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Review Paper on Glaucoma Detection Using Machine Learning

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Abstract

Glaucoma is one of the leading causes of vision loss worldwide. Glaucoma cannot be cured in its advance stages. So, early detection of disease has become an important factor in the medical field. Numerous studies quickly became clear that using different image processing methods, the retinal fundus picture could be uncovered. In this study, many automated glaucoma detection techniques were thoroughly reviewed various papers were compared on the basis of the methodologies they adopted for detecting glaucoma from 2D fundus images created using CDR. 85% of glaucoma cases can be accurately detected by the majority of machine learning algorithms. First, image segmentation techniques like Elliptical Hough transform and edge detection gave the region of interest, i.e. optic disc and cup. These extracted images were then given to the machine learning and deep learning models to detect presence of glaucoma in the fundus image of the eye. The most significant deep learning, machine learning, and transfer learning methods for analyzing retinal images were reviewed, along with their benefits and drawbacks.

Keywords: Glaucoma detection; machine learning; deep learning; segmentation; neural network; Image processing; Optic Disc detection; Optic disc; Optic cup; Disc Ratio of optic cup (CDR); Fundus image

Introduction

Glaucoma is the third most common reason for causing blindness globally with approximately 7% of total blindness cases worldwide. It is a chronic eye condition that progressively impairs vision and harms the optic nerve. Attacks from glaucoma typically do not occur until the disease is somewhat advanced even though glaucoma is treatable, and its progression can be delayed. Glaucoma can be identified early by using digital fundus images (DFI). DFI has become a favoured technique because it may be acquired in a painless way that is ideal for wide glaucoma screening. An automated system in the Glaucoma screening program analyses whether an image exhibits any glaucoma symptoms. The system will send any suspicious images to ophthalmologists for additional evaluation.

Machine Learning Techniques such as Bayesian Optimised Support Vector Machine (BO-SVM), Random Forest Classifier (RFC), Least Square Support Vector Machine (LS- SVM), Ensemble Learning, Support Vector Machine (SVM) etc. have been reviewed for the Detection of Glaucoma at an early stage. Some Deep learning techniques such as Convolutional neural network, Artificial Neural Network and Transfer learning techniques have also been reviewed to detect Glaucoma.

The primary ways to identify glaucoma are through medical history, intraocular pressure, visual field loss, and manual examination of the Optic Disc (OD) during ophthalmoscopy. The optic nerve, which is composed of ganglion cell axons which leave the eye and travel to the brain from the photoreceptors, carries visual information. The laborious and the time-consuming nature of the conventional methods of diagnosis results in blindness.

Factors responsible for Glaucoma

Age: Glaucoma can develop at any age, although older adults (particularly those over 60) are more prone to develop it.

Increased eye pressure: Optic nerve can be damaged by the increase of the Intraocular Pressure (IOP), and is responsible for glaucoma. IOP should be between 14-16 millimeters of mercury (mmHg) in a healthy individual, and anything over 22 mmHg is considered unhealthy and may harm the optic nerve cells.

Thin Cornea: Patients with narrow corneas (less than 555 microns thick) have low IOP results that are misleading. This is dangerous because if your true IOP is higher than what your reading indicates, you could get glaucoma.

HyperTensive: Hypertension can make our typically elastic blood vessels rigid resulting in high blood pressure and increment of eye pressure. It could harm eye blood vessels, preventing them from adapting to changes in blood flow.

Diabetic Patients: The tiny blood vessels in your eyes might become damaged over time by high blood sugar. Nearly one in three diabetics get retinopathy eventually. There is twice the probability of developing Glaucoma in Diabetic patients if left untreated.

History of Eye Injuries: Secondary glaucoma may develop in the ocular injured eye. Even many years after the injury, the IOP may rise and the probability of people developing it varies between 3% and 20%.

Family History: The relative significance of a patient's family history may change depending on how closely they are related to a member of the family who has an illness. According to research, there is a 2.1 times relative risk that having glaucoma in the family will result in at least probable open-angle glaucoma (OAG).

It was discovered that 60% of a sample of glaucoma patients come from families where other members also suffer from the condition.

Smoking: Studies on the link between glaucoma and smoking have shown conflicting results.

It has been proposed that exposure to environmental pressures including smoking causes glaucoma to manifest earlier in life when there are genetic risk factors present. Men may be more at risk for glaucoma if they smoke.

Migraine: It is well known that migraine attacks temporarily reduce the blood flow to the eyes. Mostly patients aged 70- 79 were found to have a significant connection between OAG and migraine.

Cup-to-disc Ratio: A non-glaucomatous nerve is one with a C/D ratio lower than 0.40. Patients with a normal optic disc, glaucoma suspects, and those with mild to moderate glaucoma can be distinguished using a C/D ratio ranging from

0.4 to 0.8. (depending on the optic disc size). If the C/D ratio is 0.8 or greater, glaucoma should be assumed to exist in the individual's disc.

Sickle Cell Anemia: A blood illness with a hereditary hemoglobin deficiency is called sickle cell disease.Sickle cells, denying the eye of oxygen can block the tiny blood vessel in the eye and result in damage. When an eye injury occurs, those with sickle cell trait (SCT) are more prone to develop glaucoma post-hyphema.

Types of glaucoma

Closed Angle: Angle closure, also known as closed angle glaucoma, is a very uncommon and hazardous condition that causes sudden blindness. The increased intraocular pressure is thought to be the primary cause of this form of glaucoma. A person with pressure and obstruction in the retina has a closed or small angle between the cornea and the iris.

Open Angle: Open and wide angle between the cornea and the iris is known as an open angle Glaucoma. It is a typical kind of glaucoma that causes a gradual obstruction in the eye and is easily treatable. And it is claimed that the symptoms are simple to recognize. This form of glaucoma affects a large number of people, primarily the elderly.

Ocular Hypertension: When IOP affects a normal human eye, the optic nerve gets damaged or even vision loss occurs. The combinations that make up the typical range of IOP are between 10 mmHg and 21 mmHg.

Normal Tension: Some people have standard tension glaucoma, but had normal IOPs. Low Tension Glaucoma can affect individuals with normal IOP because these individuals may be sensitive to normal ocular pressure. The key contributing factor may be the optic nerve head's poor blood supply.

Neovascular: The most frequent abnormality associated with this kind of glaucoma is diabetes. This type of glaucoma is especially difficult to cure because blood vessels are obstructed and the fluid in the eyes might leak out of the drainage canals.

Secondary: It is the eye illness of the cornea that is considered to have transformed from another eye condition.

Congenital: Typically, infants experience this kind of glaucoma. When a woman is pregnant, congenital glaucoma can result from the baby's eye drainage canal system not developing properly.

Pseudoexfoliative: It develops when ash-like material starts to peel off the outside of the eye's lens. The entire eye system is harmed when this substance collects up in the space that is between the cornea and iris.

Uveitic: Unfortunately, glaucoma can cause up to 20% of patients to lose their vision due to ocular inflammatory diseases (uveitis), which can happen for a variety of reasons. Some of these conditions often only affect one eye. Other types may influence each eye.

Irido-Corneal Endothelial Syndrome (ICE): The surface of the iris and the eye drain tissue are coated in cells from the front of the cornea. This causes the intraocular pressure (IOP) to increase, may lead to optic nerve damage. These cells combine to generate adhesions that bind the iris and cornea and obstruct the iris and the drainage system.

Trauma-related glaucoma: Physical modifications caused by certain traumas, accidents, or inflammatory disorders inside an eye drainage canal.

Pigmentary: The concave of the nearby glimpse eye, which is similar to that of the iris, causes hydrous humour to splash on the trabecular meshwork, closing it.

Exfoliations: It is white in colour. The trabecular meshwork closes as material accelerates on the lens.

Detailed Description

Figure 1 represents the anatomy of the human eye [15]. Figure 2 is an example of visually presented glaucoma in which (a) represents glaucomatous eye and (b) represents healthy eye [9]. It can be clearly seen that it is hard to differentiate glaucomatous and non-glaucomatous eye from images manually by the ophthalmologists. Also, Glaucoma eye illness has an impact on the CUP boundary, as seen in the figure 2. Therefore, the requirement of image analysis techniques needs to be integrated into systems for prediction with high accuracy. Figure 3 represents two fundus images including one with label i.e. (a) healthy optic disc and (b) representing optic disc which is glaucomatous [16].

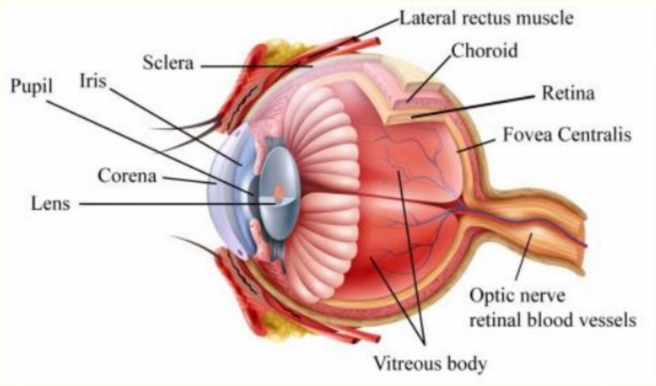

Figure 1: The Human Eye [15].

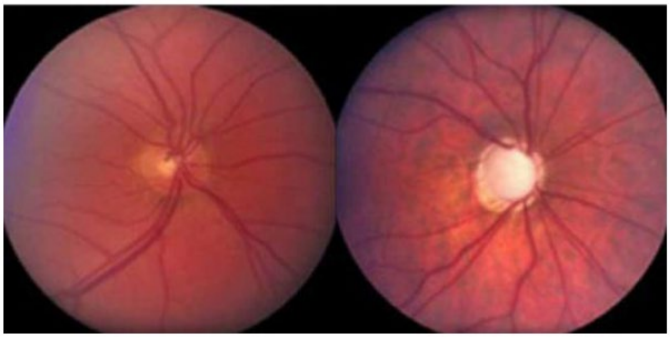

Figure 2: Glaucomatous eye(left) vs Non-Glaucomatous eye (right) [9].

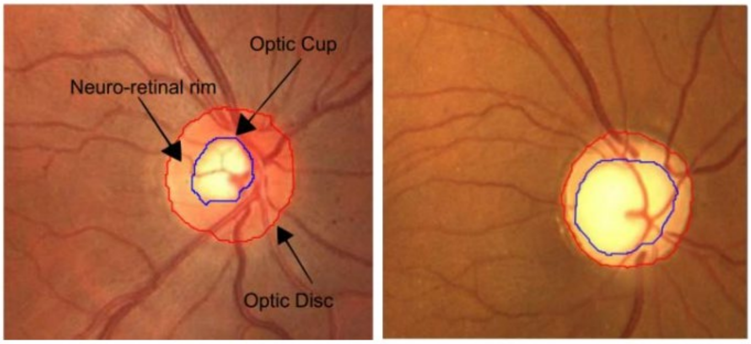

Figure 3: Fundus Images [16].

Literature Survey

Paper	*Author*	*Methods used*	*Advantages*	*Disadvantages*
[1]	Eswari MS, Balamurali S.	LSVM, MGSVM and SVM (BOSVM)	Detects Glaucoma in diabetic patients by intelligent ML based system.	Limited information available on the methodology and evaluation of the system.
[2]	Chen X et al.	The structure consists of six Deep learning layers	Proposes a deep CNN for glaucoma detection.	Limited dataset size and lack of external validation for the proposed method.
[3]	Mahapatra D, Buhmann JM	Random Forest Classifier	The proposed model achieves traditional performance for optic disc and optic cup segmentation from DFI.	Manual annotation of training data is required, which can be time-consuming and costly.
[4]	Divya L, Jacob J.	(LS-SVM)	The study provides a comprehensive comparison of different glaucoma detection methods from fundus images, helping to identify the most effective approach.	The study only considers two types of glaucoma and may not generalize to other forms of the disease.
[5]	Saxena A. et al.	Convolutional Neural Network	The proposed CNN- model achieves high accuracy and specificity for glaucoma detection from fundus images.	It needs large data for model training, which is difficult to obtain and highly expensive.
[6]	Carrillo J et al.	Cup to Disk ratio	The proposed method achieves high accuracy for glaucoma detection using a combination of optic disc segmentation and machine learning classifiers.	The study only considers a small dataset of 150 images, which may not be representative of the general population.
[7]	Guangzhou An, et al.	CNN, Random Forest model	Machine learning approach shows high diagnostic accuracy for glaucoma using both OCT and color fundus images.	Limited sample size and lack of external validation.
[8]	Baidaa Al-Bander, et al.	Convolutional Neural Network, Support Vector Machine	Automated diagnosis using deep learning could provide faster and more consistent diagnosis of glaucoma.	The study may have limited generalizability due to a small sample size and a single dataset.
[9]	J. Civ-et-Masot, et al.	Convolutional Neural Network, Ensemble Learning	Dual machine learning system enhances glaucoma diagnosis accuracy by combining cup and disc features	Small sample size and limited diversity of patients used in the
[10]	Sarkar D, Das S.	Cup to Disk ratio	Biogeography-based optimization provides accurate automated detection of glaucoma from medical images.	Limited sample size and lack of comparison with other existing glaucoma detection methods.

[11]	Rao PV, et al.	Multilayer Perceptron (MLP) and Back Propagation (BP) neural network (MLP-BP ANN), Naive Bayes Classifier	A novel approach using cup to disk ratio and artificial neural network for detecting diabetic retinopathy glaucoma provides high accuracy.	The dataset used for training and testing is limited in size, and the study does not compare the proposed approach with existing methods.
[12]	Abbas Q.	Convolutional Neural Network, Deep Belief network(dbn)	Deep learning algorithm achieves high accuracy in detecting glaucoma on retinal fundus images.	The use of small dataset may limit the generalizability of the results.
[13]	Li L, et al.	Attention-based CNN (AG-CNN)	Attention mechanism improves accuracy of glaucoma detection, large-scale database allows for robust model training.	Limited explanation of feature selection process, potential bias in dataset due to lack of diversity in patient demographics.
[14]	Thangaraj V, Natarajan V.	Support vector machine	Support vector machine achieves high accuracy in glaucoma diagnosis, and provides interpretability of decision boundaries.	Small dataset limits generalizability, features used for diagnosis not clearly explained.

Table 1: Literature Survey.

Data Description

ORIGA [2, 5]: The dataset contains 168 glaucomatous and 482 normal fundus images with clinical glaucoma diagnosis.

SCES [2, 5]: The dataset contains 1676 images of the fundus and 46 images for glaucoma.

DRISHTI-GS [3, 9]: It contains 50 patient images at a resolution of 2896 x 1944 that were acquired using a 30- degree FOV.

RIM-ONE [8, 9, 10, 13]: It consists of 151 images from the University of La Laguna's and has disc and cup labels added to them.

PRV [12]: The PRV-Glaucoma private dataset included 235 photos of normal vision and 424 images with glaucoma.

DRIONS-DB [12]: There were 110 images of 600 × 400 pixels and had 8 bits per pixel in this dataset that belonged to the ophthalmology section at Miguel Servet Hospital in Saragossa (Spain).

HRF [12]: The sjchoi86-HRF dataset included 101 retinal fundus pictures with glaucoma and 300 normal retinal fundus images. Apart from it, In the HRF dataset, there are 15 retinal fundus photos, one for each category.

Methodologies Used

Image Segmentation Techniques

Elliptical Hough transform [3, 6]

This image processing technique is used to structure an ellipse shaped disc that is used to detect the optic disc region.

Disc Segmentation using edge detection [6]

Edge boundaries are found for disc and cup using edge detection techniques so that CDR ratio can be easily calculated.

Empirical Wavelet Transform [4]

2D EWT technique is used to reduce the image size as well as detect boundaries in the image. Along with this row and column filtering is applied to enhance image components.

Discrete Wavelet transform [8]

At each level of wavelet decomposition, a 1D vertical analysis filter-bank is first used to change each column of an image. Each row of the subsampled data is applied the same filter-bank in a horizontal direction. With one level of wavelet decomposition, you get four images that have been filtered and subsampled. These are called "sub bands."

The Daubechies, Biorthogonal, and Symlets sub bands are used in this proposed research work. They are the result of the horizontal 1D-DWT and subsampling to make a 2D- DWT output image.

Optical coherence tomography [7]

OCT is a technique which produces an image of the retina, which is located at the back of the eye. The non-invasive technique generates an image by measuring the amount of red light that reflects off the retina and optic nerve.

To aid in the early detection and evaluation of retinal diseases such as glaucoma, retinal layers and thickness can be identified and measured.

U-Net segmentation [9]

The disc and cup were isolated from fundus images using a generalised U-net architecture. U-net fully convolutional network, has been increasingly utilized for the segmentation of medical images.

Level set algorithm [14]

A vibrational level set method using the best colour channel as determined by the colour histogram and edge analysis is used within the disc region to detect the cup border. It is used to identify the disc and the cup as well as to segment each item. Usually, the levels affect how cup and disc relate to one another.

Least square optimization [14]

This algorithm is used for the optimizing the edge detection problem by smoothening the edges of the image.

$$f(x, y) = ax + bxy + cy + dx + ey + f = 0$$

Where a, b, c, d, e, f are coefficients of the ellipse and (x, y) are co-ordinates of boundary points lying on it.

Machine Learning Techniques

Bayesian Optimised Support Vector Machine [1]

The following kernel functions, such as Gaussian, linear, cubic, and quadratic, are used for data transformation in Bayesian optimization support vector machines (BOSVM) to determine the potential outputs between the optimal bounds in a supervised way of a given dataset.

Using the Bayesian optimizer, the acquisition function of predicted improvement per second, and a training time constraint, an optimal solution is produced. The box constraint level and hyperparameter kernel scale range are selected to produce the best results under 10 fold cross validation.

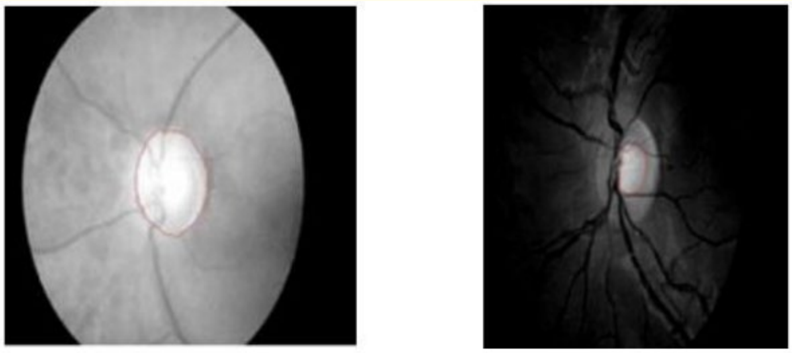

Figure 4: Right(disc boundary) and Left (Cup bounday) [14].

Random Forest Classifier [3]

FoE enhances the conventional Markov random field (MRF) models by implicitly learning potential functions across broader neighbourhoods. MRFs have a limited ability to collect image statistics. The FoE model represents picture priors more broadly and generalises outside of the training set.

A patch of an image is represented by sparse coding techniques as a linear combination of learning bases or filters. To roughly pinpoint the optic disc, researchers used the elliptical Hough transform approach.

The ROI localization approach is purposefully created to yield a big ROI that encompasses the whole disc as well as other portions. By obtaining their distinct images, one may determine the neuro-retinal rim. In order to obtain training patches from the background, they estimated the OD's bigger diameter (as it is elliptical) and chose a square bounding box whose sides were twice as broad as the OD and are centred on the OD. This box's OD is obtained by subtracting the backdrop from it.

Each class's FoE model consists of 74 filters, with the component with the highest variance being disregarded. Finding the precise filter from each class that can correctly detect the patch label is challenging. To differentiate between the three groups, they consequently utilised an RF classifier. The trained RF classifier receives the feature vectors and outputs probability maps for the ROI. Despite the RF's ability to generate a class label for each pixel, spatial consistency may not be guaranteed.

Least Square Support Vector Machine (LS-SVM) [4]

The digital found images are used to extract R, G, B, and grayscale values. Then, 2D EWT is used to create sub-band pictures using R, G, and B values. From these deconstructed components, correntropy is then extracted. Two techniques are employed for feature selection.

The student's t-test is applied in the first procedure. Then, these characteristics are normalised using a unit standard deviation and zero mean. The second feature extraction technique makes use of PCA, which computes eigenvectors and eigenvalues. The primary component is the eigenvector with the greatest eigenvalue.

As a classifier, radial basis function (RBF) with least square support vector machine (LS-SVM) as the kernel is utilised. There are several linear equations to solve when using the LS-SVM classifier. The classifier can distinguish between two classes once it has been trained, tweaked, and labelled. Here, one can determine if the displayed picture suffers from glaucoma or not.

Ensemble Learning [9]

The described tool is built on an ensemble of two distinct subsystems that use totally different technology. A segmentation-based network with a post-processing step for feature extraction makes up one of the subsystems. A very light-weight, last-generation classification network that can give the same level of performance as other, heavier, more conventional networks serves as the foundation for the second subsystem.

A key element of their methodology is the reporting tool, that merges the output of the two networks and provides ophthalmologists with a Glaucoma likelihood score.

Support Vector Machine (SVM) [14]

Data must often be divided into training as well as testing sets when performing a classification task. The training set's cases each have a target value, class labels, several properties, features, or observed variables.

The aim of SVM is to develop a model which is based on training data, that forecasts target values of test data using the characteristics of the test data.

The testing data is made up of the changed input picture matrices from pre-processing and PCA.

SVM is made to divide a collection of the images used in training into two distinct classes, (x1, y1) ….(xn, yn), where xi represents a d-dimensional feature space called Rd and yi is in a class label {-1,+1} with the i=1..n range. Based on a kernel function, SVM constructs the ideal separating hyper planes. All photos that include feature vectors that are on one side of the hyperplane are classified as class -1, while all other images are classified as class +1.

The non-linear SVM classifier is employed if the data from the two classes cannot be separated. Kernel functions are used to convert the non-linear separation hyperplane in higher dimensional feature space to a linear one.

Deep Learning Techniques

Convolutional Neural Networks (CNN) [2, 5]: CNN's architecture includes six layers. The initial four layers are the convolutional layers used in the process of Feature Extraction. The feature map is then passed to the final two fully connected layers, and its output is given to the Glaucoma Detection classifier.

Convolutional Layers: This is utilised as the characteristic that is randomly selected from any image and presented to learners on a small size. Features which are present in any point in space will be calculated utilising both the image that is present there as well as the detector that finds the elements.

Response Normalisation Layers: According to the proposed architecture, this layer functions in conjunction with the first and second convolutional layers. The formula for a neural network's output is f(x)=tanh(x), where x is the input.

Overlapped pooling layers: The total statistics for a selected area within the provided image are obtained by this layer for the CNN architecture. The max-pooling layer is used here.

Artificial Neural Networks (ANN) [11]

Two architectures, Multilayer Perceptron and Back Propagation, are employed in ANN Classification. A feed- forward artificial neural network algorithm called a multilayer Perceptron map sets of input neurons into specific sets of computational output. Back-propagation is a modified version of the linear Perceptron used by at least three hidden layers with a nonlinear activation function.

With multilayer Perceptron neural networks, the most prevalent training algorithm is back propagation. Back propagation uses gradient descent to reduce the squared error between the output value of the network and the target output value. Using these error signals, the weight updates, which reflect the strength of the network's acquired knowledge, are calculated.

The primary algorithm is Multilayer Perceptron with Back Propagation (MLP-BP). In ANN, there are two phases: a forward phase and a backward phase.

Observations and Results

The table below shows the different model evaluation metrics used in the papers, to get the accuracy of the models.

Reference	***Evaluation Metrics Used***	***Accuracy (%)***
[1]	Accuracy, Sensitivity, Specificity, AUC, ROC	BOSVM - 96.6
[2]	AUC, ROC	AUC - 88.7
[3]	F- Score, Recall, Precision,	Field of Experts Model (FOE): 94.4
[4]	Student's t-test, Principal Component Analysis(PCA), sensitivity, accuracy, specificity	LS-SVM - 99
[5]	AUC, ROC	AUC - 88.2
[6]	Absolute Error, Relative Error	88.5
[7]	AUC, 10-fold cross validation	RF-OCT (AUC) - 96.3
[8]	Accuracy, Specificity, Sensitivity	CNN - 88.2
[9]	Specificity, Sensitivity, AUC, ROC	ResNet-50 - 96
[10]	Accuracy, Sensitivity, Specificity	97.58
[11]	Accuracy, Sensitivity, Specificity	Naive Bayes - 89.6 MLP-BP ANN - 90.6
[12]	Accuracy, Sensitivity, Specificity, Precision	SVM - 87 Glaucoma-Deep (CNN, DBN, Softmax) -99
[13]	Accuracy, Sensitivity, Specificity, Precision, F2 score, AUC, ROC	Attention-based CNN (AG-CNN) - 95.3
[14]	10-fold cross validation	SVM - 93

Table 2: Evaluation Metrics and Accuracies.

Conclusion

Glaucoma causes harm that is unrepairable. The only treatment for glaucoma is early detection and treatment. Utilising CFI and OCT pictures, research is being done on automated glaucoma identification. The primary features utilised in automated glaucoma identification utilising CFI are CDR, NRR thickness, ML thickness, and ISNT rule. The blood vessels, CDR, and RNFL thickness are the features in OCT pictures. Compared to OCT pictures, automated glaucoma detection with CFI is less expensive and appropriate for mass screening. However, because OCT provides a thorough study of the retinal layers, it is more accurate and dependable for glaucoma assessment. Consequently, more accurate glaucoma assessment would be achieved by automating the identification of glaucoma and incorporating characteristics from both CFI and OCT.

This review study covers the various approaches taken to address the issue of glaucoma analysis. Since there are still certain factors that may be considered to improve the accuracy of classification. Due to the bearing of retinal vessels, it is still difficult to not under/over-segment disc and cup with small or large diameters. A better segmentation and classification approach hopes to assist ophthalmologists in effectively identifying glaucoma so that it can be prevented.

Based on the literature review, it was determined that a number of methods were available to obtain the most accurate segmented and classed fundus image in order to identify glaucoma at an early stage. Automated systems in the Future will be able to identify early signs of eyesight loss to prevent it.

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