GLAUCOMA DETECTION USING RETINAL IMAGE-AN AUTOMATED APPROACH FOR EARLY DIAGNOSIS

R.Vishnu Vardhan1 Department of ECE

P.A college of Engineering and Technology

Pollachi- India guganvishnu@gmail.com

Visva M4 Department of ECE

P.A college of Engineering and Technology

Pollachi- India vhnu06721@gmail.com

Deenu k 2

Department of ECE

P.A college of Engineering and Technology

Pollachi- India deenukamal10@gmail.com

Mohana Krishnan R5 Department of ECE

P.A college of Engineering and Technology

Pollachi- India mohanakrishnan1708@gmail.com

Uvan S3 Department of ECE

P.A college of Engineering and Technology

Pollachi- India uvanuva10@gmail.com

***Abstract*— optic nerve is harmed by which results in vision loss and ultimately blindness. Vision loss may develop as a result of the symptoms that may not be noticeable. Early therapy can to prevent further vision loss. Early treatment can stop additional eyesight loss. Glaucoma can only be identified by a comprehensive Examination of dilated eyes. For the detection of glaucoma, An architecture for in this paper image differentiation, CNN provides a Hierarchical picture structure. CLAHE, grey scaling, and resizing are some of the preprocessing methods used for images. Additionally, Canny edge detection is used for additional segmentation. The CNN categorizes This suggested approach shows the system’s reliability and promise by achieving high classification accuracy along with other characteristics.**

***Index Terms*—retina, transfer learning, CNN, nerve, vision loss.**

1. Introduction

Manually examining the human eye is one possible solution, but it takes labour. Computer visionsynthetic cognitive ability, as well as computer vision can be combined to automatically diagnose and treat glaucoma Several technologies and methods Within the fields of machine learning, digital eyesight, and image processing are being employed advance this research and produce more precise findings that could aid in a more precise and timely diagnosis of glaucoma. The inside, known as the retina. Close to optic nerve is where it is located. using the lens to collect focused light, convert it into neural impulses, and then sends these signals to the brain so that they can recognize the images. The retina contains a layer of photoreceptor cells short, cells and identify light properties, including color and intensity.

after the retina has processed the data gathered from photoreceptor cells. Following evaluation of the image created by the bright light by the retina, the brain is often used to interpret visual images.

1. *Research Objective*

Making Use of the Visual Geometry Group 19 (VGG-19) and a Support Vector Machine Neural Network..This innovative model fa- cilitates automated glaucoma identification through Computer- assisted analysis of fundus images. They are derived from VGG-19 network architecture integrated with Support Vector Machines. The proposed approach demonstrates enhanced robustness in separation and classification due to adaptive convolution, achieving satisfactory results on the DRISHTI- GS dataset. To detect glaucoma, the technique uses Publicly accessible digital color fundus images. Using a dataset of, our This study suggests a precise method for glaucoma automatic diagnosis using Convolutional Neural Networks (CNNs databases were used to detect glaucoma. Using this CNN is trained to extract characteristics, which are then label as either normal or glaucomatous images were obtained during testing.

1. *Research problems*

In 2021, Mohammed Rashid Ahmed et al. proposed an expert systems, which is difficult to achieve. This article uses the MATLAB Deep Convolutional Neural Network (DCNN) to detect glaucoma early. For this study, Fundus pictures of glaucoma sufferers and healthy individuals were collected in optimal lighting conditions to uncover all hidden features. many techniques for processing, including black and white and grayscale. On the Fundus image, complement, scaling, and Power transformation was applied. The fundus is subsequently exposed

to an extraction technique for textural features using a Deep Convolutional Neural Network (DCNN). Features such as contrast, correlation, energy, homogeneity, entropy, mean, standard deviation, variance, skewness, and Kurtosis recov- ered.

The following is a summary of the study findings: They employed the The MR-MR approach is a feature selection and ranking technique. Fundus images are finally classified as either healthy using multi-class classifiers, such as glaucoma.

1. Releated work

Utuja Shinde et al. suggested using U-Net and supervised machine learning methods to detect glaucoma in retinal fundus images. An offline computer-aided diagnostic (CAD) method for diagnosing glaucoma using retinal fundus images is , as proposed in this study. Deep learning, machine learning, and image processing methods were used in the development of this application. The Le-Net architecture is used to check inputs, and the brightest spot technique is used to identify Regions of Interest (ROI). Using the U-Net architecture, the optic disc and The cups were then divided into segments.. This model has a 97classification accuracy when using SVM, neural networks, and boost classifiers.

Acronyms and Abbreviations Inception Convolutional Neu- ral Network V3 for Glaucoma Detection was performed as previously described by Afroze et al.. An Inception V3 model based on CNN is presented in this study. In total, 6072 photographs were captured. Of these, 3736 showed A normal fundus picture and 2336 showed glaucoma. They used 5460 photos to train the model and 612 photos to test it. Following that, they were able to acquire an After that, they obtained an 0.8529. In comparison, the accuracy of the The DenseNet 121 and ResNet50 algorithms were 0.8153.

*A. Convolutions Neural Networks*

Aniket Patil et al. (2020) suggested employing convolutional Neural networks glaucoma detection. Convolutional neural A network is a technique used to diagnose glaucoma early. First, data for deep learning were generated from retinal images. The Gaussian blur technique is then used to preprocess retinal pictures to eliminate noise. The system is trained using pre- processed images, and it then determines whether a fresh input image 5 depicts glaucoma or a normal eye based on its visual content. The only region of the image where glaucoma may be detected using this recommended the Region of Interest (ROI). The system’s precision was 0.98 and 0.9607. suggested technique detects suspected glaucoma with a 97fundus pictures.

1. Existing Methodology

A large dataset of fundus images is collected from a reliable source. Common databases include the DRISHTI-GS dataset, RIM ONE database, or images from hospital Ensure the dataset has labelled images glaucoma-positive and glaucoma- negative image Resizing Resize all images to a uniform shape compatible with the CNN model normalization Normalize pixel values to improve model performance techniques like zooming, and dataset contains labelled photos are used in augmentation to expand the dataset and enhance model gen- eralization.

The Figure 1 shows which starts with the loading of the retinal fundus pictures. The use retinal input photos gathered from a dataset to identify glaucoma symptoms. These pictures usually show and which are crucial components for glaucoma diagnosis. Preprocessing is done on the photos to improve their quality and prepare them for model input. Predicting the optic disc is the specific purpose the processed photos.



Fig 1: Flow Chart of Existing Methodology

These images are structured to focus on features Relevance to disc detection. The optic disk is predicted and segmented from the input images using a CNN model (Model-1). This model’s result is the predicted disk that Model-1 produced. which segments the The optic disc region was used for further analyses and calculations. Using the predicted optic disc region, an image is constructed to focus on the optic cups. Optic design inside the cup. The Optic cup prediction was now possible for the created image. The constructed image is now set up for optic cup prediction. It helps concentrate for accurate Segmentation of cup. A second CNN model (Model 2) was developed to segment and forecast the optic cup. This model’s output is the Predicted Cap. The Cup-to-Disc calculation requires segmented optic cup region, which was obtained from Model-2. Kano. The Cup-to-Disc Ratio (CDR) is calculated using areas of predicte. A high CDR value often indicates Therefore, this metric is crucial for diagnosis. The process ends after calcu- lating the CDR, which can be used for automated glaucoma detection and further medical evaluation. This is calculated using the areas of the expected optic cap and disc. The optic cup is a depression inside the optic disc, which is the area where leaves the eye. The CDR is a critical. CDR Calculation: It helps in quantifying the relative the optic cup dimensions relative to those of the optic disc. Elevated CDR is often associated with glaucoma. This methodology ensures a systematic approach to segmenting and analyzing eye structures for the early detection of glaucoma. Nerve cells that send images to One layer of tissue called the retina contains the optic nerve. Retina’s components include a. Macula: Small central section of the retina. The best focus for reading small print in books or other objects that are directly in front of you is provided bythe macula.

b. Fovea:, sometimes referred to as the

fovea centralis, is the area of greatest focus. c. The nerve cells that allow the eye to perceive color and light are referred to as the photoreceptor cells. d. Cones: To produce full-color vision.



Fig 2: Flow chart of SVM with VGG-19

A specific class of photoreceptor cells called cones senses and interprets the colors red, blue, and green. The retina contains approximately 6 million cones. e. Rods: A distinct kind of photoreceptor cell that provides Peripheral Retinal Nerves.

1. Proposed Methodology

In order to determine CDR, which aids in glaucoma iden- tification, the OC and OD are first separated separately for The experiment was conducted to detect glaucoma. Because noisy and is saturated, the image has been processed using the green channel. saturated and the blue channel . The disparity in this channel between the nerves and veins was higher. It has been demonstrated that glaucoma may be identified using the flow diagram for the Support Vector Method (SVM) VGG-19 Network Architecture)

To segregate the OD and OC, the VGG-19 network was used. A CDR value estimate was then made using segmented OC and OD images. With SVM, the fundus images are categorised based on computed CDR values. classification system, as shown in Figure 2. It is the first stage of any procedure that involves segmenting and analysing images. A histogram enhancement procedure is used to first enhance the retinal pictures in order to precisely divide Since the green channel has a higher contrast level, it is segregated and studies. The OD and OC need to be split in order to determine the CDR ratio. The ROI extraction method speeds up the CDR estimate process. Typically, the ROI area is 11fundus image. The OD region is a little brighter than the surrounding areas in the fundus images. The optic centre is were identified as the locations with the highest intensities. The optical centre is identified as the location having the highest intensity. The ROI border, sometimes referred to as the ROI, is a circle is used for division, which is twice as large as its length. The optic nerve and retinal vessels followed the OD route. It is part of the retina that is brighter than the rest. To locate The CDR, OD, and OC were removed from the retinal



Fig 3: Flow Diagram of Proposed Methodology

In this work, the thresholding to segment . Because of the way a cup interacts with the veins and OC segmentation was difficult in the surrounding tissues. In order to segment of the optical cup, a VGG-19 structure is used. An increased CDR may indicate glaucoma since it indicates a times higher than that of the optic cups relative to the optic disc. The optic cup may increases the ability of glaucoma to harm the optic nerve fibers. In order to diagnose and cure glaucoma, the CDR is a crucial clinical criterion since it provides details regarding the One well-known machine learning approach that has been applied A Support Vector Machine (SVM) was used for glaucoma diagnosis. The supervised learning method SVM is 15 2m and is applicable to both In addition to deep learning, ensemble classifiers have been employed to enhance the VGG-19 Network Performance. The VGG-19 model has been used an ensemble support vector machine (SVM) classifier.

Two classifiers’ performances have been compared using the distance formula. It is well known for glaucoma detection among other applications. SVM is an 15 2m is a supervised learning technique suitable for situations involving both regression and classification To enhance the VGG-19 network’s performance, ensemble classifiers have were employed in conjunction with deep learning. Here, the VGG The nineteen models were combined with an ensemble SVM classifier. The distance formula has been applied to compare the performance classifiers.

To differentiate between eyes with glaucoma and those in good health, an SVM classifier is created. Thanks to the adaptive convolution, the proposed method produces results that are satisfactory for the DRISHTIGS dataset and is moreresistant to Separation and Classification. Deep learning- based VGG-19 network segmentation produces 9286.5OC and OD. Furthermore, it’s possible that the suggested approach can precisely identify the most appropriate

glaucoma stage. The performance of the classifier was also assessed.

Kaggle Dataset looks at the format and method used to collect data Nevertheless, JPEG-formatted fungal photos used in this study is separated participants into glaucoma and healthy folders. The best datasets for evaluating glaucoma fundus photos are those that contain real-time photographs of real-world network environments. Considering that it in- cludes details about glaucoma, healthy eyes, and—most im- portantly—of that specific OC and OD are first separated in this glaucoma detection experiment independently in order to calculate CDR, which helps ensure glaucoma. When processing a picture, the green channel is utilized because the red-blue channel is loud and saturated.

This channel has a sharper contrast between the blood vessels and the haemorrhages. It has been demonstrated that network architecture, Support Vector Method (SVM) and is depicted can glaucoma. The 175 photos in the database are categorised as normal, Advanced and early stage glaucoma. A 19-layer deep learning convolutional neural network (CNN) (VGG- 19) was utilised to extracted OC and OD from fundus shots. several parts or regions in image processing with the intention of making the image simpler or altering the transformation of an image into something more easily analysed and greater sig- nificance levels, respectively.

The goal of image segmentation is to distinguish between various objects or areas within an image, such as areas of similar texture, colour, or intensity or the boundaries of objects. Applications in image and speech recognition are the primary uses for One subtype of neural networks is the Convolutional Neural network (CNN or ConvNet).

Without compromising information, its built- in convolutional layer reduces the high dimensionality of an image. This study presents a deep learning architecture based in convolutional neural networks (CNNs). Eight levels could be used to evaluate the proposed method. In order to get appropriate performance in the detection of glaucoma, dropout mechanisms are used. The convolution layer is a crucial part of the CNN.

It is primarily was responsible for the other matrix, sometimes known as a kernel, The kernel has a smaller spatial footprint than a picture but is more detailed. In order to reduce impulsive, or salt-and-pepper, noise, all smoothing techniques are used, including median filtering, which is a nonlinear method. just like the Gaussian filter, but the only difference between the two is maintains its edge properties, whereas did not. Since edges are important for appearance, is an important feature convolution layer. It bears the majority of one of which represents the confined

area the receptive field and the other sets of features that may be learned, also known

kernels. Though more in- depth, the kernel has a lower spatial footprint than an image. Through the derivation of Because the spatial scale is smaller, fewer calculations and weights are required. Each representational slice undergoes separate processing for the pooling operations. Specifications True positives (TP) are the number Events which were accurately identified by the algorithm. False positives are the quantity of negative samples that the model misclassified.

positives (FP).

The number of negative events that the model incorrectly identified as negative is known as a false positive (FP). True negatives (TN) are the number of negative cases that the model correctly detected. A binary classifier’s recall in classification is a gauge of its completeness, or its capacity to accurately identify positive examples (true positives) while reducing the quantity of false negatives. To put it another way, recall quantifies occurrences classifier as positive. In classification, precision refers to the accuracy of a binary classifier, or its ability to correctly identify positive occurrences (true positives) while lowering the number of false positives. To put it another way of affirmative cases in which the classifier was accurately estimated. Precision is calculated as the ratio of true positive (TP) cases to the sum of true positives, and false positives (FP).

1. Results

The VGG-19 network separates the OD and OC. Following that, the CDR value was estimated using segmented OC and OD images. The fundus images are categorized using the SVM classifier based on the computed CDR values. There are 175 photos in the database, which are separated into There were three groups of patients with advanced, early stage, and normal glaucoma. Fundus images were processed using a deep learning convolutional neural network (CNN) with 19 layers (VGG-19) to extract the OC, and the OD was used. A simple and effective network for a variety of image processing applications is VGG 19. Pooling, convolutional, and fully connected. It is the first step in any procedure that involves segmenting and analyzing images. The retinal pictures are initially enhanced by a histogram augmentation procedure in order to precisely divides the OC and OD. Due to its higher contrast level, The green channel was isolated and used in subsequent experiments. The OD and OC must be separated in order to compute the CDR ratio.

The CDR estimate process is accelerated by the ROI extrac- tion procedure. The fundus image seems somewhat brighter than the surrounding area. The area with the maximum inten- sity has was determined to be the optic center. The ROI border,

also known as the ROI, is a circle twice as big as its length that divides the cup and the optic disc. The U-Net technique and supervised were suggested by Rutuja Shinde et al. in 2021 as a means of identifying glaucoma from retinal fundus images.

The propose an offline computer-aided diagnosis (CAD) method in this study that uses fundus images to identify glaucoma. This program was created using Regions of interest (ROIs) are found using the brightest point technique, and the input images are validated using the Le-Net architect- ture.

language for development. It has an object-oriented programming approach that is straightforward yet powerful, as well as excellent high-level data structures. its variable pressing keys,

, complex grammar, and free dis- tribution across many platforms make it the ideal language for scripting and raapplication. The same website provides links and distributions for a vast array of free third-party Python modules, apps, and tools in addition to Additional documentation.

One popular preprocessing method in image processing is gray scaling, which is sometimes referred to as a grayscale conversion. The process of changing a picture from its native colour system, such an RGBo grayscale color space is known as gray scaling. where each pixel was represented by a single brightness value. The values are averaged to create a single grayscale value for pixels during the grayscale processing. Unlike a color image, which has three channels (red, green, and blue), the resulting grayscale images have only one channel (gray). Since the human eye is most sensitive to light, the green light adds more to an image’s apparent brightness than the red or blue channels, which is why the green plane is eliminated during grayscale conversion.

Layer of pooling at some times, computes of the nearby to substitute the network’s output. This lessens Convolution layer is a crucial part of 25n.

which limited region Despite having a lower spatial footprint than an image, the kernel is more detailed. The technique of splitting an image into many regions or segments is known as segmentation during the image processing. Simplifying or changing the visual representation into a more understandable and analysis-friendly format is the goal of this approach. The main goal of picture segmentation is to discern distinct objects or regions within the image, which includes delineating the boundaries of objects or identifying areas that share similar characteristics in terms of texture, color, or intensity.

The classification process is a crucial phase in the catego- rization of the selected features. In the context of Glaucoma detection, the identified features were utilized to trained classi- fiers, enabling the differentiation of images to depict diseases that represent health.

With a good balance between sensitivity and specificity, this model is very good at identifying afflicted eyes. But lowering false negatives and false positives might increase its dependability even further. Classifying each stage of diabetic retinopathy was part of the study's objective to assist physicians in accurately determining severity levels for better treatment choices

By determining the outermost direction—that is, the intensity of every individual across the smoothed image—Canny Spine Detection reduces noise. Candidate edges are pixels that pass through a thinning process called nonmaximal suppression. During this procedure, if the edge strength of any candidate edge pixel is less than the edge strengths of the two pictures in the gradient direction, it is set to zero.



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Fig 4: Comparison Diagram

Subsequently, the flattened edge-magnitude image was sub- jected to hysteresis bathresholding. Hysteresis uses two thresh- olds for the edge strength. Any pixels are categorized as non- edges above the low threshold, whilst all potential edge pixels are categorized as non-edges below the lower threshold. Thirty normal eyes and seventy afflicted eyes made up the dataset of 100 eyes used for the model's performance study. The model accurately determined that 60 afflicted eyes were diseased.

1. Conclusion

Stopping visual loss and delaying the progression. Convolutional neural networks (CNNs) promise automated diagnosis early glaucoma symptoms in retinal fundus pic- tures thanks to innovations in computer vision deep-learning techniques. CNN algorithms learn features of glaucoma from large amounts of data and make accurate predictions based on these features, making them an effective tool for screening and diagnosing glaucoma at its early stages before it progresses to its later stages. In general, the use of CNN in early detection of glaucoma can significantly improve the diagnosis and treatment of this exhausting disease, potentially saving innumerable People with vision and blindness. Our model reaches the accuracy of 99glaucoma patients.

CNN architectures can be used in the future to evaluate glaucoma without the need for feature selection or exact measurements of the geometric elements of the optic nerve head. Techniques such as deep hybrid network-based low-light image enhancement can be used to see improvements in the outcomes.

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