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Deep Learning-Based Automated Glaucoma Diagnosis from Retinal Images

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Abstract: Because of its reliance on human sight, glaucoma presents significant diagnostic challenges and is the primary cause of irreversible blindness globally. However, recent breakthroughs in deep learning have demonstrated promise for automated review. In this study, we examine current research of the use of retina, corneal optical coherence tomographic imaging, & visual field image in AI-based glaucoma being diagnosed, with a particular emphasis on deep learning approaches. To increase the technique's repeatability, we propose a redesigned taxonomy that categorises it into structural paradigms and connects to accessible source code. We identify shortcomings in performance related to multimodal integration, generalizability, and uncertainty estimates by doing thorough benchmarking on publicly available datasets. Furthermore, our study highlights issues including bias, labelling discrepancies, and size while curating important datasets. We present open research questions and suggest fruitful avenues for further investigation. It is anticipated that this survey will be helpful for ophthalmologists looking to enhance clinical processes and diagnosis utilising the most recent AI outcomes, as well as AI researchers looking to convert breakthroughs into practice.

Index Term: Deep learning, fundus pictures, glaucoma, and early diagnosis are the index terms.

I. INTRODUCTION

The cornea, tears , eyepiece, iris, the retina, optic nerve, plus are the main parts of the eye in humans that are involved in vision [1]. The iris regulates light and is situated between the surface of the cornea with the lens. After being exposed to light, the retina transforms it into electrical impulses that are then sent to the brain for identification. The optical nerve, which is made up of one million retinal ganglion cell nerve fibres, is located in the rear of the eye [2]. This nerve is primarily responsible for sending signals related to vision from the cornea to our occipital brain. Aqueous humour, a fluid found in human eyes, is constantly being regenerated. An blockage in the outflow of the aqueous humour results in elevated intraocular pressure (IOP). Consequently, there may be visual loss due to injury to the optic nerve & retina [3]. This has something to do with the number of nerve cells in the retina degenerating [2, 4]. The premature ageing of ocular nerve fibres leads the optical region (OD) to alter form and rise in line with relations (CDR), becoming an early indication of glaucoma [5]. Figure 1 [6] displays the eye's anatomy. Glaucoma causes vision loss due to impair of the eye neurons. Ophthalmology is diagnosed due to abnormalities seen using a visual scope [6]. Figure 2 [5] depicts a larger CDR with a cataract eye.

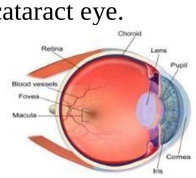

Figure 1. Human eye.

Second largest cause of blindness is glaucoma. [9] Glaucoma afflicted around 90 millions individuals globally in 2020, with the amount anticipated to get bigger of 111.9 million people. There presents other types of ocular acute-glaucoma, open-angle glaucoma is particularly widespread, effecting an estimated 57.5 ,000,000 individuals globally [10]. Routine ocular examinations beyond the median age or 50 persons has chance to lower of getting glaucoma. Ophthalmologists treat glaucoma using a variety of manual methods, including as gonioscopy, pachymetry, tonometry, & perimetry [12].

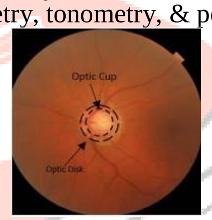

Figure 2: The glaucoma-affected picture shows an enlarged optical cup beneath the optic disc.

Tonometry monitors intraocular pressure, a significant glaucoma risk factor. Gonioscopy measures the angle among the cornea & the iris. Papymetry is a way to determine corneal thickness. Nonetheless, manual evaluation procedures for glaucoma identification are very subjective and time-consuming. Furthermore, their use may be restricted in rural places due to their reliance on a shortage of ophthalmologists. As a result, the growth of automated techniques to diagnose glaucoma in its early phases has become critical. Artificial intelligence technology have advanced dramatically during the previous few years. A lot of effort is being made in the medical industry to apply artificial intelligrnce technology into useful healing [13–15]. In medical contexts, computer-aided diagnostic (CAD) systems are frequently used to automatically identify glaucoma. These automated ophthalmology detection methods have become more accurate during diagnosis as a result due to the long-standing use of DL (deep learning) and algorithms for machine learning (ML) [16–19].

II. LITERATURE SURVEY

The literature survey conducted for this study is summarized in a tabular format, providing a comprehensive overview of relevant research works. The table encompasses crucial details such as the name of the study, author(s), publication year, research objectives, and key advantages and disadvantages identified in each work.

Title	Authors	Year	Objectives	Advantages	Disadvantages
A glaucoma detection technique that included decomposition transformation, optimisation, and classification modules	Santosh and Ajesh	2022	The objective of the research studies by Santosh et al. (2022) and Ajesh et al. (2021) is to develop and validate advanced image processing techniques for accurate glaucoma detection using retinal images. Through the application of methods like discrete wavelet transforms and Principal Component Analysis, the goal is to improve early detection rates, thereby facilitating prompt intervention to prevent vision loss. These studies aim to contribute to the field of medical imaging by providing effective tools for the early diagnosis and management of glaucoma.	The advantage of the glaucoma detection techniques proposed by Santosh et al. (2022) and Ajesh et al. (2021) is their ability to achieve high accuracy rates in identifying glaucoma-related changes in retinal images. By utilizing advanced image processing methods, such as discrete wavelet transforms and Principal Component Analysis, these techniques can effectively extract relevant features from retinal images, enabling precise detection of early signs of glaucoma. This high accuracy rate is crucial for ensuring early diagnosis and timely intervention, ultimately potentially preserving patients' vision.	The main disadvantage of the glaucoma detection techniques proposed by Santosh et al. (2022) and Ajesh et al. (2021) may lie in their computational complexity, potentially limiting their practical application in settings with limited resources. Additionally, reliance on extensive datasets for validation could pose challenges in terms of data availability and generalizability across different populations or imaging protocols.
Application of vascular bundle displacement in the optic disc for glaucoma detection using fundus images.	De La Fuente-Arriaga, J.A., Felipe-Riverón, E.M., GarduñoCalderón	2022	discusses a method for glaucoma detection using fundus images based on the displacement of vascular bundles in the optic disc. Using fundus images for glaucoma detection is non-invasive, making it suitable for regular screening and monitoring of patients without causing discomfort or risks associated with invasive procedures.	The displacement of vascular bundles in the optic disc provides an objective measurement for glaucoma detection, reducing the reliance on subjective assessments and potentially improving diagnostic accuracy. Fundus imaging-based methods have the potential for population-wide screening for glaucoma, allowing for early identification of individuals at risk and targeted intervention to prevent vision loss.	Optic disc morphology can vary widely among individuals, making it challenging to establish a universal threshold for glaucoma detection based on vascular bundle displacement. The accuracy of glaucoma detection using fundus images relies heavily on the quality of the images obtained. Poor image quality, such as blurriness or artifacts, may reduce the reliability of the analysis and lead to false-positive or false-negative results.
An automated and robust image processing algorithm for glaucoma diagnosis from fundus images using novel blood vessel tracking and bend point detection.	Soorya, M., Issac, A., Dutta, M.K	2022	presents an automated image processing algorithm for glaucoma diagnosis using fundus images, focusing on blood vessel tracking and bend point detection. The automated nature of the algorithm streamlines the process of glaucoma diagnosis from fundus images, reducing the need for manual intervention and expertise, which can lead to faster and more efficient diagnosis.	The robustness of the algorithm, as mentioned in the paper, suggests its ability to perform reliably across different fundus images and in the presence of variations in image quality, such as blurriness or artifacts. Once developed and validated, automated image processing algorithms can be easily scaled and deployed across various healthcare settings, including clinics and hospitals, potentially improving access to glaucoma diagnosis in underserved areas.	The algorithm's performance may be sensitive to variations in image quality, including factors such as illumination, contrast, and focus. Poor-quality fundus images may lead to inaccurate or unreliable diagnosis outcomes. While the algorithm may provide accurate diagnostic results, the interpretability of its output is crucial for clinical acceptance. Clinicians need to understand the rationale behind the algorithm's diagnosis to trust and effectively utilize its findings in patient care.

Title	Authors	Year	Objectives	Advantages	Disadvantages
Combination of clinical and multiresolution features for glaucoma detection and its classification using fundus images. Biocybern.	Kausu, T., Gopi, V.P., Wahid, K.A., Doma, W., Niwas	2021	proposes a method for glaucoma detection and classification using a combination of clinical and multiresolution features extracted from fundus images. By combining clinical features (which may include patient data such as age, intraocular pressure, etc.) with multiresolution features extracted from fundus images, the method leverages a comprehensive set of information for glaucoma detection. This holistic approach may improve the accuracy and robustness of the classification system.	Multiresolution features capture information at different scales or levels of detail, allowing for a more nuanced representation of the underlying structures and patterns in fundus images. This can enhance the discriminative power of the classification system. Combining multiple types of features from different sources can lead to improved performance compared to using individual features or modalities alone. The complementary nature of clinical and image-based features may help compensate for each other's limitations and enhance overall performance.	Integrating clinical and image-based features may increase the complexity of the classification system, requiring sophisticated algorithms for feature extraction, fusion, and classification. This complexity can pose challenges for implementation, interpretation, and validation. The effectiveness of the method relies on the availability and quality of both clinical data and fundus images. Variability in data availability, completeness, and reliability across different datasets or healthcare settings may impact the generalizability and robustness of the classification system.
Glaucoma diagnosis based on both hidden features and domain knowledge through deep learning models.	Chai, Y., Liu, H., Xu, J	2020	proposes a method for glaucoma diagnosis utilizing both hidden features learned from deep learning models and domain knowledge. Deep learning models can automatically learn intricate features from raw data, potentially capturing complex patterns and structures that are crucial for glaucoma diagnosis but may be difficult to extract manually.	Deep learning models enable end-to-end learning, where the entire diagnostic pipeline, from feature extraction to decision-making, is learned directly from data. This holistic approach may lead to better performance by optimizing the entire process jointly. Deep learning models are highly scalable and can accommodate large volumes of data efficiently. This scalability allows for the inclusion of diverse datasets and the potential for continuous learning and improvement over time.	Deep learning models require large amounts of labeled data for training, which may be challenging to obtain, particularly for rare or underrepresented conditions. Insufficient or biased training data can lead to suboptimal performance and potential biases in the model's predictions. Deep learning models are often complex, black-box systems, making it challenging to interpret their decisions and understand the underlying reasoning process.
Optic disc and optic cup segmentation from retinal images using hybrid approach.	Thakur, N., Juneja, M	2021	A hybrid approach combining multiple segmentation methods may lead to increased accuracy compared to using a single method alone. By leveraging the strengths of different techniques, the hybrid approach can compensate for individual method limitations and improve overall segmentation performance.	Combining multiple segmentation techniques enhances robustness against image artifacts, variations in illumination, and other challenges commonly encountered in retinal imaging. The hybrid approach may provide more reliable segmentation results across diverse retinal image datasets. The hybrid approach is flexible and adaptable, enabling researchers to incorporate new segmentation methods or modify existing ones as needed.	Implementing a hybrid segmentation approach involves integrating multiple algorithms and optimizing their parameters, which can increase the overall complexity of the segmentation pipeline. This complexity may make the approach challenging to implement, debug, and maintain. The hybrid approach may require more computational resources compared to individual segmentation methods due to the increased complexity and computational overhead limiting the approach's applicability.

Title	Authors	Year	Objectives	Advantages	Disadvantages
"Advancements in Glaucoma Detection: A Comparative Analysis of FAWT-based and CNN-based Approaches"	1. Parashar et al. (2020) 2. Gomez-Valverde (2018)	2020	The objective of this comparative analysis is to evaluate and compare two different approaches for glaucoma detection: the Flexible Analytical Wavelet Transforming (FAWT)-based method proposed by Parashar et al. (2020) and the convolutional neural network (CNN)-based approach employed by Gomez-Valverde (2018). Through this analysis, the aim is to assess the effectiveness, accuracy, and potential advantages of each technique in identifying glaucoma-related changes in retinal images.	One advantage of the FAWT-based method by Parashar et al. (2020) is its ability to extract detailed coefficients from retinal images, enabling precise analysis of features relevant to glaucoma. This method's use of binary classification techniques ensures efficient categorization, while cross-validation enhances the reliability of results. Overall, the FAWT-based approach offers improved accuracy in glaucoma detection through advanced image processing.	One potential disadvantage of the FAWT-based method by Parashar et al. (2020) is its reliance on manual feature extraction, which may limit scalability and introduce subjectivity. This method may require careful tuning of parameters and wavelet functions, impacting its performance and generalizability across different datasets or patient populations.
Machine Learning-Based Glaucoma Detection Using Retinal Neuron Fiber Properties	Christopher et al.	2020	employed a machine learning approach for the detection of glaucoma-related retinal images. They evaluated the quality of pretreatment retinal photographs by analyzing the properties of retinal neuron fibers within the source images. Specifically, the study focused on evaluating the deepest parts of retinal pictures and creating feature ratings for each fiber's internal layer. By utilizing a large dataset of retinal images, established glaucoma detection systems were evaluated, aiming to enhance the accuracy and reliability.	The machine learning-based approach offers the advantage of automated analysis of retinal neuron fiber properties, enabling efficient evaluation of retinal photographs for glaucoma detection. This method enhances accuracy by systematically assessing deep retinal layers and utilizing a large dataset for robust model development.	A potential disadvantage of the machine learning-based approach could be its reliance on large datasets for training, which may pose challenges in terms of data acquisition, storage, and computational resources. Additionally, the effectiveness of the method may be impacted by variations in image quality and characteristics across different datasets, potentially leading to reduced performance in real-world clinical settings. Furthermore, the interpretation of results from machine learning algorithms may require validation by ophthalmologists.
Glaucoma Detection using Convolutional Neural Network	Saxena, A.; Vyas, A.; Parashar, L.; Singh, U.	2020	The objective of the study was to develop a glaucoma detection system using Convolutional Neural Network (CNN) technology. The aim was to leverage CNNs to accurately identify signs of glaucoma in retinal images, thereby aiding in early diagnosis and treatment of the condition. By employing advanced deep learning techniques, the study sought to enhance the efficiency and reliability of glaucoma detection, ultimately contributing to improved patient outcomes and vision health.	One advantage of the glaucoma detection system by Saxena et al. is its potential for high accuracy in identifying glaucoma signs in retinal images, enabled by Convolutional Neural Network (CNN) technology's ability to extract relevant features automatically.	A potential disadvantage of the glaucoma detection system by Saxena et al. using Convolutional Neural Network (CNN) technology could be its reliance on large datasets for training, which may be time-consuming and resource-intensive, and its susceptibility to overfitting.

III. System Model

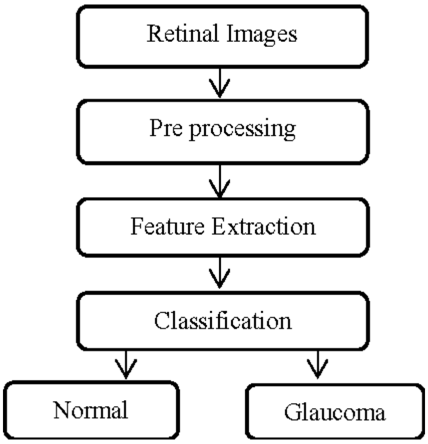

Figure 3: Flowchart for Glaucoma Detection

Detecting glaucoma using the VGG16 model involves the following steps:

1. Data Collection: Gather a large dataset of retinal images, including images from both healthy individuals and those diagnosed with glaucoma. Ensure that the dataset is diverse and representative of different stages and variations of glaucoma.

2. Data Preprocessing: Preprocess the images to enhance their quality and prepare them for input into the VGG16 model. Common preprocessing steps include resizing images to the required input size of VGG16 (usually 224x224 pixels), normalization, and possibly data augmentation techniques such as rotation, flipping, and scaling to increase the robustness of the model.

3. Model Selection: Choose the VGG16 model as the base model for glaucoma detection. VGG16 is a convolutional neural network (CNN) architecture known for its effectiveness in image classification tasks. Pretrained weights can be used to leverage the model's learned features from large-scale image datasets like ImageNet.

4. Transfer Learning: Perform transfer learning by fine-tuning the pretrained VGG16 model on the glaucoma dataset. Freeze the weights of the initial layers (usually up to the convolutional base) to retain the learned features and only train the top layers of the model to adapt to the specific task of glaucoma detection.

5. Model Training: Split the dataset into training, validation, and testing sets. Train the modified VGG16 model on the training data while monitoring performance on the validation set to prevent overfitting. Use techniques such as early stopping and learning rate scheduling to optimize model training.

6. Evaluation: Evaluate the trained model's performance on the testing set using appropriate evaluation metrics such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). Additionally, visualize model predictions and analyze any misclassifications to gain insights into the model's strengths and weaknesses.

These steps are used to develop an effective glaucoma detection system using the VGG16 model, contributing to early diagnosis and better management of this sight-threatening condition.

IV. VGG Based Method to Detect Glaucoma

Glaucoma is a common eye illness that, if not recognised and treated early, can cause irreversible vision loss. Deep learning techniques, notably neural networks based on convolution (CNNs), have made substantial advances in automated recognition of glaucoma using retinal pictures. This essay focuses on the utilization of the VGG-19 architecture, a deep CNN, for glaucoma detection and its implications in ophthalmology.

The optic nerve is harmed by glaucoma, mostly as a result of increased intraocular pressure. It is often asymptomatic in its early stages, making early detection challenging. However, the progression of the disease can be slowed or halted with timely intervention. Hence, efficient screening methods are crucial for preventing vision loss.

Retinal Imaging in Glaucoma Detection

The monitoring and early identification of glaucoma are aided by retinal imaging. Conventional techniques need ophthalmologists to manually examine retinal pictures, which takes time and is prone to interobserver variability. Deep learning algorithms-driven automated systems provide a possible option by producing reliable and consistent evaluations.

VGG-19 Architecture

In 2014, Simonyan & Zisserman introduced VGG 19, an architecture for a deep convolutional neural network that is artificial. There are three completely connected layers and three max-pooling layers after the first 16 convolutional layers, totaling 19 layers. Despite its simplicity compared to more recent architectures like ResNet or DenseNet, VGG-19 has demonstrated excellent performance in image classification tasks.

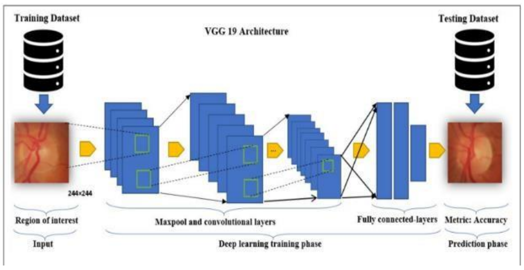

Figure 4: Schematic block diagram of VGG19

VGG19, on has been widely utilised for a variety of applications. VGG19, as the name says, comprises 19 layers, 16 of which are convolutional and three are completely linked [28]. VGG19 has a default input dimension of 244×244 for colour images. To counteract overfitting, this study changes the input size to 299×299 and increases the number of stages to 25.

Similar to Inception ResNet, the majority of the parameters were trainable, with a tiny proportion left as default. VGG19 contains three completely linked layers at the end, and all hidden layers employ the rectifier units (ReLU) that activate them. VGG19 offers a versatile architecture for many needs.

Application of VGG-19 in Glaucoma Detection

Researchers have leveraged the power of VGG-19 for automated glaucoma detection using retinal images. The architecture's ability to extract hierarchical features from images makes it well-suited for this task. By training the network on a large dataset of labeled retinal images, VGG-19 can learn discriminative features associated with glaucomatous changes.

Advantages of VGG-19-Based Glaucoma Detection

High Accuracy: VGG-19 exhibits high accuracy in distinguishing between healthy and glaucomatous retinas, thereby aiding in early diagnosis.

Robustness: The network's robust feature extraction capabilities enable it to perform reliably across different imaging modalities and datasets.

Efficiency: Automated systems based on VGG-19 can analyze large volumes of retinal images rapidly, facilitating mass screening efforts.

Interpretability: The hierarchical nature of the features learned by VGG-19 allows clinicians to interpret the model's decisions and gain insights into disease pathology.

V. Conclusion

The utilization of deep learning techniques, particularly the VGG-19 architecture, holds immense potential for revolutionizing glaucoma detection using retinal imaging. By providing accurate, efficient, and interpretable assessments, VGG-19-based systems can aid clinicians in early diagnosis and management of glaucoma, thereby reducing the burden of this sight-threatening disease on global health systems. Continued study and creativity in this field are critical to realising the full promise of artificial intelligence within ophthalmology.

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