Grenze International Journal of Engineering and Technology, June Issue

Early Detection of Glaucoma using Deep Learning

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***Abstract*—Glaucoma is a chronic condition affecting the optic nerves that causes partial or total vision loss. An increase in intraocular pressure within the eye, which damages the optic nerve, is the primary cause of this condition. Retinal images provide important information about an eye's health. Based on advancements in retinal image technology, it is possible to develop frameworks that can analyse these retinal images for better determination. This study describes a method for diagnosing glaucoma using fundus images to assess the CDR (Cup to Disc Ratio). The optical disc and optic cup sizes are used to diagnosis glaucoma. As a result, the first step is to segment the optic disc and optic cup in the diagnosis of glaucoma. The two competing goals are to reduce inaccuracy and feature count. The proposed glaucoma recognition method is divided into three steps: image acquisition, feature extraction, and glaucoma evaluation.**

I. INTRODUCTION

A. Glaucoma Detection

The ocular disease group known as glaucoma is defined by progressive optic neuropathy leading to an optic disc defect and irreversible visual field loss, which are frequently linked to increased intracranial pressure. Glaucoma is the world's second leading cause of blindness, behind cataracts, and the primary reason for blindness that results in permanent blindness. So, to prevent vision loss, early detection and good treatment are essential. The word "glaucoma," which derives from the ancient Greek and originally meant "clouded or blue-green tint," most likely referred to someone who had an enlarged cornea or was quickly developing a cataract, both of which might be brought on by chronic (long-term) high pressure inside the eye.

Convolutional neural networks (CNNs) were employed in the technique to transform high dimension images into low-dimension numerical data, which were used to construct the nodes of random forest decision trees. every pixel of the image would have been stated as a feature, which results in an excessively high number of features, making the random forest unworkable. The important features of every image dataset may be automatically extracted by CNNs. As a result, the suggested technique, the Random Forest Classifier, which employs an ensemble of decision trees to identify glaucoma, is more generalizable when CNN's predictions are used as features.

So, there are many techniques designed for glaucoma detection using Deep learning and machine learning which are two types of learning. In the proposed method deep learning is used in order to detect brain tumors from retinal fundus pictures.

B. Convolutional Neural Network

Convolutional neural networks are a specific kind of multi-layered neural network. It can analyze what has been arranged in a grid-like a pattern after that it extracts important properties. The huge advantage of using CNNs is

Grenze ID: 01.GIJET.9.2.6_1

that can reduce the amount of pre-processing of the picture.[4] A. Sallam et al CNNs can determine which refinement parameters are most important. As a result, we don't need as many parameters, this saves time and trial-and-error labor.Before working with high-resolution photographs that have hundreds of pixels, it doesn't appear like a significant saving. Convolutional neural network technology's main goal is to transform data into more understandable formats without sacrificing the characteristics that are crucial for doing so. They are excellent candidates for managing large datasets because of this. Figure 1 shows the block diagram of CNN method.

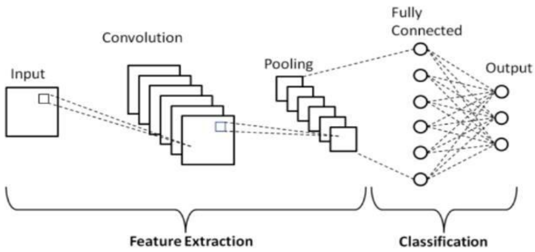

Figure 1. Block Diagram of CNN Method

Neuroscientific results are the foundation of convolutional neural networks. [2] The layers of synthetic neurons that make them up resemble nodes. With the help of these nodes' functions, an activation map is produced after the inputs have been weighed. The convolutional layer of a neural network. The weight values of each node in a layer define it. When a layer of data is provided, such as a photograph, it evaluates the pixel values and chooses some of the visual qualities. In recent years, the discipline of machine vision has been completely dominated by convolutional neural networks (CNN). Input, output, and several hidden layers, including three, make up a CNN.

C. Random Forest

It combines the outcomes of many decision trees to reach a single result. Its popularity has been fueled by its simplicity and versatility, as it deals with both regression and classification issues. It is composed of various decision trees, just like a forest contains a variety of distinct trees. Additionally, the method makes advantage of randomization to enhance precision and avoid overfitting, which can be a serious issue for such a complicated system. Using a random sample of data, these techniques create decision trees, and each tree produces a prediction. They then vote to determine which is the most workable solution. Fig 1.3 shows the block diagram of Random Forest classifier.

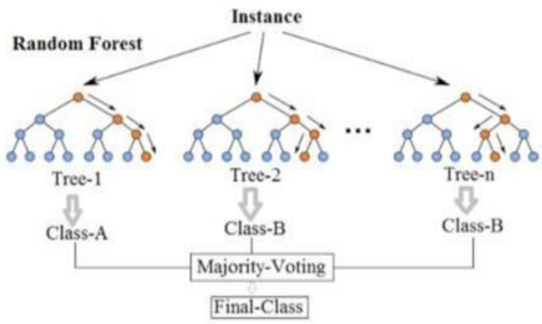

Figure 2. Block Diagram of Random Forest Classifier

D. Programming Languages and Tools Used

Jupyter Notebook

Jupyter Notebook allows users to create and share documents that include visualisations, equations, narrative text, and live code. It enables users to gather all of the components of a data project in an one location, making it easier to display the complete process.

Python

An interpreted object-oriented programming language is Python. There are no declarations of any methods, functions, variables, parameters, or types in the source code. As a result, the code is both short and adaptable. Python offers a large number of libraries and frameworks, which is one of its main advantages.

There are different libraries from python are used for this application as NumPy, Pandas, SK learn, Keras, Tensor Flow, matplotlib, etc.

II. Related Work

Rohit Varma, et al[2] .'s estimation of the number of people affected by the glaucoma disease worldwide by age groups found to reintegrate epidemiologic data with some of the economic and personal pressure of glaucoma which highlights the cause of glaucoma on individuals, In health systems, and Societies. According to estimates the occurrence of POAG (Primary Open-Angle Glaucoma) is 13 times higher in individuals between the ages of 50 and 59 and 16 times higher in those over the age of 80. The drawback of this strategy was that glaucoma treatment was incredibly cost-effective when diagnostic expenses were left out and positive treatment efficacy assumptions were made.

Payal N. Rabade, Radhika Harne, and other authors [1] proposed Glaucoma Detection using Tree Bagging Algorithm from Fundus Images Machine Learning techniques. Machine learning approach works in two phases one is training and the other is testing both the processes are similar, It mainly focusses on the ROI (region of interest) of the Image, Where the Input image has been pre-processed then the centroid is computed to find the centre of optical disc region. Bagging is a machine learning algorithm which improve the stability and accuracy. They used the online available database ‘Drishti-GS1, consisting only about 101 images. here, 50 for training and 51 for testing are used. By Tree bagger classifier by confusion matrix, out of 6 normal images 4 are correctly detected and 2 are incorrectly detected. Error rate is about 4.1% achieves 92 testing accuracy. Deep learning architecture is adopted to get a more Accuracy.

J. Ayub, et al. [3], By applying Color models RGB (Red, Green, and Blue) and HSV (Hue - Saturation Value) with K-mean Clustering Techniques, the segmentation of the cup and disc used to treat glaucoma disease is highlighted. 86 percent of the time, this method is accurate. This model does not account for the circulatory system that runs all through the disc, which essentially overlaps with accuracy of identifying the right disc portions.

A. Sallam et al. [4], presented the Glaucoma detection using Learning Algorithm from Pre-trained CNNs such as Pre-trained AlexNet, VGG11, VGG19, and VGG16 models using Deep learning techniques, with accuracy of 81.4 percent, 80 percent, 82.2 percent, and 80.9 percent on the LAG dataset (Large Scale Attention Based Glaucoma).

Patil and Nikam [5] presented a MATLAB GUI (Graphical User Interface) for glaucoma identification using fundus images. To diagnose a sickness. Image processing techniques of the CDR (Cup - to - Disc Ratio) type and ellipse methods are utilized. The optic disc and the optic cup’s boundaries are detected in this case. The segmentation and the precision of the disc and cup is inefficient.

Dhumane and Patil [6] had presented glaucoma detection automated using CDR by super pixel segmentation. This technique does not require patience at the time of testing as only the retinal image is sufficient by the method of Super pixel Segmentation Techniques. This uses a simple linear iterative clustering algorithm where High Sensitivity values are generated, therefore signifying the role of image-based classification. From a minimal number of components, a fully working, affordable, handheld, nonmydriatic fundus camera can be easily made. A camera like this with a combination of transfer learning-based web app could be beneficial for a range of healthcare practitioners, especially those who work in places where a standard table mounted nonmydriatic fundus camera would be uncomfortable and not at all user friendly to carry around.

III. Proposed Method

A. Dataset

The dataset by Kaggle contains 519 images. The images are divided into two files, test and train, each of which contains class0 and class1 files with retinal fundus images with glaucoma and without glaucoma respectively. Fig 3.1 shows the block diagram of proposed method.

B. Data Preprocessing

Pre-processing is the collective term for all the adjustments performed to the raw data before the algorithm for machine learning or deep learning receives it. [5] For instance, convolutional neural network training on unprocessed images is likely to produce poor categorization results. Pre-processing is essential for accelerating training. Grayscale image extraction from RGB image. Images are converted to grayscale to increase testing accuracy. enlarges the image less.

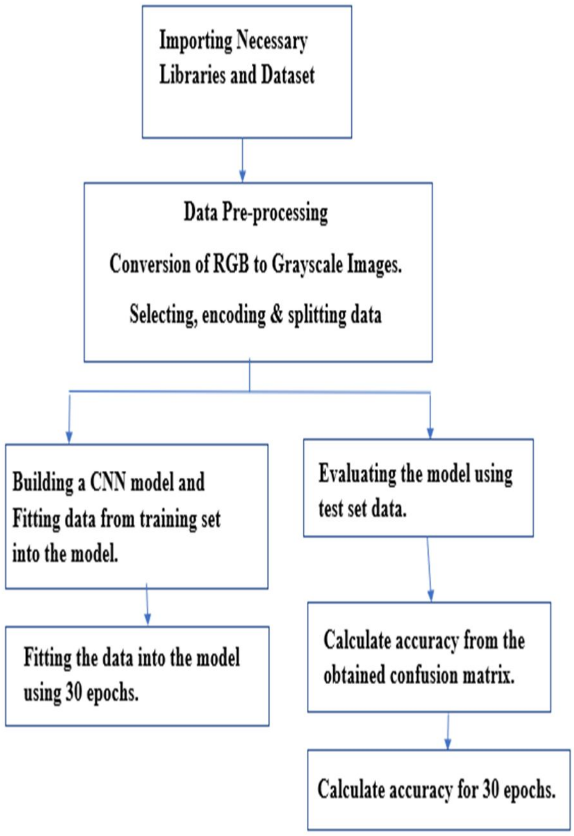

Figure 3. Block Diagram of Proposed Method

C. Data Augmentation and Splitting the Data

On photos from all Classes, rotation, zooming, shearing, horizontal flipping, and vertical flipping are performed. To balance the classes with an equal number of photos, data augmentation is used. Using the, the data is separated into x train, x test, y train, and y test. function "train test split." Test-size takes percentage from 0 to 1 of the size of the dataset. Random-state=7 gives same train, test set across different executions.

D. Model Building

CNN layers are used to train the model.We used three convolutional and max pooling layers: a dropout, a dense layer, and a fully connected layer.

Convolution layers: Convolutional Layers are always the initial layer in a convolutional neural network. Convolutional layers operate on the input by performing a convolution and the communicating the result to the following layer. A convolution converts each pixel into a single value in its receptive area.

Pooling layer: The primary purpose of the pooling layer is to gradually lower the spatial size of the input image so that the network has to perform fewer calculations. Pooling minimizes the sample size and instructs CNN to pass only the important data to the subsequent layers.

The Fully Connected Layer is made up of feedforward neural networks. The network's last tiers are Fully Connected Layers. Flattening the output of the final pooling or convolutional layer

Convolution layers are used to extract features from the input image. It is necessary to use a kernel to converge the image (or filter). The height and width of a kernel are determined by the convolution image's dimensions. It is also known as a convolution matrix or convolution mask. Adopting The fundamental goal of a pooling layer is to gradually lower the spatial size of the input image, which minimizes the computing load on the network. By pooling data, CNN sends only the most crucial information to its deeper layers, hence reducing the sample size.

Feed-forward neural networks dominate the Fully Connected Layer. The fully connected layer obtains and flattens the final pooling or convolutional layer output before using it as an input. In order to prevent overfitting on the training data, some neurons' contributions to the next layer are removed using the dropout layer. Another technique that is frequently used in deep learning is batch normalization. Instead of only normalizing once before applying the neural network, the outcome of each level is normalized and used as the input of the subsequent level. The output layer in a CNN, as was previously said, is a completely linked. The layer that flattens and offers input from the other layers in order to change the outcome into the required number of classes. Adamax optimizer is utilized as the optimizer, while category cross entropy is the loss function.

E. Model Fitting

The process of modifying the model's parameters to improve accuracy is known as fitting. The process involves applying an algorithm to data. The model's output is then compared to the actual values of the target variable to determine accuracy. In machine learning, an epoch is the number of times the entire training dataset is passed through the model. The epoch size of 30 was used while training the model. The batch size determines how many samples will be sent across the network. A batch size of 32 was used.

F. Model Evaluation

Model evaluation is the process of comprehending the performance of a machine learning model as well as its advantages and disadvantages. The training loss illustrates how well the model fits training data, as opposed to the validation loss, which shows how well the model creates new data. The validation loss statistic is used to assess the performance of a deep learning model on the validation set. The validation set is a subset of the dataset that has been set aside to assess the model's effectiveness or precision.
A confusion matrix is a table used to assess how well a classifier works. The model's many parameters can be calculated using the confusion matrix, such as accuracy and precision. The Confusion matrix is used in the calculation of accuracy. We can determine the various model parameters, such as accuracy, with the aid of the confusion matrix. True positive (TP), False positive (FP), True negative (TN) and False negative are the four values provided by the confusion matrix (FN).
The Confusion matrix is used in the calculation of accuracy. The formula below is used to compute it:

$$\text{Accuracy} = (TP + TN) / (TP + FP + TN + FN)$$

IV. RESULT

A. Output When the Input is an Image with Glaucoma

A random image from the dataset which has glaucoma is given as input and the model predicted it has glaucoma. Figure 3 shows the output of the model. In an eye with glaucoma, the cup may appear shallower, with a less well-defined border, or the cupping may be asymmetrical. Other features that may be seen in an image of glaucoma include nerve fiber layer thinning, neuroretinal rim loss, and other optic disc changes.

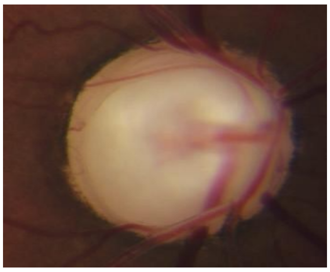

Figure 3. Output of the model when an image with glaucoma is given as input

B. Output when the Input is an Image without Glaucoma

A random image from the dataset which does not have glaucoma is given as input and the model predicted it's not glaucoma. Figure 4 shows output of the model when an image without glaucoma is given as input. Additionally, the image could show the surrounding structures of the eye, such as the eyelids, lashes, and surrounding tissue, all in good health.

C. Confusion matrix

The amount of accurate and inaccurate predictions made by a classifier is summarized in a confusion matrix, which is a table. When an artificial intelligence model's output can be divided into two or more classes, it is said to be performing well. The matrix provides True negative, False positive, False negative, and True positive predictions and contains anticipated and actual values, as well as the total number of projections.

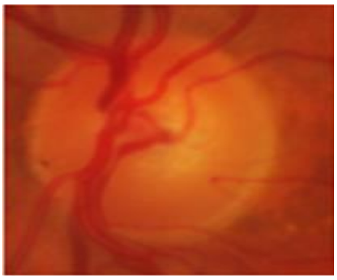

Figure 4. Output of the model when an image without glaucoma is given as input

TABLE I. CONFUSION MATRIX PARAMETERS

Number of images given for testing the model	181
Images with Glaucoma and predicted as ‘yes’	106
Images without Glaucoma and predicted as ‘no’	43
Images with Glaucoma and predicted as ‘no’	24
Images without Glaucoma and predicted as ‘yes’	8

D. Bar Graph for Accuracy, Sensitivity, and Specificity

Sensitivity is used to judge the performance of a model by allowing us to know how many instances the model correctly identified. Accuracy is the model's percentage of true predictions and can be represented as a bar showing the percentage of correct predictions.

Specificity (also known as True Negative Rate) is the proportion of correctly diagnosed negative cases and can be represented as a bar showing the proportion of properly detected negative cases by the model. The model's sensitivity is 92.98%. Specificity can be defined as the algorithm's or model's ability to predict a true negative of each available category. The model's specificity is 64.17%. Fig 4.3 shows the bar graph of accuracy, sensitivity and specificity.

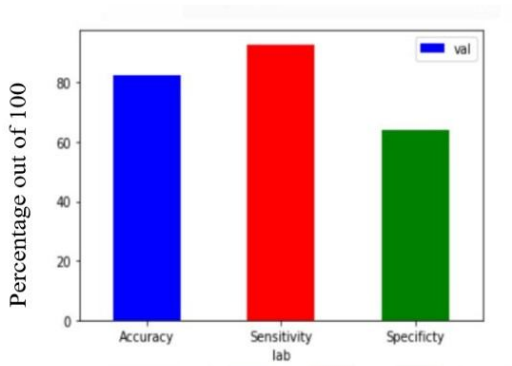

Figure 5. Accuracy, Sensitivity, and Specificity Values

V. CONCLUSION

One of the main reasons for blindness is glaucoma. It has an impact on a significant number of populations around the world. The random forest algorithm has the greatest accuracy rating of 82.3% in identifying glaucoma due to its excellent accuracy and precision. Our research shows that the Random algorithm has the highest Specificity and Sensitivity values.

The created model is capable of accurately classifying an unknown image as either normal or glaucomatous. The primary benefit of CNN is that it will use the complete image rather than just the damaged portion, and its filtered outputs are combined, avoiding the intricate design of handcrafted features. As a result, it does away with segmentations and offers strong attributes to describe both healthy and glaucoma-affected people.

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