the time it is detected, the damage becomes significant and irreversible, with the optic nerve damage resulting in vision reduction caused due to around 40% loss of axons. However, it may be possible to delay the vision impairment caused by Glaucoma if it gets diagnosed sufficiently early. The causes of Glaucoma are for the most part linked with the development of Intra-Ocular Pressure (IOP) in the eyes that stems from blockage in intraocular fluid's drainage flow. The increased IOP damages the optic nerve which carries visual sensory information to the brain from the eye. Damage caused to optic nerve fiber weakens the visualization ability and object recognition that may lead to blindness. Figure 1: shows Glaucoma, non-Glaucoma in (a) and (b).

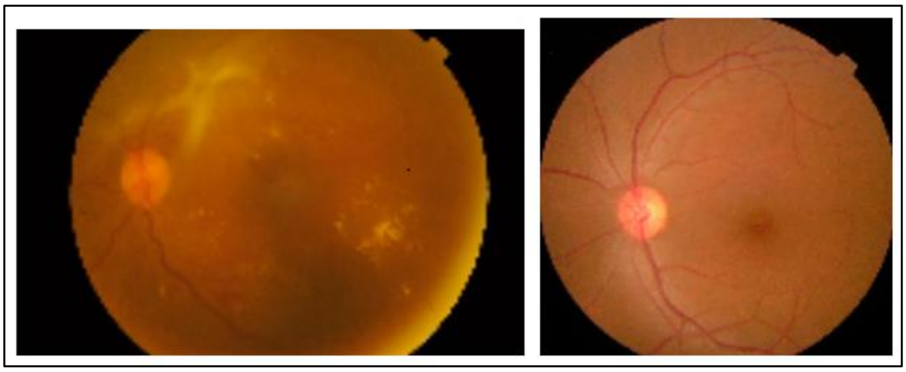

Fig. 1. - Fundus image (a) Glaucoma (b) Non-Glaucoma

Numerous research scholars have employed a variety of methods to identify Glaucoma disease, but among all, the convolution neural networks method has given better results. So, in the system that we propose, CNN (Convolution Neural Networks) is used to build the model which predicts Glaucoma from just an image given as input. Replacing the usage of handcrafted features, a CNN can be utilized as it learns a hierarchy of features, which can well be used for the purposes of image classification. As the hierarchy approach is available to learn more complex features, as well as translation and distortion features in higher layers, the accuracy of the CNN-based image classification method can be higher. Based on this assumption, we explore the use of the CNN-based method for Glaucoma test in this work.

The core intent of the proposed approach is to classify the images and get the scale of severity to what extent Glaucoma disease has affected the eye. To procure such composite classification of images, a robust and enormous training is essential. Hence our approach is to apply deep convolutional neural networks to perform training and testing. Apprehending the deep features of the disease effectively based on deep CNN is our main interest.

The later part of this paper is categorized as follows: Section 2 gives out an overview of previous work done in relative fields, section 3 describes the training methods used in the proposed course of action along with the architecture of the CNN, section 4 presents the results achieved out of our experiments, section 5 ends the paper with discussion on the results obtained and the scope of advancements that can be brought in future.

2 Literature Survey

Septiarini, Harjoko et al. in [1] have considered Retinal Nerve Fiber Layer (RNFL) loss as a main parameter for Glaucoma detection, which is not very common. The fundus image is processed from the gray level matrix of co-occurrence for feature extraction, such that the ONH (Optic Nerve Head) region is removed and the rest of the RNFL is divided into sub-sectors based on ISNT regions.

Support Vector Machines (SVM) have been used by Rahul Sarma et al. in [2], which have been memory efficient. SVMs are also observed to be highly effective when dealing with high dimensional spaces. Phase information seems to be amiss, as it is not preserved by the Radon Transform. Moreover, some information contained in the image is lost by used projections. RT further increases mathematical complexity and introduces error. They have achieved a classification accuracy of 98.8% and 95%.

Zhao, Zuanlin Chen et al. have implemented a combination of unsupervised learning for the purpose of feature representation in [3] and performed supervised learning for CDR regression. Feature extraction and representation are achieved by using MFPPNet which employs 3 dense connectivity blocks along with pyramid pooling. Dataset used for testing has 934 images from 443 clinical subjects, validation performed on ORIGA dataset with an AUC of 0.90.

In [4], Khairina, MKom et al. have taken statistical features for classification like the mean, entropy and 3rd moment. Smoothness, uniformity and standard deviation were also considered. They have extracted these features and fed them to KNN classifier to perform classification. The dataset they used has 84 images with an accuracy of 95.24%.

Pavithra G. et al. in [5] have proposed a system which can be easily implemented on hardware kits which may in turn be connected directly to the optical instruments and prediction can be done along with diagnosis. They process the image using histogram equalization, finding the ROI and finally estimating the Cup-to-disc ratio, based on which prediction takes place.

The authors Atheesan et al. have achieved optic disc segmentation using observations of vasculature present in the retinal area, through red channel analysis in [6]. Clustering is applied first using Simple Linear Iterative Clustering (SLIC) followed by k-Means Clustering algorithm, along with Gabor filter for edge detection. Prediction is done using CDR. The dataset employed is of 100 images with an F-score value maintained at 96%.

Guangzhou An, Omodaka et al. in [7] have employed parametric inferences of area swept by the curve characterizing receiver operations (AUC) with a cross validation of 10 folds on a random-forest classifier. This RF was derived from color fundus images, RNFL thickness maps, GCC macular maps showing thickness, disc maps showing deviation in RNFL and GCC macular deviation maps. They have adopted VGG19 CNN architecture consisting of 19 layers.

Adaptive Neuro-Fuzzy Inference, hemorrhage detection has been used in [8] and [9] respectively. In [10], vessel structure segmentation of colored retinal images is employed.

Unlike existing methods, in which features were handcrafted from the optic disk, in our method extraction of the features is automatically done by CNN from raw images, which are eventually fed to the classifier. Then, the classifier performs classification on the images into respective labels (No Glaucoma, Mild, Moderate, Severe, Proliferative Glaucoma). Analysis of the ophthalmic images manually is a time-consuming procedure. Also, the accuracy varies with the variation in expertise and skill of the professionals. Our method offers way better responses to the drawbacks involved in manual processes of Glaucoma perception. Most established detection techniques need either selection of features or very accurate measurements of geometric ONH structures, which is CDR. The phases of detection, analysis, diagnosis, treatment time, and prevention of associated risks can be made efficient using automation. Convolutional Neural Networks (CNNs) and other DL (Deep Learning) systems are proved to be useful.

3 Objectives

- To propose a system which checks and detects for possible occurrences of Glaucoma whenever a fundus image is generated by a technician without the intervention of a skilled person like a doctor.
- To preprocess the available images so as to extract and focus on the ROI.
- To diagnose correctly on the image whether it is Glaucoma or not and if yes, measuring the severity of the effect using a deep learning model.

4 Proposed System

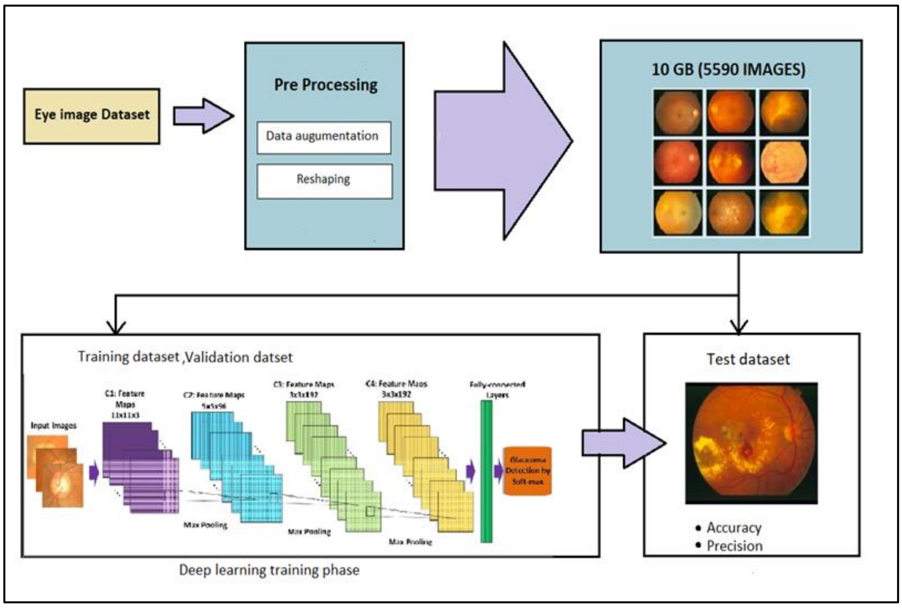

Fig. 2. - The complete architecture of the system used

4.1 Dataset

The high-resolution Funduscopic images of the retina taken from the data science community website named Kaggle (https://www.kaggle.com/) are considered under the datasets used for the process. Since our project is in the bio-medical domain and requires accurate results, we have chosen a huge dataset. Each image is rated for the severity of the disease on a scale of 0 to 4, as portrayed in figure 3. (0 >> No Glaucoma, 1 >> Mild, 2 >> Moderate, 3 >> Severe, 4 >> Proliferative Glaucoma). There are 5,590 images in the dataset. All the images are divided into train, test and validation sets. High quality training dataset is useful for training the classifier model but not all the images in our data are labelled. For this reason, we have considered a total of 3,362 images which are labelled. A normal computer wouldn't be able to accommodate such huge data due to low computation power. Hence, we have used Google Colab as a platform.

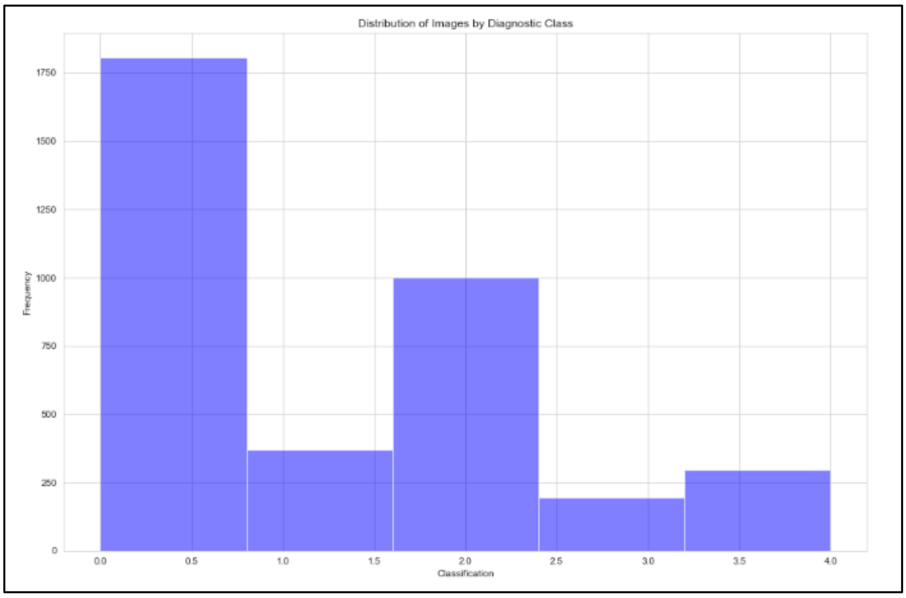

Fig. 3. - Distribution of images by diagnostic class

4.2 Preprocessing

Patients of varying age groups, gender, nationality are considered for fundus photography performed at extremely distinct levels of lighting and images are collected to form the dataset. Considering such varied data leads to the change in pixel dimensions within the images which might create futile variations. In order to negate this, image pre-processing methods like cropping the image, color normalization, making the dimensions, data augmentation etc. were performed on the images. The image data is converted to a hierarchical data format to facilitate preprocessing, followed by data augmentation, and then trained accordingly. Images were increased in real-time for improvisation in the capability of network localization and also supporting reduced overfitting. Techniques like horizontal flip, vertical flip, zoom in of 20% were performed to make the data uniform since the number of images for each type were not distributed equitably in the dataset. As observed in figure 2, data augmentation makes the model more robust to slight variations, and hence prevents the model from Overfitting. The dataset has been formatted to 128*128 pixels which enabled the retention of intricate features that are to be identified.

4.3 Training & Testing

Initial training was applied on the CNN until it gained remarkable progress. This was a time saving method executed to achieve a comparatively quick classification result with no delay. After 2 epochs of training on the images the network was then trained for a further 5 epochs. We used a residual learning framework to ease the training of networks that are substantially deeper. Neural networks suffer from severe over-fitting. To solve this issue, we stopped training the neural network early before it overfitted the training dataset and finally improved the generalization of deep neural networks.

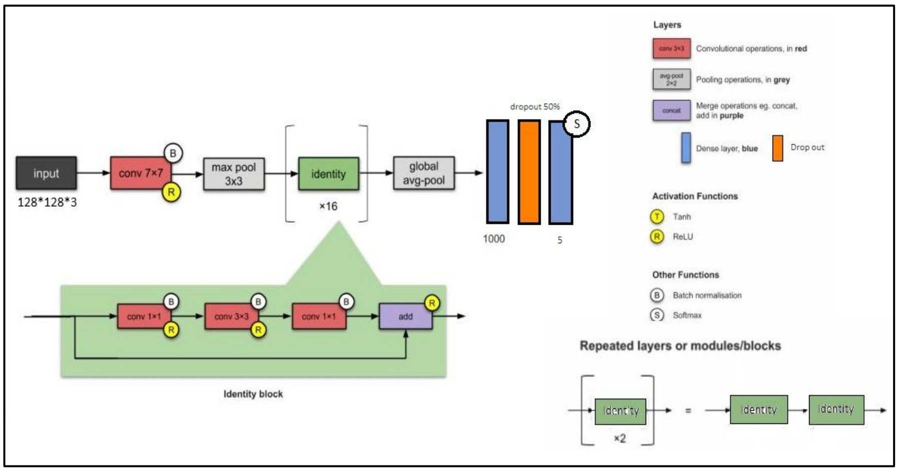

Fig. 4. - CNN Architecture

The proposed CNN architecture is shown in figure 4. This model consists of an input layer with input size 128*128 and it is followed by convolution layers with different window sizes followed by an activation function and max pooling layers of pool size 3x3. Convolution2D are filters, which specifies the number of filters to use, kernel size is length and breadth of the kernel used, padding specifies whether to use an extra layer of zeros around the image or not. Here we have used two activation functions 1. ReLu, 2. Softmax. These functions enable to decide whether a neuron should be activated or not. These are also used to add non-linearity to the output of neurons. Max pooling is used to reduce the spatial volume of input image by taking the largest element from the rectified feature map. Batch Normalization is used to normalize the activations of each layer by transforming the inputs to be mean 0 and unit variance. It helps in regularizing the model. Then we apply the Flatten function to convert a 2D array to 1D array. To eliminate overfitting, we drop 50% neurons using the Dropout function. Dense layers and Softmax regression are used in the classification stage. Softmax activation function is used to generate probabilities of each class using the output neurons. We used Adam optimizer.

4.4 Transfer Learning

It's a complex task to train a CNN from the beginning. It requires a huge measure of labelled information - which can become a challenging problem. Besides, the computational resources required are large in scale. However, a substitute to train a CNN without any preparation comprises fine-tuning an existing CNN that has been trained utilizing a comparatively larger labelled dataset from a different application (e.g.

ImageNet). Transfer Learning is the process of overcoming the isolated learning worldview and using knowledge earned for one use case to some other related ones. It is, in essence, using a model that was designed for some purpose and implementing it for a different purpose. Transfer Learning likewise applies to adjusting a pre-trained ANN to perform a new function. The use of pre-trained deep CNNs and subsequent fine-tune of the weights of the network applying the new labelled images, could lead to even better performance metrics and a potential reduction in training resources in terms of time, memory and computational operations, as depicted in figure 5.

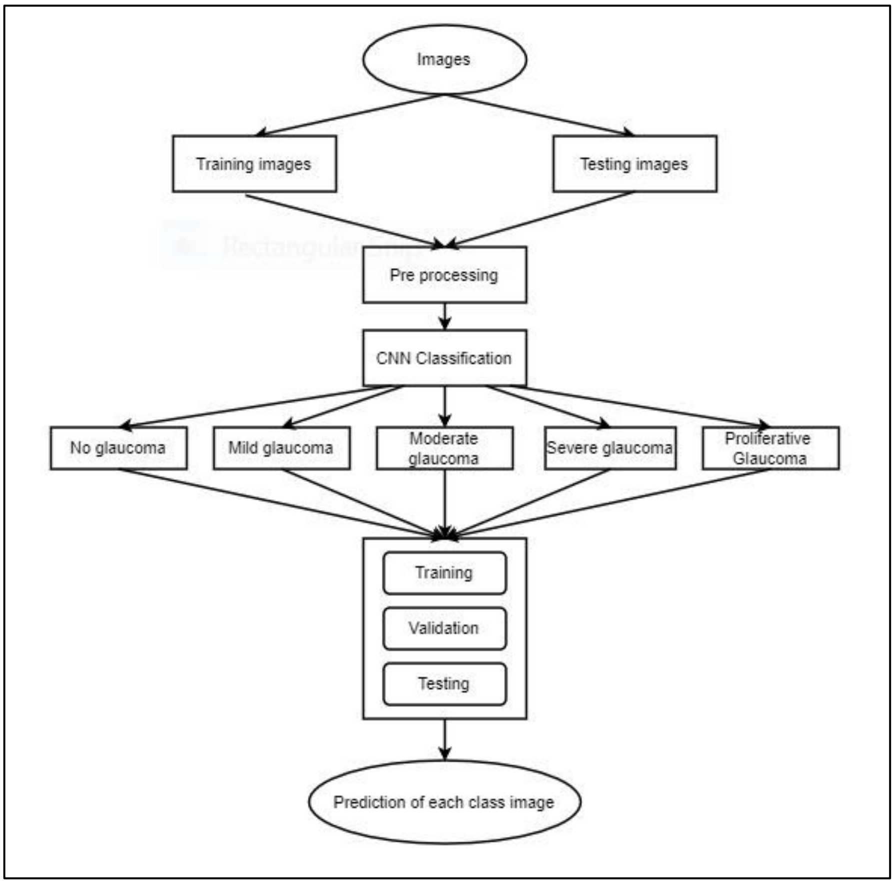

Fig. 5. - Flow chart of the proposed system

5 Result

This project classifies the Glaucoma disease and shows the severity of the disease. We have trained our model on a total of 3,662 images. The images in the training set are divided as No Glaucoma - 1805 images, Mild - 370 images, Moderate - 999 images, Severe - 193 images, Proliferative - 295 images. The accuracy was calculated using the following equation

Accuracy = (Number of accurate Predictions/Total number of Predictions)

By checking the precision and accuracy we have got the below scores for each:

Precision score - **82.76839723142821%**
Accuracy score - **89.57219251336899%**

In the interest to analyze the implementation of our CNN classifier, we have adopted the measure of accuracy. We have used 1928 images for Glaucoma detection in which we have achieved training accuracy of **93.41%** and validation accuracy of **90.96%**. Figure 6 shows the graph of model accuracy against train data and validation data.

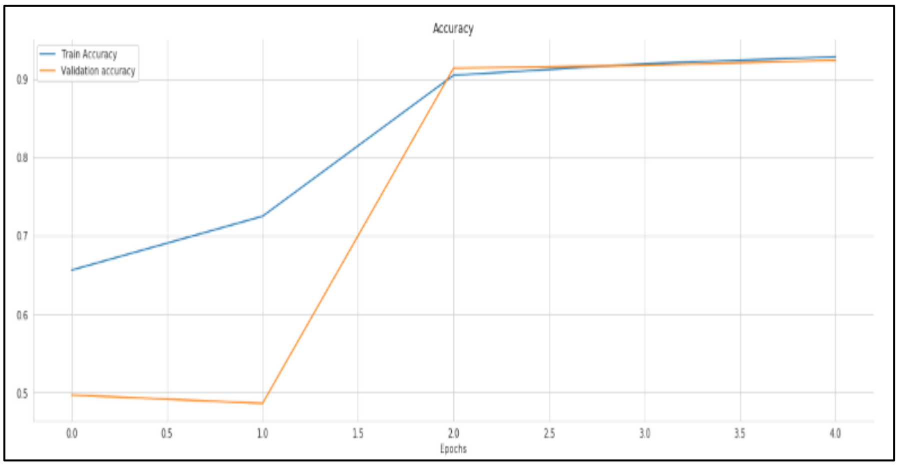

Fig. 6. - Model accuracy against train data and validation data.

Efficiency parameter of a classifier and its capability are described by the confusion matrix. This matrix has information about the predicted and actual classifications performed by a classification system. Our proposed classification model's confusion matrix consists of five each of rows and columns. The performance measure parameter of the classification model in the process of classifying Glaucoma has been depicted in the matrix. The confusion matrix obtained as the output is shown below in figure 7. The rows of the matrix in the order of top to bottom (rows 1 to 5) correspond respectively to actual classes, in the order of severity: no, mild, moderate, severe and proliferative. The columns of the matrix from left to right (columns 1 to 5) correspond to predicted classes in the same order of increasing severity: no, mild, moderate, severe and proliferative.

From a set of 187 non-Glaucoma images 173 were predicted correctly as "No Glaucoma" thereby achieving an accuracy of 92.51%.

From a set of 37 mild-Glaucoma images 30 were predicted correctly as "Mild Glaucoma" thereby achieving an accuracy of 81.08%.

From a set of 100 moderate-Glaucoma images 88 were predicted correctly as "Moderate Glaucoma" thereby achieving an accuracy of 88%.

From a set of 20 severe-Glaucoma images 16 were predicted correctly as "Severe Glaucoma" thereby achieving an accuracy of 80%.

From a set of 30 proliferative-Glaucoma images 28 were predicted correctly as "Proliferative Glaucoma" thereby achieving an accuracy of 93.33%.

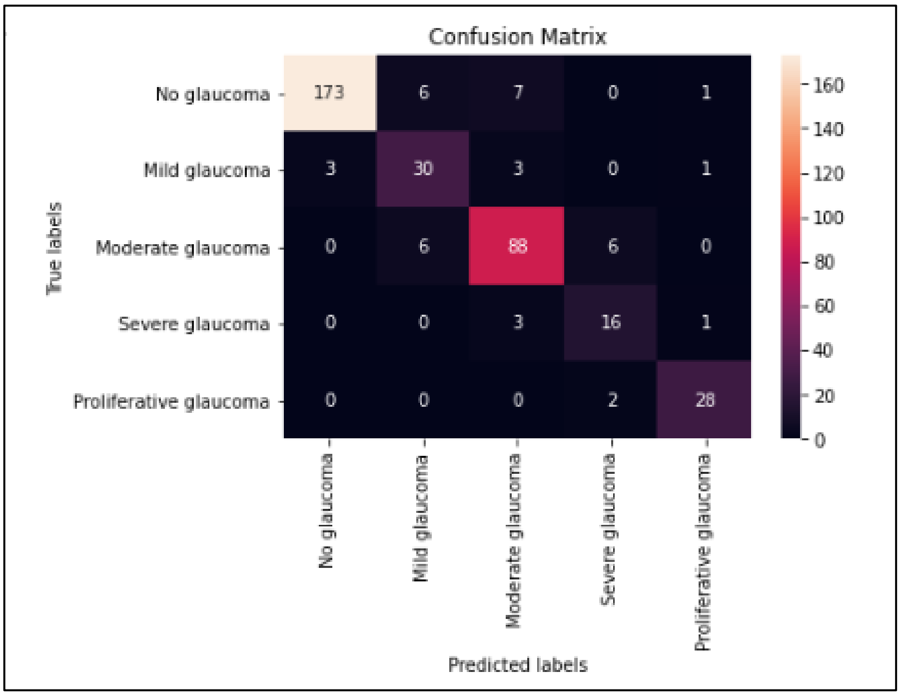

Fig. 7. - Confusion Matrix

6 Conclusion

To conclude, automation aids in prediction, prevention and early diagnosis for the risks associated with the disease. We presented a deep neural network framework to detect Glaucoma and also stages of its severity. In this paper, a structure of deep learning for Glaucoma disease detection relies on significant CNN, which can get the discriminative features that better depict the hidden models related to Glaucoma. An accuracy percentage of **93.41%** is achieved through this technique which shows its efficiency to contribute in the process. Future scope of this research work is to improve the accuracy with enhanced cost effectiveness and also to implement a procedure of checking every fundus image generated in the hospital for Glaucoma so that a patient can take necessary steps at the earliest.

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