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A Comprehensive Survey of Deep Learning and Ensemble Techniques in Glaucoma Detection

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Abstract: ***Glaucoma stands as a primary contributor to irreversible blindness, necessitating precise and prompt diagnoses for effective management. Recent progress in deep learning, particularly through the use of ensemble methods involving Convolutional Neural Networks (CNNs), has demonstrated considerable potential in automating the detection of glaucoma by analyzing ocular imaging data, such as fundus and Optical Coherence Tomography (OCT) images. This survey provides a thorough overview of the latest ensemble-based approaches developed for glaucoma detection, emphasizing the advantages of integrating various CNN architectures, including ResNet, VGG, and DenseNet, to enhance feature extraction and classification capabilities. The paper explores current trends in transfer learning, multi-modal data integration, and hybrid methodologies that reinforce the performance and adaptability of ensemble methods in clinical environments. Additionally, it addresses challenges like the necessity for high-quality labeled datasets, model interpretability, and generalization across different populations. By exploring into recent studies, the survey aims to identify limitations in existing systems and propose advancements in ensemble- based glaucoma detection, ultimately offering valuable insights into future research path that can narrow the gap between experimental findings and practical clinical applications.***

Keywords: Glaucoma Detection, Deep Learning, Ensemble Methods, Convolutional Neural Networks, Optical Imaging

I. INTRODUCTION

Glaucoma is a chronic eye condition that progressively damages the optic nerve, frequently linked to increased intraocular pressure, and remains a top cause of irreversible blindness globally. Early detection is crucial, as the disease typically advances without symptoms in its early stages, making prompt intervention essential to prevent significant vision impairment. Without treatment, glaucoma can gradually cause vision loss. Impacting millions worldwide, because it progresses without symptoms in the early stages, allowing substantial damage to occur before any noticeable vision problems emerge [1]. This subtle nature makes early detection critical, as timely intervention can slow or prevent further vision loss, underscoring the importance of reliable diagnostic methods. In this criterion, the need for accurate and early detection of glaucoma has become increasingly vital. Traditional diagnostic methods, such as fundus photography and Optical Coherence Tomography (OCT), rely heavily on manual analysis by ophthalmologists, which can be time-consuming, subjective, and prone to human error [2]. Moreover, due to the challenges and complex nature of glaucoma in its early stages can make detection problematic even for trained professionals. These limitations have encouraged a growing interest in automated, reliable, and efficient diagnostic systems that can assist clinicians in early glaucoma detection and monitoring.

In recent years, deep learning specifically through ensemble methods utilizing Convolutional Neural Networks (CNNs) has gained substantial attention for its applications in medical imaging. CNNs, as a subset of deep learning, are particularly adept at analyzing complex image patterns, making them ideal for detecting structural changes in the optic nerve and retina associated with glaucoma. By leveraging ensemble techniques that combine various CNN architectures, researchers have developed models capable of detecting glaucoma with high accuracy from fundus and OCT images, thereby potentially reducing the diagnostic burden on healthcare professionals. Ensemble methods have shown significant promise in enhancing diagnostic accuracy, improving sensitivity, and offering rapid processing, which are essential for large-scale screening programs.

Despite these advantages, deploying CNN-based models in glaucoma detection presents several challenges. Issues such as limited availability of labeled medical images, variations in imaging conditions, and the inherent complexity of interpreting deep learning models can impede practical adoption. Additionally, the 'black box' nature of CNNs raises concerns about interpretability [3], as a lack of transparency in the decision-making process can reduce clinical trust in these systems. Model generalization remains a critical challenge, as models trained on specific datasets may perform poorly when applied to new patient populations or imaging devices.

This paper aims to offer a comprehensive survey of ensemble-based CNN techniques for glaucoma detection, which collects recent works and helps in finding future works. By examining state-of- the-art methods and discussing their performance [4], limitations, and adaptability to clinical practice, this paper seeks to present a cohesive view of the current view in ensemble-based glaucoma detection. The objective is to evaluate existing methodologies and identify areas where further research and innovation are needed to bring these technologies closer to clinical implementation.

This paper's main contributions include an in-depth review of recent studies employing ensemble

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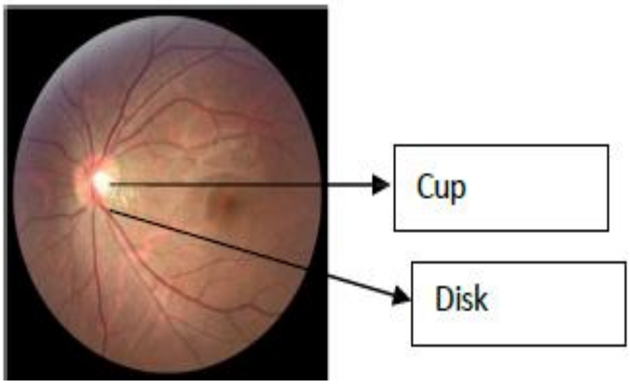
techniques for glaucoma detection. It provides an analysis of various studies along with their outcomes and discusses the key challenges that ensemble methods face in the context of glaucoma detection. In addition, this paper provides a comprehensive analysis and comparison of those recent studies along with its merits and demerits. By synthesizing recent advancements, this aim to guide future research and highlight promising directions that can address current gaps in the field.

The paper organized into different sections, the section 2 provides the basic information about glaucoma detection with the anatomical structure of eye retina from fundus image. Section 3 provides the deep learning process in the process of glaucoma detection. Section 4 gives the literature survey from recent studies which highlight the ensemble based methods and common CNN based methods for glaucoma detection. The comparison table is made from the literature content and provided in the same section. The final section 5 gives the conclusion and possible future directions from the findings.

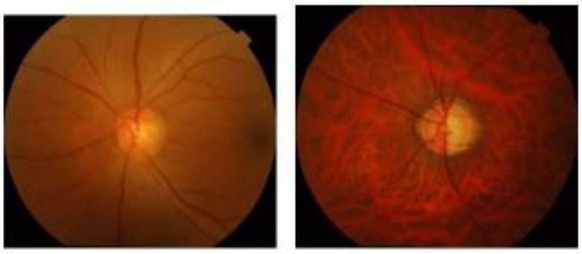
II. GLAUCOMA DETECTION

Glaucoma detection involves identifying the presence of glaucoma, a progressive eye disease that damages the optic nerve and can lead to irreversible blindness. Early detection is crucial because glaucoma is often asymptomatic in its early stages. With advancements in imaging processing and deep learning techniques, especially CNNs, automated glaucoma detection has become progressively more effective [5]. The glaucoma can be detected form fundus photographs or OCT scans.



[Fig.1: Fundus Image and its Anatomical Structure]

The figure 1.0 illustrating a sample fundus image with the optic disc and cup highlighted typically serves to point out the anatomical structures relevant for glaucoma identification. The fundus image is a photograph of the interior surface of the eye, including the retina, optic disc, macula, and posterior pole. This image provides a clear view of the optic disc and cup. The optic disc is where the optic nerve fibers converge to enter the eye, and it typically appears as a lighter, circular or oval area compared to the surrounding retina. At the center of the optic disc lies the optic cup, which is a small depression. In a healthy eye, the cup is relatively small in comparison to the disc, but in glaucoma, the cup can expand as the disease causes damage to the optic nerve. The difference between healthy and glaucoma-affected eye images from fundus photography can provide valuable insights for the detection process.



[Fig.2: (a) Normal Image (b) Glaucoma Image]

The figure 2.0 includes two images labeled "a" and "b," where image "a" depicts a normal fundus and image "b" shows a glaucoma-affected fundus. In the normal fundus image, the optic disc appears well- defined with a healthy pinkish hue, indicating good vascularization and a small optic cup, resulting in a low cup-to-disc ratio (CDR). The neuroretinal rim is thick, and the retinal vessels are organized and of normal caliber, reflecting overall retinal health. In contrast, the glaucoma-affected fundus image reveals significant changes: the optic disc is pale with a thinner neuroretinal rim, while the optic cup is enlarged, leading to a high CDR, a hallmark of glaucoma. Additionally, the retinal vessels may appear crowded, and other features such as disc hemorrhages or notching of the rim could be present. This visual comparison effectively highlights the structural changes associated with glaucoma, underscoring the importance of monitoring these features for early diagnosis and management of the disease.

III. RETINAL IMAGE ANALYSIS USING DEEP LEARNING

Retinal image analysis is important for detecting and classifying eye diseases like glaucoma, diabetic retinopathy, and age-related macular degeneration. These diseases can be identified by analyzing at images of the retina, where abnormalities are clearly visible. Two-dimensional imaging is particularly useful for early screening and diagnosis of glaucoma, one of the leading causes of blindness. Additionally, retinal images can be easily stored and shared, making it possible for doctors around the world to access them. This accessibility helps improve eye care by allowing timely treatment and better management of eye health, ultimately reducing the risk of vision loss. Deep learning is an ultimate choice to recognize the patterns automatically and helps in classifying or identifying Glaucoma. The figure 3.0 outlines a deep learning process for classifying glaucoma severity using retinal images. Starting with a labeled dataset of retinal images, each image is categorized by experts as "Normal," "Mild," "Moderate," or "Severe" based on glaucoma signs. These images then undergo pre- processing such as resizing and enhancing to ensure consistency and quality. The prepared images are used to train a model, allowing it to learn the visual patterns associated with each severity level. Once trained, the model is tested on new, unlabeled images, predicting the severity of glaucoma by categorizing each image into one of the four levels. This classification supports clinicians in diagnosing glaucoma stages more efficiently, aiding in timely and tailored treatment decisions.

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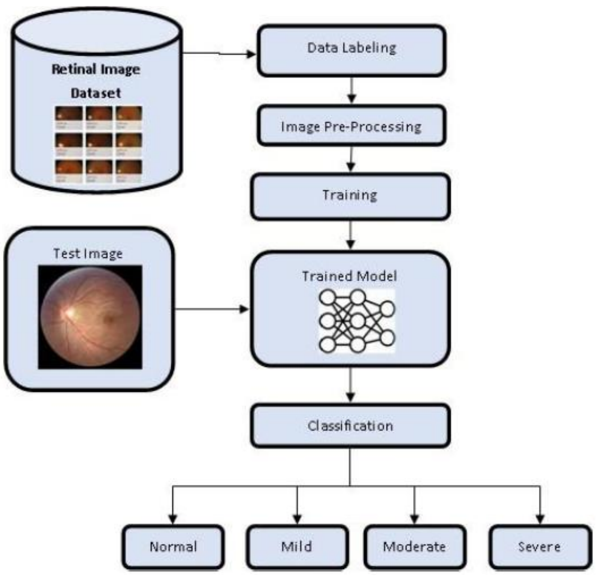

[Fig.3: Process of Deep Learning in Glaucoma Detection]

IV. LITERATURE REVIEW

Zilly et al. presented a general framework for retinal image segmentation using CNN architectures based on ensemble learning [6]. A deep CNN network was trained on numerous patches from the same Drishti-GS dataset. An entropy sampling technique was used for information point reduction and allowed to reduce the computational complexity. The proposed approach achieved a Dice of 0.970 for OD segmentation and a Dice of 0.870 for OC segmentation in the Drishti-GS dataset.

Civit-Masot et al. used an ensemble approach to predict glaucoma on a combined dataset consisting of RIM-ONEand Drishti-GS datasets in such a way that OD and OC were segmented using a generalized U- Net to calculate the CDR [7], and Random sample consensus (RANSAC) was used to find out if the predicted shapes are similar to ellipse. The transfer learning on MobileNet V2, pre-trained with weights from the ImageNet 1K challenge, was used for the prediction of glaucoma. The results were blended to provide a likelihood score for glaucoma. The applied approach achieved the Dice of 0.920 and 0.840 for OD and OC segmentation, respectively, on the RIM-ONE dataset, and the Dice of 0.930 and 0.890 for OD and OC segmentation, respectively, on the Drishti-GS dataset.

Taj et al. proposed a two-stage glaucoma classification scheme based on four pre-trained deep convolutional neural networks (deep CNNs) AlexNet, NasNet Large, InceptionResNetV2 and InceptionV3 [8]. The usage of transfer learning where the weights in pre-trained networks are used as the starting point for the training process helped to reduce the training time. These four Deep CNNs were tested using extracted Optic Nerve Head (ONH)from three publicly available datasets ACRIMA, ORIGA-Light, and RIM-ONE, and private datasets collected from local hospitals. The classification accuracy has been improved by combining these four Deep CNNs into one classifier where the final decision has been made by the five voting techniques, i.e., Proportional Voting (PV), Majority Voting (MV), Averaging (AV), Accuracy/Score based Weighted Averaging (ASWA), and Accuracy based Weighted Voting (AWV). In the case of the ACRIMA dataset, the accuracy of 0.995 of AlexNet and NasNet-Large has been improved to 0.996 by the ensemble with AWV.FortheORIGA- Light,the accuracy has increased from 0.879 to 0.883 with ASWA.

Ali et al. presented an OD segmentation system based on an ensemble of ten deep learning-based semantic segmentation models such as U-Net [9], Gated SkipConnections (GSCs), DoubleU-Net, DeepLabV3+, CGNet, ERFNet, SegNet, ESNet, LinkNet, and SQNet. For the aggregation step, the Ordered Weighted Average operator has been used. The aggregation has been applied to each pixel of the input image. A threshold of 0.5 was applied to the result and the class with the maximum activation has been taken as a label. The best results for segmenting the OD in fundus images collected from the Hospital Sant Joan de Reus have been obtained with the ensemble of models GSCs, DoubleU Net, and DeepLabV3+ achieving an IoU of 0.954, Dice of 0.951, a precision higher than 0.960, and a recall higher than 0.930.

Kim et al. proposed two ensemble models based on three Fully Convolutional Networks (FCN) with a modified U-Net structure to segment OD and OC where a different region of interest (ROI) was used as input for each FCN [10]. In each ensemble model, the final results were estimated by merging the results of three FCNs using an averaging operator. The raw ROIs were used as input for the OD segmentation model and masked ROIs were used as inputs for the OC segmentation model. The RIGA and the REFUGE datasets were used for the training and evaluation of the proposed method. The proposed method achieved an IoU of 0.930 and a Dice of 0.964 in OD segmentation and an IoU of 0.810 and a Dice of 0.892 in OC segmentation accordingly.

Elangovan and Nath presented a deep ensemble model based on stacking ensemble technique implementing such Deep CNNs as Xception [11], Inceptionv3, Densenet-201, Mobilenet-v2, Efficientnet-b0, VGG-16, VGG-19, Googlenet, Alexnet, Resnet-18, Resnet 50, Resnet-101, Squeezenet, and using support vector machine (SVM) for the final classification of glaucoma and normal images. With the suggested approach the classifica tion accuracy of 0.996, 0.995, 0.934, 0.913, 0.796 in LAG-R, ACRIMA-R, Drishti-GS1-R, RIM-ONE2-R, ORIGA-R has been achieved.

Kurilová et al. applied an ensemble method composed of deep learning models VGG-16 [12], MobileNet, and ResNet 50 using hard voting and average voting to classify OD using fundus images from the REFUGE dataset. The models were monitored using binary accuracy, precision, recall, Area Under the Curve (AUC), true positives, true negatives, false positives, and false negatives. The best accuracy of 0.980 and AUC of 0.880 were achieved using the average voting method.

Akbar et al. introduced a novel detection method for glaucoma that combined the architectures of DenseNet and DarkNet [13]. This fusion approach demonstrated superior performance, achieving the highest accuracy of 99.7% on the High-Resolution Fundus (HRF) dataset, outperforming results obtained on other datasets such as RIM and ACRIMA. This indicates the potential of integrating different deep learning models to enhance diagnostic capabilities in glaucoma detection.

Saha et al [14]. proposed a system that focuses on glaucoma detection by classifying the Optic Nerve Head (ONH) regions as 'glaucomatous' or 'non- glaucomatous' utilizing MobileNetV3Small [17]. ONH detection is carried out using the YOLO architecture, specifically targeting YOLO Nano and its variants for efficient processing on resource-limited devices [18]. The architecture incorporates advanced techniques such as Residual Projection-Expansion-Projection and Fully- connected Attention to enhance efficiency [19]. Extensive experiments demonstrated that the simplified YOLO Nano outperformed YOLO Nano and YOLO-v5 Nano in both performance and computation time. The system achieved an impressive accuracy of 97.4%, showing its capability to detect glaucoma effectively while requiring fewer resources. Future evaluations will assess the system's performance on lower- capability hardware to determine its applicability in practical settings.

Table 1: Comparative Study of Recent Papers

Ref No	Algorithm/Technique Used	Merits	Demerits
[6]	Ensemble Learning with CNNs	Achieved high Dice scores (0.970 for OD, 0.870 for OC); reduced computational complexity.	Relies on the quality of the Drishti- GS dataset; potential issues with generalization.
[7]	Generalized U-Net with RANSAC and Transfer Learning	High Dice scores (0.920 for OD, 0.840 for OC on RIM-ONE; 0.930 for OD, 0.890 for OC on Drishti-GS); effective integration of datasets.	Complexity in model training; blending results may introduce variability.
[8]	Two-stage classification with multiple CNNs	Improved accuracy through ensemble voting techniques; effective across multiple datasets.	Requires extensive training; potential overfitting with more complex models.
[9]	Ensemble of ten segmentation models	Achieved high precision (>0.960) and recall (>0.930) for OD segmentation; robust results.	Computationally demanding due to multiple models; potential difficulties in model tuning.
[10]	Ensemble models using FCNs and modified U-Net	High Dice score (0.964 for OD segmentation); effective use of region of interest.	Complexity in determining optimal regions of interest; may require extensive training.
[11]	Stacking ensemble model with deep CNNs	High classification accuracy across various datasets; effective final classification with SVM.	Model complexity and training time can be significant; reliance on multiple pre-trained networks.
[12]	Ensemble method with VGG-16, MobileNet, ResNet	Achieved 0.980 accuracy and 0.880 AUC; effective use of voting techniques.	Variability in results depending on input data quality; potential bias in voting methods.
[13]	Combined DenseNet and DarkNet architectures	High accuracy of 99.7% on HRF dataset; demonstrates effectiveness of model integration.	Limited to specific datasets; performance may vary across different data sources.
[14]	MobileNetV3Small with YOLO for ONH classification	High accuracy of 97.4%; efficient processing for resource-limited devices.	May not generalize well outside tested environments; performance varies based on hardware.
[15]	Deep learning method utilizing fundus images and OCT	Strong kappa score of 0.886; good potential for early detection and monitoring.	Requires high-quality labeled datasets; complexity in incorporating clinical parameters.
[16]	Multi-level automated detection with U-Net	Enhanced accuracy and reliability in glaucoma diagnosis; effective use of ensemble models.	Dependence on multiple pre-trained models can increase computational overhead.

This table 1.0 summarizes the contributions and evaluations of various studies related to glaucoma detection and retinal image analysis, highlighting their methodologies, strengths, and limitations.

Ferreira, Marcos Melo, et al. proposed a deep learning method that utilizes fundus images and OCT volumes to assist in the early detection and monitoring of glaucoma [15], which is critical for identifying severe cases of the disease. The method has demonstrated a kappa score of 0.886, indicating strong agreement with clinical diagnoses. The author suggests that future research should focus on improving glaucoma detection methods by using transfer learning with well-labeled fundus image datasets and fine-tuning models with specific datasets like the GAMMA dataset. They also recommend exploring advanced techniques, such as vision transformers and Self- Organized Operational Neural Networks, which require larger datasets but have shown promise in detecting glaucoma. Additionally, incorporating clinical parameters like the optic disc cup ratio could enhance prediction accuracy. However, challenges include the need for high-quality datasets and the added complexity from using more parameters. Overall, a more integrated approach is encouraged to advance glaucoma detection.

Vasquez-Rochin et al. proposed a multi-level automated glaucoma detection system that incorporates an ensemble of three pre-trained models alongside a U-Net architecture [16]. This innovative approach leverages the strengths of established models while utilizing U-Net for precise segmentation tasks, further enhancing the accuracy and reliability of glaucoma diagnosis through advanced image analysis techniques.

The collective findings from recent studies indicate that deep learning techniques, particularly those employing ensemble methods and transfer learning, are highly effective for improving the accuracy and reliability of glaucoma detection and retinal image analysis. The successful implementation of various CNN architectures demonstrates the potential to enhance diagnostic capabilities while addressing computational efficiency. The diverse approaches, including the integration of multiple datasets, innovative segmentation methods, and the use of pre- trained models, highlight the ongoing evolution in the field. However, challenges remain, such as the need for high-quality datasets and the incorporation of clinical parameters to further refine predictions. Overall, these advancements point towards a promising future for automated glaucoma detection systems, which could significantly aid in early diagnosis and treatment, ultimately reducing the burden of vision impairment caused by this disease. The table 1.0 represents the comparative study of the literature with reference numbers,

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algorithms/techniques used, merits, and demerits.

V. CONCLUSION

The survey on "A Comprehensive Survey of Deep Learning and Ensemble Techniques in Glaucoma Detection" underscores the transformative impact of deep learning and ensemble methods in automating and enhancing glaucoma diagnosis. Our analysis reveals that ensemble approaches, combining diverse Convolutional Neural Network (CNN) architectures, consistently improve detection accuracy by leveraging complementary model strengths. Techniques like transfer learning and multi-modal data fusion further amplify these results, offering adaptability to diverse datasets and increased diagnostic reliability. Despite these advancements, challenges persist, including the limited availability of high-quality labeled data, concerns around model interpretability, and issues with cross-population generalization. Addressing these barriers will be essential for deploying these systems in real-world clinical environments. Future research must prioritize refining interpretability, improving dataset diversity, and developing models that are robust to variations in imaging and patient demographics. By addressing these gaps, ensemble-based deep learning models hold the potential to greatly enhance early glaucoma detection, enabling scalable, reliable, and more accessible diagnostic solutions that can ultimately contribute to preventing blindness caused by glaucoma. This survey provides a foundation for further research and innovation, with a view towards clinical translation and impactful healthcare outcomes.

DECLARATION STATEMENT

After aggregating input from all authors, I must verify the accuracy of the following information as the article's author.

- **Conflicts of Interest/ Competing Interests:** Based on my understanding, this article has no conflicts of interest.
- **Funding Support:** This article has not been sponsored or funded by any organization or agency. The independence of this research is a crucial factor in affirming its impartiality, as it has been conducted without any external sway.
- **Ethical Approval and Consent to Participate:** The data provided in this article is exempt from the requirement for ethical approval or participant consent.
- **Data Access Statement and Material Availability:** The adequate resources of this article are publicly accessible.
- **Authors Contributions:** The authorship of this article is contributed equally to all participating individuals.

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