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Glaucoma Detection Using Explainable AI and Deep Learning

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Abstract

INTRODUCTION: Glaucoma is an incurable eye syndrome and the second leading reason of vision loss. A retinal scan is usually used to detect it. Glaucoma poses a challenge to predict in its nascent stages because the side effects of glaucoma are not recognized until the advanced stages of the disease are reached. Therefore, regular eye examinations are important and recommended. Manual glaucoma screening methods are labour-intensive and time-consuming processes. However, deep learning-based glaucoma detection methods reduce the need for manual work and improve accuracy and speed.
OBJECTIVES: conduct a literature analysis of latest technical publications using various AI, Machine learning, and Deep learning methodologies for automated glaucoma detection.
RESULTS: There are 329 Scopus articles on glaucoma detection using retinal images. The quantitative review presented state-of-art methods from different research publications and articles and the usage of a fundus image database for qualitative and quantitative analysis. This paper presents the execution of Explainable AI for Glaucoma prediction Analysis. Explainable AI (XAI) is artificial intelligence (AI) that allows humans to understand AI decisions and predictions. This contrasts with the machine learning "black box" concept, where even the designer cannot explain why the AI made certain decisions. XAI is committed to improving user performance. To provide reliable explanations for Glaucoma forecasting from unhealthy and diseased photos, XAI primarily employs an Adaptive Neuro-fuzzy Inference System (ANFIS).
CONCLUSION: This article proposes and compares the performance metrics of ANFIS & SNN fuzzy layers, VGG19, AlexNet, ResNet, and MobileNet.

Keywords: ANFIS & SNN Fuzzy layer, VGG19, AlexNet, ResNet, MobileNet, Fundus image

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1. Introduction

Globally, glaucoma is thought to impact 76 million individuals, and by 2040, this figure is projected to rise to 112 million. [15]. The human eye is highly susceptible to diseases such as cataracts, glaucoma, and myopia, and over time these diseases become more complicated, and the visual acuity of the human eye gradually deteriorates. In fact, preliminary detection is essential to rule out complete sightlessness, dissimilar to other ocular diseases, there is no accepted reference standard for the diagnosis of glaucoma, making data comprehension is time-intensive and making firm conclusions even more complicated. About 80 million people worldwide have glaucoma. About 12 million people in India have glaucoma. However, as in many developing countries, approximately 50-80% of glaucoma cases in India go undetected. Several diagnostic tests are performed in real life, such as visual acuity, retina, and tonometry, but these are extremely exhaustive and challenging for the patient [14]. Automated glaucoma detection and tracking saves time and money while improving clinical processes and making the most use of scarce resources. Early treatment and diagnosis of glaucoma would be achieved by an automated system, preventing individuals from

irreversibly losing their eyesight. An integrated system can make use of the expertise of many ophthalmologists to produce findings that are precise and reliable. Figure 1 depicts the study of people who had had glaucoma for several years.
Funding opportunities exist at the National Eye Institute (NEI) of the National Institutes of Health (NIH), the Indian Council of Medical Research (ICMR), and the All-India Institute of Medical Sciences (AIIMS) in India. Additionally, Glaucoma Research Foundation and L.V. Prasad Eye Institute are some of the non-profit organizations that provide funding for glaucoma research. A key approach to combating the rising glaucoma problem should be raising awareness of the disease's risk factors and symptoms. People over the age of 60 should have their eyes checked for glaucoma every one to two years, those between the ages of 40 and 60 should undergo screening every three to five years, and those under the age of 40 should see a doctor every two to four years to aid in the early diagnosis of glaucoma.

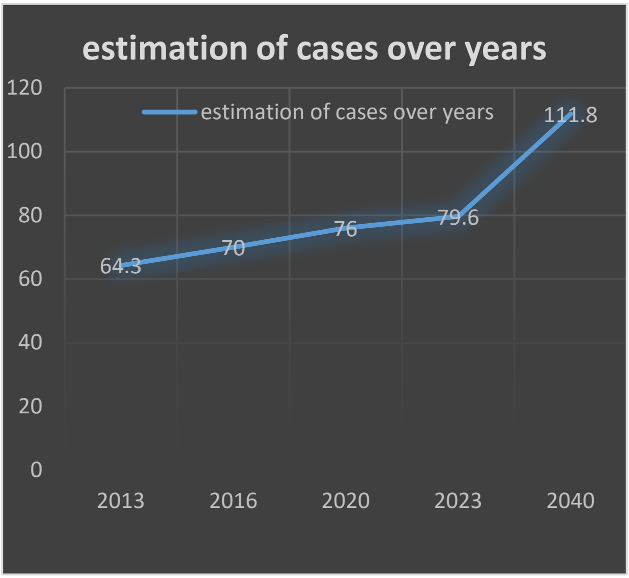

Figure 1: Prevalence of glaucoma over the years in millions

Automated glaucoma decision-making has received attention from numerous studies to help ophthalmologists identify glaucoma early. The advancement of various technologies for the quick and precise identification of glaucoma has been a subject of focus of research. Artificial intelligence methods have been successful in identifying Glaucoma using visual components such as fundus photos and optic coherence tomography (OCT) scans. Researchers were able to assess or classify the condition using artificial intelligence to predict its severity and course. In Ophthalmology, where conventional AI solutions have been used for a while, a big number of potentials have been used as a result of the relentless advancements of deep learning. Deep learning methods were especially used to image data obtained by digital photography, optical coherence tomography, and other means [44]. Unlike more conventional machine learning methods, deep learning-based systems don't need human intervention at each stage of the process, from feature extraction through model tuning. The fundus pictures used as input are displayed in Figure 2.

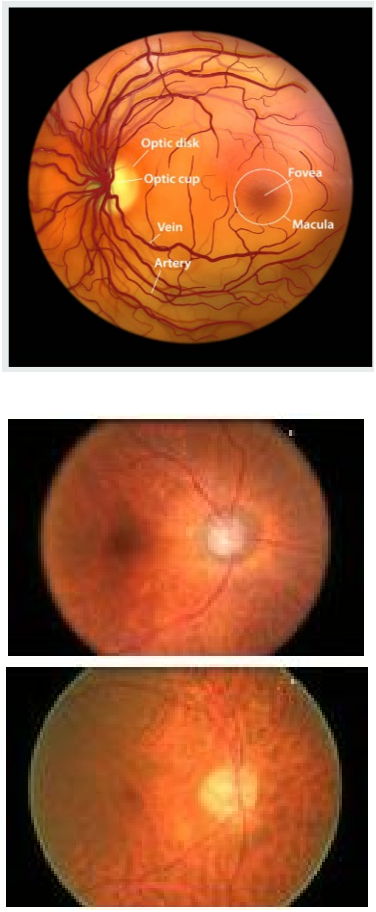

Figure 2: Retinal Fundus image
a) Glaucomatous image
b) Normal image

Deep learning is a subfield of machine learning that enables artificial neural networks to self-learn via supervised, semi-supervised, and unsupervised learning. In recent years, Convolutional Neural Networks (CNNs) have witnessed explosive growth in popularity (CNN). A system of deep learning that generates features mechanically. When used for picture recognition, it can yield reliable results, according to numerous research. As a result, ophthalmologists may find a deep learning-based CAD system to be highly helpful in making earlier diagnoses in a quicker and more effective manner [41]. In recent years, CNN, RCNN, VGG, Resnet, and other commonly used deep learning approaches for glaucoma diagnosis have been used. In our proposed model we will be working on different deep learning techniques such as mobileNet, AlexNet, VGG19, ResNet along with XAI techniques.

Explainable AI technology has been instrumental in aiding healthcare professionals in accurately and precisely diagnosing glaucoma. By combining advanced Machine Learning models used with medical imaging and ophthalmologic data, this new AI-enabled glaucoma detection is able to provide results that are not just more accurate, but whose diagnosis can also be explained to a much greater degree than traditional methods of diagnosis. Additionally, Explainable AI can help doctors explore the reasons behind a clinical decision, be it at the individual or larger population level. Its ability to shine a light on various levels of complexity related to situations such as glaucoma will no doubt be essential for improving future diagnostics in the healthcare field.

2. Related Study

Maede Zolanvari, Zebo Yang [1] highlighted the issue with AI, which makes it difficult for researchers and industry experts to explain the choices made by sophisticated AI algorithms because they (as AI users) are unable to fully comprehend the factors that go into these "black boxes'" decision-making. They emphasized the significance of integrating Explainable AI (XAI) into an AI-based IoT system. Using statistical theory (TRUST), which is used in numerical data like security systems and network data for IoT, they proposed an XAI model that offers transparency.

Erico Tjoa [2] has discussed that AI and ML models have demonstrated outstanding performance across a range of disciplines. But because there is a great need for accountability and openness in the medical industry, it is necessary to provide explanations for the decisions and predictions made by machines in order to support their accuracy. They collected data from studies on the interpretability of machine learning algorithms or computer algorithms in general, categorized them, and then used the same categories for interpretability in the medical area. In particular, the category aims to provide physicians and practitioners with a viewpoint on the usage of interpretable algorithms that are offered in a variety of formats.

Luciano Caroprese[3] has discussed the necessity for a fully transparent and explicable artificial intelligence (XAI), as opposed to artificial intelligence, which is sometimes viewed as a black box since it offers no explanation. By demonstrating how their intrinsic qualities of explainability and expressiveness aid in the construction of moral, justifiable intelligent systems, they investigated the advantages of adopting logic techniques for explainable AI. By summarising existing strategies in the literature, they concentrate on a single problem linked to application of argumentation theory in medicinal informatics.

Cyras et al. [4] have provided a fascinating review of AF-based explanations, which use strategies and tactics that come from the field of computational argumentation to explainable AI models. The term "model" is used extremely broadly in this study to pertain to a wide range of categories, including planning, LP tools, decision assistance, and recommender systems. The poll begins by outlining the various kinds of argumentation explanations and categorizing them as either intrinsic or post-hoc complete and posteriori approximate explanations have been created from the posteriori explanations. What the model describes, and the reasoning framework employed to complete the task is at the center of the survey.

Kashif Siddiqui, Thomas E. Doyle [5] have talked about how trustworthy AI in medicine is. In their study, a framework was created to analyse the credibility of AI in medicine in relation to common shareholders in the creation of medical devices. Through the assessment of a collection of explainable AI (XAI) techniques, they investigated AI models. The four components of trust—explainability, verifiability, fairness, and robustness—have been defined.

To anticipate aggregates and clarify the predictions with regard to alterations in the microbiome's component prompted by dissimilarity in phenotypic features, Anna Paola Carrieri and Niina Haiminen [6] have devised an approach called logical artificial intelligence (XAI). Inferring microbial signatures affiliated with each trait and aptly predicting a variety of phenotypes from the leg skin microbiome, including age, skin moisture, and, shockingly, menopausal and smoking status, are just a few of the outcomes of their study. This demonstrates the ability of explainable AI. They also considered using skin hydration model on a second, independent cohort to examine the model's efficacy in terms of prediction and its capacity for explanation.

Koji Fujita, Toshiki Shibahara [7] have identified misclassified malicious activities using XAI. They talked about how utilizing machine learning; it is nearly challenging to obtain 100% classification accuracy because these classifiers would always produce false positives negatives. Human confirmation is essential to ensure that these false positives and false negatives are not actually happening. A characterization verifier, an artificial intelligence model has been developed for the purpose of the study, compares the classification results of a classifier with the clarification findings of any associated questions asked.

Abeyagunasekera, S. H. P., Yuvin Perera [8] have proposed a strategy to detect COVID-19 patients from photographs. “They've adopted a unified concept based on the use of Intelligent Fake Sharp (XAI) devices to develop the sensitivities of the assumptions made by Convolutional Neural Networks (CNNs) with medical images. This system makes it possible for several methods to be used in order to provide justifications for the assumptions made by Blackbox models. These include LISA, also known as Close by Interpretable Model Cynic Explanations (LIME), integrated slants, Anchors, and Shapley Added substance Explanations (SHAP), which is based on the Shapley values.”

Bryce Murray, Derek T. Anderson [9] have investigated a human-machine interaction process. For the ChI, they analyzed older low-level XAI techniques, which we then categorised based on how and where they fit into the most recent XAI jargon. Two case studies—one synthetic and the other an unresolved real-world issue—were the subjects of their study. The case studies highlighted the initial set of suggested actions in light of both events that humans can influence and act upon and those that we cannot.

Erik Cambria [10] have delved at XAI strategies that use natural language to convey what has been done, what is happening at the now, what will happen in the future, and provide the information upon which these happenings are founded (via text or dialogue systems). They examined 70 XAI publications with natural language explanations that appeared between 2006 and 2021 in major journals and conferences. With the use of three distinct layers—definition of context, explanation construction, and message generation—they developed a framework for examining the whole learning process, from the black-box model to the final user. They also compiled a list of each layer's properties and compared it to the main XAI literature techniques.

Huazhu Fu, Jun Cheng [11] have discussed that the current glaucoma diagnostic techniques divide the optic disc (OD) and optic cup (OC) and rely on manually created visual features from fundus photographs. The authors have produced an M-Net deep learning system that simultaneously addresses the OD and OC division gives on a single platform with several names. They also used a polar change, which converts the original fundus image into the polar direction framework to further enhance the division outcome.

Eduardo Pinos-Velez, María Flores-Rivera [12] have implemented the ancillary tools for identifying and analysing human eye medical pictures to help in the provisional diagnosis of glaucoma. They focused on biomedical image processing to identify the characteristics regarded most significant within pictures collected from the back of the eye in order to diagnose glaucoma, a disorder that predominantly affects the physical statistics of the cup and the optical disc.

Dhaval Vaghjiani, Sajib Saha [13] They have created novel visualisation techniques that make it possible to comprehend the innate image elements that bestow to glaucoma identification at various CNN levels in addition to CNN-based methods for glaucoma detection. They also built a collection of interpretable notions to help them better comprehend the contributing picture characteristics involved in the illness detection process. A VGG16 model was used on the clipped fundus pictures. They have utilised the visualisation approach suggested by Zeiler et al. to better understand which picture aspects are impacting CNN's predictions for glaucoma detection.

Md.Tariqul Islam, Sheik Asif Imran, Asif Arefeen [14] have assessed convolutional neural networks' (CNN) performance and discussed a novel strategy for identifying eight different forms of ocular diseases. They have put up a fresh, practical, and clever replacement for existing techniques to detect early-stage optical disorders using indicators of ocular pathology based on neural networks. They developed a method that can accurately identify eight disorders, including glaucoma. Their illness detection technology has undergone real-time testing on a variety of images with various sorts of ocular disorders and is therefore supported by evidence of its viability in real-world applications. Their study will significantly influence ophthalmology and the field of medical science.

Kaveri A. Thakoor, Sharath C. [15] models using convolutional neural networks (CNNs) to find glaucoma in optical coherence tomography (OCT) images have been developed, and CNNs have been tested using thought sanctioning vectors (TCAVs) to identify which image concepts are used by CNNs to produce predictions. Researchers also compared the TCAV outcomes with the eye obsessions of specialists to identify regular dynamic features used by both artificial intelligence and human trained professionals.

Sadikul Alim Toki, Sohanoor Rahman [16] have attempted to use deep neural networks to automatically classify photos of healthy and sick retinoid fundus. The major objective of their study was to develop a system that would combine CNN and deep learning to recognise, extract, and evaluate disease-specific features in retinal fundus pictures. This tool will facilitate early disease detection, enabling patients to maintain good vision while preventing significant vision loss and blindness. They showed how effectively CNN can separate exudates in colour fundus images.

Andres Diaz-Pinto, Adrián Colomer [17] have utilised a poorly disposed model to develop a retinal image synthesiser and a semi-managed learning approach for automated glaucoma evaluation on both a large unlabeled data set and a small glaucoma-named data set.

Mhd Hasan Sarhan, M. Ali Nasseri [18] have talked about numerous machine-learning methods for analysing ophthalmic data. They looked at machine learning methods that had been put forth in the previous four years for the diagnosis of eye problems. Anyone with glaucoma, AMD, or diabetic retinopathy may find the results of this poll very interesting.

Anita Manassakorn, Supatana Auethavekiat[19] have assessed CNN's capability to identify glaucoma in OCTA images. They created GlauNet, a specially designed CNN model. And suggested GlauNet was capable of distinguishing between eyes with and without glaucoma. They came to the conclusion that glauNet could be trained with a limited dataset and was resistant to image artefacts and various camera projection settings. If training is done on actual data that has more variation, this robustness can be increased even more.

Juan Carrillo, Lola Bautista [20] have developed models to identify glaucoma from photographs of the eye's fundus. Even though there have been a number of works on automatic detection based on colour fundus pictures, they claimed that the key challenge was to give a precise estimation of the CDR. developed a computational tool for automatically detecting glaucoma in fundus photographs of the eye and proposed a novel method for cup segmentation that exhibits increased accuracy when compared to existing techniques.

Alexandru Lavric, Adrian I. Petrariu [21] have described in detail the creation of a sophisticated deep learning system that, when presented with pictures of the fundus of the eye, can reliably identify glaucoma. They nurtured the GlauNet deep learning system to improve early-stage ID performance. Many AI glaucoma detection architectures were demonstrated, each one utilising ML and deep learning. They found that their ingenious strategy was about 99.05% accurate. According to the researchers, this is the highest degree of accuracy yet achieved in identifying glaucoma using deep learning CNN computations without motion learning.

Gauri Ramanathan, Diya Chakrabarti [22] have created and presented a technique to quickly allow patient detection of glaucoma, cataract, and retinal disorders using machine learning models. To complete the recommended assignment and achieve high-performance efficiency, they carefully investigated and observed the many already-existing works. They compared the accuracy of various ML models.

Parag Jibhakate, Shreshtha Gole [23] have talked about employing the VGG-16 and ResNet-50 machine learning models to diagnose glaucoma early. These two transfer learning algorithms were compared to one another. They looked into how convolutional network depth affected accuracy in big environments for picture recognition.

To aid in the diagnosis of glaucoma, Javier Civit-Masot [24] developed a system that analyses photographs of the inside of the eye (the fundus) using a trained and tested neural network. By using machine learning, they found both the optic disc and cup. then transferred their knowledge to a pre-trained CNN. To increase final detection and differentiate glaucoma-positive cases, the findings of both methods were integrated.

Chethan M, Chandrashekar Dasari [25] have developed a machine learning model for glaucoma diagnosis with reliable estimations. By gathering datasets, performing analysis in numerous instances, and reviewing the distinctions between clinical diagnosis and algorithmic features, they took a step and gave advice to the doctor about which type of glaucoma develops in the human eye as well as other problems.

Anuradha Pandey, Mrs. Pooja Patre [26] have discussed how inaccurate the traditional image processing method was. "They extracted features like CDR and RDR from images using image processing techniques, and then classification was carried out using machine learning models from the neural network, support vector machine, decision tree, and K nearest neighbours. These models were contrasted with deep learning models.

Diping Song, Bin Fu, Fei Li [27] have suggested using OCT and VF data together with a Deep Relation Transformer (DRT) to do glaucoma diagnosis. To investigate implicit pairwise links between OCT and VF information in both global and regional contexts, a novel deep reasoning mechanism is proposed. In order to improve the representation with complementary information for each modal, a carefully thought-out deep transformer method is built using the pairwise relations." Three sequential modules, based on reasoning and transformer methods, are created to extract and gather crucial data for glaucoma diagnosis.

Silvia Ovreiu, Elena-Anca Paraschiv [28] have noticed that CNN performs well in the early diagnosis of a number of diseases; they have lately been utilised in the ophthalmological area for the diagnosis of a number of eye disorders, including glaucoma. As a result, they suggested a novel technique for glaucoma diagnosis that makes use of 201-layer DenseNet neural networks that are densely coupled. They gave an overview of some new glaucoma detection work utilising deep learning algorithms and talked about the advantages and disadvantages of the more advanced methods currently available.

Zhang et al. [29] have developed an AI order structure that classifies glaucomatous and healthy eyes using OCT data from the macula and the plate. Researchers in Guangzhou used a 19-layer CNN architecture that took into account issues such visual ID dropout, data enhancement, flat reflection, asymmetrical rotation, and random deletion. Despite the absence of an automated glaucoma diagnosis, this method has demonstrated 96% accuracy when used in conjunction with image processing techniques. suggesting that it may be utilised to identify early glaucoma.

Rakhmetulayeva Sabina, Syrymbet Zarina [30] have suggested a strategy for merging and contrasting all outcome data for glaucoma definition criteria to help a larger investigation to enhance feature discovery. The method, specifically the convolutional neural network deep learning algorithm, was suggested as a means of evaluating machine learning's potential. Using picture cropping and a CNN model, we looked for signs of glaucoma and identified the illness at its observable stages.

Anshul Thakur [31] have built models that use convex representation to identify clinically significant patterns of glaucomatous vision loss and can detect glaucoma years before symptoms appear. To detect the patterns of glaucomatous vision loss, they conducted a thorough archetypal analysis and then projected visual fields over the patterns. The picture produced by projections was more reliable in identifying glaucomatous visual loss.

Hansi Gunasinghe, James McKelvie [32] have discovered that current research only takes ROI or the full set of picture attributes into account. To develop an enlarged feature set, they blended features from the ONH with features from the entire retinal fundus image. Using standard PC vision layout coordination and an analysis of existing pre-prepared deep learning models as component extractors, they determined which models performed the best for the task of glaucoma localization in retinal fundus images. Both the entire retinal fundus image and a specific area of the image were examined.

Barros, D.M.S., Moura, J.C.C., Freire, C.R. et al [33] have outlined the goal of assessing the most recent algorithms put out by various parties and outlining the crucial elements in the creation of an automated diagnosis system. Additionally, they evaluated the potential of machine learning algorithms to automate the detection of glaucoma and other abnormal eye illnesses in their earliest stages.

L. Li et al [34] have explored how effective the current methods are at removing significant amounts of duplication from fundus pictures for the purpose of glaucoma identification, that may lower the dependency and accuracy of glaucoma detection. To overcome this drawback, they proposed the AG-CNN, a metric-based convolutional neural networks (CNNs) for glaucoma detection. To be more precise, we first create a sizable attention-based glaucoma (LAG) database.

"Shubham Joshi [35] has presented a computer-aided design framework to help in detecting glaucoma at an early stage and in screening for and treating the disease. The major objective was to evaluate the picture inspection model for its efficacy in the early detection and diagnosis of glaucoma and in the evaluation of other visual illnesses. Great images have been used in conjunction with advanced machine learning algorithms for glaucoma diagnosis."

Ratuja Shinde [36] have proposed developing a CAD system that can automatically detect glaucoma. They validated input images using the lightweight Le-Net architecture and segmented using the U-Net CNN model. By use of the cutting-edge augmented spot method, they have extracted the Region-of-Interest (ROI).

Ajitha S [37] has demonstrated the capability of the deep learning model to find glaucoma from fundus images and suggests that proposed system can assist ophthalmologists in a quick, accurate, and reliable diagnosis of glaucoma. has proposed a model for detecting glaucoma using deep learning techniques such as Softmax classifier, SVM classifier.

Ana-Maria Tefan [38] Taking into account advancements in deep learning, transfer learning, and artificial intelligence's capacity to process retinal images, researchers have examined the pros and cons of the most effective glaucoma ID approaches. We looked into AI systems based on highlight extraction, deep learning, and recursive learning to determine the proper sequence and locate glaucoma in retinal images.

Faizan Abdullah [39] has described the difficulties that glaucoma brings in terms of image processing and machine learning, which will be able to spot gaps in existing studies. They gave a thorough discussion of the many methods currently in use for using machine learning to identify and classify glaucoma from fundus pictures. They gave an overview of computational methods for diagnosing glaucoma illness. They discussed cutting-edge supervised and unsupervised learning techniques and came to the conclusion that, in terms of analytical performance, supervised learning techniques outperformed unsupervised techniques.

Lauren J. Coan,[40] a thorough evaluation of the pros and cons of using artificial intelligence-enhanced glaucoma localization frameworks that generate and use segmented fundus images. They highlighted the two approaches, provided a comprehensive overview of the two fundus imaging systems utilised in state-of-the-art artificial intelligence-powered glaucoma location strategies, and analysed the development of AI-powered glaucoma discovery procedures while praising research gaps. The review was made more accessible to ophthalmologists by including definitions of important artificial intelligence terms relevant to AI-enabled glaucoma detection.

Mamta Juneja,[41] recent research has suggested that even if trailblazing architectures like Xception, Inception, ResNet, DenseNet, VGG, etc., produce satisfactory results on clinical classification tasks, they are not yet ready for deployment. Hence, an Xception-based architectural recommendation with 85 layers was implemented, and its efficacy as a screening tool was confirmed by testing on real-time data. They introduced the CoG-NET model, which uses 85 layers of deep neural networks and relies heavily on separable convolution, to boost classification accuracy.

Bingyan Liu [42] has released a new, self-contained model predicated on flawed thinking about how to more precisely and broadly complete the tasks of separating the optic plate and cup and testing for glaucoma. We use an effective division and ordering network and the latest developments in solo area variation on the division organization's result space to solve the area shift problem. More precise and reliable glaucoma screening predictions may be made through the usage of grouping and division organisations to carry out glaucoma screening activities.

de Zarza` [43] has unveiled a sophisticated glaucoma detection system that operates automatically. "The method is built on a three-step process based on forms of EfficientNet, a proposed group of models discovered using NAS that achieves convincing accuracy on Imagenet, producing consistent results that outperform the benchmark techniques, and applying Move Gaining from Imagenet to the specific task at hand. According to the results obtained, the proposed keen framework for the primary task is trustworthy, shows high accuracy, produces stable expectancies, and necessitates fewer preparatory bounds.

Omer Deperlioglu [44] has put out a hybrid approach that combines deep learning and image processing with Explainable Artificial Intelligence (XAI) to ensure reliable diagnosis of glaucoma utilising enhanced coloured fundus image data. An explicable convolutional neural network used the augmented picture data for the diagnosis (CNN). The Class Activation Mapping (CAM) method used by the XAI enabled heat map-based justifications for the CNN's visual interpretation. The public datasets such as Drishti-GS, ORIGA, and HRF were used to test the hybrid solution's performance over the course of twenty classification tries." The ORIGA-Light dataset has the greatest mean values when taking the performance evaluation into account. Except for the XAI contributions, Efforts were also made to create a straightforward solution that employs deep learning in conjunction with more conventional image processing methods.

"Diping Song [45] has claimed that by evaluating data from several tests, including peripapillary optical coherence tomography and visual field (VF) testing, deep learning has had remarkable success in the diagnosis of glaucoma. However, due to a number of limitations, implementing these created models to clinical practise is still difficult. To improve the glaucoma indicative performance of the first OCT technique, they established a cross-modular refining system to communicate data across the OCT&VF and OCT teams." In order to direct element extraction from OCT inputs, they created a one-of-a-kind AFR module for model preparation. Several of this early research used a matched dataset to test out the proposed strategy.

"Kim et al. [46] proposed a deep learning-based CAD system for treating glaucoma. Gradient activation maps similar to CNN were used to locate and classify the input images. With fine-tuned weights and a 32-batch learning batch size, the final layer of the VGG model was modified for training. Finally, with an accuracy of 91% after 80 iterations, training was conducted on 50% of the dataset and testing on the remaining 50%."

Bala Prabhakar [47] argued that the increased likelihood of conventional techniques' misdiagnosis by currently used regular systems for discovering solutions makes more advanced methods, such as the use of manmade reasoning, possible (simulated intelligence). The authors updated their readers on the numerous AI strategies utilised in glaucoma diagnosis and evaluation, with a particular emphasis on how artificial intelligence (ML) may be used to expose software as a medical device (SaMD) in correct diagnosis or early illness detection.

Tae Joon Jun [48] has disseminated an Adaptive Positioning Convolutional Neural Network (TRk-CNN) that performs very well when classes of images to be identified share a strong level of similarity. They separated the glaucoma image dataset they used to evaluate TRk-CNN into three groups: normal eyes, eyes with a glaucoma suspicion, and eyes with glaucoma.

Yue Wu [49] has claimed that the conventional approaches of assessing disease activity are effective at capturing the structural and functional changes in glaucomatous eyes. To identify glaucoma early and more precisely, a novel technology is still required. Clinical diagnostics for glaucoma, such as optical coherence tomography, visual field, and intraocular pressure testing, were discussed in detail. "New technologies and existing clinical tests for detecting glaucoma disease activity were summarised, including the visual field (VF) test, intraocular pressure (IOP) test, and optical coherence tomography (OCT)."

Ying Xue [50] has claimed that a single feature is insufficient to explain the course of glaucoma alone and that more accurate and thorough diagnostic techniques must be developed immediately. In order to categorise glaucoma into four severity categories, in light of intraocular pressure (IOP), corneal fluorescein angiography (CFP), and visual field testing, they suggested a multi-highlight profound learning (MFDL) strategy (VF). They developed a coarse-to-fine approach to determining glaucoma severity that involves screening, localization, and characterisation.

Supiksha Jain [51] has confirmed that automated glaucoma diagnosis relies heavily on the extraction of the cup from retinal fundus pictures. They developed an efficient method for detecting glaucoma by employing a General Ill-disposed Organization (GAN) trained on the Rider Manta-Beam Rummaging Enhancement (Rider MRFO), in which the optic plate division process is carried out by Fluffy Nearby Data C-Means grouping (FLICM bunching), and the vein discovery process is also carried out by starting. To improve the detection of glaucomatous pictures, several important features were extracted.

Bajwa M. N et al. [52] developed a significant improvement in diagonising glaucoma from retinal fundus images. At first, the optic plate and the fundus picture were isolated and constrained using Areas with Convolutional Brain Organization (RCNN). After that, Deep CNN was used to classify glaucoma in the retrieved optic disc. For automatic disc localization, a order-based semi-automatic ground truth generating technique was also used. Although this method's efficiency was determined to be higher, it was still unable to shorten the computation time.

Juneja M et al. [53] formed the Disk Cup Glaucoma Network (DC-Gnet) using extensive knowledge of glaucoma detection in retinal fundus photographs. After first isolating the blue, green, and red channels from the data images, pre-handling was used to block out the abnormalities. Afterwards, using the refined technique, the optic plate and cup were separated. Using the low-passpass channel, we were able to lessen the visibility of the images' high-recurrence components. The connected shroud of the optic plate and optic cup was used to ascertain crucial aspects like the Second rate Unmatched Nasal Common (ISNT), the Circle Mischief Likelihood Scale (DDLS), and the CDR.

Henry Shen-Lih Chen [54] "The thickness of the retinal nerve fibre layer (RNFL) may be evaluated and abnormalities in the RNFL can be recognized using spectral domain optical coherence tomography (SD-OCT) images." After gathering this data, an algorithm for early glaucoma diagnosis using colour fundus pictures is developed using deep learning (DL). They developed and tested a DL method for regenerating RNFL thickness distribution pictures utilising thickness information extracted from fundus images in a manner akin to OCT measurement.

Andres Diaz-Pinto [55] has claimed that the handmade features based on segmentation used by existing algorithms for automatic glaucoma evaluation rely on fundus pictures. The analysts automated the glaucoma assessment procedure by using fundus photos and five distinct ImageNet-arranged models (VGG16, VGG19, InceptionV3, ResNet50, and Xception). Photographs from an unanticipated data collection were used to test the method. they discovered that the fine-tuned model performs competitively.

Shaswat Singh [56] has proposed a segmentation technique utilising Convolutional Neural Networks (CNN) was proposed. An optic cup and plate separation was used because to the sophisticated convolutional neural network layout of the Glaucoma Organization (G-Net). Accuracy in division between the optic plate and cup was 95.8% and 93.0%, respectively. for the presented technique, which functioned with two networks operating simultaneously.

WangMin Liao [57] has put forth a unique clinically interpretable ConvNet design for correct glaucoma diagnosis as well as for more opace interpretation by emphasising the different regions that the network recognises. They obtained a highly accurate clinically interpretable diagnosis result. According to their experimental findings, the suggested EAMNet can segment the optic disc and make an accurate diagnosis of glaucoma (0.88 AUC) (0.9 Adisc and 0.278 Edisc).

Fengze Wu [58] has suggested a method for extracting the matching VCDR, finding, including a method for mechanically separating OD and OC in fundus pictures. Our approach relied on Detectron2's Mask R-CNN to perform object identification and instance segmentation. To differentiate between OD and OC, they developed two distinct models. They measured the success of the initiative utilising DSC for OD/OC segmentation and MAE for VCDR.

N S Jeya Shyla [59] has proposed a new method in this work to increase classification accuracy with less time features. The ELM classifier is used to extract many features for high-precision glaucoma detection. Numerous variables, including statistical features, HoG, and DWT, are thought to have an impact on ELM training.

Tomaz Ribeiro VianaBisneto [60] has created a GAN-based, ordered-variety-file-based automated glaucoma detection method. We used a GAN to segment the OD from the rest of the retinal picture. As the general characteristics of concrete objects serve as a unifying principle for coordinating pixels, the semantic segmentation produced by GANs yields optimal markings on various images.

Deepak Parashar[61] has said that early glaucoma detection is crucial for preventing permanent visual loss. A brand-new FAWT-based technique for the automatic classification of glaucoma phases was also provided. FAWT deconstructed components have yielded a variety of entropy and FD properties. They discovered that retrieved features from FAWT are helpful for detecting glaucoma. LDA has also been used to rank the features and reduce their dimensionality.

Yasmeen George [62] has implemented a full-blown DL system for detecting glaucoma and calculating VFI. The model is prepared on 3D volumes using data from three different sources: the initial 3D-OCT block, data generated during training using 3D graduate CAM heatmaps, and data from the training dataset itself. By utilising the abundant main data inborn in the high-goal 3D OCT forms under the supervision of the graduate CAM consideration map, the model demonstrates superior performance when compared to gauge models and element-based ML approaches.

Shamia D [63] has suggested a deep CNN network for the early diagnosis of glaucoma and other eye disorders. They created an online GUI platform that allows users to find the eye defect.

Guangzhou An [64] has created a classification model for glaucomatous optic discs using objective machine learning, and it provides the classificatory criteria to help with clinical glaucoma therapy. Each eye's data was retrieved along with the patients' background information, yielding a total of 91 parameters. The request models (GBDT) were developed using computerised reasoning classifiers like the brain organisation (NN), guileless Bayes (NB), support vector machines (SVM), calculated choice trees (ADT), and an examination investigation was conducted.

M.Shanmuga Eswari [65] has created a technique that uses sophisticated machine learning to detect glaucoma in diabetic individuals. They used a Bayesian optimization support vector machine to predict glaucoma with 96.6% accuracy using a local real-time dataset of diabetic individuals.

Narmatha Venugopal [66] has used the PH-CNN model to create an automated model for classifying Glaucoma images. This model works through the stages of classification, feature extraction and reduction. Discrete Wavelet Transform is used in the initial stage of the feature extraction process (DWT).

Wheyming Tina Song [67] has developed an effective, dependable, Moreover, automated methods for addressing the challenges of manual glaucoma recognised proof are pricey and time-consuming, and present mechanised glaucoma location procedures lack either better execution or any quantitative heartiness testing approaches. They demonstrated the potential to replace the currently used manual diagnosis of glaucoma, and they provided a framework with clear mathematical notations and comprehensible graphics to make it easy for others to confirm our findings.

Ali Serener [68] employed ResNet and GoogLeNet deep neural network classification methods after performing image pre-processing (including RGB channel histogram equalisation for each image). Approximately one million images from the ImageNet collection were used to initialise the model, which was then refined using new imagery. The histogram evening out approach was used as part of the pre-handling process, which included isolating the blue, red, and green components of each image before applying it separately to each channel.

Yunzhe Sun [69] has proposed a GAN based Domain Adaptation Method for glaucoma detection. They offer comprehensive approach to address the issue of a significant homogeneous domain change. They said that looking at the optic plate/cup and its surroundings was the key to tracking down glaucoma. To bridge the gap between the original and final spreads, they employed a crafty recreating accident that not only uses raw data but also maintains the original space photographs' visual integrity. Experiments performed on different open-and-shut name datasets reveal how the method has the potential to enhance the future accuracy of glaucoma diagnosis.

Sreng et al. [70] suggested a two-stage, automated glaucoma architecture that uses Multiple Deep Convolution Brain Networks (MDCNN) in place of encoders to ease the burden on ophthalmologists and the DeepLabv3+ optic disc region.

Rui Fan [71] We looked into the transferability and interpretability of the state AI approach ViT for using fundus pictures in glaucoma diagnosis. Numerous experiments have shown that ViT has a high-performance level on external test sets made up of fundus photos from people of various racial and ethnic origins, including those of Chinese, Japanese, Spanish, African, and European heritage.

Raghavendra et al. [72] It was suggested that retinal fundus images be run via a Convolutional Neural Network (CNN) model to ensure accurate glaucoma CAD. With a total of 1426 images, split evenly between 589 healthy subjects and 837 glaucoma sufferers, they increased classification performance using an 18-layer CNN (the accuracy was 98.13% in this study).

2.1. Comparison of Different Models for Diagnosis of Glaucoma

In this study, there are different collected papers related to Glaucoma detection on different ML, and DL models. Based on how these works were effective in the detection of glaucoma an analyzed study of their statistics, merits, and demerits are mentioned. Explainable AI has been another hot research topic in recent years and there will be further analysis of it in our research paper. Compared with ML models Dl models work well in analysing glaucoma at a beforehand stage.

To facilitate readers checking the literature, Table 1 shows summarization and analysis, which lists the approaches for detection of glaucoma at an early stage, its parameters, advantages, and disadvantages.

Table 1
Table of Collected Papers

S.no	Author's Name	Model used	Parameters			Merits	Demerits	Dataset used
			sensitivity	Specificity	accuracy			
1	Raghavendra et al.[72]	18 layer CNN	98%	98.30%	98.13	results demonstrate the robustness of the system	Starting from scratch to train a CNN is a difficult task. They need a bunch of data that has been labelled.	Medical College
2	Dhaval Vaghjiani[13]	VGG16	92%	94%	93%	High accuracy and simple sequential nature	For VGG16, the robustness against artefacts was not examined.	ACRIMA, Drishti-GS, sjchoi86 HRF and DRIONS-DB
3	Mamta Juneja[41]	CoG-NET	95%	99%	95.3%	indicating enhanced learning	Computational time is more	RIM-One, Drishti, REFUGE and

						and improved prediction.		ACRIMA.
4	Anita Manassakorn[19]	GlauNet	88.9%	89.6%	87.05%	GlauNet had 93.5% negative predictive value.	The quality and diversity of training data used to build the model may impact on how accurate the GlauNet algorithm is.	OCTA public dataset
5	Javier Civit-Masot[24]	ResNet50	91%	89%	90%	ResNet architecture is best suited as a feature extractor for glaucoma identification from retinal fundus pictures	On the test set for the Fundus Image Dataset for Glaucoma Analysis and Research, ResNet-50 does not generalise well.	RIM-OneV3, DRISHTI dataset
6	Javier Civit-Masot[24]	MobileNetV2	89%	82%	86%	The network is lighter and is feasible	Accuracy density is higher compared to VGG16	RIM-OneV3, DRISHTI dataset
7	Javier Civit-Masot[24]	Xception	93%	85%	89%	Compared to the other architectures, the Xception architecture offers superior trade-off between the		RIM-One V3, DRISHTI dataset

						quantity of parameters and the acquired AUC.		
8	Andres Diaz-Pinto[55]	Inception V3	92%	87%	90%	This sturdy substitute for an automatic glaucoma screening equipment is available.	more resources and processing power are needed	ACRIMA database, HRF, Drishti-GS1, RIM
9	Anuradha Pandey[26]	SVM	92%	98%	97%			online accessible dataset
10	Anuradha Pandey[26]	LDA	90%	93%	97%			online accessible dataset
11	Anuradha Pandey[26]	Decision Tree	92%	98%	87%			online accessible dataset
12	Anuradha Pandey[26]	KNN	98%	99%	98%			online accessible dataset
13	Anuradha Pandey[26]	Neural Network	-	-	97%			online accessible dataset
14	Silvia Ovreiu[28]	DenseNet	0.941	0.1	97%	In contrast to conventional convolutional neural networks, DenseNet has dense connections	It requires significant computational resources and time for training	ACRIMA dataset.

						between its layers, allowing for effective information flow and less overfitting.		
15	Shaswat Singh[56]	G-Net	-	-	95%	G-Net enables it to record intricate connections between the images of the fundus and the existence of glaucoma.	If the training data is biased or inaccurate, the model may make incorrect predictions.	DRISHTI-GS dataset, Aravind eye hospital
16	Wangmin Liao[57]	EAMNet	-	-	88%	The precise area of activity that processes to the diagnosis of glaucoma is provided by EAMNet.	To train, a lot of data and computer power are needed.	ORIGA dataset
17	Tomaz Ribeiro Viana Bisneto[60]	GAN	30.1	69.7	69.7	With the use of retinal pictures, GAN seeks to carry out OD		RIM-ONE and Drishti-GS

						detection, feature extraction, and pattern classification in order to offer a quick, precise, and automatic glaucoma diagnosis.		
18	Yunzhe Sun[69]	DAGD	75.00	94.44	89.58	In the task of domain adaptation for glaucoma diagnosis, it performs exceptionally well.		Drishti-GS dataset, PrivateDataset1 and PrivateDataset2, REFUGE challenge dataset
19	N S Jeya Shyla[59]	Histogram of oriented gradients(HoG), Discrete Wavelet transform (DWT),	89.9	95.8	98.5	An ELM classifier is used to extract many features for high-precision glaucoma detection.	drawbacks of DWTs are Shift invariance, constant time-frequency coverage, and poor frequency resolution	DR HAGIS database was developed.
20	Deepak Parashar[61]	Flexible Analytic Wavelet Transform (FAWT)	93.20	96.67	93.40%	FAWT is a developed variant of DWT, a transform that is		ORIGA-light, Drishti, HRF and RIM-ONE.

						highly helpful for analysing medical images.		
21	Liu Li[34]	AG-CNN	84.8	87.43	85.2	In terms of generalisation capabilities, the AG-CNN method performs admirably, far better compared to other cutting-edge techniques.	The model's performance depends on the quality and variety of the training data, and limited training data may result in poor performance or biased results.	LAG database
22	Narmatha Venugopal[66]	PH-CNN	97.10	90.63	95.04	PH-CNN model gives more accuracy and robustness	Poor-quality images might affect the performance of model and lead to inaccurate results.	Private database
23	Narmatha Venugopal[66]	GoogLeNet	80%	90.96%	85.48	Outperformed various models in terms of specificity	Has low accuracy	Private database
24	Rui Fan[72]	DeiT(Data-efficient image Transformer)[72]	85%	81%	90%	To increase the generalizability of AI	Usually, training requires a lot of data.	OHTS test set

						models in healthcare applications, DeiT may be especially helpful.		

3. Summary of Research Findings

Qualitative comparisons for the methods across categories and necessary explanations are discussed here for Table 2. Moreover, the common techniques used today for glaucoma detection have been discussed.

Increasingly, machine learning is being employed in medical applications like computer-aided diagnostics. Many researchers have utilized machine learning to categorize glaucoma and healthy eyes because it can find links between input characteristics and labels. Even while machine learning has its own benefits, it was not always the most effective method for detecting glaucoma because of how complex ML models are and how many iterations and hyperparameters they require. They are essentially determined by how well they perform on the dataset under study, which does not persuade physicians, medical professionals, or patients. They frequently just affect the computer industry [73].

As the technology grew and much unlabelled data started generating, the researchers moved towards a more sophisticated approach like Deep learning models, after trying their best in ML models. [73][74] The most popular deep learning models such as CNN have been discussed as they gave a best-in-class performance in glaucoma detection. Medical diagnostics have benefited from the use of DL algorithms for the screening of oculopathy in retinol fundus images, the [78] diagnosis of diabetic retinopathy, and the prediction of glaucoma subtypes. Despite this, these approaches are frequently criticized for giving no chance to comprehend the processes involved in classification determinations. A well-liked deep learning model, CNN is well-known for its useful results in medical applications. [6] Since it has numerous optimized parameters to demonstrate a sufficient success level for the target challenges, XAI components are still required.

In other words, trust remains meaningless in the absence of clinical implications. Due to these factors, AI and ML systems must be both interpretable and explicable in order to follow clinical protocols while analysing data and making decisions to improve patient care. These models can enhance our capacity to find novel biological phenomena.

4. Feature Extraction

A step towards developing a standardized, clinically accepted collection of OCT or retinal characteristics for glaucoma diagnosis is identifying properties that are similar to humans and machines for reliable glaucoma identification. Understanding the characteristics (or "concepts"") that the top-performing CNN uses to distinguish between glaucomatous and healthy pictures will help researchers develop their own algorithms. In order to classify or segment pictures using machine learning algorithms, features must be extracted that accurately describe the input data. Features are either created by hand, that is, manually specified, such as by an algorithm developer, or they are retrieved using a predetermined filter bank, or they are eventually learned during training to carry out suitable task-specific processing of the incoming data.

Convolutional Neural Networks (CNNs) emerged as the preferred feature extraction method in medical image analysis and it is widely used for ophthalmic image analysis [18]. In this review, two primary picture modalities that are frequently utilized to look into ophthalmic-related disorders are taken into account. (1) Fundus color images that display the macula, optic disc, and retinal vasculature, as well as different abnormalities associated with ophthalmic disorders. (2) High-resolution cross-sectional scans of the retinal layers in the posterior segment or anterior segment structure are obtained using optical coherence tomography (OCT) imaging. When we talk about OCT images in [11] the author used layers of CNN to classify the images of OCT where each layer is followed by RLU and the maximum pooling layer. In [15] the author utilized Concept Activation Vectors [CAVs] in order to determine the rate of change of class prediction as a function of pixel intensity at a specific pixel location. When it comes to using fundus images it is based on both classification and segmentation, in [17] they cropped all the fundus images around the optic disc using CNN based method to find the most probable pixels in the optic disc region. In [11] the authors have performed automation segmentation of OD and OC from fundus images using a multi-label deep network. In [12][20][40][41][42][44][48][50][71] the authors emphasize on the main feature for the detection of glaucoma is CDR i.e., the ratio between the cup and the disc and the thickness of optic nerve.

5. Preprocessing Methods

After the input picture has been obtained, pre-processing is used to remove extra noise from the image. When assessing medical photos, the pre-processing step is crucial. To improve picture contrast, the input image goes through pre-processing. Pre-processing's main objective is to smooth the input picture.

The authors of [11] employed polar transformation to convert the fundus picture into a polar coordinate system, which provides the benefits of spatial restriction, equivalent augmentation, and balancing cup proportion while improving segmentation performance. The pre-processing methods of images mostly involves around resizing the images as in [44][50], in [16] the authors used min-max normalization in an attempt to reduce the background noise of the image, resized the images at a particular height, width and count and further they have used Prewitt operator to find the edges of the images. In [41][42][48][54][71] the author has pre-processed the initial image using cropping and augmentation.

6. Proposed Model

The proposed XAI methods include Spiking Neural Network (SNN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) both employing fuzzy logic in their models to arrive at conclusions based on input data. A fuzzy layer is employed in ANFIS to draw conclusions about the input data and the model's rules. In order to transfer input data to a lower-dimensional representation and make judgments based on the characteristics that were learned, the SNN additionally employs a fuzzy layer, which is commonly implemented as a Kohonen layer. These fuzzy layers in ANFIS and SNN aid to deal with the ambiguity and uncertainty in the input data, strengthening and improving the models' ability to address practical issues. Based on retinal fundus pictures, ANFIS and SNN can be utilized to create predictions in reference to glaucoma detection.

The most compelling contributions of this research are highlighted:

- Use Explainable AI methods for identifying of glaucoma using retinal fundus images [1].
- Evaluating the existing algorithms ANFIS and SNN and Further compare these models with deep learning models.
- Propose an approach using XAI and DL for Glaucoma detection.

Figure 2 provides the basic methodology of the suggested system. It explains the process as it takes fundus images as input, different image pre-processing methods such as rescaling, flipping, and resizing are applied and the main proposed model ANFIS and SNN fuzzy layer is applied on the images with other DL methods and finally, the images are tested to find glaucoma positive and negative images.

Future Advancement

An in-depth study has been conducted over the past ten years whose main focus has been the utilization of computational approaches for the purpose of treatment and diagnosis diseases related to eyes. Numerous techniques try to combine feature selection with classification using classifiers like SVM, Random Forest Gaussian approach, etc., CNN methods like AG-CNN, GAN, etc. In terms of detection accuracy, these approaches have attained a certain level of entitlement. With the combination of fine-tuning applied to the XAI models, a model that is both considerably more accurate and efficient than the current model can be built in the future. The accuracy can be enhanced with a more efficient and accurate dataset. Future research may explore utilizing our technique on a bigger and more diverse set of images.

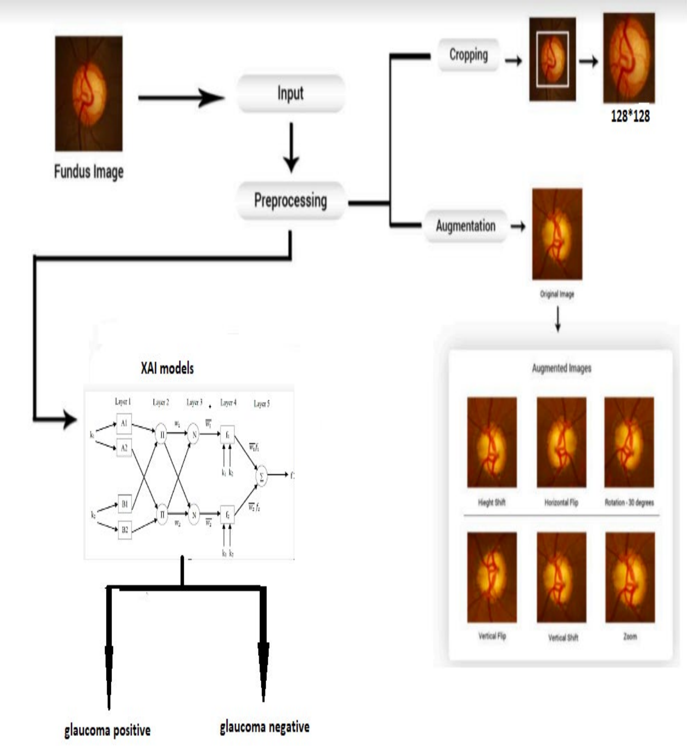

Fig 3: Basic methodology

Conclusions

This article presented detailed investigation of various glaucoma detection methods. Early diagnosis of glaucoma is essential as it is among the most dangerous eye conditions that can asymptomatically result in sightlessness, is necessary to help patients avoid total loss of vision. Deep learning models have been shown to be helpful for facilitating this early diagnosis. In this study, various methods for diagnosing glaucoma are examined and mean accuracy, specificity, and sensitivity are considered. The approaches' benefits and drawbacks are examined. XAI models are a step forward toward glaucoma detection and are expected to contribute more to medical fields. The suggested method might help doctors identify glaucoma early.

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