



Glaucoma Detection in retinal Fundus Images using various Deep Learning architectures

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Abstract -Glaucoma has become one of the most common reasons why people go blind all over the world. It's a disease that never goes away and can't be cured. Early diagnosis and screening for glaucoma are two of the most important things you can do to fight this disease. The use of deep learning in this situation looks very promising. In this study, proposed tested the effectiveness of three different deep learning (DL) architectures. One of them was a Convolutional Neural Network (CNN) model that used maximum pooling. Glaucoma is a type of neuropathy that affects the optic nerve and gets worse over time. It is one of the main reasons why people lose their eyesight for good. This condition, which is also a common cause of blindness, is most common among older people. It's not very common for glaucoma to go unnoticed, which delays treatment and makes it more likely that damage will happen that can't be fixed. The goal of this study was to do a literature search on glaucoma and how to treat it so that a short but comprehensive analysis of management strategies could be made. Techniques from the field of artificial intelligence are being used in a wide range of medical applications, from spotting diseases and identifying activities to helping doctors make a diagnosis with the help of a computer. When computer science techniques are used in conjunction with medical knowledge, they make the different procedures and tools easier to use and improve their accuracy. This study looks at the latest research on glaucoma screening, segmentation, and classification based on images of the papilla

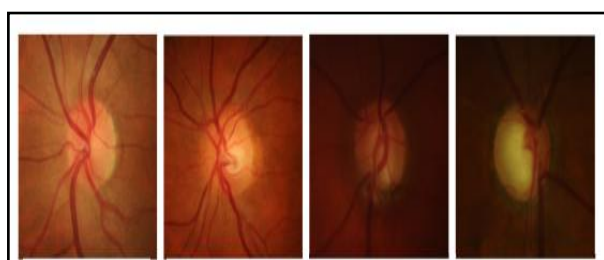
and excavation and algorithms for deep learning. It was written as a response to these changes and was based on them. Based on papilla and excavation images, it has been shown that these ways of screening for glaucoma have a high sensitivity and specificity. After that, the automatic segmentation of the optic disc's edges and the excavation make it possible to find out what kind of glaucoma a person has and how bad it is getting. Because of this, Proposed looked into whether deep learning techniques could be used to make accurate and cost-effective glaucoma measurements. If this works, it will encourage patients to take care of themselves and help doctors keep a better eye on them.

Keywords: eye diseases; glaucoma screening; artificial intelligence; deep learning; image processing; glaucoma classification,

I INTRODUCTION

Glaucoma afflicted 64 million people in 2016 and is expected to affect 95 million people by 2030, according to the World Health Organization [1]. Glaucoma, if left untreated, can result in permanent visual loss by injuring the optic nerve. High intraocular pressure in the eye pushes against the optic nerve, resulting in irreversible vision loss [2]. It is currently the biggest cause of blindness in the world. The area around the optic nerve has a wider cup and a narrower inferior rim as a result of the wounded nerve fiber. The condition's progression may result

in a "pale disc" and disc hemorrhage. They both have different warning symptoms, yet they are both connected to high intraocular pressure (IOP). Angle-closure glaucoma expresses itself in a multitude of ways due to the disease's angle-closure nature. Open-angle glaucoma, as opposed to swiftly advancing and leaving no symptoms, takes its time and leaves no evidence until peripheral vision is lost. Because the percentage of individuals with glaucoma increases rapidly with age, especially for those with early warning signs, a yearly eye exam is essential and recommended for early glaucoma screening. Clinical glaucoma screening now involves intraocular pressure measurement, visual field testing, and optic nerve head examination, but only the latter can detect early-stage glaucoma [3]. As a result, evaluating the optic nerve in retinal images has become a standard glaucoma diagnostic technique. Glaucoma damage to the OD region causes OD anomalies such as an expanding cup to disc ratio, a pale color, hemorrhage, or modifications surrounding the OD. In Figure 1, the OD of a healthy eye is compared to that of a glaucoma sufferer and displays a patient at different stages of glaucoma development.



a) Healthy OD (b)Mild Glaucoma (c) Moderate Glaucoma (d) Severe Glaucoma

Figure 1. Grading of glaucoma diseases: (a) healthy OD; (b) Mild Glaucoma; (c) Moderate Glaucoma and (d) severe glaucoma.

As people age or acquire early warning symptoms, the number of patients increases substantially. Clinical glaucoma screening now involves intraocular pressure measurement, visual field testing, and optic nerve head examination, but only the latter

can detect early-stage glaucoma. As a result, evaluating the optic nerve in retinal images has become a standard glaucoma diagnostic technique. Glaucoma damage to the OD region causes OD anomalies such as an expanding cup to disc ratio, a pale colour, hemorrhage, or modifications surrounding the OD. In Figure 1, the OD of a healthy eye is compared to that of a glaucoma sufferer. Figure 1. displays a patient at different stages of glaucoma development. As seen in Figure 2 one eye has normal pressure while the other has excessive pressure (right).

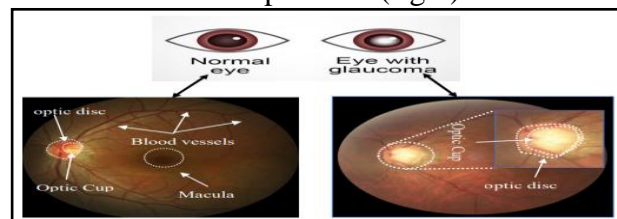


Figure 2 Images of a healthy retina (left) and one with glaucoma (right).

Digital images account for a significant amount of multimedia data, and content-based image analysis is employed in a wide range of computer vision applications. Medical image analysis has advanced significantly in recent decades, with several novel applications developing. A significant focus of medical image analysis research is to study pictures for sickness identification [5]. The optic nerve of the eye is gradually destroyed by chronic glaucoma. Because it is a neurodegenerative illness, it has the potential to cause blindness. Because nerve degeneration is irreversible, it results in permanent vision loss. Much research has been conducted in order to ascertain the number of people afflicted by this chronic illness. Glaucoma is the second most prevalent cause of visual loss [6]. By 2020, the number of people suffering from glaucoma will have climbed from 60 million to more than 80 million. Glaucoma causes irreversible vision loss by increasing intraocular pressure (IOP) and damaging the optic nerve. The illness has received the moniker "hushed burglar of vision" due to the difficulties in describing and quantifying early-stage glaucoma symptoms. Even

though there is no cure for glaucoma, it is possible to keep from going blind if the disease is found, treated, and kept under control early on [7].

Computer-Aided Diagnosis (CAD) assists in the treatment of damaged eyes. Several studies have employed fundus imaging as a technique to detect glaucoma early and avoid additional damage. Glaucoma, a group of illnesses and conditions that result in reduced vision and imparity, is caused by alterations in the retinal nerve fiber cushion and nervous optic head [8]. Researchers seek to reduce the impact by using improved illness diagnostics and therapies, such as the immediate Trabecular Micro-Bypass (TMB). The authors [9] did a brief evaluation of current state-of-the-art approaches for detecting glaucoma early. Methods such as the Optic Cup Disc Ratio and the Retinal Nerve Fiber Layer (RNFL) have been scrutinized. As a consequence of their results, this research helps to more reliably diagnose glaucoma. For the purpose of clarity, they've divided the survey findings into two categories: those that employ segmentation and those that don't. [10] Examined current techniques for detecting glaucoma, which assisted them in forecasting their own proficiency and accuracy. This is a fantastic survey that defines the leading information for researchers in terms of glaucoma approach and dataset selection for future study.

II LITERARURE SURVEY

Glaucoma is a neuropathic disease characterized by ganglion cell loss. As a result, as the optic nerve fiber decreases, the rim tissue erodes, resulting in the formation of a cup. Detecting glaucomatous structural damage and changes is one of the most difficult aspects of disease detection methods currently Intraocular pressure (IOP), which should be more than 22 mmHg without treatment, glaucomatous cupping of the optic disc, and glaucomatous visual field abnormalities are all ways to tell if someone has glaucoma. One of the most challenging elements of glaucoma diagnosis is

determining whether or not someone has the ailment when there are no symptoms. The number of patients who have not been diagnosed outnumbers those who have. However, the size and shape of the optic cup disc should be considered when diagnosing glaucoma so, an extension of the cup in the vertical direction is a sign of glaucomatous optic neuropathy[11-12].

Nazmus Shakib et. al. 2022 [13] Glaucoma is known to be one of the most common causes of blindness around the world. Early diagnosis and screening are two of the most important parts of fighting this disease. The use of deep learning in this situation looks very promising. In order to figure out how well deep learning models work, public datasets with 1250 different pictures were used. Images of the fundus are the main source of information that doctors use to confirm glaucoma in a clinical setting. This study looks at how far along the deep learning framework for diagnosis is on its way to being fully grown up. Measures of how well different kinds of deep learning frameworks work are looked at and compared. At the end, a summary of how machine learning works and some suggestions for where future research should go are given. Glaucoma is an irreversible disease of the nervous system that causes high pressure inside the eye. This happens when the aqueous humor level goes up and the drainage system between the eye and the cornea gets clogged. It's hard to figure out at an early stage, so screening at regular times is strongly recommended. [14-15].

Yves Attry, Kalin, et. al. 2022[14] Glaucoma is an example of a condition that might threaten an individual's vision. This illness, which affects the optic nerve in the eye and can cause sudden blindness, is potentially lethal. Attempts have been made to identify glaucoma by combining Machine Learning and Deep Learning Models with other concepts; nevertheless, the diagnostic efficiency of these models is insufficient for a disorder of such basic importance. In this

work, proposed have assembled a variety of Deep Learning Architectures depending on an assortment of criteria. MobileNetV2, DenseNet121, InceptionV3, InceptionResNetV2, ResNet50, and VGG16 are among these. These architectures are intended to appeal to more than two classes classified as "G" and "NG." The dataset was compiled from numerous sources and preprocessed to provide the best degree of precision. To validate the efficacy of our inventions, numerous metrics, including precision, recall, F1-score, Cohen Kappa Score, and area under the curve (AUC), have been added.

D. Shamia et al 2022 [15] Diabetes-related retinopathy, glaucoma, and cataracts have been identified as the three most common causes of blindness in one or both eyes. In light of this, the authors of this paper describe an automatic or self-diagnosing technique that employs a deep learning model. This technology can accurately anticipate and diagnose all three diseases in less than one minute, with a high rate of accuracy. In this research, proposed propose a DCNN-based expert system that uses an internet platform to detect three distinct diseases. This system would contain input, neurons, hidden layers, and output, akin to the human brain. The accuracy of detection was 91% for images impacted by glaucoma, 90% for images impacted by cataracts, and 91% for images damaged by DR. Designed alongside the system is a Graphical User Interface (GUI) that is intuitive, user-friendly, and accessible online.

Hongyong Zhang et. al. 2019 [16] Applying a controlled force to in-vitro-grown retinal cells suggests a method that is both doable and effective for studying the quantitative relationship between high intraocular pressure and glaucoma. In this research study, alginate hydrogel microbeads are made so that retinal cells can be grown in the lab. In order to make alginate microbeads successfully, a simple flow-focusing

microfluidic system was made out of syringe needles and silicone tubing. The first step in making these tiny beads is for water droplets to form in oil inside of a silicone tube. The alginate droplets are then cross-linked with the calcium solution. After the cultivation process, a cell is effectively sealed inside the hydrogel microbeads, where it can live and grow.

Chaodong Ling et. al. 2019[17] This research talks about a way to divide up blood vessels that is based on the Markov model and takes place in the wavelet domain. To get accurate segmentation results, the algorithm must take into account both the presence of a visible vein of blood and the fact that the object is inside of something else. Guided Filter can be used to make photos have more contrast. It also makes the intricate vein patterns in blood vessels stand out. After the pretreatment is done, pictures of the retina are taken from inside the blood vessels. Simulation results are given to show that the proposed segmentation method can be used and is effective. The DRIVE, STARE, and FIRE data sets were used to come to these conclusions.

Weingart, Mircea, et. al. 2019[18] Some ways to process images of the retina are explained below. These include getting rid of noise and using the ARIA and B-COSFIRE filters. With these methods, images of blood vessels in the retina can be broken up into their parts. Eye-fundus images are used as the source of data for experiments with the KSVD and BM3D methods for getting rid of noise. The contrast limited adaptive histogram equalization technique is another method Proposed use to improve image contrast. Proposed also offer a powerful method for image segmentation that is based on a method of optimization that is inspired by the natural world. Particle Swarm Optimization is the name for this method. In the end, machine learning techniques are used to automatically classify images of the back of the eye (fundus) to find diseases.

This is done by automatically putting the images into groups.

Xiao et. al. 2018 [19] Because of retinal vascular segmentation, eye diseases can be seen clearly and diagnosed correctly, early treatment can be given, and surgery can be planned. Deep learning-based methods for segmenting the blood vessels in the retina have recently reached a level of performance that is considered to be state-of-the-art. Even with these approaches, there are still problems with small, thin vessels, low discriminative capacity in the area of the optic disc, and other problems caused by the large changes in the shape of the vessels against a noisy background. In this piece of research, proposed came up with a model similar to U-Net that uses a weighted attention mechanism and a skip connection strategy to deal with these problems. Using two benchmark datasets, the proposed methods were tested to show how useful they were, and the results were convincing.

Xiao-Min Li et. al. 2020[20] But because pooling and convolution are done one after the other, spatial information is lost. In this research, proposed show what call DAS-UNet, a network architecture. It is a U-Net with a lot of connections. It also has a parallel atrous convolution block and a big computing block. Second, the parallel atrous convolution block, which is also called the PAC Block, uses a number of receptive fields to create more abstract features that help with precise segmentation. Third, by using the salient computing block (SCB), can highlight responsive areas and hide unimportant ones. This lets us make a more clear vessel segmentation map than Proposed could with the U-Net. Extensive testing on the DRIVE benchmark shows that DAS-UNet has a performance that is considered to be at the cutting edge, with a result that is especially clear.

Behnam Azimi et al.,2020[21] Optical coherence tomography (OCT) images can show if there is a problem with the retina

because OCT can show many of the signs that there is a problem with the retina. Fluid areas could show signs of diseases like age-related macular degeneration (AMD) and diabetic macular edema (DME) (DME). Ophthalmologists can use automatic segmentation of these areas to help them find and treat these conditions. The graph shortest route layer segmentation and fully convolutional networks are used in this study to come up with a fully automated method for separating fluids (FCNs). The proposed method was put to the test by having OCT scans done on 24 different people a total of 600 times. The results show that the suggested FCN model does a better job of fluid segmentation than three current approaches, with an improvement of 4.44 percent in dice efficiency and 6.28 percent in sensitivity, respectively.

Ahmed A. Sleman et. al. 2018[22] Optical coherence tomography (OCT) images can show if there is a problem with the retina because OCT can show many of the signs that there is a problem with the retina. Fluid areas could show signs of diseases like age-related macular degeneration (AMD) and diabetic macular edema (DME) (DME). Ophthalmologists can use automatic segmentation of these areas to help them find and treat these conditions. The graph shortest route layer segmentation and fully convolutional networks are used in this study to come up with a fully automated method for separating fluids (FCNs). The proposed method was put to the test by having OCT scans done on 24 different people a total of 600 times. The results show that the suggested FCN model does a better job of fluid segmentation than three current approaches, with an improvement of 4.44 percent in dice efficiency and 6.28 percent in sensitivity, respectively.

Jie Wang et. al. 2021[23] Domain shift is widely seen as a major factor in making a large number of models more stable overall. Recently, it was suggested that unsupervised

auxiliary learning, like input reconstruction, could improve the model's ability to move between domains and stop performance from dropping when moving between domains. Even so, the features taken from different tasks are used in the same way in the existing paradigm, which makes learning less than perfect. The Disentangled Reconstruction Neural Network is a unique unsupervised domain adaptation method for cross-domain retina vascular segmentation that Proposed have come up with (DRNN). This will help us deal with the problem the one facing. DRNN uses two tandem nets to tell the difference between features that are domain-specific and features that are not domain-specific when it is learning to do more than one task at once. When it comes to getting state-of-the-art results for retina vessel segmentation, proposed run a lot of tests on publicly available retina datasets, and our suggested DRNN beats the competition by a large margin.

Tavakoli et.al. 2017[24] developed three retinal vascular segmentation methods for the automatic detection of ONH. Mashhad University of Medical Sciences in Iran provided the databases MUMS-DB, DRIVE, and CHASE DB1. Even though fundus photos are colorful, the green channel was chosen because it provides strong contrast. Morphological methods were used as a preprocessing step to increase the contrast between the vessel and the background. To prevent incorrect or missing vessel detection, the image has been inverted to compensate for the backdrop brightness variation throughout the whole fundus image. The multi-overlapping window's size and window overlapping have a substantial impact on the method's accuracy. To separate retinal vessels, edge detectors such as Laplacian of Gaussian, Canny, and Matched filters are used. Higher sensitivity and specificity ratings indicate higher performance as an evaluation criterion. The recognition and segmentation of retinal vessels is a vital step in automated diagnosis and a critical field of medical image

processing. Because manual detection is a time-consuming and labor-intensive activity, no technique or methodology for real-time automated detection has yet been established.

Bibiloni et.al.2019 [25] developed a real-time retinal segmentation method based on fuzzy morphological operations that take into consideration the costs and operations required. Retinal imaging may identify several medical conditions, such as glaucoma and diabetic retinopathy. The fundus camera captures images of the retina. Because the images are noisy, indistinct, and low in contrast, there is some ambiguity, which might lead to a lack of information and an unpredictable consequence. In fuzzy mathematical morphology, top-hat transformation was used to address the ambiguity in the images and increase contrast via top-hat transformation. The DRIVE and STARE databases used Preciseness, Accuracy, Specificity, and Sensitivity as performance evaluation criteria. The findings were contrasted with other cutting-edge approaches.

This technique is more efficient than real-time systems and improves segmentation. Agarwal et al. suggested automatic techniques for strategic OD segmentation. They used morphology-based and edge detection techniques, as well as snake-based active contour fitting, to achieve accurate OD segmentation. The fundus was photographed 60 times for use in the investigations. In terms of processing time and overlapping scores, segmented optical disc and ground truth overlapping scores have been obtained. The results show that the proposed method has a higher overlap score than 90%, which shows that it is accurate and useful for automatic screening of likely patients.

Fengze Wu (2022):[26]Glaucoma is a chronic, degenerative visual neuropathy that is the main reason why people go blind for good. A person with glaucoma may not

notice any changes to their vision for many years. So, it is important to look for and treat this condition as soon as possible to stop permanent vision loss. The vertical cup-to-disc ratio (VCDR) is a structural sign of glaucoma. It is the ratio of the vertical diameter of the cup to the vertical diameter of the disc in the area of the optic nerve head. For VCDR estimation, the optic disc (OD) and optic cup (OC) must be correctly cut out of fundus images. Manually annotating the disc and cup region, on the other hand, is time-consuming and depends on the biases and insights of the observer. In this study, we used Detectron2, a cutting-edge platform for identifying objects, to show an automated deep learning strategy for separating the OD from the OC and figuring out the VCDR from fundus images. We trained Mask R-CNN models so that we could measure VCDR and separate ODs and OCs. Using the Retinal Fundus Glaucoma Challenge (REFUGE) dataset, we checked how well our method worked by using the Dice similarity coefficient (DSC) for OD and OC and the mean absolute error (MAE) for VCDR. For the hold-out test photos, we got a DSC of 0.9622 for OD, a DSC of 0.8870 for OC, and an MAE of 0.0376 for VCDR, all of which are very accurate. With gains of 0.2% and 0.4% in OD and OC DSC and a reduction of 9% in VCDR MAE, respectively, this implementation did better than all other approaches in the REFUGE competition. Our method gave us a fully automated, accurate way to divide OD and OC into groups and estimate VCDR.

ManopPhankokkruad (2021):[27]The clinical information helps the doctors and nurses correctly diagnose the disorders and figure out the best way to treat them. Glaucoma is the most common disease that leads to permanent blindness. Vision loss can be stopped if the problem is found early and the right treatment is given. In this work, ResNet50V2, VGG16, InceptionV3, and Xception were used along with deep transfer learning of the CNN model to find glaucoma. People who have been told they have glaucoma can benefit from the models

that are available. The Glaucoma picture dataset was used to train the model with CNN architecture so that it could learn from it. In this work, data augmentation techniques are used to make it seem like there are more photos than there really are. This is necessary because the original dataset only has a small number of images. According to the results, the proposed models have done a good job of classifying information to find people with glaucoma. When compared to VGG16, ResNet50V2, InceptionV3, and Xception, the suggested model was accurate 97.27 percent of the time, 94.53% of the time, 95.31 percent of the time, and 94.92% of the time, respectively. In this study, the models are also judged based on how well they meet clinical performance criteria. The F1 score is one of these metrics. The others are accuracy, precision, specificity, and sensitivity. All of the models come up with the high level of confidence. Based on what the study found, the best test results came from the deep transfer learning model that uses the VGG16 architecture. On average, the VGG16 model was able to get an AUC-ROC value of 98.94%.

Akanksha Singh Patel (2021):[28]Glaucoma is an eye disease that makes it hard to see. It has become more common in recent years because the pressure in the eyes has gone up. This increased pressure is the main reason why the number of people with glaucoma is going up. One of the signs of this disease, which is always fatal once it shows up, is vision loss. As we've already talked about, glaucoma has already been diagnosed using a number of different deep learning (DL) algorithms. This publication shows the results of our research on how to spot glaucoma disease. We used a deep learning method called a Convolutional neural network to build the model we used to find the disease (CNN). The Mask Region-Based convolutional neural network, which is also called the Mask-RCNN, shows a different pattern for both glaucoma-affected eyes and healthy eyes. Researchers could use

machine learning techniques to use this pattern to find people with glaucoma. In this particular research project, Mask-RCNN was used to make a hierarchical structure that could tell the difference between pictures of eyes with glaucoma and eyes without it. This led to a much more accurate way of putting glaucoma patients into groups. With the method we've suggested, you can evaluate up to 33 convolutional layers and six levels of complexity. The dropout mechanism is used in the proposed research to improve the overall effectiveness of the performance, which has already been shown. This makes it easier to find out if someone has glaucoma. In this study, the SCES and ORIGA datasets were used to analyse the planned work, and the results of that analysis are given in this publication. According to the results, RCNN was 92.32 percent accurate on the ORIGA dataset, Faster-RCNN was 93.89 percent accurate, and Mask RCNN was 95.72 percent accurate. The results showed that the RCNN was 91.56 percent accurate when it was used on the SCES dataset, the Faster-RCNN was 94.32 percent accurate, and the Mask RCNN was 97.56 percent accurate. The mAP for RCNN was 89 percent, for Faster-RCNN it was 92 percent, and for Mask-RCNN it was 90 percent. Based on what was found, the mAP of RCNN is 90%, the mAP of Faster-RCNN is 91%, and the mAP of Mask-RCNN is 93%.

Silvia Ovreiu (2021):[29]Glaucoma is the most common cause of permanent blindness around the world. It is a disease that has no symptoms but damages the head of the optic nerve. Glaucoma symptoms don't show up until the disease is very far along, by which time the patient has already lost a lot of his eyesight. Regular eye exams are needed to find glaucoma and keep people from going blind. Still, these tests may not be needed to figure out if someone has glaucoma. Still, digital fundus pictures can be used to find glaucoma early because deep learning algorithms are getting better all the time. Recently, convolutional neural networks (CNNs) have been used in the field of ophthalmology to diagnose eye diseases like

glaucoma. This is because CNNs have been used successfully to find many diseases early on. This study suggests a new method that uses densely connected neural networks (DenseNet) with 201 layers. It does this by using the ACRIMA dataset and initial pre-training on ImageNet. We got a f1-score of 0.969 and an accuracy of about 97%. This gives us reason to be cautiously optimistic about using our classification model to find glaucoma early.

Parag Jibhakate (2022):[30]This article talks about how to find glaucoma in its early stages. We compare and contrast two different transfer learning algorithms. Machine learning algorithms were used to measure the morphological signs of glaucoma that can be used to predict when problems will start. Testing for glaucoma takes a lot of time and money, and people often make mistakes when they do it. In places with less money and less development, there are fewer eye doctors. This effort will help save time, money, and other resources by making it easier for people to get checked for glaucoma. Glaucoma is the leading cause of blindness in the United States, so it is important to find it early. We hope that what we do will make people's lives better.

Amer Sallam (2022):[31]Glaucoma is one of the most common diseases that cause people over 65 to lose their side vision. An increase in intraocular pressure (IOP), which is caused by an imbalance of fluids in the eye, can damage the optic nerve head (ONH), which is in charge of sending visual nerve impulses to the brain. Conventional ways to find out if someone has Glaucoma either take a long time or cost a lot of money. If the ONH doesn't work, it could cause permanent blindness. Because of this, it is very important to find Glaucoma as soon as possible. This study suggests a way to automatically spot Glaucoma from pictures of the fundus by using models of the disease that have already been trained with a Convolutional Neural Network (CNN). The proposed method not only helps optometry

professionals make quick decisions with low-cost tools, but it also helps them find Glaucoma early on. The Glaucoma detection method that was suggested was made by using models that had already been trained. These models were AlexNet, VGG11, VGG16, VGG19, GoogleNet (Inception V1), ResNET-18, ResNET-50, ResNET-101, and ResNET-152. Large-scale Attention-based Glaucoma (LAG), a very big data set, was used to test how well the technique worked. On the LAG dataset, models like AlexNet, VGG11, VGG16, VGG19, GoogleNet (Inception V1), ResNET-18, ResNET-50, ResNET-101, and ResNET-152 all did well, with scores of 81.4%, 80%, 82.2%, 80.9%, 82.9%, 86.7%, 85.6%, 86.2%, and 86.9%, respectively. In this analysis, ResNet-152 was found to be the best model. It had a high level of accuracy (86.9% precision and 86.9% recall).

Juan S.(2022): [32] Carrillo wrote the book in 2022. A healthy eye is needed to see, so it's important to keep it safe from things that could cause blindness. This study is about glaucoma, which is the most common cause of blindness around the world. This study aims to help ophthalmologists with screening by creating an automated system that uses mimetic anisotropic filtering, preprocessing of pictures of the fundus of the eye, and regression using convolutional neural networks. We show that using mimetic anisotropic filtering as a preprocessor before sending pictures to convolutional neural networks improves accuracy by 1.5 percentage points and sensitivity by 3.27 percentage points. Juan S. Carrillo (2022): Vision is a very important sense, and taking care of it is important to avoid diseases that can cause blindness that can't be fixed. This paper is about glaucoma, a disease that affects people all over the world and is one of the main reasons why people go blind. This work aims to help ophthalmologists by making an automated algorithm that combines preprocessing of images of the fundus of the eye with mimetic anisotropic filtering and regression through

convolutional neural networks. This will help screen people who might have this disease. In this work, we show that by preprocessing images with mimetic anisotropic filtering before sending them to convolutional neural networks, we can improve accuracy by 1.5% and sensitivity by 3.27%.

HansiGunasinghe(2021):[33]Doctors need a lot of time to figure out if someone has glaucoma because they have to do it by hand. The diagnosis and treatment of this condition can be sped up with the use of automated image analysis (for instance, of retinal fundus pictures) (for instance, of retinal fundus pictures). In this study, 26 deep learning models that have already been trained to recognise objects are compared as possible feature extractors for glaucoma detection from retinal fundus images. Using a template matching algorithm at three different sizes, the area around the head of the optic nerve was automatically cropped, and features were taken from both the cropped and full pictures using networks that had already been trained. Features from cropped areas were added to features from the whole picture to make feature sets with more information. Lastly, we figured out how accurate models were that were trained on each feature set separately and on different combinations of feature sets from the full and cropped pictures by using random forest and optimised logistic regression base classifiers to run a lot of ten-fold cross-validation tests. With an AUC-ROC of 0.97 in cross validation, the residual network (ResNet) turned out to be the best feature extractor for glaucoma diagnosis when used with the random forest classifier that uses concatenated features. Based on the data, it appears that using two feature sets (full and cropped) with the ResNet architecture is optimal for identifying glaucoma in retinal fundus pictures.

Zuha Khan (2021):[34]AI has a huge amount of potential to work well and meet the needs of the business world. AI has

become very popular in part because of the technology used to process images. Artificial intelligence is very important in the field of ophthalmology, which is the study of the eyes. This is because many eye problems can only be diagnosed by looking at pictures of the eyes. "Intelligent diagnosis" has been able to grow because of this. During this study, a model for early detection of glaucoma will be made using Artificial Intelligence, especially Deep Learning (DL), and Virtual Reality (VR). This would let patients start treatment sooner, lowering the chance of losing their sight completely. When glaucoma is found too late, valuable time is lost, and the eye suffers damage that can't be fixed. Because of this, the idea behind making this model instead of other methods that are more effective but harder to use and can be found in hospitals is that it will be easier to use. To figure out if someone has glaucoma, an experienced doctor must look at both the optic disc and the nerve fibre layer of the retina around it. Because of this, glaucoma diagnosis has always had limited economic value because it requires specific skills and a lot of work. Because public health is becoming more of a concern, especially after the COVID-19 epidemic, efforts to improve glaucoma screening and diagnosis have been given full support. In addition to the different inputs that would be taken for the DL model, the proposed method would use a VR environment to get information like the maximum peripheral distance that would be needed. Because of this combination, a good and accurate diagnosis would likely be made, which would save a lot of money on expensive eye tests.

III SEGMENTATION APPROACH

A-Modelbasedsegmentationapproaches

According to [35]proposed early glaucoma detection by model-based segmentation. Because this approach only exploits a small

fraction of the problematic region, the images are collected locally rather than globally. Deng et al. used the Fourier transform to pinpoint the centre of glaucomatous images by superimposing the Gaussian filter's dimensional function over the linear processes. The characteristics are then separated using K-Means clustering. Different models are chosen based on the searcher's needs as the size of the block varies. The akakie information criteria are used to choose the best model. This research used a dataset of 20 that was built using STARE data. To begin with, the image is converted to a grayscale version. The model utilized is low-cost and easy-to-use, but it faces certain difficulties due to its resilience in operation and the potential uncertainty induced by the tiny scale ratio. The algorithm has 82 percent sensitivity and 93 percent specificity.

According to [36]several methodologies are employed to diagnose glaucoma in fundus images, but the findings are not always trustworthy and gratifying. However, he proposes a one-of-a-kind approach to achieving this aim. In this scenario, the Laplace technique is applied. The photographs for this model, which employs two separate sorts of images, were chosen by Gx, a laser-based technique. You may have both bright and dark blood vessels if you use this approach. The image below has been smoothed using a Gaussian filter. This pattern begins in the darkest portion of the space and progresses outwards. This filter divides the items into smaller groups using a Laplacian algorithm.

Separating tiny objects removes noise, but this method removes fine details of vital characteristics. To solve this issue, split vessels and then separate them. For the diagnosis of glaucoma, Orlando et al. suggested a conditional random field model. The various parameters are employed here and are automatically learnt with the assistance of a vector machine. This is accomplished via the use of several datasets.

Table 2 shows an overview of the model-based techniques.

B-Approaches to Optic Cup Segmentation

Segmentation in the optic cup is more difficult due to the larger density of blood vessels in the optic cup compared to the optic disc. Furthermore, the progressive shift in optical cup intensity and NRR hampers optical cup segmentation. When someone has glaucoma, their cup size changes automatically as a result of the disease. The identification of glaucoma CDR, according to Ingle et al., is a vital procedure with a region of the cup to disc. The suggested approach uses the dataset to determine the cup's area. The ROI changes depending on the picture. In this study, an automated cup region approach was used. Oshi et al. suggested an automated method for detecting glaucoma early on. An automated OD parametrization approach is used to segment monocular retinal pictures in this study. Cup segmentation is done using vascular bends, which are quite similar to glaucoma diagnosis. There is a variation between the mathematical and photometric modifications. This method of OC segmentation is very efficient and effective. Damon et al. developed a technique for detecting the optic cup fused with kinks in the same way as Finkelstein et al. did. Blotches are removed from the OD using kinks, and the color and borders of vessels are identified using patches for vessel identification.

C-Fusion-Based Approaches

Fusion-based techniques to improve the performance of image classification models are employed in computer vision and image analysis. According to Ho et al., various characteristics are retrieved for the diagnosis and detection of glaucoma. Dissemination is computed using earlier studies of optic pictures presented by Chang et al. to distinguish between the optic disc and the optic cup histogram. For early detection, the active contour model is applied to various vessels. The use of erosion and dilation methods for identifying key peaks is applied

here. Additionally, the major peak was extracted utilizing the reverse histogram employing eroded and dilated image differentiation. Wong et al. presented ARGALI, which is utilized for the segmentation of the optic disc and optic cup, as an automated approach for detecting glaucoma. Instead of ARGALI, SVM and NN fusion were used in this investigation. The results show that SVM is more consistent than NN, indicating that SVM is a superior alternative to the ARGALI approach. With the goal of measuring CDR, Khalid et al. suggested Fuzzy c-Mean (FCM) approaches for segmenting the optic cup and disc. The green channel was chosen from the RGB fundus photos since it had a higher contrast than the others. To minimize vernacular, basic morphological processes like erosion and dilation are performed. The removal of the vernacular element is critical for obtaining good segmented findings with better accuracy, sensitivity, and specificity. The suggested approach for segmentation was evaluated using ground truth and ROC analysis. The result shows that the FCM segmentation method works well when it is combined with morphology.

D-Approaches Based on Multiple Scales

Using a texton dictionary-based segmentation technique, [10] were able to discriminate between pixels that belonged to vessels and those that did not. Instead of learning filter parameters from manually labeled picture pixels, the suggested approach generates filter parameters using a small set of image features known as keypoints. Using a SIFT-inspired method, the Gabor Filter bank was utilized to extract keypoints that represented features. Proposed begin with k-means clustering and use it to construct a texton dictionary for another training set using the seeds from the validation set. For testing, the NN classifier is used, and the DRIVE database is used to judge how well the results work.

According to the findings, key point-based clusters are more trustworthy than those based on manually labeled pixels. As a

consequence, employing texton as a representation of vessel and non-vessel classifications reduced inter- and intra-observer variability. According to Li et al., segmentation algorithms require ground truth to be assessed. However, estimating ground truth from manual segmentation collections is currently difficult. An appropriate estimating strategy must be devised to deal with inter-rater variance. They conducted a study to better comprehend and identify the importance of the patterns discovered through manual segmentation of ground truth. The authors believe that combining a level-set technique with a probabilistic framework can aid in estimating ground truth. According to the authors, segmentation is the initial stage in developing computer-based applications, and precision is crucial. The utilization of computer-based skin lesion methods for segmentation is also critical. The model makes use of previous design information. Experiments were done with both fake and real data, and it was found that prior knowledge gives more accurate, close, and original results for GT.

[37] developed vascular segmentation for the computer-aided detection of retinal disorders, such as glaucoma. A line detector is used in the green channel of the RGP retinal picture. The green channel is used since it produces the greatest results when it comes to vessel backgrounds. When compared to the backcloth, the vessels have a gleaming finish. Furthermore, the boats seem to be blazing over the green channel, so a green channel is chosen here. In this case, two separate segmentation techniques are applied. Both segmentation methods provide effective results.

[38] suggested a supervised retinal image segmentation technique. A supervised algorithm is employed for the instinctual process of segmentation. For picture processing and segmentation of retinal fundus images, two databases are used: DRIVE (Niemeijer et al.) and STRIVE [39] The algorithm starts with a training picture,

then extracts vessel characteristics from the training image and labels samples. Manual segmentation of the labeled samples is done first, and then the classifier is used to train the labeled data. After that, test photos are acquired, and vessels are extracted in the same way as in the training images. The picture is then divided after vessel characteristics and classifiers work together to conduct vessel classification. The overall accuracy rate is 95.79 percent.

E-Texture Feature-Based Approaches

According to [42] the nerve fiber layer in healthy people's eyes is continually disturbed and clear, but it is muddled in glaucoma sufferers' eyes. Septiarini et al. suggested a technique for automatically recognizing RNFL based on textural and morphological characteristics. Proposed obtained the co-occurrence matrix from outside the optical nerve head if blood vessels should be eliminated since RNFL identification in this location is simple. Different classifiers are used to identify RNFL, but the Back Propagation Neural Network (BPNN) classification strategy is more accurate. In the experiment, 40 pictures of the back of the eye were used, and the sensitivity, specificity, and accuracy were calculated to see how well the test worked.

[40] suggested an Empirical Wavelet Transform (EWT) and a Discrete Wavelet Transform-based computer-assisted diagnostic (CAD) technique for glaucoma using fundus pictures (DWT). After preprocessing, the input pictures are deconstructed using EWT, DWT, EWTDWT, and DWTEWT operations, and feature layers are created, which are then concatenated in the next phase, followed by normalization and feature selection. To determine the best characteristics, these features were put through SVD (Singular Value Decomposition) and then classified using SVM. Many performance assessment criteria such as accuracy, sensitivity, specificity, negative predictive rate (NPR), rate of negative predictions (RNP),

Matthews Correlation Coefficient (MCC), and others were employed using 505 pictures from the MIAG image collection. The suggested technique's performance and classification have been compared to those of existing approaches.

According to [41] glaucoma causes visual loss. Therefore, they created a wavelet-based contourlet transformation (WBCT) approach for glaucoma identification. A weighted adaptive gamma correction approach was utilized to improve visual contrast. By adopting a Gabor filter, OD is segmented and blood vessels are eliminated. Coefficients are retrieved from the segmented OD area using a wavelet-based contourlet transformation, and then features are extracted from the calculated coefficients. An SVM classifier is used to identify glaucoma. The studies were carried out on the FAU dataset with the goal of evaluating accuracy, specificity, sensitivity, and positive predictive ratio. However, only accuracy was compared to other approaches.

IV CLASSIFICATION BASED APPROACH

A-Deep Learning Approaches for Glaucoma Classification

DL-based models have been applied in a variety of medical image analysis applications in recent years. that CNN is linked to DL systems, which the authors utilize to distinguish between glaucomatous and non-glaucomatous pictures in the proposed research. The CNN network has six layers, the first four of which are convolutional, and the latter two are completely linked. For glaucoma prediction, the output of the final completely linked layer The photograph was preprocessed by the authors to eliminate the excessive lighting and improve the image. Later on, the image's ROI is defined, and the ROI is used to do additional calculations. The suggested CNN architecture comprises six layers through which the picture is transferred before being evaluated. Finally, to improve

glaucoma detection accuracy, dropout and data augmentation methods are used to increase the ROI. The ORIGA dataset, which included 168 glaucoma and 482 normal fundus pictures, was employed.

There are 1676 fundus photos in the SCES collection, and 46 of them are of glaucoma patients. The findings demonstrated that the strategy outperformed existing state-of-the-art techniques for detecting glaucoma. Pictures from the ORIGA dataset were utilized for both training and testing; 99 images were used for training and 551 images were tested.

Nguyen et al. provided an unsupervised approach for the extraction of blood vessels that uses a line detector. The writers concentrated on the location of each pixel and calculated the matching grayscale, as well as assigned a window to it. Twelve lines were drawn down throughout the area, with all of them crossing through the region's center. After that, the average grey levels of each line were calculated. The winning line had the most votes and had the greatest gray value of all the lines, and it was used to partition blood vessels. The line detector had various flaws. For example, it tended to blend vessels that were close together. At crossroads, it creates an appendix. It causes misleading vascular responses near strong vessels in the background pixels. By altering the length of the basic line detector, these flaws may be rectified.

The suggested technique was evaluated using three publicly accessible datasets: DRIVE, STARE, and REVIEW. The suggested approach detected 515 false positives around the OD area. To overcome this issue, a post-processing phase may be used to eliminate false positives and further enhance the method's performance. JH Tan et al. developed a feedforward neural network (FNN). The Drive dataset is utilized with 40 glaucoma photos. First and foremost, picture normalization is performed before classification as a preprocess by the authors. The projected CNN has seven tiers. The data is trained using a standard back propagation approach. As a result, the learning rate is

adjusted appropriately. The system conducts testing at the conclusion of each training session, achieving an accuracy of 92.68 percent. Methods based on CNN. Were the first to deploy a deep learning methodology to identify glaucoma. He uses CNN and CNN with dropout, as well as CNN with four six-layer deep convolutional layers with filter sizes of (11, 5, 3, 3) and two dense layers.

Chai et al.[42] build a structure on a collection of fundus images gathered from several hospitals by incorporating both feature learned and domain information from the deep learning model. The authors derived 2554 retinal fundus pictures from 1542 individuals, including 1023 images from glaucoma patients and 1531 images from non-glaucoma patients. The authors presented an approach that makes use of deep learning as well as domain expertise. The identification of glaucoma is accomplished using a multi-branched neural network model. The network is made up of a faster RCNN, CNN, and a fully convolutional network.

B-Criteria for Evaluating Glaucoma Detection Techniques

The outcomes of automatic detection are assessed by utilizing a wide range of assessment indicators. The metrics used to evaluate the system must be well-defined and connected to the domain of the system under examination. A confusion matrix, is a table that shows the visual depiction of an algorithm's performance. It is also known as the contingency matrix or error matrix. In the area of machine learning and classification methods, this matrix is extensively employed.

C-Deep Learning Methods Vs. Traditional Methods

A short comparison of techniques using deep learning methodology and classical methodologies has been undertaken. The accuracy and performance of DL techniques seem to be excellent in most cases. DL has pushed the boundaries of image processing

and method automation, producing extraordinary results. Because ML has a high sensitivity and specificity for detecting glaucoma, conventional techniques are thought to be less successful than the former. DL is mostly built on artificial neural networks (ANNs), which are brain-like structures that function similarly to the brain. Because they use trained neural networks that aren't coded, they are more accurate than traditional methods.

According to machine learning is the capacity to learn from experience and improve performance in accomplishing a task. Machine learning (ML) systems can learn from data, recognize patterns, and make decisions with little to no human intervention. As a result, when using the classification paradigm for diagnostic modelling, the learning process is reliant on inspecting data instances. In this scenario, the model is formed by learning from annotated data. When dealing with image processing issues, it is vital to reduce the number of data inputs before employing specific ML models. A photograph can be blown up to millions of pixels in size for purposes such as categorization. In this manner, data entry would make processing considerably more complicated. To further simplify matters, the picture is reduced to just a few crucial components. The representative properties of the reduced input data are chosen and assessed. The information contained in such a collection is required to complete a certain task. There are several ways to express it, including the use of colour, texture, shape, or even a small portion of an image.

Studies in this field are aimed at identifying characteristics that decrease memory and processing time requirements, eliminate irreversible traits, and simplify the resulting model as much as possible. To manually extract intended characteristics, prior research often used computer vision approaches like depth perception and computer vision depth estimation. Since non-segmentation approaches create properties such as entropy, wavelet or fractal

dimensions, they were employed in part of the research. On the other hand, alternative techniques use a strategy based on segmentation to get common glaucoma diagnostic measures.

Image segmentation is the process of separating the target area, which corresponds to the real-world item, from the backdrop of the picture. Cheng et al. suggested a super pixel classification optic disc and optic cup segmentation method for this approach. A technique for segmenting the optic nerve head (ONH) was also created by [52] and validated using morphological procedures on the ONH. The target region is determined by the application's requirements in both ways. It usually reflects the operator's subjective perceptions and experiences.

D-Methods for Glaucoma Diagnosis Based On Feature Extraction

Noronha et al. developed a technique in 2014 using HOS cumulants. The image was first divided into projections using the Radon transform. This was used to compute high-order statistical moments. As a result, the high-order cumulative properties were generated. Following that, an attempt was made to reduce the dimensionality of the data using PCAs, ICAs, and linear discriminant analyses (LDA). The LDA is the final result of all of this.

The greatest degree of classification accuracy was asserted, and the results were employed in Fisher's discrimination index feature ranking approach (F). also employed support vector machines (SVMs) and naive Bayes techniques in the categorizing phase (NBs). The technique was tested on 272 fundus images from a private database. Using the tenfold cross-validation approach, 100 photographs were taken under normal conditions, and 72 and 100 shots were taken under moderate or severe glaucoma conditions, respectively.

[58] developed a method in 2015 that used Gabor Transform-derived features. As a consequence of this procedure, numerous coefficients were derived: the average value, the range of values, the degree of dispersion,

the kurtosis, and the quantity of energy. Following that, they obtained features and ran them through PCA. Furthermore, the proposed algorithm's feature ranking approach is critical since it allows the best representative qualities to be picked. To do this, T-tests, Bhattacharyya space algorithms, Wilcox tests, receiver operating curves, and entropy ranking approaches were used. To test if the technique works, 510 fundus images were analyzed in a private database and categorized as normal (266), mild (72), moderate (86), or severe (100). (86). the scientists also created a numerical risk index for glaucoma to distinguish between individuals who had it and those who did not. The SVM and the NB were used in the classification procedure.

Issac et al. 2015, [59] developed an adaptive threshold-based technique to segment the OD and OD-cup for glaucoma diagnosis. To begin, researchers examined the ONH. The green channel's histogram was then used to segment the OD. The CDR, the area of the neuroretinal rim (NRR), the region occupied by blood vessels, and the ISNT rule were utilized to detect ODs and their associated cups.

provide further information on the CDR, NRR, and ISNT rules. Aside from that, SVM, RBF, and an Artificial Neural Network were used to make classifications (ANN). The method was put to the test using a private dataset of 67 photos, 35 of which were healthy and 32 of which were glaucomatous.

Moreover, in the same year, Raja et al. devised a method based on PSO and GSO (GSO). The PSO framework was used to extract the population's g-best values. During this period, the world's best and brightest members were scouted to find better prospects for membership. The preprocessing was finished using grayscale conversion and histogram equilibration. For feature extraction, a wavelet transform and a hyper-analytic wavelet transform (HWT) were utilized. This method was used to obtain the mean, energy, and entropy, which were then employed in the classification

step. A public database called RIM-ONE was used to test the technique, and the SVM classifier gave the best results.

This was followed in 2016 by the publication of Singh et al., who proposed a method based on wavelet feature extraction. Its key hallmarks are OD segmentation and blood vessel removal. Using this method, the center of the optical disc is located by looking at the brightest portion of the disc. The wavelet feature extraction approach was also used in the segmented OD. As a consequence, PCA was utilized to reduce dimensionality, while z-score was employed to normalize. The test and training technique, which comprised 63 images from their records, were performed on patients ranging in age from 18 to 75 years old. This data was obtained from a personal computer. To sort the data, however, classifiers such as random forest NB, KNN, and artificial neural networks (ANN) were utilized. Finally, the best results were obtained using KNN and SVM.

E-Glaucoma Diagnosis Methods Based On Deep Convolutional Network Architectures

[58] developed an assessment approach for glaucoma optic neuropathy (GON) screening using a deep learning system in 2018. Throughout the training method, a mini-batch gradient descent of size 32 was used to include Inception-v3 [56] into the network architecture. After that, the Adam Optimizer was used to achieve convergence. The best results were obtained at a learning rate of 0.002. To put the method to the test, a private database containing 70,000 images was employed. Only 48,116 people with a discernable optic disc were used. So, using the ground truth labels given by medical professionals, two detection criteria for non-referable GON and referable GON (made up of suspected and certain GON) were made.

In the same year, [52] proposed employing an ensemble network for automated glaucoma screening that was aware of both global and local image levels (DENet). As a result, at the global level, there were two streams. For

the first stream, the Residual Network was utilized to establish a standard classification network (ResNet). The second was a segmentation-guided network that was based on the U-shape convolutional network. At the local image level, the standard classification network is based on ResNet and the disc polar transformation.

were employed to translate the OD area into the polar coordinate system. A system like this contains four deep streams, one for each section of a disc, as well as a global image stream and a segmentation-guided network. The final screening result was created by integrating the findings of all deep streams. The research investigations made use of ORIGA the Singapore Chinese Eye Study (SCES), and the SINDI private database.

[43] devised a strategy in 2018 that used 18-layer CNN architecture with convolutional and max-pool layers for increased performance. For the classification layer, employed logarithmic soft-max activation. Using one output neuron, the probability for each class was then computed. For training and testing, 589 pictures from the Kasturba Medical College private database were utilized, with the latter number signifying irregularity. About 70% of the data was picked at random for training and 30% was picked at random for testing.

In 2018, dos Santos Ferreira et al. developed a technique for image segmentation as well as image classification. To begin with, a U-net convolutional network was used to train the OD segmentation. At this stage, 80 percent of the data was being utilized for training, with just 20 percent being used for testing. Blood vessels were then removed using the Otsu algorithm. In the following stage, texture-based properties were extracted. The texture of the ROI was defined using the phylogenetic density of this structure. The final CNN classification layer served as the foundation for implementing a neural network. It contains 100 totally connected layers, a dropout of 0.5, was tested across 1,000 epochs, and has a learning rate of 1.105. The images used in the test and training phases came from the

databases RIM-ONE, DRIONS-DB and DRISHTI-GS0

V METHODOLOGY

The goal of this systematic literature review is to find and evaluate studies that have looked at the effect of each intervention on glaucoma adherence based on the quality of their outcome measure so that a useful suggestion for future research can be made.

A systematic literature review is a type of scientific research that focuses on a specific question and uses clear, pre-defined scientific methods to analyze, critique, and synthesize all of the

literature on a certain topic. In addition, the systematic review gives people who make guidelines for clinical practice something to build on [10]. During this investigation, used a method called a "systematic review" to find and evaluate the relevant scientific data from both qualitative and quantitative research. During this investigation, only journal articles were looked at. Other types of publications, like book chapters, newspaper articles, and conference proceedings, were not looked at.

The following methods were used to cut down on mistakes and bias in the literature review and to make a clear, well-structured, and complete summary of the existing literature (see Figure (3)).

The goal of this systematic review is to take a look at the different machine-learning and deep neural network algorithms that have been used to identify Glaucoma based on pictures of infected Glaucoma plants. In the review method, the following steps are included:

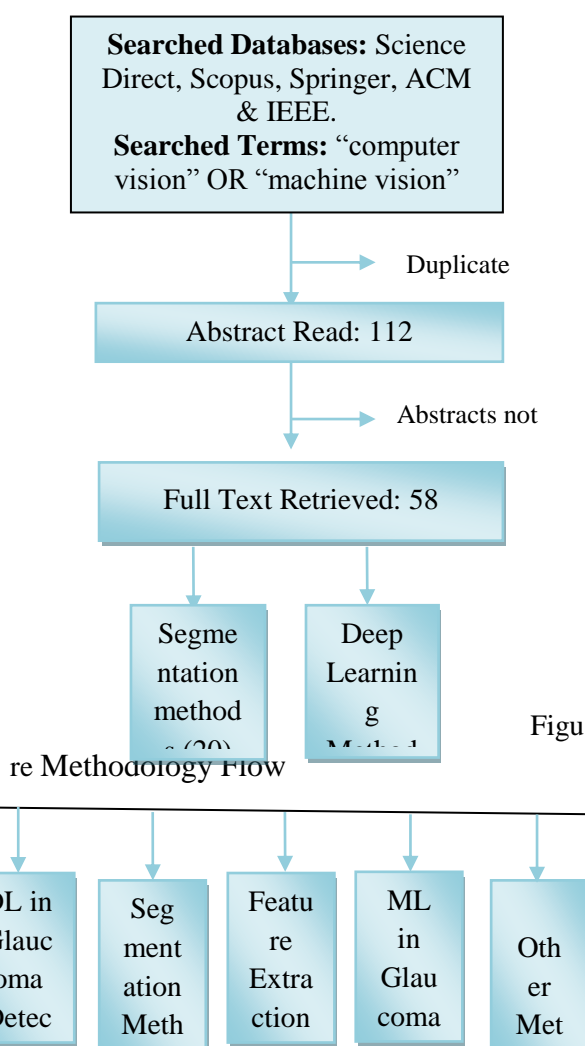
1. Data Collection
2. Searched databases

Proposed to use the five databases Science Direct, Scopus, Springer, the Association for Computing Machinery (ACM), and the Institute of Electrical and Electronic Engineers (IEEE) to do this review of the relevant literature (IEEE Explore Digital Library). For this poll, the years 2015 to 2020 were chosen as the time period to look at.

Searched Terms:

For the survey of papers, the following search expression was defined: ("Convolutional Neural Network" OR "Machine Learning" OR "Artificial Neural Network" OR "Deep Learning") AND ("Glaucoma")

Inclusion criteria:



Figure

in order to find the paper that meets the criteria given, the first part of the selection process was to look at the titles and abstracts of the papers. The second part was to get rid of any papers that were already there.

Exclusion criteria

The research did not include papers that did not directly deal with using deep learning or CNN to identify and classify glaucoma diseases.

Data Analysis

After more than 50 papers that were thought to be good for the evaluation were chosen, the data were analyzed with the following things in mind:

Year of Publication

Over the past few decades, the field of CNN/Deep Learning for Glaucoma Detection has become more and more interesting to researchers. Because of this, it's important to know when it was published if you want to find out what caused this interest to grow.

Purpose of the study

In the study, different types of tasks were done for various Glaucoma detection activities, such as finding discolorations and lesions, classifying, and segmenting, among other things.

Deep Learning Architecture

Deep learning architectures like Deep Neural Networks, CNN, and Recurrent NN have all been used in different ways to find Glaucoma.

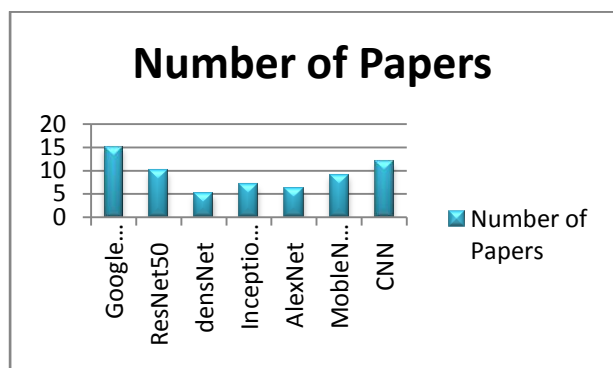


Figure 4 : Summary of the DL models used to detect Different types of Glaucoma disease

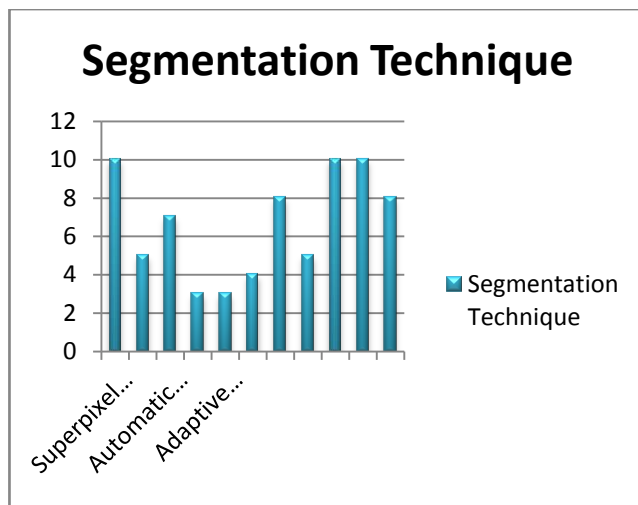


Figure 5: Summary of the papers for Different types of diseases detection using DL

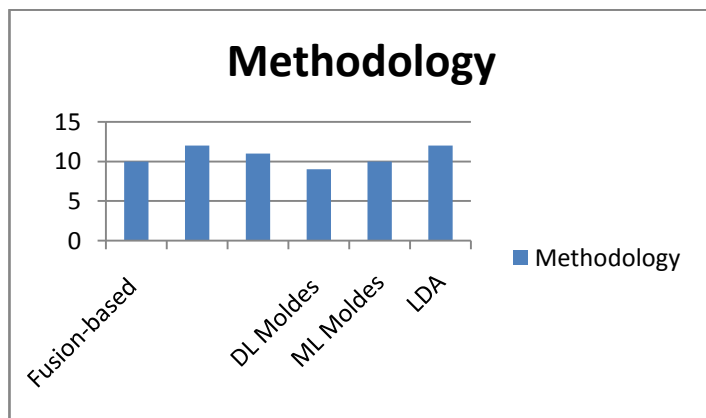


Figure 6: Summary of the DL models used to detect Different types of Glaucoma disease

VI DATASETS AVAILABLE FOR RETINAL IMAGES

The majority of the strategies mentioned in this study rely on publicly accessible data. These datasets are included in the table

below, which includes a short description and explanation. These are the datasets that researchers often employ to carry out recommended procedures and draw conclusions. the datasets that are available for glaucoma detection studies that may be utilized.

HRF Dataset-This dataset is divided into two picture sets: training and testing. The training set consists of 50 pictures, with ground truth for each image providing information on area boundaries, segmentation soft map, and cup-to disk ratio. The testing set, on the other hand, has 51 photos, and the ground truth for the test set is only available after registration. The image is 2896 x 1944 pixels in size and resolution, with a PNG uncompressed image format. The dataset's retinal picture type is Fundus Images. HRF is a freely accessible archive of high-resolution fundus pictures. The collection consists of three groups of fundus images: healthy retinas, glaucomatous retinas, and diabetic retinas. The first group has 15 photos of healthy people who do not have any signs of retinal disease. The following photographs are of 15 individuals with DR who had pathological alterations such as brilliant lesions, neovascular nets, and spots after laser therapy, and hemorrhages. The last batch of photos comprises 15 photos of individuals with severe glaucoma who are exhibiting signs of nerve fiber layer loss, both localized and diffuse. Fundus pictures are the retail kind of the dataset. The database's picture quality is 330 2336 pixels.

ONSHD-The fundus has been photographed 99 times by 50 different patients. The type of dataset is pictures of the fundus. These pictures were taken with a Kowa VX-10 alpha digital fundus camera that has a field of view of 50 degrees (FOV). The photos are saved using the JPG file type, and their resolution is 4288 by 2848 pixels. Each individual photo is about 800 KB in size.

IDRiD-IDRiD is a freely accessible retinal fundus picture library that consists of 516 photographs divided into two categories: 1. Retinal age exhibiting DME and/or DR

symptoms 2. Normal retinal scans that do not show any signs of DME or DR.

RIGA datasetThe RIGA dataset consists of 4,500 manually tagged photos and 750 images acquired from three sources. The photos, which include both glaucomatous and normal images, are stored in JPG and TIFF formats. Three sources have a resolution of a. 2240x1488 **MESSIDOR PIXELS** (460 Images) Riyadh 2743x1936 B. Magrabi Eye Center (95 Images) 2376x1584 Bin Rushed Ophthalmic Center in Riyadh (195 Images) Fundus images are the most common type of retinal image in the collection.

DRIONS-It includes 110 retinal pictures with a resolution of 600 x 400 pixels and a 36-landmark optic disc analyzed by two specialists. The dataset has a resolution of 600x400 pixels. Fundus pictures are a form of retinal image.

DIARETDB1-Each picture is coded by colour, and there are five normal pictures and 84 pictures of moderate non-proliferative diabetic retinal abnormalities. - There are 650 photos in this collection as a whole. 482 didn't have glaucoma, 168 did, and 168 did.

ACRIMA-The dataset is made up of 705 tagged photos, 396 of which show glaucoma and 309 of which show normal conditions. Anyone can access the dataset.

VII CONCLUSION

In this study, look at all of the available evidence about the role of TPD in open-angle glaucoma. This evidence comes from a systematic review of the literature (OAG). All of the library databases that were available were looked at, including PubMed (Medline), OVID Medline, Science Direct, and SpringerLink. The results of the subsequent meta-analysis of pooled mean differences are reported when it makes sense to do so. Five articles with a total of 396 patients met the requirements to be part of the study. Importantly, included all observational studies, even though the ways they measured ICP were different. This is because there is no consensus on the best

way to measure ICP in glaucoma, so there is no agreement. According to the results of our study, the TPD is not only much higher in people with glaucoma than in healthy people, but it is also linked to the structural changes that happen in the optic disc when glaucoma is present. Based on our study, it looks like there needs to be more longitudinal, prospective research done to find out how TPD affects OAG. The main goal of these studies should be to get rid of methodological problems that were present in earlier research. In this survey, looked at recent studies on identifying fifty different types of glaucoma, such as fusion-based, texture feature-based, multi-scale-based, DL Moldes, ML Moldes, and LDA detection using a variety of DL models. 10 of the papers that were looked at on GoogleNet are connected to ResNet50, 5 of the papers that were surveyed are connected to densNet, studies are connected to Inception V3, studies are connected to AlexNet 9, studies are connected to MobileNet, and 12 of the papers that were surveyed are connected to CNN.

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