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Glaucoma Screening Using Novel Evaluated CNN Architecture: An Automated Approach to Early Diagnosis

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Abstract - *Glaucoma is a collection of eye conditions which harms the optic nerve, that can result in vision loss and eventual blindness. The symptoms can start slowly leading to vision loss one may not notice them. Treatment at an early stage can prevent the further vision loss. A thorough dilated eye exam is the only approach to detect glaucoma. In this paper an eight-layer based Convolutional Neural Network architecture is proposed for the detection of glaucoma. For image distinction, CNN provides a hierarchical structure of the pictures. With a total of eight layers the proposed work can be evaluated. The image is preprocessed using techniques like resizing, gray scaling, CLAHE. Further segmentation is done using canny edge detection. Using CNN the system classifies the images as normal eye or glaucoma eye based on the features extracted during training. The proposed methodology manages to obtain high classification accuracy thus demonstrating the system's dependability and promise.*

***Key Words*: Glaucoma, Convolutional Neural Network (CNN), Kaggle dataset, fundus images, classifier .**

1. INTRODUCTION

The rear of the eye's interior is lined with a thin layer of tissue called the retina. It is located near to the optic nerve. The retina's job is to collect the light that the lens has focused, transform it into neural signals, and convey those signals to the brain for visual identification.

There is a layer of photoreceptor cells in the retina that process light. In essence, these are light-sensitive cells that can recognize characteristics like color and light intensity. After the photoreceptor cells collect the information, it is analyzed by the retina and transmitted to the brain through optic nerve. In general, the concentrated light creates an image for the retina to analyze, and the brain is then left to determine what the visual is.

The retina is nearly 0.5mm thick that extends down the rear side of the eye. The optic nerve also has incoming blood arteries that flow into the retina in addition to the ganglion cell axons that proceeds to the brain. It vascularize the retinal layers and neurons. The photosensors, or rods and cones, are situated next to the pigment epithelium and choroid, while the ganglion cells, which are the retina's output neurons, are situated in the radial part of the retina, which is font and nearer to the lens of the eye. Therefore, for light to reach and activate the rods and cones, it must first pass through the retina and activate the rods and cones, it must first pass through the retina's thickness.

Following that, the photons that are absorbed by the visual pigment of the photoreceptors are transformed into an electrical message that can subsequently activate all of the retina's succeeding neurons. The retinal communication regarding the photic input and some preliminary structuring of the visual image into various sorts of emotion is transmitted to the brain via the ganglion cells' spiking discharge pattern.

1.1 Retinal diseases

Our eyes send our brain one-fifth of the information it receives. Many both common and uncommon eye disorders can impair eyesight. For eyesight to be clear, the retina must be healthy. Due to the fact that they can affect any area of the retina, retinal disorders are common. The following are possible diseases.

Diabetic Retinopathy

Diabetes has a side effect called diabetic retinopathy, which can damage the retina and lead to blindness. The eye's essential sustaining blood vessels deteriorate, deviate, and multiply inexplicably. The most popular form of treatment today for preventing blood vessel growth and fluid leaking into the retina is laser therapy.

Cataract

Cataracts are the term for the blinding of the eye's lens. Normally, this region is unobstructed. Light rays are prevented from going through the lens and focusing on the retina when this clouding takes place. A tissue lining that is sensitive to light is the retina. It is situated behind the eye. When a portion of the protein that makes up the eye's lens starts to change its structure, cloudiness develops. The vision is then hampered as a result.

A cataract's early phases might not be problematic. Only a small portion of the lens may be affected by the cloudiness. On the other hand, the cataract could enlarge with time and cover more of the lens. It is significantly more challenging to see when less light reaches the retina. Dull and fuzzy vision is experienced. Unlike cataracts, which can go from one eye to the other. However, a lot of people do develop cataracts in both eyes.

Retinal Microaneurysms

The most common lesions of diabetic retinopathy are retinal microaneurysms, although they can also occur in other microvessel-related illnesses. Capillary walls narrow slightly as a result of microaneurysms. It is unclear whether retinal microaneurysms are brought on by neovascularization or damage to blood vessel walls. However, the end outcome is the formation of small saccular structures, roughly between 10 and 100 m in size, which appear as brilliant hypersensory spots on retinal fluorescein angiography but as rounded, red spots on coloured fundal imaging. Because both are tiny, spherical patches with a dark crimson colour and the same proportions, they cannot be distinguished from little bleeding.

Glaucoma

Glaucoma is a chronic, progressive eye illness caused by optic nerve damage, which results in vision field loss. It is often called "silent thief of sight" as it has no symptoms. One of the primary risk factors is eye pressure. When the drainage system fails, fluid can build up in the eye, which can cause significant pressure that damages the optic nerve. The optic nerve, which connects the retina and the brain, is a group of nerve fibres. Damage like this leads to vision loss. Before gradually impairing the centre of the visual area, vision loss initially affects its edges. The symptoms may not appear for months or even years after the nerve damage has happened. Once lost, vision cannot be regained.

1.2 Types of Glaucoma

1) Open-Angle Glaucoma

2) Acute Angle-Closure Glaucoma

Open-Angle Glaucoma

When the eye is unable to adequately drain fluid, it causes intraocular pressure or IOP which is inner eye pressure to increase. Drainage canal apertures in open-angle glaucoma should be functioning and obvious. The clogging problem spreads deeper into the drainage canals, much like a clogged pipe under a sink's drain. A large percentage of persons exhibit no symptoms or warning signals.. Open-angle glaucoma that is undiagnosed and untreated can cause a gradual vision loss. This glaucoma of this type develops slowly, occasionally for many years without any apparent sight loss.

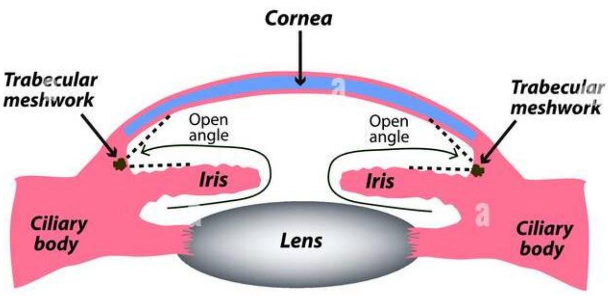

Figure – 1: Open-angle Glaucoma

Acute Angle-Closure Glaucoma

The ocular emergency known as acute angle-closure glaucoma is brought on by a sudden rise in intraocular pressure brought on by aqueous humour outflow restriction. There are many reasons for the cause of Acute angle-closure glaucoma, but the anatomical anatomy of the anterior chamber, which results in iris -cornea angle to be shallow, is the main risk factor. Acute angle-closure glaucoma manifests as a sudden, intense headache or pain in one eye, along with nausea, vomiting, rainbow-colored halos surrounding bright lights, and blurred vision. A fixed midway pupil and a foggy or hazy cornea with obvious conjunctival injection are visible on physical examination.

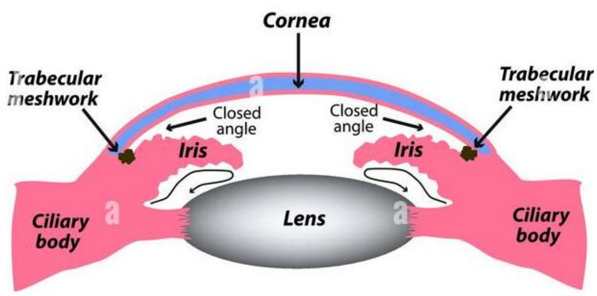

Figure - 2:Acute-angle Closure Glaucoma

2. EXISTING METHOD

Separating the picture samples into training and test samples is the first step in the technique. The initial picture processing performed by the fundus image aims to enhance certain areas, improve the image information, and reduce deception. Three significant ConvNet architectures—ResNet-50, GoogLeNet and VGGNet-16 were trained on the preprocessed ImageNet data set. To extract deep features, three ConvNet topologies are used. A prediction vector is created using the result of trained neural networks, and a decision is made by majority vote. The final division of fundus images into normal and abnormal (glaucoma) images is class 0, which displays a healthy image, and class 1, which displays a glaucoma image. The architecture is tested using the data sets from the PSGIMSR (Polygonal Shaped Image Microstructure), DRISHTIGS, DRIONS-DB, HRF (Head and Neck Fracture) and combined images. In the PSGIMSR data set, 471 images are found to be normal, and 577 images are discovered to be abnormal. There is cross-validation. 102 images have been inaccurately grouped. With ResNet-50, VGGNet-16, and GoogLeNet models, the accuracy, precision, sensitivity, specificity, and F1 score were all improved. The accuracy ratings for the GoogLeNet, VGGNet-16 and ResNet-50, designs 86.86% , 87.04% and 88.60% respectively.

2. PROPOSED METHOD

The detection of glaucoma eye disease is based on feature extraction from fundus images. Various steps are taken like pre-processing, segmentation, classification and detection.

2.1 Dataset

The Kaggle Dataset examines the manner and form in which data is frequently retrieved from the Kaggle repository. Data is in the MPEG or.JPEG format. However, the fungal photographs for this research are in.JPEG format and are divided into two folders for the healthy and glaucoma images. The datasets that include screenshots of actual network environments are the most helpful for analysing Glaucoma fundus images. Given that it contains information on glaucoma, healthy eyes, as well as importantly sensitive data regarding the fundus images for the particular network's expert system, this dataset is easily accessible to the general public. Furthermore, it takes a tremendous amount of work to convert the raw network traces into a tagged dataset. As a result, researchers frequently turn to the best dataset that may be made available to the research group on Kaggle.

2.2 Pre-Processing

Adjusting pixels is the main task of image processing. Modifying an image's pixels to take the desired shape. Preprocessing of data is typically done to lessen contrast, undesirable image noise, and luminous content. In preprocessing stage, the changes not connected to the glaucoma illness are removed from the photos to emphasize the desirable traits.

i. Grayscale

Grayscale representations are often used for extracting descriptors rather than working directly with colour photographs since it is more straightforward and computationally efficient. In fact, adding extraneous information may increase the quantity of training data necessary to attain acceptable performance, while colour may be of minimal utility in many applications.

ii. Medianblur filter

A nonlinear method for minimizing impulsive, or salt-and-pepper noise, is median filtering. To eliminate noise, all smoothing methods are employed. Like the Gaussian filter, the median filter is a type of smoothing technique, however the sole distinction between the two is the fact that the median filter retains edge property while the Gaussian filter will not. Because edges are crucial for look, edge preservation is a crucial characteristic. Median filters are frequently employed in digital image processing for edge preservation.

$$I'(x,y) = \text{median}(I(x+i, y+j)),$$

where $i,j = [-w/2, w/2]$ and $(x+i, y+j)$ are the coordinates of the neighboring pixels within the window centered at (x,y).

iii. CLAHE

Contrast Limited Adaptive Histogram Equalization is a varied adaptive histogram equalisation (AHE) which handles the issue of contrast overstimulation. CLAHE operates on separate sections called tiles instead of processing the entire image. The false borders are then eliminated by combining the adjacent tiles using bilinear interpolation. One can use this algorithm to make photographs' contrast better.

Just altering the brightness channel of an HSV image yields far better outcomes than modifying the BGR image's several channels do. Although it is frequently used on the luminance channel, CLAHE may also be implemented to colour pictures.

There are two considerations for CLAHE. One is Clip Limit This variable controls the contrast limiting threshold. The default value is 40. Title Grid Size - Sets the number of tiles in the row and column. This defaults to being 8x8. It is utilized for applying CLAHE while the image is tiled. In terms of improving edges, CLAHE is the most successful.

2.2 Segmentation

The edges of objects in photos are found using an image processing technique called edge detection. Using a linear filter with Gaussian kernel, the canny edge detector first smooths the noise for calculating the edge strength and direction for each pixel in the smoothed image. Three parameters from the user must be provided into the Canny edge detector. The Gaussian filter's pixel-based standard deviation is known as sigma, and it is the first factor. The low threshold, which is the second parameter, is supplied as a percentage of the calculated high threshold. The distribution of gradient magnitude values for the candidate edge pixels is used to determine the third parameter high, which specifies the high threshold to apply in the hysteresis. The mathematical equation for the Canny edge detection algorithm can be expressed as follows:

- Smoothing: Apply a Gaussian filter to the image to reduce noise and remove small details.

G(x, y) = (1 / (2 * pi * sigma^2)) * exp(-(x^2 + y^2) / (2 * sigma^2))

Smoothed.Img = Image * G(x, y)

Gx = [-1 0 1 ; -2 0 2 ; -1 0 1]

Gy = [-1 -2 -1 ; 0 0 0 ; 1 2 1]

Gradient Magnitude = sqrt(Gx^2 + Gy^2)

Gradient Orientation = atan2(Gy, Gx)

- Non-Maximum Suppression: Suppress non maximum edges to obtain thin edges.

For each pixel: If the pixel is a local maximum along the gradient direction, keep it. Otherwise, suppress it.

- Hysteresis Thresholding: Use two threshold values to distinguish between strong and weak edges.

An edge is said to be strong edge if the magnitude of the gradient is above the high threshold. Similarly it is not an edge if the magnitude of the gradient is below the low threshold. An edge is strong also if the magnitude of the gradient is between the low and high thresholds and connected to a strong edge.

Strong Edges = Pixels with Gradient Magnitude > High Threshold

Weak Edges = Pixels with Gradient Magnitude > Low Threshold and < High Threshold

Non-Edges = Pixels with Gradient Magnitude < Low Threshold

Final Edges = Strong Edges + Weak Edges (connected to strong edges)

2.4 Feature Extraction

The most vital and delicate task is feature extraction. System accuracy is mostly dependent on feature quality. The method of glaucoma detection is improved with the use of several automated feature extraction approaches. To find features like the median, mean, and variance, a random pickle technique approach was employed.

To detect features including brightness, translation invariance, papilla rim, and cup size, a variety of extraction techniques were applied, including Pixel Intensity Value, Textures, FFT Coefficients Pixels intensity, and Histogram Model. By extracting new features from the current ones in a dataset, feature extraction seeks to lower the overall number of features in the dataset. Thus, the majority of the data in the original set of features should be able to be summarised by this new reduced set of characteristics.

2.5 Classifier

Deep neural networks like the convolutional neural network (CNN) are frequently utilised in computer vision and image classification applications. By implementing CNN using the Python Tensor Flow library, this article will show you how to build your own image classification model.

AlexNet is a classic convolutional neural network architecture. Convolutions, max pooling, and dense layers make up its fundamental building elements. The model is fitted over two GPUs using grouped convolutions. The AlexNet has eight learnable layers. All five levels of the model use ReLu activation, except for the output layer, which utilizes max pooling and is proceeded by three fully connected layers. The first convolution layer is then applied, using 96 filters with a size of 11x11 and a stride of 4. ReLu is the activation function utilized in this layer. The output feature map is 55X55.

4. RESULTS AND DISCUSSION

Retinal image offers a less expensive, simpler, and more practical way for non-clinical practitioners to identify glaucoma in underprivileged individuals. Using a better and smarter algorithm, we have created a system with more benefits. Our project's goal is to use a different algorithm to increase the system's efficiency and accuracy.

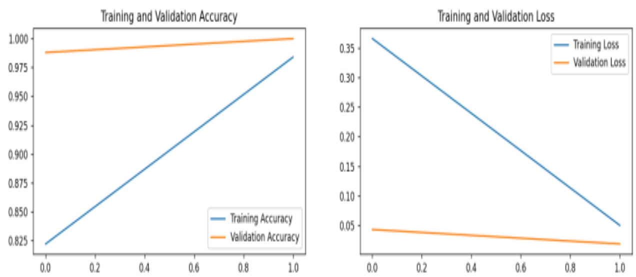

Figure - 3: Training and Validation accuracy

The Figure 3 represents the training and validation accuracy and loss of a Glaucoma detection. Using a specific algorithm and convolutional neural network the validation accuracy is achieved to 99% and training accuracy is reached to 97.5%. The training and validation loss is detected and it is 0.7% and 0.2%.

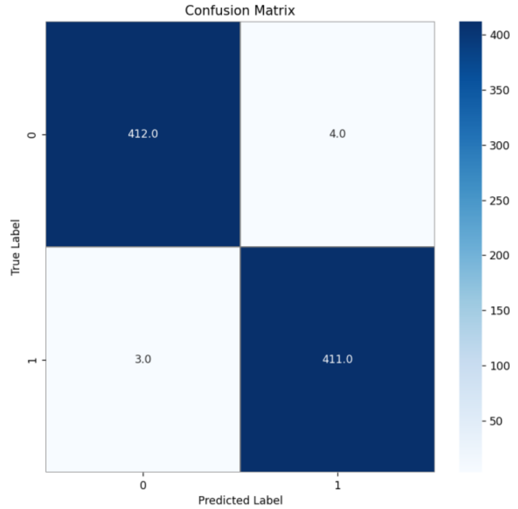

Figure - 4:Confusion matrix

The above confusion matrix depicts the class 1 with normal images and class 0 with glaucoma images. A Confusion matrix is a table that is used to calculate the performance of a classification system by comparing the predicted and actual values of the target variable. It is also known as an error matrix or a contingency table. The Confusion matrix can be used to compute various performance matrices of a classification model, such as F1-score, precision, accuracy, recall and others. These metrics can help to evaluate the model's performance and identify areas for improvement.

A confusion matrix typically consists of four categories:

True Positives (TP): The total count of positive instances that were classified correctly by the model.

False Positives (FP): The total count of negative instances that were classified incorrectly as positive by the model.

False Negatives (FN): The total count of positive instances that were classified incorrectly as negative by the model.

True Negatives (TN): The total count of negative instances that were classified correctly by the model.

The model correctly identified normal eye 412 times (True Positive) and glaucoma 411 times (True Negative), but incorrectly predicted normal eye 4 times as glaucoma eye (False Positive) and glaucoma eye as normal eye 3 times (False Negative).

5. CONCLUSION

A model was created in the proposed study to improve the early diagnosis of glaucoma. The model suggests the use of convolutional neural network to extract feature data from the images to distinguish between healthy images and glaucomatous fundus images. A variety of public and private data sets are used to test the proposed strategy. The proposed algorithm performs more effectively than the most recent method. Using the KAGGLE data set, the suggested model has a 99% accuracy. The proposed model outperforms both the convolutional neural network architecture and traditional computer –aided diagnosis methods, according to experiments on both open-source and closed-source data sets. The further investigation can be carried out to create a fully convoluted network that can differentiate between the optic disc and optic cup in the subsequently suggested work using a large experimental data collection.

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