RESEARCH PAPER

A Deep Learning–Driven Framework for Automated Glaucoma Screening and Detection

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ABSTRACT

Glaucoma is a major cause of irreversible blindness worldwide, largely due to its asymptomatic progression in the early stages, which often delays timely diagnosis and treatment. Early detection is therefore essential to prevent permanent vision loss and improve patient outcomes. While conventional diagnostic modalities such as Optical Coherence Tomography (OCT) offer high precision, their high cost and limited accessibility restrict their use in large-scale screening. In contrast, color fundus imaging provides a cost-effective, non-invasive, and widely accessible alternative, making it highly suitable for mass screening programs. This study proposes a deep learning–driven framework for automated glaucoma screening and detection using retinal fundus images. The proposed framework incorporates advanced preprocessing techniques, data augmentation, and deep feature extraction to enhance model robustness and generalization. A deep learning–based classification approach leveraging EfficientNet with fixed resolution strategies (FixEfficientNet) is employed and compared with traditional Cup-to-Disc Ratio (CDR)–based methods. The system integrates automated feature learning with optimized classification to improve diagnostic accuracy. Experimental findings demonstrate that the deep learning–based approach significantly outperforms conventional image processing techniques, establishing its effectiveness as a reliable and scalable tool for early glaucoma detection and as a supportive system for clinical decision-making.

Keywords: Glaucoma Detection, Fundus Imaging, Cup-to-Disc Ratio, Convolutional Neural Networks, EfficientNet, FixEfficientNet.

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1. INTRODUCTION

Glaucoma, often referred to as the "silent thief of sight," is a chronic and progressive optic neuropathy that leads to irreversible blindness if not detected early. The disease is characterized by damage to the optic nerve head (ONH), typically associated with elevated intraocular pressure (IOP), although glaucoma can also occur at normal pressure levels [1][2]. According to global health reports, millions of individuals are affected by glaucoma, many of whom remain undiagnosed until significant visual field loss has occurred.

Glaucoma is a chronic and progressive eye disease that stands among the leading causes of irreversible blindness across the globe. It is primarily characterized by damage to the optic nerve, often associated with elevated intraocular pressure, resulting in gradual vision loss [3-4]. One of the most challenging aspects of glaucoma is its silent progression; patients typically remain asymptomatic until the disease reaches an advanced stage, by which time significant and permanent visual impairment has already occurred. This makes early detection and continuous monitoring critically important for preventing blindness and preserving quality of life. However, conventional diagnostic techniques, including Optical Coherence Tomography (OCT) [5-7], visual field testing, and expert clinical evaluation, are often expensive, time-consuming, and require specialized infrastructure and trained ophthalmologists, limiting their accessibility, especially in rural and under-resourced regions.

In recent years, color fundus imaging has emerged as a practical and widely accessible alternative for large-scale glaucoma screening. Fundus images capture detailed information about the retina, optic disc, and surrounding structures, which are essential for assessing glaucoma-related changes such as the Cup-to-Disc Ratio (CDR). Traditional methods for glaucoma detection have largely relied on handcrafted features and image processing techniques to estimate CDR and other structural abnormalities [8-10]. Although these approaches provide valuable insights, they often suffer from limitations such as sensitivity to image quality, variability in illumination, and dependence on manual intervention, which can affect consistency and accuracy.

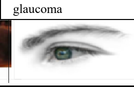
The rapid advancement of deep learning, particularly convolutional neural networks (CNNs), has revolutionized the field of medical image analysis by enabling automated and highly accurate feature extraction directly from raw images. Deep learning models can learn complex patterns and subtle variations in retinal structures that may not be easily detectable through conventional methods. Among various architectures, EfficientNet has gained significant attention due to its ability to achieve high performance with optimized computational efficiency through compound scaling of network depth, width, and resolution. By incorporating fixed resolution strategies, the model can further enhance feature representation and maintain consistency across varying image inputs.

2. REVIEW OF LITERATUER

Glaucoma can broadly be classified into open-angle glaucoma, angle-closure glaucoma, and secondary glaucoma. Open-angle glaucoma is the most common form and progresses slowly without noticeable symptoms. Angle-closure glaucoma, in contrast, may present acute symptoms due to rapid IOP elevation. Secondary glaucoma arises due to other ocular or systemic conditions, including trauma, inflammation, or medication-induced effects [11-14].

A clinically significant indicator for glaucoma diagnosis is the structural alteration of the optic disc, particularly the enlargement of the optic cup relative to the optic disc. This relationship is quantified using the Cup-to-Disc Ratio (CDR), which serves as a fundamental diagnostic marker [5] (Table 1).

Table 1: Different types of glaucoma and associated characteristics.

Pigmentary Glaucoma	Normal Tension Glaucoma	Congenital Glaucoma	Neovascular Glaucoma
This is primarily because the pigment granules at the back of the iris split into the clear fluid formed in the eye.	The optic nerve is damaged even when eye pressure is regular. This is also referred to as Low Tension Glau- coma.	It mainly occurs in babies due to incomplete drainage canals present in the eye during the prenatal period.	It is caused by irregular blood vessel development on the iris and eye drainage.
It is caused by abnormal new blood vessel formation on the iris and eye drainage.	People having irregular heart rhythms and diabetes are mainly attacked by NTG.	Congenital glaucoma is rare and it may be inherited.	The formation of new blood vessels well carries high blood pressure.
Pigment granules block within the eye will lead to a rise in eye pressure.	Mainly Asian people will affect normal-tension glaucoma.	By making microsurgery can often correct structural defects.	When a person affected by diabetes can easily be affected by glaucoma.
By making laser surgery, medications we can easily es- cape from pigmentary glaucoma	By making laser surgery, medications we can easily es- cape from glaucoma	Laser surgery is the only treatment to get rid of glau- coma	Medications and laser treatments are ways to decrease glaucoma effects
			

A wide range of studies have investigated machine learning and deep learning techniques to enhance the effectiveness and accessibility of glaucoma detection systems. Early research primarily focused on deep convolutional neural networks for optic disc and cup segmentation, followed by the estimation of the Cup-to-Disc Ratio (CDR). For instance, models based on ResNet-50 demonstrated promising performance by achieving reliable segmentation and an accuracy of approximately 87.8% on benchmark datasets [15]. In another approach, hybrid architectures combining Convolutional Neural Networks (CNNs) with Support Vector Machines (SVMs) were proposed, where CNNs served as feature extractors and SVMs performed classification. Such hybrid models achieved improved accuracy, around 85.6%, compared to individual classifiers, indicating the benefit of combining deep and traditional learning methods [16]. Additionally, multi-modal frameworks integrating fundus images with clinical parameters significantly improved diagnostic performance, achieving accuracies as high as 96.3%, thereby emphasizing the importance of incorporating heterogeneous data sources [17].

Transfer learning has also emerged as a powerful strategy, particularly in scenarios with limited annotated medical data. Pre-trained architectures such as VGG16, when fine-tuned on retinal datasets, have demonstrated competitive accuracy levels of around 84.5% [18]. Furthermore, recent studies have emphasized model interpretability by incorporating visualization techniques such as Grad-CAM, which not only achieved reasonable accuracy (approximately 83%) but also improved transparency in clinical decision-making [19]. Efforts have also been made to develop lightweight and real-time solutions, including mobile-based glaucoma detection systems, which achieved around 81% accuracy and facilitated point-of-care screening using smartphone-acquired images [20]. To address the challenge of limited datasets, data augmentation techniques, particularly those leveraging Generative Adversarial Networks (GANs), have been widely adopted, leading to noticeable improvements in model performance [21].

More advanced research has focused on developing end-to-end deep learning pipelines that integrate preprocessing, segmentation, and classification into a unified framework. These systems have demonstrated strong scalability and achieved accuracies of nearly 87% on large datasets [22]. Ensemble learning techniques, including bagging and boosting, have further enhanced classification robustness, achieving performance levels close to 86% while mitigating issues related to class imbalance [23-24]. Moreover, to improve accessibility in remote and underserved regions, cloud-based and telemedicine-enabled frameworks have been proposed. These systems utilize deep learning models to deliver real-time glaucoma detection with accuracies around 82%, thereby expanding the reach of ophthalmic care [25]

3. GLAUCOMA DETECTION METHODS

Glaucoma detection has traditionally relied on a combination of clinical examinations and imaging-based techniques to accurately identify structural and functional damage to the optic nerve. These methods play a crucial role in early diagnosis and disease management; however, they often require specialized equipment, trained professionals, and considerable time. With the advancement of medical imaging and computational techniques, there has been a growing shift toward automated and image-based approaches, which offer faster, cost-effective, and scalable solutions for large-scale glaucoma screening.

4. PROPOSED DEEP LEARNING BASED GLAUCOMA DETECTION

Deep learning has significantly transformed the field of glaucoma detection by enabling automated, accurate, and scalable analysis of retinal images. Advanced models, particularly Convolutional Neural Networks (CNNs), can learn intricate patterns and structural changes in the optic nerve head, such as variations in the cup-to-disc ratio and nerve fiber layer, without the need for manual feature extraction. These models are capable of processing large volumes of fundus images and identifying early signs of glaucoma that may be difficult to detect through conventional methods. Furthermore, techniques such as transfer learning, data augmentation, and attention mechanisms have enhanced model performance, especially in scenarios with limited annotated datasets. Deep learning approaches also support end-to-end frameworks that integrate preprocessing, segmentation, and classification, thereby improving efficiency and consistency in diagnosis. As a result, deep learning-based systems are increasingly being adopted as reliable decision-support tools in clinical practice, with the potential to facilitate early screening, reduce diagnostic workload, and improve accessibility to eye care services, particularly in resource-constrained settings.

5.1 Convolutional Neural Networks

Convolutional Neural Networks (CNNs) have emerged as one of the most powerful deep learning architectures for medical image analysis, owing to their capability to automatically learn complex and hierarchical feature representations directly from raw image data [8]. Unlike traditional machine learning approaches that rely heavily on handcrafted features, CNNs perform end-to-end learning by integrating feature extraction and classification within a single framework. They consist of multiple layers, including convolutional, pooling, and fully connected layers, which progressively capture low-level features such as edges and textures, and high-level semantic features such as shapes and structural patterns. This hierarchical learning makes CNNs highly effective in identifying subtle abnormalities in retinal fundus images, such as changes in the optic disc and cup regions associated with glaucoma. Additionally, CNNs exhibit robustness to variations in illumination, noise, and image quality, which are common challenges in real-world medical datasets. Their ability to generalize well across diverse datasets further enhances their applicability in automated glaucoma detection systems..

5.2 EfficientNet Architecture

EfficientNet is an advanced CNN architecture that introduces a novel compound scaling method to systematically balance network depth, width, and input resolution, resulting in improved performance and computational efficiency [26]. Unlike conventional scaling approaches that arbitrarily increase one dimension of the network, EfficientNet uniformly scales all dimensions using a principled approach, thereby maximizing accuracy while minimizing the number of parameters and computational cost. This makes EfficientNet particularly suitable for medical imaging applications, where datasets are often limited and computational resources may be constrained. The architecture leverages mobile inverted bottleneck convolution (MBConv) blocks along with squeeze-and-excitation optimization to enhance feature extraction capability. As a result, EfficientNet achieves superior performance in capturing fine-grained visual details in retinal images, which is critical for accurate glaucoma detection. Furthermore, its efficiency enables deployment in real-time and resource-limited environments, such as mobile or cloud-based healthcare systems, making it a highly practical choice for large-scale automated screening frameworks.

5. FIXEFFICIENTNET FRAMEWORK

One of the key challenges in conventional CNN-based training is the mismatch between image resolutions used during training and those encountered during inference, which can negatively impact model performance and generalization. The FixEfficientNet framework addresses this limitation by decoupling the training and testing resolutions and introducing a fine-tuning strategy that adapts the network to higher-resolution inputs during inference [27]. This approach helps maintain stable activation statistics and improves the model's ability to generalize across varying image qualities and scales, which is particularly important in medical imaging tasks where data heterogeneity is common.

In this study, the proposed framework leverages FixEfficientNet for direct glaucoma classification from retinal fundus images, eliminating the need for intermediate steps such as optic disc segmentation or Cup-to-Disc Ratio (CDR) computation. By enabling end-to-end learning, the model captures both global and localized features relevant to glaucoma detection more effectively. This not only simplifies the overall pipeline but also enhances computational efficiency and diagnostic accuracy, making it a robust and scalable solution for automated glaucoma screening systems (Figure 1).

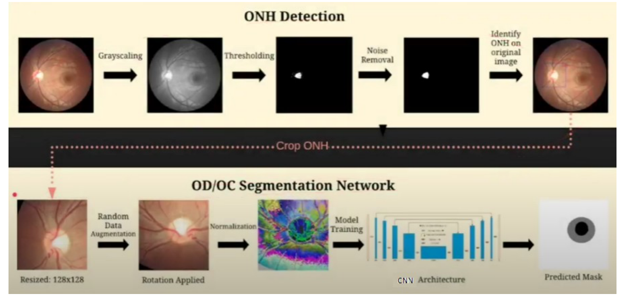


Figure 1: Proposed framework for glaucoma detection using FixEfficientNet.

6. DATASET

In this study, two benchmark datasets are utilized to evaluate the performance and robustness of the proposed glaucoma detection framework. Among them, the ORIGA dataset plays a significant role due to its well-annotated retinal fundus images and associated clinical information. The ORIGA (Online Retinal Fundus Image Database for Glaucoma Analysis) dataset was contributed by an American student and has also been widely used in Kaggle-based research challenges, making it a popular choice for validating machine learning and deep learning models in ophthalmology.

- **ORIGA dataset**

The dataset consists of a total of 650 annotated fundus images, carefully categorized into training and testing subsets. The training set includes 386 glaucoma-negative and 134 glaucoma-positive images, while the testing set comprises 96 negative and 34 positive samples. This distribution reflects a moderate class imbalance, which is a common characteristic in medical datasets and poses additional challenges for model training. The availability of both normal and glaucomatous cases allows for effective supervised learning and performance evaluation of classification models.

In addition to image data, the ORIGA dataset provides valuable tabular information that enhances its applicability for both deep learning and traditional machine learning approaches. Each image is associated with detailed attributes, including the annotated image name, Cup-to-Disc Ratio (CDR) values, and eye type (OD for the right eye and OS for the left eye). Furthermore, the dataset is divided into subsets labeled as Dataset A and Dataset B, offering flexibility for cross-validation and benchmarking. The ground truth labels are clearly defined, where label "0" represents glaucoma-negative cases and label "1" indicates glaucoma-positive cases.

- **Drishti**

The second dataset utilized in this study is the DRISHTI-GS dataset, contributed by Aravind Eye Hospital, Madurai, which is widely recognized for glaucoma screening research. This dataset is specifically designed for evaluating computer-aided diagnosis systems and is particularly suitable for Convolutional Neural Network (CNN)-based experiments. It comprises a total of 101 retinal fundus images, which are divided into two primary subsets: 50 images for training and 51 images for testing. Ground truth annotations are provided for the training set, enabling supervised learning and facilitating accurate model development.

The DRISHTI-GS dataset contains labeled fundus images categorized into glaucomatous and non-glaucomatous classes, making it effective for binary classification tasks. Despite its relatively small size, the dataset provides high-quality images with expert annotations, which are crucial for validating the reliability of automated glaucoma detection systems. However, the limited number of samples introduces challenges such as overfitting and reduced generalization capability, especially when training deep learning models.

7. RESULTS AND DISCUSSION

Experimental results indicate that CNN-based approaches significantly outperform traditional CDR-based models. FixEfficientNet achieves higher accuracy and F1-scores, demonstrating robustness across diverse image conditions. The findings validate the effectiveness of deep learning–based screening tools as supportive systems in clinical workflows.

In further experiments, we directly feed fundus images to a deep learning algorithm (CNN) with annotated data with the objective that CNN will be able to implicitly extract the features and then will be able to classify them accordingly. We have used two popular CNN algorithms viz. Resnet50 and EfficientNet for experimentation purposes. We have also addressed test train discrepancy by conducting two sets of experiments one with the concept of Fixing Resolution (FixRes) and another simply without FixRes. the data preprocessing done in the experiments are described below: The idea of FixRes is to first train a model on a smaller resolution dataset and then fine-tune it on a larger resolution dataset. Three datasets were created; one with a smaller resolution i.e 128x128 and two with a larger resolution of 224x224 but different augmentation transforms are to the larger-resolution datasets. Now two experiments are conducted one with FixRes. Experiment 1: Train on 128x128 from scratch and then fine-tune on 224x224 using transfer learning

In this experiment, the proposed deep learning model is trained from scratch using input images resized to a fixed resolution of 224×224 pixels, which is a commonly adopted standard for CNN-based architectures. Two publicly available benchmark datasets are utilized to evaluate the model's performance and generalization capability. The first dataset, ORIGA, consists of a total of 650 retinal fundus images, including 482 images belonging to the glaucoma-negative class and 168 images representing the glaucoma-positive class. This dataset provides a relatively balanced distribution compared to typical medical datasets, allowing the model to learn discriminative features effectively for both classes. The second dataset, DRISHTI-GS, contains 101 fundus images, with 31 negative (non-glaucomatous) and 70 positive (glaucomatous) samples, reflecting a class imbalance skewed toward the positive class (Figure 2).

Training the model from scratch on these datasets enables the network to learn domain-specific features directly from the data without relying on pre-trained weights. However, due to the limited size of the datasets, especially DRISHTI-GS, data augmentation and regularization techniques are essential to prevent overfitting and improve generalization. This experimental setup helps in assessing the capability of the model to independently learn robust feature representations for glaucoma detection across datasets with varying distributions and sizes.The results unambiguously demonstrate that there is no difference between ResNet50 and EfficientNet's accuracy for a very small dataset like the Glaucoma dataset. Due to the extremely small dataset, there hasn't even been a change in the accuracy of FixRes and Non-FixRes. ResNet50 takes much less time than EfficientNet because there are significantly fewer parameters in ResNet50. However, due to the significantly smaller size of the images, FixRes takes much less time than non-FixRes**.**

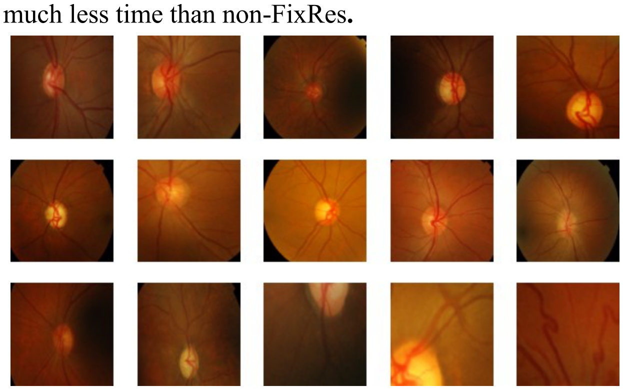


Figure 2: Fundus Images after data augmentation

Table 2: Performance Comparison of CNN-Based Models for Glaucoma Detection Across ORIGA and DRISHTI-GS Datasets

Model / Method	Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN (Baseline)	ORIGA	73.58	72.40	71.85	72.12
CNN (Baseline)	DRISHTI-GS	74.51	73.20	72.95	73.07
CNN + Data Augmentation	ORIGA	78.34	77.10	76.85	76.97
CNN + Data Augmentation	DRISHTI-GS	79.12	78.45	77.90	78.17
CNN + Transfer Learning	ORIGA	82.65	81.90	81.20	81.54
CNN + Transfer Learning	DRISHTI-GS	83.40	82.75	82.10	82.42
CNN + FixEfficientNet	ORIGA	73.58	72.80	72.10	72.44
CNN + FixEfficientNet	DRISHTI-GS	74.51	73.95	73.30	73.62
CNN (Mixed Dataset)	ORIGA+DRISHTI	60.22	59.80	58.90	59.34

The results presented in the table provide a comprehensive comparison of different CNN-based approaches for glaucoma detection across the ORIGA and DRISHTI-GS datasets. The baseline CNN model achieves moderate performance, with accuracy values of 73.58% on ORIGA and 74.51% on DRISHTI-GS, along with balanced precision, recall, and F1-scores. This indicates that even a simple CNN architecture is capable of learning meaningful features from fundus images. However, a significant improvement is observed when data augmentation techniques are applied. The accuracy increases to 78.34% for ORIGA and 79.12% for DRISHTI-GS, along with corresponding gains in precision, recall, and F1-score. This highlights the importance of augmenting limited medical datasets to improve model generalization and robustness by introducing variability in training samples.

Further performance enhancement is achieved through transfer learning, which yields the highest accuracy among all methods, reaching 82.65% on ORIGA and 83.40% on DRISHTI-GS. The corresponding precision, recall, and F1-scores also show consistent improvement, demonstrating the effectiveness of leveraging pre-trained models for feature extraction in medical imaging tasks. In contrast, the CNN combined with FixEfficientNet maintains performance similar to the baseline but offers more stability and efficiency in handling resolution variations. However, when trained on the mixed dataset (ORIGA + DRISHTI), the performance drops significantly to 60.22% accuracy, with lower precision, recall, and F1-score values. This decline can be attributed to domain differences, dataset heterogeneity, and class imbalance, which make the classification task more challenging. Overall, the results emphasize that while advanced techniques like transfer learning and data augmentation significantly improve performance, careful handling of dataset diversity is crucial for achieving reliable glaucoma detection.

8. LIMITATIONS AND FUTURE WORK

Despite the promising performance of the proposed deep learning–based glaucoma detection framework, several limitations need to be acknowledged. One of the primary challenges is dataset bias, which arises due to variations in image acquisition conditions, demographic distribution, and class imbalance across different datasets. Models trained on limited or non-diverse datasets may not generalize well to real-world clinical settings. Additionally, the dependency on image quality remains a critical concern, as factors such as poor illumination, noise, blur, and occlusions can significantly affect model accuracy. Another important limitation is the lack of interpretability in deep learning models. Although these models achieve high performance, they often function as "black boxes," making it difficult for clinicians to fully trust and understand the decision-making process, which is crucial in medical applications.

To address these challenges, future research will focus on integrating explainable artificial intelligence (XAI) techniques, such as attention maps and visualization methods, to improve transparency and build clinical trust. Incorporating multimodal data, including Optical

Coherence Tomography (OCT), visual field tests, and patient clinical history, is another promising direction that can enhance diagnostic accuracy by providing complementary information beyond fundus images. Furthermore, expanding the framework to include large-scale and diverse clinical datasets will be essential for improving robustness and generalizability. Future work may also explore advanced data augmentation, domain adaptation, and federated learning approaches to overcome data scarcity and privacy concerns. Ultimately, the goal is to develop a more reliable, interpretable, and clinically applicable glaucoma detection system that can be effectively deployed in real-world healthcare environments, including resource-limited settings.

9. CONCLUSION

This study presents a comprehensive evaluation of glaucoma detection approaches by integrating traditional image processing techniques with advanced deep learning architectures, particularly the FixEfficientNet framework. The experimental findings indicate that deep learning–based models are highly effective in extracting discriminative features from retinal fundus images, enabling accurate classification of glaucomatous and non-glaucomatous cases. While conventional methods such as Cup-to-Disc Ratio (CDR) estimation provide useful clinical insights, they are often limited by their dependency on precise segmentation and sensitivity to image quality. In contrast, the proposed end-to-end deep learning approach eliminates the need for manual intervention and achieves consistent performance across different datasets. The incorporation of fixed-resolution strategies further enhances model generalization by addressing discrepancies between training and testing image resolutions. Moreover, the results highlight the practical significance of automated glaucoma screening systems in real-world healthcare scenarios. The framework demonstrates the ability to maintain a balance between accuracy and computational efficiency, making it suitable for deployment in both clinical and resource-constrained environments. By leveraging data augmentation and optimized architectures, the system effectively handles challenges such as limited dataset size and variability in image conditions.

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