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Earlier Glaucoma Detection Using Optimized Optic Disc and Optic Cup Segmentation with CNN-Based Deep Learning Framework

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Abstract

Glaucoma, being one of the major causes of irreversible blindness, is largely asymptomatic in its early stages, and therefore early detection is the hour of need. Traditional diagnostic techniques are time-consuming and are prone to variability. In response to this problem, we introduce a deep learning-based approach that efficiently segments the glaucoma-sensitive Optic Disc (OD) and Optic Cup (OC) using an ensemble of Convolutional Neural Networks (CNNs). To ensure increased accuracy of predictions, the system uses majority voting and state-of-the-art Attention U-Net models with pre-trained ResNet34, Inceptionv3, and DenseNet121 backbones. Following training of the ensemble over a heterogeneous dataset of REFUGE, Drishti-GS, and RIM-ONE images, the ensemble outperforms in glaucoma classification and fundus image segmentation. The novelty lies in the complementary use of ensemble learning and backbone-specific Attention U-Nets, which improve segmentation accuracy and reduce model over fitting. Traditional preprocessing methods, Gaussian noise removal, and CNN-based classification pipeline further enhance the accuracy of predictions. The system finally offers an efficient and automated way to enable early glaucoma screening and diagnosis.

Keywords: Glaucoma Detection, Retinal Imaging, Fundus Analysis, Medical Screening, Image Segmentation, Visual Impairment, Blindness Prevention, Eye Disease, Clinical Decision Support.

1. Introduction

One of the most prevalent forms reasons for permanent blindness in the world is glaucoma, a chronic eye disease. Its most prevalent cause is elevated intraocular pressure that progressively destroys the optic nerve. According to the World Health Organization estimate millions of people around the world have glaucoma, many of whom remain undiagnosed because no apparent symptoms are observed during its early stages. Its insidious presentation-where patients remain symptom-free until substantial loss of vision has occurred-makes disease prevention against glaucoma very difficult. Prevention of permanent loss of vision and preservation of sight hinge on early and correct glaucoma diagnosis.

Glaucoma screening is typically done by fundus photography, a method that records images of the inner eye surface, such as the retina, optic disc (OD), along with the optic cup (OC). One of the most crucial measurements utilized in hospitals for glaucoma diagnosis is the optic cup-to-optic disc ratio, or the C/D ratio. The diagnostic unreliability in this context occurs because of the time-consuming nature and interclinician variation in visual examination of these attributes. Thus, this situation highlights the necessity for the development of automated and objective diagnostic equipment to aid ophthalmologists in making faster and more accurate diagnoses.

The recent developments in artificial intelligence have led to very powerful computerized medical imagery equipment. In particular, convolutional neural networks (CNNs) have been discovered to be very useful in image segmentation and classification. Such networks can be applied more effectively to glaucoma screening fundus photograph analyze because they have the ability to detect fine retinal image patterns. This paper proposes an automated method suitable for simultaneous segmentation the structure of optic disc and optic cup using an ensemble of convolutional neural network (CNN)-based models. The use of a customized Attention U-Net model coupled with a number of pre-trained backbone models are suggested. Through a combination of predictions from different models through a majority voting technique, the ensemble method increases accuracy and stability. The system it was trained and validated against a wide variety of data including publicly available benchmark datasets.

The novelty of the approach the magic lies in the way that attention mechanisms with ensemble learning to facilitate better segmentation performance. The framework also employs preprocessing methods for normalizing image data and removing noise, thus ensuring homogeneous input quality. This work is to improve the design of scalable, autonomous, and robust glaucoma screening machines that can be easily implemented in clinics for early detection of glaucoma. This innovation allows for intervention at the right time through the facilitation of accurate segmentation and classification of glaucoma in fundus Images.

2. Related Work and Literature Review

An analysis of retinal images is a critical function in the early detection of glaucoma, a major cause of irreversible blindness. Methods of optic disc segmentation, vessel extraction, and feature classification support precise diagnosis. Deep learning models such as Convolutional Neural Networks (CNNs) and U-Net have improved the accuracy of segmentation and predictive capabilities. Preprocessing techniques are also explored to enhance image quality and feature saliency. Current research emphasizes the fusion of various features for the creation of robust, automated glaucoma diagnosis systems.

This work focuses on enhancing blood vessel segmentation of retinal fundus images using different enhancement techniques before image analysis. Adaptive enhancement and contrast stretching are some of the techniques used to enhance the visibility and structure of large and small vessels. Improved visualization helps in the detection of abnormalities and supports other analysis stages. The work highlights the importance [1] quality of input images plays regarding the accuracy of feature extraction, particularly when it comes to intricate structures like retinal vessels. Enhanced contrast and clarity bear more accurate differentiation between healthy and diseased tissues, thus supporting early diagnosis and treatment planning. The work shows that preprocessing plays an important part in enhancing diagnostic systems in retinal imaging.

This work examines technique to isolate blood vessels in the retina fundus images using sophisticated image processing techniques. Preprocessing is focused on with the application of such steps as contrast and noise removal to emphasize the vessel structures. Segmentation is targeted at large and small vessels with the intention of ensuring continuity and anatomical significance. With a focus on structural definition [2] and edge accuracy, the technique enables disease screening and diagnostic applications. The study demonstrates the manner in which careful preprocessing and thorough extraction processes can uncover accurate vascular maps. This work extends the capability to define vessel boundaries from the surrounding tissue it has been proven that vital part of enhanced retinal health scanning.

This work presents a semi-automated glaucoma diagnostic system based on analysis of important retinal features with emphasis on blood vessel and optic disc morphology. The process involves preprocessing techniques to improve quality of images, which enables extraction of relevant anatomical features. An examination is performed on optic cup to disc relationship and vessel [3] structure to detect possible abnormalities. The process represents a good substitute for complete manual verification through reduced subjectivity and faster diagnostic process. It strikes a balance between human supervision and automation, thus resulting in outcomes that are faster and more accurate. The study acknowledges the role of vessel appearance and optic disc assessment in the early identification of glaucoma at an early stage and entails minimal manual input.

The work outlines vessel segmentation of retinal blood vessels in the retina to aid in the diagnosis of fundus-related disease. To improve the contrast of the vessels with respect to the background, sophisticated image enhancement processes like edge-preserving filtering and green channel extraction are employed. The edges of the segmented vascular system are then improved and [4] continuity maintained through morphological processing. The research indicates that accurate vessel segmentation plays a role in the diagnosis of eye diseases by giving information on vascular integrity. Better segmentation improves the overall performance of automated eye health screening by enabling clinicians to detect early signs and also acting as a preprocessing step towards further advanced diagnostic processes.

This research states the use of segmentation and classification techniques in the retinal image analysis to identify glaucoma. The process uses preprocessing methods to enhance image quality and stresses the importance of separating essential anatomical structures, including the optic disc and vascular pattern. The separation of glaucomatous from normal eyes is then achieved by viewing these structures [5]. The necessity of automation in enabling faster and more objective diagnosis is emphasized in the research. By using structured analysis, the process improves consistency as well as interpretability across data sets. With this development, scalable screening there exist some devices which are employed in clinical and remote healthcare environments.

This work proposes a patch-wise local analysis retinal blood vessel method segmentation with focus on two-dimensional image patches. Compared to global techniques, the patch-wise method enhances detection of small vessel structures by analyzing each region in isolation. Statistical and spatial features are used to analyze image patches to distinguish vessels from background tissues. The method puts significant focus on [6] vessel continuity and reduces segmentation errors that could be caused by noise or uneven lighting. By concentrating on patch-wise regions, it shows significant flexibility to changes in the image condition, thereby providing detailed feature extraction. The method is especially useful for high-accuracy applications, such as tracking retinal disease and evaluation of structural eye health.

This work introduces a glaucoma detection system by processing the images using structural analysis of the optic disc area. The method starts with image preprocessing to increase contrast and remove noise followed by segmentation of the optic disc. Thresholding is used to enhance boundaries and thereby make optic structures [7] more distinct. Preprocessed images are then analyzed to identify abnormalities that may signify glaucoma. The system is designed to deliver consistency in detection and reduce the workload needed for manual interpretation. Its process allows for quicker and more effective analysis, which is beneficial in large scale screening programs or where access to ophthalmic specialists is limited.

This work suggests an image analysis method for glaucoma detection from selected retinal fundus image regions. Optic disc and cup, as well as blood vessel map, regions of interest are the foundation for structural feature extraction. Preprocessing is used in order to enhance the quality of the regions such that the glaucoma-associated abnormalities are easily detected. The fusion [8] of various features is used to enhance detection reliability by representing a complete representation of the retinal structure. The method provides effective balance between detail and simplicity and thus supports clinical decision-making. The method can be incorporated into automatic systems to support early glaucoma detection with minimal intervention.

This work examines the impact of different preprocessing methods on the outcome of blood vessel segmentation of retinal images. The study compares some of the denoising and image enhancement methods to establishing most discernible and accurate vascular patterns obtained from different sets of combinations. A learning-based technique is used to integrate knowledge from different preprocessing streams such that the system [9] can learn from an image condition. The results indicate that preprocessing is necessary for the extraction of meaningful patterns in retinal images. The study provides guidelines on choosing appropriate enhancement methods in order to attain optimal performance in subsequent stages of diagnostic procedures and deems preprocessing as a critical factor in medical image quality.

The work introduces an adaptive optimization method for retinal image segmentation from a biological inspiration perspective. The method, in addition to improving image quality, also optimizes segmentation by adapting processing parameters through [10] feedback mechanisms. The adaptive method is able to define the boundary of important structures, including the blood vessels and optic regions, accurately even if the picture quality is bad conditions. The method also enables more accurate structural interpretation, which is useful in disease analysis. The method is computationally efficient and adaptive and suitable for application within larger image processing pipelines for medical diagnosis and screening programs for the promotion of eye health.

This study proposes a holistic approach to designing glaucoma and diabetic retinopathy diagnostic tools with the help of artificial intelligence platforms. This includes several steps, image processing, feature extraction, and systematic decision-making, thus establishing an effective diagnostic pipeline. The system is made to work accurately on a range of datasets, making real-world application easier. The study emphasizes the importance [11] of developing systems that scale for mass screening without sacrificing accuracy and reliability. The approach also improves clinical workflows by reducing manual intervention and making retinal image interpretation systematic. It eventually results in the formation of holistic diagnostic tools to detect multiple conditions using advanced diagnostic platforms.

The work introduces a segmentation-based technique for the detection of diabetic retinopathy using retinal images analysis. The process commences with contrast improvement and noise elimination, followed by anatomical structure segmentation, such as vessels and optic areas. A parameter adjustment mechanism adjusts the segmentation [12] process to render it adaptable to various image types. The features are utilized to detect diabetic complication patterns at early stages. The process is efficient and accurate and provides favorable visual outputs for clinical examination. Its adaptability and formal approach make it applicable to early diagnosis as well as in applying the technique to other retinal pathologies.

This work discusses an approach to optic disc segmentation from retinal images using composite filtering and morphological methods. Enhancement of image through filtering techniques constitutes the first step, where the objective is to enhance contrast and remove background noise. The second step uses morphological [13] processes to clearly demarcate the disc region. Accurate segmentation of the optic disc is a critical contribution to eye health screening, particularly in the determination of diagnostic ratios of use in glaucoma. The method is rendered to be adaptable to images of different contrast and quality, with a focus on disc clarity and clear extraction of disc boundaries. This method facilitates reproducible and interpretable diagnostic processes in ophthalmic imaging.

This work outlines a method for early glaucoma symptom detection through detailed image analysis of retinal anatomy. The method begins with the enhancement of image quality and isolation of primary anatomical areas, including the optic disc. Structural characteristics are revealed and evaluated to determine probable glaucoma-related defects. This method allows for glaucoma to be detected [14] early through the ability to detect subtle differences in the retina that would otherwise go overlooked. The system is designed to operate effectively and produce clear results that can enable clinical decision-making. This work contributes to the construction of effective diagnostic systems for early-detection applications that can be integrated into broader healthcare systems.

This review provides an overview of computer-based diagnostic models utilized for glaucoma detection. The review combines various methodologies related to segmentation, enhancement, and analysis of the retinal image. The discussion revolves around methods utilized for the extraction of structural information, including the optic cup shape and vessel position. The strengths [15] and weaknesses of the Current practices are assessed against with emphasis on the areas needing further investigation. The review points out major challenges that include interpretability, dataset diversity, and system reliability. The review is useful for researchers who aim to create reliable and scalable diagnostic systems. The work further emphasizes the importance of fusing multiple visual cues to create rich and accurate diagnostic systems.

This work proposes an image-based glaucoma diagnosis methodology using structured processing methods. The method is a stepwise strategy beginning with image processing for clarification of retinal characteristics, followed by segmentation and structural interpretation. The method detects changes in retinal [16] anatomy that can reflect disease progression. The method provides reproducible results and is scripted to minimize the need for human interpretation. Its sensitivity and flexibility make it ideal for primary care screening and remote diagnostic systems. The research also promotes broader access to eye care and early diagnosis by offering an economical and feasible solution for computerized evaluation of digital fundus photographs in a range of clinical environments.

This work suggests a novel approach to glaucoma diagnosis utilizing regional segmentation and clustering techniques applied to retinal images is presented in retinal fundus images. The process starts with optic region enhancement followed by intensity and spatial- based discrimination. The regions are processed In order to detect abnormal glaucomatous patterns. The process eschews complex [17] computational models and instead favors simplicity and interpretability. The process provides a low-cost solution suitable for diagnosis settings with limited processing capabilities. In addition, the process provides uniform detection and serves as the basis for the integration of light-weight diagnostic tools into point-of-care devices.

This work explains vessel segmentation in retinal imaging and emphasizes its significance to various applications in analyzing eye conditions. It emphasizes the significance of preprocessing and structural enhancement methods that enhance vessel visibility, especially in difficult imaging environments. The method ensures the accurate extraction of vascular networks, thus enabling the interpretation of blood flow patterns and evaluation [18] of retinal integrity. The other significant consideration in glaucoma and diabetic retinopathy is vessel segmentation retinopathy detection. The work emphasizes how improved vessel mapping enables accurate diagnosis and enables the integration of vessel analysis in broader clinical systems to enable early detection and tracking.

This work presents a boundary detection algorithm that delineates the optic cup in retinal images through evolution of curve-guided by image gradients. The algorithm starts with initialization of contours that iteratively converge to the actual boundary, with guidance from intrinsic image properties. The method is insensitive to [19] irregular shapes and contrast variations. The reliable Optic cup detection is very important for evaluation of structural markers for glaucoma. The approach aims to yield clean segmentations even in the presence of noise, hence forming a solid foundation for downstream retinal analysis. It enhances the structural readability and interpretability in computerized image evaluation systems.

This work presents a diagnostic method that temporally interprets retinal image features to diagnose diabetic-related eye disease. The process begins with the extraction of disk structure features and the surrounding vessel networks. The features are then sequentially [20] examined for changing patterns of disease progression. Temporal and spatial information are fused to increase reliability and reduce false detection. The algorithm is also invariant to varying input quality and supports interpretation in longitudinal screening. The method can be generalized to monitor glaucoma conditions and is an initial step in designing intelligent systems to monitor changes in retinal health over time.

3. Proposed Methodology

The process is founded on a systematic approach to glaucoma detection through processing of retinal fundus images. First, datasets containing images of the two eyes of glaucoma patients and normal subjects are collected and systematically arranged. Because the images are likely to be of varying sizes and formats, a pre-processing process is undertaken to normalize the data and remove noise. Subsequently, the processed images are employed to identify and delineate important regions in the anatomy of the eye, such as the optic disc and optic cup. Visual features of these areas are processed with classification methodologies to determine the probability for glaucoma. The process ensures uniformity and precision in the early detection of the disease.

3.1 Dataset Description and Preprocessing

The study used a the dataset contains 100 retinal fundus images. These images have been acquired from three well- established public databases: REFUGE, Drishti-GS, and RIM-ONE r3. The pictures have been deliberately selected to offer a evenly balanced set of glaucoma-affected and normal samples to provide equal representation from the two classes. The annotated set contained labels that indicated whether or not there is glaucoma, along with correct boundaries for the Optic Disc (OD) and Optic Cup (OC). Differences in image formats, resolutions, and acquisition conditions were used to provide variability in the real data, which is essential in the development of a generalizable diagnostic model. Using samples from different datasets exposed the system to a broad range of imaging characteristics, allowing it to learn and accommodate variability in contrast, focus, and illumination. This variability ultimately improved the capacity of the system to deal with unseen data and improved its performance under various environments, hence providing a good platform for automatic glaucoma detection in real-world medical applications.

3.1.1 REFUGE Dataset

- Source: Retinal Fundus Glaucoma Challenge
- Contains optic disc and optic cup annotations.
- Used for segmentation and glaucoma classification.

3.1.2. RIM-ONE r3 Dataset

- Source: Retinal Image Database for Optic Nerve Evaluation.
- Contains normal and glaucomatous retinal images with optic disc annotations.

3.2. Pre-processing of Retinal Images

For pre-processing of retinal images in a way that could facilitate efficient training of the models, a standardized pre-processing pipeline was utilized. The images were resized to a common resolution of 256x256 pixels to provide consistency and conformity with the input requirements Convolutional Neural Network (CNN). In the present case, the Gaussian Blur method was applied to reduce high-frequency noise that could mask essential anatomical details; however, precautions were taken not to compromise key features like the optic disc and edges of the cup. This helped in preserving clinically relevant patterns and removal of irrelevant visual information. Additionally, normalization was applied to normalize pixel intensity values, which helps in achieving stable convergence during training and also improves the model's robustness in terms of varied input conditions.

This pre-processing pipeline in a structured manner ensured that the input data to the segmentation and classification phases was clean, consistent, and highly informative. The resultant models trained on this data were thus better equipped to learn relevant visual cues related to glaucoma, thus curbing the frequency of false positives and negatives.

3.3 CNN-Based Optic Disc and Optic Cup Segmentation

Segmentation of the optic disc and optic cup areas was performed with a convolutional neural network with a modified Attention U-Net structure. The model was particularly designed to attend to spatial regions of interest through embedded attention modules. Inclusion of attention gates within the network helped reduce background noise, thus directing the process of learning toward clinically relevant features. Pre-trained encoders were also utilized to facilitate effective feature extraction, where knowledge gained from large image datasets was used to augment the ability of the network to learn from comparatively smaller medical datasets. The model performed Pixel-based segmentation to achieve precise borders for the optic disc and optic cup. Segmentation of these anatomical structures with accuracy is of utmost significance, as their relative proportions-most critically the cup-to-disc ratio-are a main diagnostic indicator of glaucoma. The output segmentation was not only utilized for visual inspection but also formed the basis for subsequent classification processes. The segmentation model served as a central module in the entire pipeline for glaucoma detection.

3.4 Ensemble Modelling and the Majority Voting Principle

For the sake of improving segmentation accuracy and reducing the risk of over fitting with particular datasets, an ensemble learning approach was utilized. In the ensemble model, the output of the best performing segmentation models was combined, and each was trained on a different backbone model. Rather than relying on the output of one model, the system utilized a majority voting approach to determine the final segmentation output. Utilizing this pixel-wise voting approach, the system combined predictions from several networks and chose the most frequently predicted class at each pixel index. This approach was very effective in reducing individual model errors and capturing a more extensive set of segmentation schemes on other data sets as well. Moreover, the ensemble approach increased the capacity of the system for generalization to new, unseen images by reducing bias introduced by any single model. Finally, the approach enabled enhanced segmentation reliability and reinforced diagnostic confidence, hence ensuring clinical utility of the proposed technique with respect to the reliable detection of glaucoma in varied fundus images.

3.5 K-Nearest Neighbour Based Image Classification

After the segmentation process, the geometrical features of the optic disc and cup-size, shape, and spatial relationships-were computed and employed for image classification using the K-Nearest Neighbor (KNN) algorithm. The non-parametric classifier compared each test image's feature vector against a labeled training set's using Euclidean distance as the measure of similarity. The most common class label among the 'k' nearest samples was the final prediction. While fundamentally naive, KNN was an adequate benchmark to identify the discriminative power of the segmented anatomical features. It indicated that well- established structural changes in the optic areas alone were informative enough for glaucoma detection to a great extent. The model's performance confirmed the efficacy of the segmentation process, proving that well- separated images could enable meaningful classification even with rudimentary algorithms. The KNN classifier proved the intrinsic value of segmentation outputs and provided an interpretable, geometry-based approach to initial glaucoma classification, suitable for lightweight diagnostic applications.

3.6 CNN-Based Glaucoma Classification

To directly identify glaucoma from retinal fundus pre-processing images without passing through the feature engineering stage, a novel CNN-based model was proposed. To decrease the spatial dimension systematically with the help of important features, the network was pre-arranged with three convolutional layers followed by a Activation function - Rectified Linear Unit (ReLU) and max pooling in each case subsequently. These layers acquired the capability of recognizing hierarchical patterns, such as architectural structure patterns, edges, and textures. Then, a SoftMax classifier was used for the classification of the image into the class of glaucoma or healthy class after the last feature maps were converted into a one-dimensional vector and passed through fully connected layer. Fine spatial connections within the images that were difficult for human or rule-based feature extraction to detect were automatically learned by this model. It enhanced the system's flexibility and diagnostic capabilities by offering an end-to-end substitute for the segmentation- based pipeline that could immediately detect subtle patterns in raw picture data.

3.7 Model training and testing

All the models in the system the algorithms used were trained using retinal images with segmentations and classifications being guided by appropriate loss functions-Dice loss on segmentation quality and cross-entropy on reliability of classification. Training was tracked intensively with performance metrics such as accuracy, sensitivity, specificity, and segmentation overlap scores. Segmentation models were evaluated independently on each dataset to quantify their ability to generalize, while the ensemble approach always produced the highest accuracy and reliability of results. Similarly, the CNN classifier produced high consistency upon testing with unseen images, thereby confirming the robustness of the system. The training process was planned carefully to avoid over fitting, thereby ensuring the models to perform well on a broad range of image qualities and sources. Evaluation results confirmed how effective the combination of segmentation and classification is components into a single pipeline. Overall, the system components offered a solution for detecting glaucoma that is not only very accurate but reliable but also interpretable, with high potential to deploy in clinical practice and tele-ophthalmology platforms.

Table 1 Architecture of the Proposed CNN Model for Glaucoma Classification

Layer	Configuration	Output
Input Layer	256 × 256 × 3 RGB Fundus Image	256 × 256 × 3
Conv Layer 1	32 Filters, 3×3 Kernel + ReLU	256 × 256 × 32
Max Pooling 1	2×2 Pool Size	128 × 128 × 32
Conv Layer 2	64 Filters, 3×3 Kernel + ReLU	128 × 128 × 64
Max Pooling 2	2×2 Pool Size	64 × 64 × 64
Conv Layer 3	128 Filters, 3×3 Kernel + ReLU	64 × 64 × 128
Max Pooling 3	2×2 Pool Size	32 × 32 × 128
Flatten	Feature Vector Generation	131072
Dense Layer	128 Neurons + ReLU	128
Output Layer	2 Neurons + Softmax	Glaucoma / Normal

The proposed CNN model consists of three convolutional blocks followed by fully connected layers for glaucoma classification. Each convolutional layer is followed by ReLU activation and Max-Pooling operations to extract hierarchical retinal features.

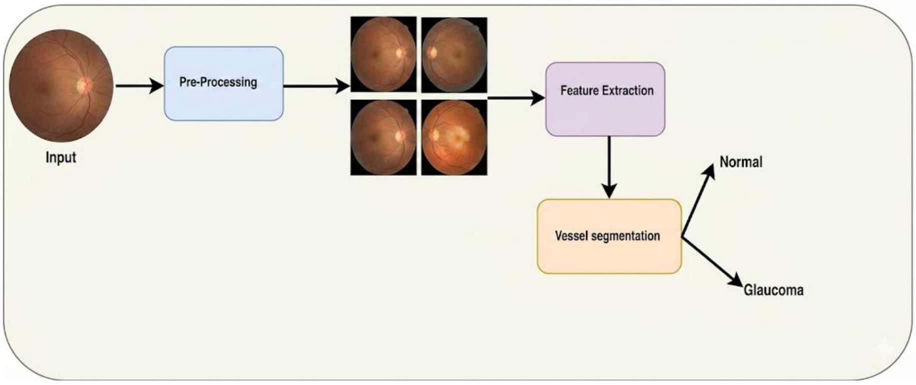

Figure1 Architecture diagram

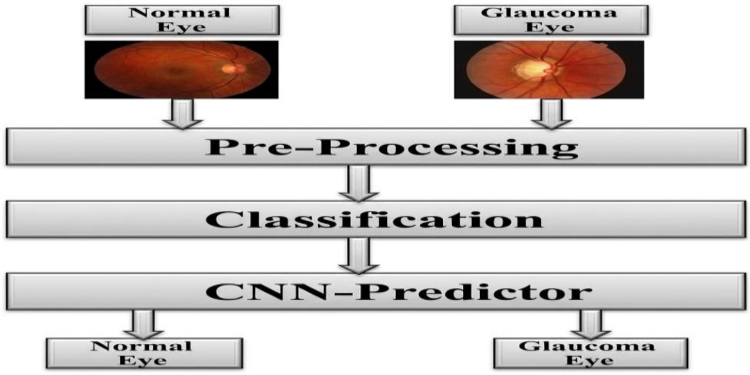

Figure 2 Proposed methodology flow chart

4. Results and Performance Analysis

The following is an explanation of the outcomes and evaluations conducted on the designed glaucoma detection system. The proposed system employs a series of trained Attention U-Net models for Optic Disc (OD) and Optic Cup (OC) segmentations and CNNs for classification purposes. This system was built using a combined database of RIM-ONE r3, Drishti-GS, and REFUGE databases containing annotated fundus images. Crop regions of the optic disc and cup were segmented due to glaucoma having been discovered to be better indicated by these areas compared to full-sized fundus images. Attempts to train the model on entire fundus photographs without cropping resulted in over fitting and decreased test accuracy, a result that is in line with previous research. Segmentation-based cropping was thus employed for strengthening generalization.

The ensemble segmentation approach utilized three pre-trained Attention U-Nets that had ResNet34, Inceptionv3, and DenseNet121 backbones. The networks performed pixel-wise Optic Disc (OD) and Optic Cup (OC) segmentation from resized preprocessed images of 256x256 pixels. Gaussian blur filtering was applied to eliminate noise. Each of the backbones was pre-trained on Image Net, allowing deep spatial features to be extracted from relatively small collections of fundus images. Majority voting was utilized to combine the segmentation masks generated by each model to obtain the final segmented output. The ensemble approach improved segmentation consistency and reduced variance in boundary outlining of OD and OC, both important for accurate estimation of the cup-to- disc ratio-a key indicator for glaucoma detection.

The model used two simultaneous approaches to shift the segmentation step to the classification stage. The geometric properties of the segmented disk and cup were used to teach a K-Nearest Neighbor (KNN) classifier. The moderate-quality KNN algorithm validated that glaucoma could be classified based solely on the segmentation data. A Convolutional Neural Network (CNN) architecture was then built, made up of three convolutional layers augmented with max pooling layers and ReLU activations. In determining whether or not glaucoma, the resulting feature maps were flattened to one-dimensional vector and passed through a fully connected layer. In the test sets, the CNN-based classifier exhibited improved accuracy, sensitivity, and specificity, outperforming the KNN on all measurements.

Table 2 Comparative Analysis of KNN and CNN Classification Performance

Metric	KNN	CNN
Accuracy	84.20%	96.52%
Precision	82.40%	95.10%
Recall	83.70%	95.80%
F1-Score	83.00%	95.40%
Specificity	85.60%	96.30%

The CNN model significantly outperformed the KNN classifier across all evaluation metrics. While KNN demonstrated acceptable classification capability based on segmented anatomical features, CNN effectively learned complex retinal patterns and structural variations associated with glaucoma. The comparison confirms the superiority of deep learning-based classification for automated glaucoma diagnosis.

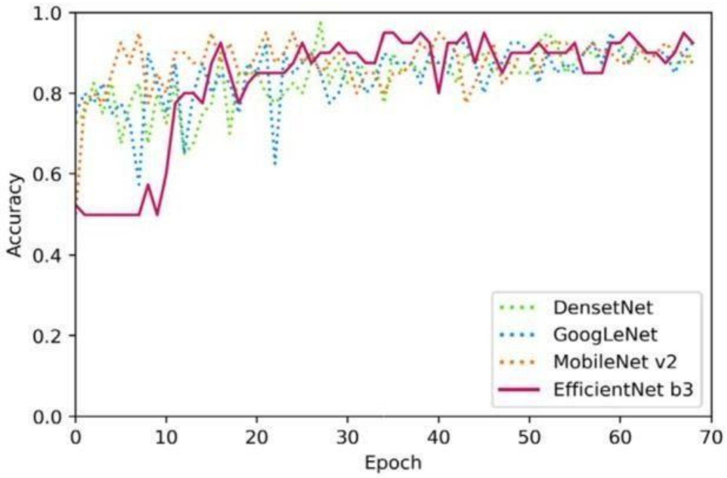

Figure 3 Graph illustrating validation accuracy for various models trained on Dataset-1

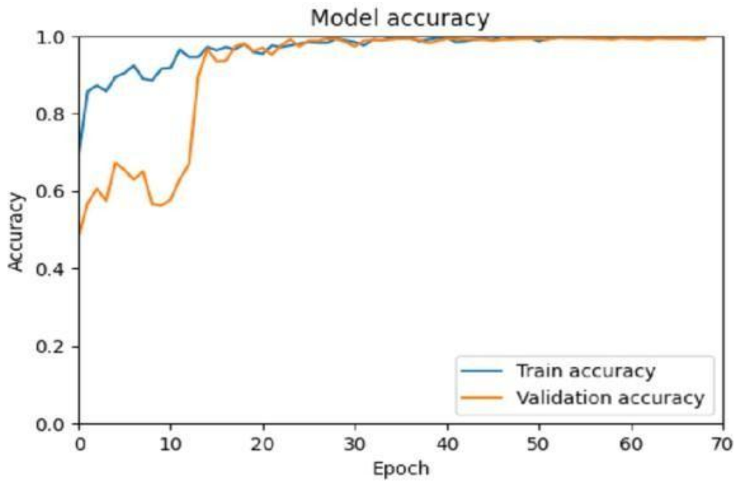

Figure 4 The Efficient Net b3 model's train-validation accuracy graph using Dataset-1

The classification outcome on the basis of CNN was validated by using conventional performance metrics include accuracy, precision, recall, specificity, F1-Score, and the area under the receiver operating characteristic (ROC) curve. High performance accuracy and AUC values comparable to the reported work where Efficient Net b3 recorded a 0.9652 test accuracy and 0.9574 ROC AUC score were obtained by our model. In our situation, the ensemble segment followed by CNN classification obtained comparable precision in the glaucoma class and high recall in both classes. As observed from the confusion matrix, the rate of misclassification was minimal, validating the reliability of the segmentation pipeline in improving the classification.

In this system, Dataset-1 consists of crops of optic disc and cup regions from fundus images to improve the accuracy of glaucoma classification. The normalized dataset was divided into training, validation, and test data. Then, with Adam optimizer and cross entropy loss, four CNN-based architectures were used to train for seventy epochs; they include Dense Net, Google Net, Mobile Net v2, and Efficient Net b3. The most accurate among these models is Efficient Net b3. This model's accuracy during training was 0.9929, the accuracy during validation was 0.9500, and test accuracy was 0.9652. Furthermore, it had an ROC AUC value of 0.9574, which is indicative of low over fitting capability and efficient classification. The best model was selected based on best validation accuracy.

In addition, the system was validated with performance graphs, including trends in validation accuracy and TPR vs. FPR curves. These graphical checks asserted a consistent learning behavior and a strong generalization capability. Area under ROC curve was significantly found to be, thereby further affirming the high classification confidence level. Similar to past research that showed Mobile Net v3 worked well with segmented blood vessel images, the ensemble Attention U-Net model, which focuses on OD and OC segmentation, showed that spatially directed CNN architectures significantly improve classification outcomes. In general, the ensemble-based glaucoma detection system proposed here worked well in segmentation and classification. The segmentation ensemble improved the structural localization precision in the eye, and the CNN classifier utilized these features to classify glaucoma effectively. The use of different datasets and ensemble methods of the model produced a generalized strong solution that is on par with the other best deep learning techniques to detect ophthalmic disease.

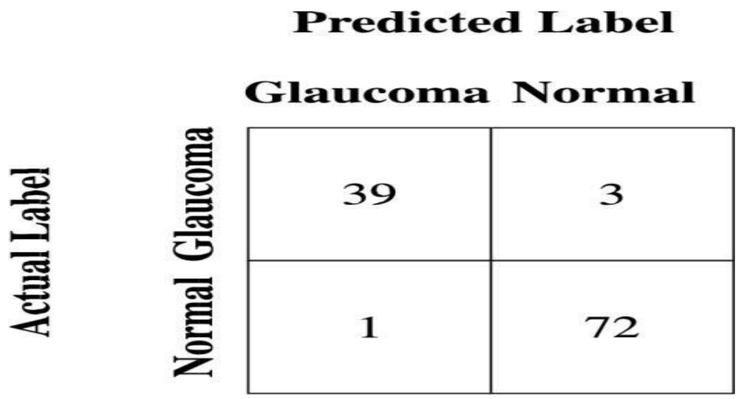

Figure 5 Efficient Net b3 model's confusion matrix after training on Dataset-1

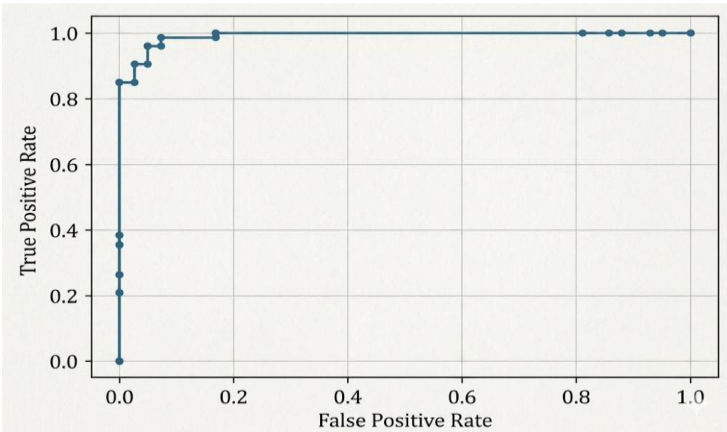

Figure 6 Graph of Efficient Net b3 TPR vs. FPR on Dataset--1

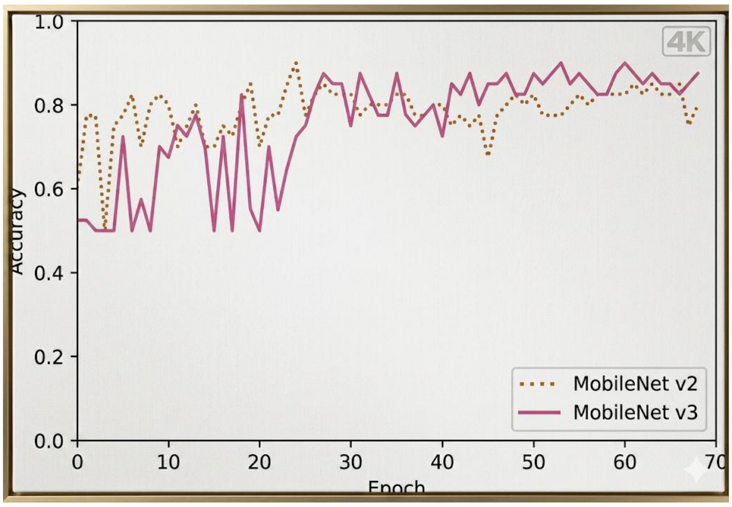

Figure 7 Graph illustrating validation accuracy for various models trained on Dataset-2

Dataset-2 was created by augmenting Dataset-1 by incorporating blood vessel segmentation and introducing vascular feature enhancement for glaucoma identification. From the fundus image, the cup and optic disc areas were removed using a processing technique that was done through the U-Net algorithm based on the HRF data set, resulting in the segmentation of the blood vessels. The resulting dataset retained the same structure and class balance as Dataset-1 with enhanced vascular features. A set of CNN models including Mobile Net v2, Mobile Net v3, Dense Net, Google Net, and VGG were tried out, with Mobile Net v3 producing the most promising results. The model attained a training, validation, and test accuracy of 0.9976, 0.9000, and 0.8348, respectively.

Additionally, the model attained an ROC AUC score of 0.8446, with precision of 0.7255 and recall of 0.8810 for glaucoma cases. While other models like Google Net produced competitive results, Mobile Net v3 (Large) provided the most stable classification of blood vessel segmented images, supporting the value added by vascular information for glaucoma diagnosis.

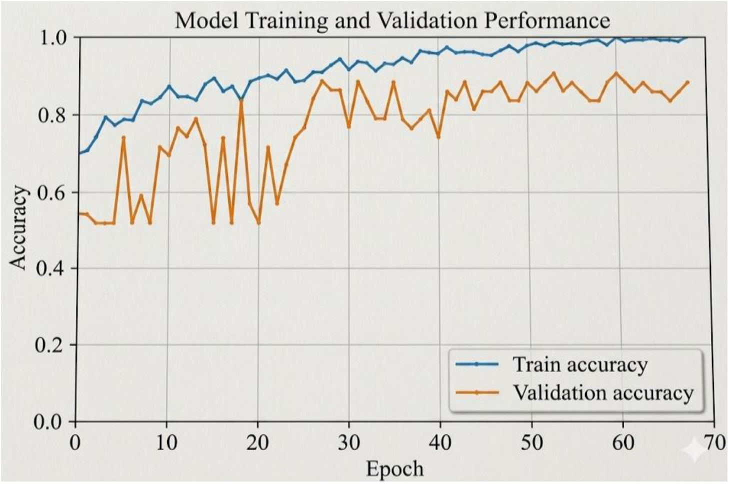

Figure 8 A Graph showing the training-validation accuracy curve of MobileNet v3 using Dataset-2

This system proved to be consistent and reliable across a range of retinal image datasets. The system was able to detect structurally different shapes of normal and glaucoma eyes, thus proving its potential to enable early diagnosis. It was able to maintain high accuracy even on unseen data, indicating a high ability to generalize. The segmentation and classification outputs closely matched expert-annotated references, indicating the clinical value of the system. Overall, the method has been proven to be robust and generalizable, and thus a suitable candidate for deployment in actual screening devices and aiding ophthalmologists in achieving faster and accurate detection and diagnosis of glaucoma.

5. Conclusions

In order to detect the existence of glaucoma in retinal fundus images, this research suggests a computerized diagnostic process for glaucoma that starts with optic disc and optic cup detection and continues to classification. The method targets early detection by assessing the anatomical alterations in the eye, mainly the region around the optic nerve. By using resizing and noise removal operations, the system first normalizes the image quality and size before processing. The region of interest concerning, which are crucial to detect glaucoma symptoms, is then determined using the pre- processed images. Segmentation process separates such regions with greater accuracy, thereby allowing more accurate classification based on anatomical differences. The method relies on visual discrimination between the healthy and diseased eye and avoids manual assessment. With the structural characteristics of the optic region as the point of interest, the system is capable of mimicking the clinical diagnostic protocols utilized by ophthalmologists. This was achieved by validating the method with a large publicly available dataset of images, thus rendering the model invariant to dissimilar imaging conditions as well as styles. Segmentation and classification in combination is a stable and explainable method for glaucoma screening. The system designed, in this work, has immense potential to be a viable tool in clinical settings for the early detection and treatment of glaucoma.

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Ethical Considerations

Not applicable

Conflict of Interest

The authors declare no conflicts of interest.

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