Identification of Glaucoma from Fundus Images Using Deep Learning Techniques – A literature Review

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Abstract- **Glaucoma, a leading cause of irreversible blindness worldwide, necessitates early and accurate diagnosis to prevent significant vision loss. Recent advancements in deep learning have revolutionized medical imaging, offering promising tools for automated glaucoma detection from fundus images. This review paper provides a comprehensive overview of the current state-of-the-art deep learning techniques for glaucoma identification, summarizing various methodologies, datasets, performance metrics, and highlighting the challenges and future directions in this domain.**
Keywords: Machine Learning, Deep Learning, Glaucoma, optical coherence tomography, CNN

1. INTRODUCTION

Glaucoma is a progressive optic neuropathy characterized by the degeneration of retinal ganglion cells, leading to visual field loss and potential blindness. Traditional diagnostic methods, such as intraocular pressure measurement and visual field testing, are often supplemented by fundus imaging for a more comprehensive evaluation. Fundus images provide a detailed view of the optic nerve head, retinal nerve fibre layer, and other retinal structures crucial for glaucoma diagnosis.

According to the World Health Organization [1], Glaucoma affected 64 million individuals in 2016 and is projected to impact 95 million individuals by 2030. Untreated glaucoma can lead to permanent vision loss by damaging the optic nerve. Elevated intraocular pressure within the eye exerts pressure on the optic nerve, leading to permanent loss of vision [2]. Presently, it stands as the primary factor leading to visual impairment on a global scale. The peripapillary region has an enlarged cup and a diminished inferior rim due to damage to the optic nerve fibers. The progression of the illness may lead to the development of a 'pale disc' and disc hemorrhage. Although they exhibit distinct warning symptoms, both conditions are linked to elevated intraocular pressure (IOP). Angle-closure glaucoma manifests in several ways as a result of the disease's angle-closure characteristic. Open-angle glaucoma progresses slowly and remains asymptomatic until peripheral vision is compromised. Due to the exponential rise in the prevalence of glaucoma in older adults, particularly those displaying initial symptoms, it is imperative and advised to get an annual eye examination for timely glaucoma screening [3-8].

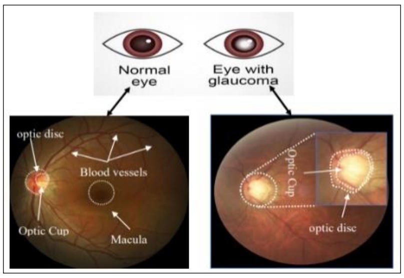


Figure 1: Images of a healthy retina (left) and one with glaucoma (right)

Currently, "clinical glaucoma screening includes measuring intraocular pressure, doing visual field tests, and examining the optic nerve head. However, only the optic nerve head examination is capable of detecting glaucoma in its early stages [9]. Consequently, the assessment of the optic nerve in retinal pictures has now become a widely accepted diagnostic approach for glaucoma. Glaucoma-induced damage to the optic disc (OD) region results in several abnormalities in the OD, including an increasing ratio of cup to disc size, a loss of color, bleeding, and alterations in the area surrounding the OD. Figure 1 compares the optic disc (OD) size of a healthy eye with that of an individual suffering from glaucoma. Figure 2 depicts a patient at various phases of glaucoma progression.

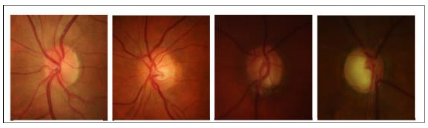


Figure 2: Grading of glaucoma diseases: (a) healthy OD (b) Mild Glaucoma (c) Moderate Glaucoma and (d) severe glaucoma

The number of patients significantly increases as individuals age or have early warning indicators. Current clinical glaucoma screening methods include measuring intraocular pressure, doing visual field tests, and examining the optic nerve head. However, only the optic nerve head

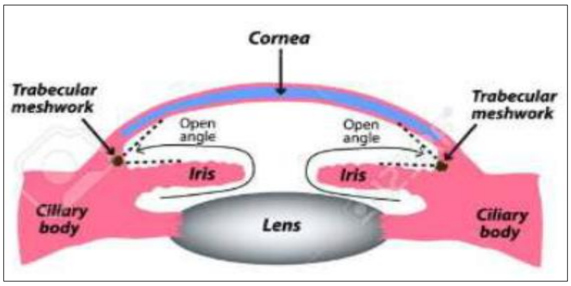
examination is capable of detecting glaucoma in its early stages. Consequently, the assessment of the optic nerve in retinal pictures has now become a widely accepted diagnostic approach for glaucoma. Glaucoma-induced damage to the optic disc (OD) region results in several abnormalities in the OD, including an increasing ratio of cup to disc size, a loss of color, bleeding, and alterations in the area surrounding the OD.
Several studies have been carried out to determine the prevalence of this chronic condition among individuals. Glaucoma ranks as the second most common reason for visual impairment [8, 9]. The prevalence of glaucoma is projected to increase from 60 million to over 80 million individuals by the year 2020. Glaucoma leads to permanent loss of eyesight by elevating intraocular pressure (IOP) and causing harm to the optic nerve. Early-stage glaucoma symptoms are challenging to describe and measure, which is why the sickness has been nicknamed the "hushed burglar of vision." If glaucoma advancement is not stopped in its early stages, the damage of the optic nerve results in permanent blindness [11]. The following facts make early glaucoma screening critical:

1. In its early phases, there are no discernible indicators.
2. It is a serious condition since the harm it causes is permanent.
3. If not treated quickly, it might result in permanent blindness.
4. Although there is no cure for glaucoma, it is feasible to avert blindness by diagnosing, treating, and controlling the disease early on [12].

Computer-Aided Diagnosis (CAD) aids in the treatment of impaired eyes. Various research investigations have utilized fundus imaging as a method to identify glaucoma at an early stage and prevent further harm. Glaucoma, a collection of diseases and syndromes that lead to decreased vision and impairment, is caused by changes in the retinal nerve fiber layer and optic nerve head [13]. Researchers aim to mitigate the effects by employing enhanced disease diagnoses and treatments, such as the prompt utilization of Trabecular Micro-Bypass (TMB). The authors [15] conducted a concise assessment of the most advanced methods now available for early detection of glaucoma. Techniques such as the Optic Cup Disc Ratio and the Retinal Nerve Fiber Layer (RNFL) have been carefully examined. These research findings contribute to a more accurate and dependable diagnosis of glaucoma. To enhance clarity, the survey findings have been categorized into two groups: those that utilize segmentation and those that do not. In their study, Sarhan et al. [16] investigated existing methods for detecting glaucoma. This analysis helped them predict their own skill and precision. This survey provides comprehensive guidance for researchers on the strategy of studying glaucoma and selecting datasets for further analysis.

Glaucoma is one of the most prevalent disorders which causes vision impairment. It is the predominant reason behind irreversible blindness globally affecting greater than 87 million people. Although, as the disease persists to be largely asymptomatic, medical scientists estimate that greater than 50 percentiles of people are oblivious that they are harmed until it is pretty late. Basically, Glaucoma is an inflammation of the optic nerve that destroys retinal ganglion cells in a hallmark form of optic neuropathy and it turns out terrible over time. The eye is under strain very recently, like the blood, which is called intraocular pressure (IOP). At a stage where this IOP rises to a certain degree, the optic nerve is impaired. In common terms, damage of optic (visual) nerve that transmits visual images to brain owing to increased pressure is called IOP. This will contribute to impaired fringe perception and eventually visual impairment. Without timely therapy, Constant glaucoma is the commonest glaucoma. Constant glaucoma is caused through drain canal blocking, leading to an elevated pressure in retina. It contains a broad angle between cornea and iris as portrayed in Figure 3, In constant glaucoma, the channel structure (trabecular mesh work) in eye appears as normal; however liquid doesn't flow out like it should. Extreme glaucoma is caused through clogged drain canals resulting in abrupt rise in IOP. It contains a confined angle between cornea and iris as depicted in Figure 4. In extreme glaucoma, the channel region between cornea and iris becomes extremely thin leading to abrupt weight development in eye. During the beginning phases of glaucoma, generally patient's do not present any signs or visual signs but as the glaucoma progresses, patient's start to lose their vision, followed by severe visual disability.

Figure 3: Constant Glaucoma [1]



Glaucoma (black-cataract) is a severe global health crisis and the second top cause of sightlessness worldwide. With the anticipated growth of life span, the predicted count of people becoming visually impaired from glaucoma is expected to rise extensively in the foreseeable future. Despite availability of improved, innovative technological diagnostic tests, equipment and increasing health awareness in developed nations, a huge proportion of cases remain undetected in society. Traditional diagnostic techniques are inefficient for disease management. Therefore, advanced platforms or technologies are required for disease handling. Improved strategies and approaches for executing more accurate and earlier glaucoma diagnosis facilitate timely implementation of suitable treatment choices, and subsequently reduce the expected growing disease burden in the coming days. Early detection by complete and frequent eye tests is the solution to prevent sightlessness occurring owing to glaucoma. Glaucoma advancement can happen without any prior indication or physical symptoms in patients". Thus, early prognosis of glaucoma would be greatly supportive for avoiding permanent sightlessness. The primary intention of this work is to create an intelligent diagnostic system for glaucoma- an eye related disease through information acquired from clinician exploiting several examination equipment or devices employed in ophthalmology.

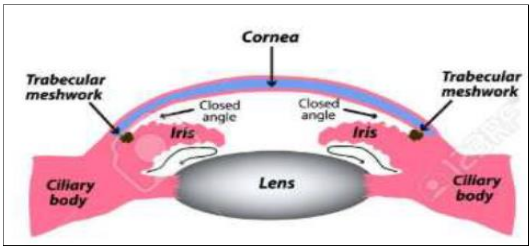


Figure 4: Extreme Glaucoma [1]

2. LITERATURE REVIEW

Glaucoma is a neurodegenerative disease characterized by the loss of ganglion cells. Consequently, when the optic nerve fiber diminishes, the tissue surrounding the rim deteriorates, leading to the creation of a cup. Currently, "the diagnosis of glaucomatous structural damage and alterations poses significant challenges in disease detection approaches. Glaucoma can be identified through several indicators, including intraocular pressure (IOP) over 22 mmHg in the absence of therapy, the presence of glaucomatous cupping of the optic disc, and the existence of glaucomatous visual field abnormalities. A significant challenge in diagnosing glaucoma is the identification of the condition in individuals who do not exhibit any symptoms. The quantity of undiagnosed patients surpasses the quantity of diagnosed patients. When diagnosing glaucoma, it is important to take into account the size and shape of the optic cup disc. An elongation of the cup in the vertical direction is indicative of glaucomatous optic neuropathy [11-12]. .In [13] Glaucoma is a leading cause of global blindness. Prompt identification and screening are crucial in order to discover this ailment at an early stage. Deep learning has a significant and encouraging impact in this particular situation. The performance of deep learning models was evaluated using a dataset consisting of 1250 publicly available photos. Physicians use on fundus pictures to clinically validate glaucoma. This study examines the level of development and effectiveness of the deep learning framework for the purpose of diagnosis. An assessment and comparison are conducted on the performance metrics of several deep learning frameworks. At the conclusion, the machine learning workflow is succinctly outlined, along with suggestions for further research. Glaucoma is a progressive neurological disorder characterized by the buildup of pressure inside the eye caused by excessive production of fluid and obstruction of the drainage system connecting the iris and cornea. Early diagnosis of this condition might be challenging, making regular screening very advisable [14-15].

Shanmuga Eswari et al. [16] says that glaucoma refers to a collection of disorders characterized by damage to the nerve connecting the eyes and the brain. This research employs a novel deep learning approach to accurately detect the disease with great intensity. The Deep Neural Classification Network (DNCN) achieves a precision rate of 97.3% in its results.

Glaucoma is a condition that poses a risk to vision and can result in the damage of the optic nerve, leading to abrupt loss of sight as stated by Yves Attry, Kalin, et. al.[17]. There have been attempts to use Machine Learning and Deep Learning Models to detect Glaucoma, however their effectiveness is not suitable for such a significant disease. This work presents a compilation of different Deep Learning Architectures, including MobileNetV2, DenseNet121, InceptionV3, InceptionResNetV2, ResNet50, and VGG16. These architectures are evaluated based on various parameters and are applied to classify data into two classes, "G" and "NG". The dataset has been collected from multiple sources and carefully processed to ensure maximum efficiency. We have incorporated numerous metrics to validate the effectiveness of our devices, including Precision, Recall, F1-Score, Cohen Kappa Score, and AUC.

Shamia, D et al. [18] presents a Deep Convolutional Neural Network (DCNN)-based expert system that mimics the structure of the human brain. The system consists of input, neurons, hidden layers, and output components, and is designed to diagnose three diseases using an online platform. The detection accuracy for images affected by diabetic retinopathy (DR) was 91%, for images impacted by cataract was 90%, and for images affected by glaucoma was 86%. A user-friendly and easily understandable online Graphical User Interface (GUI) was created alongside the system. Some other hybrid approaches can be used but DCNN was more accurate than other approaches like SVM ,KNN, Random Forest, Back Propagation.

Ping Ong et al. [19] propose a new method for classifying retinas as glaucoma or not using optical coherence tomography angiography. Classifying glaucoma involves examining the optic disc's tiny blood vessels using an enface OCTA. We recommend extracting the "optic disc microvasculature." to simplify this research. Next, we suggest extracting various microvasculature region characteristics. After training a machine classifier with the given features, OCTA data is classified. A support vector machine classifier with a linear discriminant analysis classifier yielded 100% accuracy [20].

According to Hongyong Zhang et al. [21]. Quantifying the relationship between intraocular pressure and glaucoma by applying precise force to laboratory-grown retinal cells is practicable and effective. This paper details the laboratory production of alginate hydrogel microbeads for retinal cell culture. Using flow-focusing, a syringe needle and silicone tube microfluidic device created alginate microbeads. Encapsulating water droplets in oil in a silicone tube and crosslinking alginate droplets with calcium creates microbeads. The hydrogel microbeads surround a cell, which grows rapidly after a few days.

Chaodong Ling et al. [22] apply the Markov model to wavelet domain blood vessel segmentation. The segmentation results integrate blood vein visibility and internality into the algorithm. The Guided Filter enhances photo contrast and highlights blood vessel vein characteristics. Isolating retinal blood vessels after pre-treatment yields retina images. Simulation findings employing the DRIVE, STARE, and FIRE data sets show the segmentation method's relevance and usefulness.

Many retina picture segmentation methods are presented by Weingart, Mircea, et al. [23]. ARIA and B-COSFIRE filters and noise reduction are described. Eye-fundus images are used to test noise removal methods like KSVD and BM3D. We also improve image contrast with contrast limited adaptive histogram equalisation (CLAHE). A nature-inspired optimisation technology called Particle Swarm Optimisation is used to segment images effectively. Finally, machine learning is used to classify retina eye-fundus images to diagnosis diseases.

Xiao et al.[24] Retinal vascular segmentation is essential for accurate eye disease visualisation, diagnosis, early therapy, and surgical planning. Recently, deep learning algorithms for retinal blood vessel segmentation performed best. Due to vessel shape and background noise, these methods struggle to detect optic disc features in small, thin vessels. This study presents a U-Net-like model with weighted attention and skip connection to address these concerns. Experimental results on two benchmark datasets show the proposed strategies uses GAN(Generative Adversarial Network) for the image generation fake images .This technique is used because the DRIVE and STARE dataset is very small to resolve the problem of dataset limitation. GAN is used to generate some images but the images generated by using this technique are not able to provide accurate result and many of the images quality is low which will effect the accuracy of the model so the authors uses the DRIVE and STARE dataset instead of using GAN images

Xiao-Min Li et al.[25] degrades spatial information by consecutive pooling and convolution. This paper introduces DAS-UNet, a densely connected U-Net design with a parallel atrous convolution block and a prominent computing block. Parallel atrous convolution generates more abstract features with different receptive fields in the PAC Block, improving segmentation accuracy. A salient computing block (SCB) identifies responsive regions and suppresses irrelevant regions, creating a more accurate vessel segmentation map than the U-Net. In extensive DRIVE benchmark evaluations, DAS-UNet achieves cutting-edge performance, providing a distinct result.

Behnam Azimi et al. [26] claim that OCT images help detect retinal diseases because they appear visually aberrant. Fluid regions may signify AMD and DME. Segmenting these regions automatically helps ophthalmologists diagnose and treat these diseases. This study automates fluid segmentation utilising graph shortest path layer segmentation and fully convolutional networks. A dataset of 600 OCT images from 24 participants was used to evaluate the suggested approach. This study shown that the FCN model outperforms three fluid segmentation algorithms in both efficiency and sensitivity by 4.44% and 6.28%, respectively.

Ahmed A. Sleman et al. [27] describe a patient-specific retinal atlas and an appearance model tailored to distinct patients for 3D OCT data segmentation. A combined Markov Gibbs Random Field (MGRF) integrates the shape, intensity, and spatial data of 12 retinal layers to segment the centre retinal area. The proposed approach was tested on 30 people with normal or abnormal OCT images. The methodology was compared to a carefully established reference standard, and retinal medicine professionals validated the results. The Dice Similarity Coefficient (DSC), agreement coefficient (AC), and average deviation assessed performance. The segmentation method's accuracy shows its promise and improves on the current state-of-the-art 3D OCT segmentation technology. Multimodal imaging systems with IR-SLO and OCT [27] may help diagnose retinal illness early. Using IR-SLO to analyse retinal structure and OCT can help diagnose a variety of diseases. This study automates IR-SLO fundus segmentation using morphological filters and image enhancement. Morphological filters are used to make retinal vessels visible. After that, CLAHE and bilateral filtering exclude the backdrop. Our methodology was tested using 26 IR-SLO pictures and two reference image sets.

Table 1: Comparison of different Techniques

S. No.	Author's Name	Technique And method	Result	Limitation
1	Nazmus Shakib et al. (2022)	Deep Learning (DL) Convolutional Neural Network (CNN), Xception model	97.63% training accuracy, 98.11% validation accuracy	Number of Glaucoma and Non Glaucoma images are not mentioned
2	Shanmuga Eswari et al. (2022)	Deep Neural Classification Network (DNCN)	97.3% accuracy	Tested on a single dataset
3	Yves Attry, Kalin, et. al. (2022)	MobileNetV2, DenseNet121, InceptionV3, InceptionResNetV2, ResNet50, and VGG16,	88.56% accuracy	Number of images are not mentioned
4	D. Shamia et al (2022)	DCNN, SVM, Back Propagation, Random Forest, KNN	86% for glaucoma affected images	Only Glaucoma affected res is mentioned no mention of normal images
5	Ee Ping Ong et al. (2017)	optical coherence tomography angiogram (OCTA) , support vector machine classifier, linear discriminant analysis classifier	93% accuracy 95% specificity 87% sensitivity 98% area under the curve (AUC)	Validation accuracy decreases in other glaucoma image dataset
6	Hongyong Zhang et. al. (2019)	Alginate hydrogel microbeads, 3D Cell cultivation, HEPES buffer solution (pH 7.1)	91% accuracy	No mention of validation accuracy in it
7	Chaodong Ling et. al. (2019)	Markov model in wavelet domain	85% accuracy	Small size dataset images are used
8	Weingart, Mircea, et. al. (2019)	KSVD and BM3D methods, e ARIA and B-COSFIRE filters methods	87.79% accuracy	Image qualities are very low
9	Xiao et. al. (2018)	Retinal Vessel Segmentation, Deep Learning, Weighted Res-UNet, CNN	96.55% accuracy	Small size dataset images are used
10	Xiao-Min Li et. al. (2020)	UNet ,DAS-UNet , salient computing block (SCB),drive data set, e parallel atrous convolutional block (PAC Block)	95.63% accuracy	No mention of validation accuracy
11	Behnam Azimi et al. (2020)	age-related macular degeneration (AMD), fully convolutional networks (FCNs), graph shortest path	sensitivity of 87.38% ,	Image quality is degraded due to lack of computational resources
12	Ahmed A. Sleman et. al. 2018	OCT, Retinal Layers, Segmentation, Markov Gibbs Random Field (MGRF)	95% accuracy	Size of images is not mentioned
13	Aqsa Ajaz et al. (2017)	Contrast Limited Adaptive Histogram Equalization (CLAHE), IR-SLO and OCT	90% accuracy, 85.5% Sensitivity, 96.5%Specificity	Name of optimizer is not written
14	Jelena Novosel et. al. (2017)	Loosely coupled level sets, central serous retinopathy, diabetic-macular edema	88% accuracy	Imbalance dataset is used in it number of Glaucoma images are high and normal images are low
15	Muhammad Nauman Zahoor et al. (2017)	Retinal image analysis, Segmentation	95.94% accuracy 88% Sensitivity	Validation accuracy of smaller dataset is higher than large dataset
16	Jie Wang et. al. (2021)	Disentangled Reconstruction Neural Network (DRNN), Feature disentanglement, multi-task learning, Retina vessel segmentation,	90.82% accuracy	Un-Annotated dataset is used

According to Muhammad Nauman Zahoor et al. [30], separating the optic disc (OD) from retinal images is the first step in developing an early glaucoma diagnosis method. This study introduces a hierarchical method for quickly recognising and partitioning OD. During initial processing, morphological techniques identify and eliminate retinal vasculature and disorders, followed by the circular Hough transform to detect the optic disc. By defining the region of interest and using a novel polar transform-based adaptive thresholding technique, the optic disc (OD) border may be correctly determined. The methodology is tested using public retinal image datasets MESSIDOR, DIARETDB1, DRIONS-DB, HRF, DRIVE, And RIM-ONE. Compared to conventional methods, it improves accuracy and processing speed.

Jie Wang et al. [31] considered Domain change a crucial component that impacts the resilience of numerous models. Recently, unsupervised auxiliary learning, such as input reconstruction, has been suggested as a way to enhance the model's ability to transfer across different domains and reduce the decline in performance when moving between domains. However, existing approaches in this paradigm share the features extracted from different tasks, leading to suboptimal learning. In order to address this issue, we suggest a new technique called the Disentangled Reconstruction Neural Network (DRNN) for unsupervised domain adaptation. This method specifically focuses on cross-domain retina vascular segmentation. The DRNN model utilizes two sequential neural networks to separate the domain-invariant characteristics from the domain-specific characteristics during the multi-task learning procedure". We conduct numerous tests on publicly available retina datasets, and our proposed Deep Recurrent Neural Network (DRNN) significantly surpasses the competition, achieving state-of-the-art results in retina vascular segmentation.

3. DEEP LEARNING TECHNIQUES FOR GLAUCOMA DETECTION

3.1 Convolutional Neural Networks (CNNs)

CNNs have been the cornerstone of deep learning applications in medical imaging due to their ability to automatically extract hierarchical features from raw images[32][34].Various architectures, such as VGGNet, ResNet, and Inception, have been adapted for glaucoma detection.

3.1.1 VGGNet

VGGNet, known for its simplicity and depth, has been applied to glaucoma detection with modifications to suit the specific requirements of fundus image analysis. Studies have demonstrated its effectiveness in capturing fine details in retinal images, crucial for identifying glaucomatous changes.

3.1.2 ResNet

ResNet, with its residual learning framework [33] allows for the training of deeper networks by mitigating the vanishing gradient problem. Its application in glaucoma detection has shown superior performance in identifying subtle retinal features associated with early glaucoma.

3.1.3 Inception

The Inception architecture, with its inception modules, captures multi-scale features effectively. This characteristic is particularly useful in analysing fundus images where glaucomatous changes can vary significantly in size and location.

3.2 Transfer Learning

Transfer learning leverages pre-trained models on large datasets, fine-tuning them for specific tasks like glaucoma detection. This approach has proven advantageous in medical imaging due to the limited availability of labelled medical datasets.

3.3 Ensemble Learning

Ensemble methods combine multiple models to improve the robustness and accuracy of predictions. In glaucoma detection, ensemble techniques have been employed to integrate the strengths of various CNN architectures, leading to enhanced diagnostic performance.

4. CONCLUSION

Despite the significant advancements in using deep learning and image processing techniques for the detection and diagnosis of glaucoma and other retinal diseases, there are still some notable research gaps that need to be addressed. Many of the studies mentioned focus on a specific dataset or a relatively small number of datasets. To ensure the generalizability of the models and algorithms, future research should consider using larger and more diverse datasets from multiple sources and patient populations. Rare retinal illnesses like glaucoma limit annotated data for deep learning model training. Diagnostic model accuracy and reliability depend on addressing uncommon disease sample size issues. Data collection and annotation procedures vary, which can affect study comparability. Sharing retinal imaging data using common protocols and formats would encourage research collaboration and benchmarking. Complex deep learning models, especially deep neural networks, are typically considered black boxes. To overcome the problem of taking a large dataset of CNN and remove the chances of overfitting in our model we can build a lightweight architecture by using Resnet-50 and Densenet-121 architecture for better result. Many research demonstrate promising results on test datasets, but these models need real-world clinical validation to measure their efficacy in clinical contexts. These models must be integrated into healthcare systems and validated in clinical trials before being used in clinical practice. Unbalanced datasets can bias models by underrepresenting specific groups or diseases. Data imbalance should be addressed in research to provide fair and reliable diagnostic outcomes across disease categories. Protecting patient privacy is crucial since medical picture data contains personally identifying information. Protecting privacy while maintaining diagnostic accuracy should be studied. Resolution, noise, and artefacts affect retinal image quality. For practical use, deep learning models must be resilient to such fluctuations. Many studies focus on illness classification, but more study is needed on automated lesion detection and segmentation to help ophthalmologists plan treatment.

Clinical situations require real-time diagnosis and decision-making using deep learning models. Model optimisation for efficient inference and low-latency processing is crucial research. Filling these research gaps would improve deep learning-based retinal disease detection and diagnosis methods like glaucoma. Bridging these gaps will enable wider implementation of such technology, improving patient outcomes and eye healthcare services. Fundus image glaucoma detection using deep learning, particularly CNNs, appears promising. Despite progress, data variability, class imbalance, and interpretability must be addressed. To integrate models into clinical practice, future research should build more robust, generalizable, and interpretable models.

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