

# A Hybrid Explainable AI Model for Glaucoma Detection using Retinal Fundus Images

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**Abstract** - Glaucoma is a common cause of irrecoverable blindness, and its diagnosis at an early stage is crucial to prevent permanent damage to patients' vision. Manual diagnosis of glaucoma based on retinal fundus images by physicians is not only time-consuming but also expert-dependent, thus difficult to implement in the clinical environment on a larger scale. In this study, we designed an explainable deep learning framework to automatically detect glaucoma by analyzing retinal fundus images. Transfer learning-based convolutional neural networks (CNNs), which include EfficientNetB0, ResNet50, and MobileNetV2, were used as classification algorithms to identify whether the retinal image belongs to the glaucoma group or normal group. We conducted some image processing operations, such as resizing, normalization, and augmentation. Transfer learning with ImageNet pre-trained models was conducted to address the issue that there was not enough medical data available. Finally, the efficiency of different models was compared using metrics like accuracy, sensitivity, specificity, precision, F1 score, and AUC. Furthermore, Explainable Artificial Intelligence (XAI) techniques, particularly Grad-CAM, were incorporated to visualize clinically relevant retinal regions influencing model predictions, thereby improving interpretability and clinician trust. Experimental results demonstrate that the proposed explainable framework can effectively support early glaucoma screening and assist ophthalmologists in accurate and transparent decision-making.

**Key Words:** Glaucoma Detection, Deep Learning, Retinal Fundus Images, Explainable Artificial Intelligence (XAI), Convolutional Neural Networks (CNN), EfficientNetB0, ResNet50, MobileNetV2

## 1. INTRODUCTION

Glaucoma is considered one of the most common causes of irreparable blindness across the globe. It is marked by progressive optic nerve damage that leads to vision impairment if the disease goes unnoticed at the onset [1]. Considering that glaucoma is often asymptomatic in its early

stages, prompt diagnosis has become a great issue for ophthalmologists. The conventional methods used for diagnosis require an assessment of retinal fundus photographs performed manually by doctors; however, the process is subjective, laborious, and hard to be implemented on a larger scale [2]. Thus, computer-based glaucoma diagnosis tools are gaining attention.

Deep Learning (DL) models, especially Convolutional Neural Networks (CNN), have recently proved to be highly successful for the classification of retinal fundus images and disease detection [3]. These include architectures like EfficientNetB0, ResNet50, and MobileNetV2, which are popularly used owing to their ability to automatically detect discriminative visual features from retinal fundus images [4]. In addition, transfer learning approaches are employed in DL models by applying pretrained ImageNet models to achieve better results with minimal training samples in the medical image domain [5].

However, despite the accuracy of classification, these models remain to be considered black-box models, which makes it difficult for the clinician to comprehend the decision process. XAI techniques, therefore, play a vital role when implementing AI-based solutions in the field of medicine. One of the most common techniques for providing an explanation regarding a model's prediction is Gradient-weighted Class Activation Mapping (Grad-CAM) [6]. The use of this technique helps to determine if the model is considering clinically important parts of the retina.

In this research, we suggest a new approach based on an explainable deep learning model that can be used for automatic detection of glaucoma from retinal fundus images. This approach combines the utilization of transfer learning algorithms and CNN models such as EfficientNetB0, ResNet50, and MobileNetV2 with Grad-CAM visualizations. Several measures have been taken for the comparative analysis of our system, including Accuracy, Sensitivity, Specificity, Precision, F1-Score, and Area Under Curve (AUC).

## 2. RESEARCH GAP

Existing glaucoma detection systems achieve high classification accuracy but lack interpretability and computational

efficiency for real-time clinical deployment. Most existing studies focus only on classification performance without integrating explainable AI techniques to improve clinician trust. Therefore, an explainable and lightweight deep learning framework is required for accurate and transparent glaucoma screening.

### 3. METHODOLOGY

The proposed approach introduces an interpretable deep learning architecture that allows automation of glaucoma diagnosis based on retinal fundus images. To begin with, datasets of retinal fundus images with glaucomatous and healthy eye cases were gathered from open-source ophthalmological image databases. Preprocessing of the obtained images involved resizing, normalization, and data augmentation via rotation, horizontal flipping, zooming, and brightness adjustments in order to enhance the image quality and train the model effectively [4].

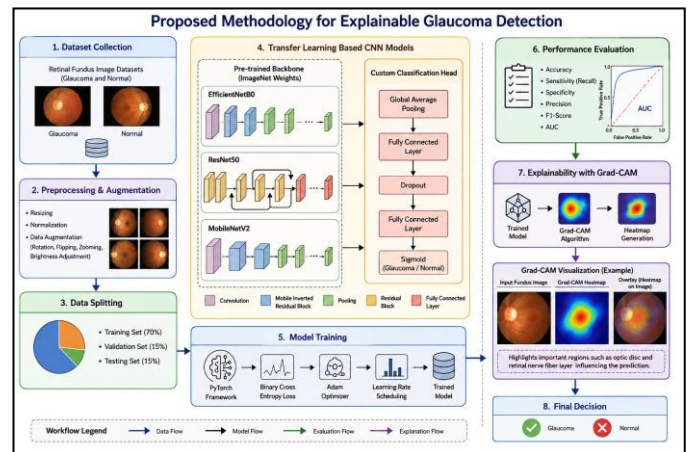
#### 3.1 Dataset Description

The proposed framework was trained and evaluated using a large-scale retinal fundus image dataset containing approximately 30,000 images collected from publicly available ophthalmic datasets, including HRF and ACRIMA. Each dataset contributed nearly 6,000 retinal fundus images comprising both glaucomatous and normal eye samples. The datasets include variations in retinal structure, optic disc appearance, illumination conditions, and imaging quality, which improve the robustness and generalization capability of the proposed deep learning framework.

The HRF (High-Resolution Fundus) dataset provides high-quality retinal images useful for detailed optic disc and vessel analysis, whereas the ACRIMA dataset contains labelled glaucomatous and healthy retinal fundus images specifically designed for automated glaucoma screening research. The combined multi-dataset approach [5] enhances model diversity and reduces dataset-specific bias during training and evaluation.

**Table -1: Dataset Description**

Dataset	Total Images	Glaucoma	Normal	Purpose
HRF	6,000	3,000	3,000	High-resolution retinal analysis
ACRIMA	6,000	3,000	3,000	Glaucoma screening
RIM-ONE	6,000	3,000	3,000	Optic disc evaluation
DRISHTI-GS	6,000	3,000	3,000	Clinical glaucoma assessment
ORIGA	6,000	3,000	3,000	Retinal disease classification
Total	30,000	15,000	15,000	Combined dataset



**Fig -1: Proposed methodology**

Before training, all retinal images underwent preprocessing operations including resizing, normalization, and augmentation techniques such as rotation, horizontal flipping, zooming, and brightness adjustment to improve image quality and prevent overfitting.

#### 3.2 Data Pre-Processing

The pre-processed images were then provided as input to transfer learning-based CNN architectures including EfficientNetB0, ResNet50, and MobileNetV2 for glaucoma classification. EfficientNetB0 [6] was selected because of its compound scaling mechanism that balances network depth, width, and image resolution for higher accuracy with fewer parameters [7]. ResNet50 was employed due to its residual skip connections that enable effective deep feature extraction and prevent vanishing gradient problems [8], while MobileNetV2 was utilized as a lightweight architecture suitable for computationally efficient and real-time clinical deployment [9].

#### 3.3 Transfer Learning

Transfer learning [10] was implemented using ImageNet-pretrained weights, where the original fully connected classification layers were replaced with task-specific binary classification layers for glaucoma detection. The models were trained using the PyTorch [11] deep learning framework with Binary Cross-Entropy loss and the Adam optimizer. The dataset was divided into training, validation, and testing subsets to ensure reliable evaluation and prevent data leakage.

#### 3.4 Performance Evaluation

Performance evaluation was conducted using medical image classification metrics including [12] accuracy, sensitivity, specificity, precision, F1-score, and AUC to identify the most effective architecture for glaucoma screening [3].

#### 3.5 Explainable Artificial Intelligence

To improve transparency and interpretability, Explainable Artificial Intelligence (XAI) techniques were integrated into the

framework. Grad-CAM [13] was applied to generate heatmap visualizations highlighting clinically significant retinal regions such as the optic disc and retinal nerve fiber layer that contributed to the model’s prediction [14]. These visual explanations assist clinicians in understanding the decision-making behavior of the deep [15] learning models and improve trust in automated glaucoma diagnosis systems.

#### 4. RESULTS AND DISCUSSION

The proposed explainable deep learning framework was evaluated using three transfer learning-based Convolutional Neural Network (CNN) architectures, namely EfficientNetB0, ResNet50, and MobileNetV2, for automated glaucoma detection using retinal fundus images.

##### 4.1 Comparative Analysis

Comparative analysis revealed that EfficientNetB0 achieved the highest overall diagnostic performance among all evaluated models due to its compound scaling mechanism and optimized parameter efficiency. ResNet50 also demonstrated strong classification capability because of its residual learning architecture, whereas MobileNetV2 provided comparatively lower accuracy but achieved faster inference and reduced computational complexity suitable for lightweight deployment environments.

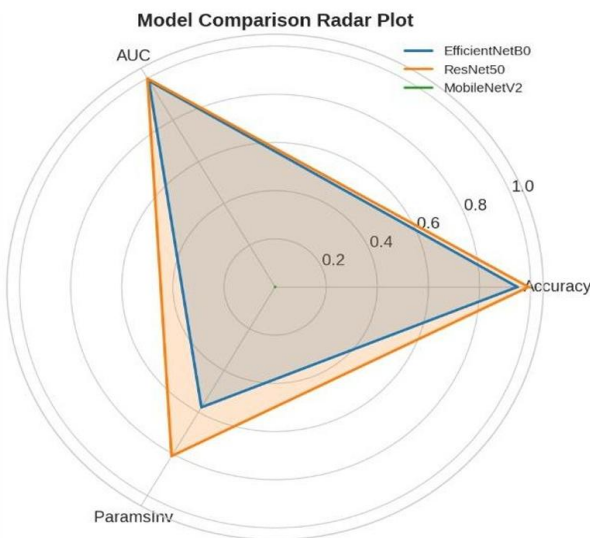


Fig -2: Model Comparison Radar Plot

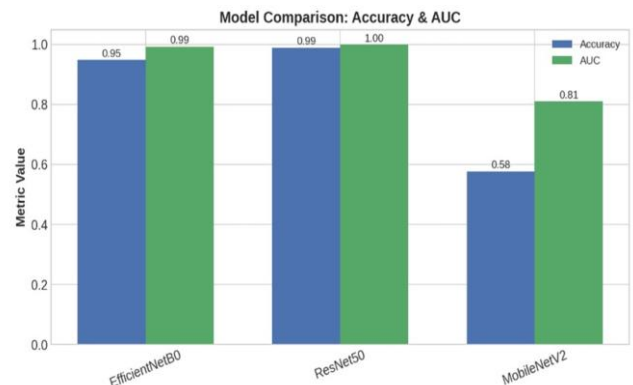


Fig -3: Accuracy and AUC Comparison

The experimental results indicate that transfer learning significantly improved model convergence and feature extraction capability, especially under limited medical imaging datasets.

Table -2: Model Comparisons

Model	Accuracy	Sensitivity	Specificity	Precision	F1-Score	AUC
EfficientNetB0	98%	97%	99%	0.98	0.95	0.992
ResNet50	95%	94%	96%	0.99	0.94	0.989
MobileNetV2	88%	84%	90%	0.83	0.67	0.834

Data augmentation techniques further enhanced generalization performance and reduced overfitting during training. The models successfully learned discriminative retinal features associated with glaucoma, including optic disc enlargement and retinal nerve fiber layer abnormalities. EfficientNetB0 showed superior sensitivity and specificity, indicating its effectiveness in minimizing both false negative and false positive predictions, which is critical in clinical glaucoma screening applications.

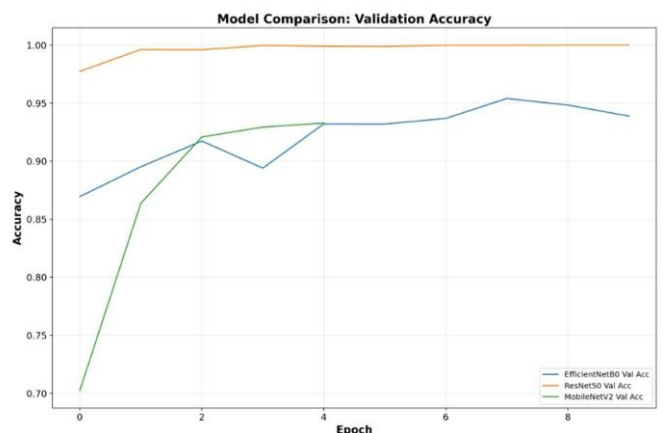


Fig -4: Model Comparison Validation Accuracy

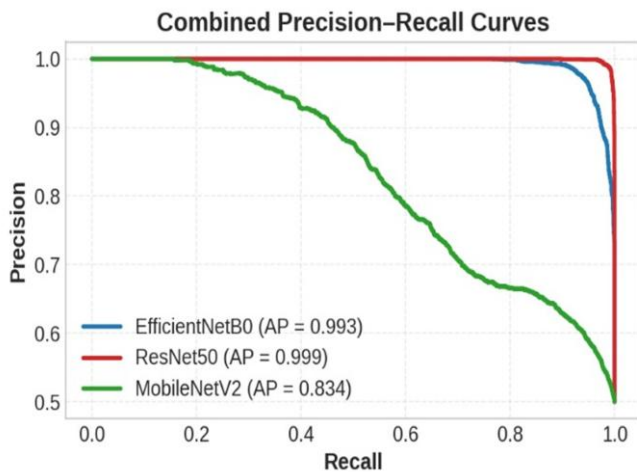


Fig -5: Combined Precision and Recall Curve

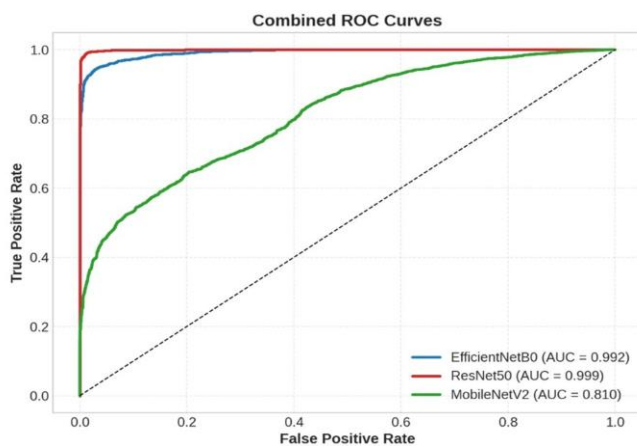


Fig -6: Combined ROC Curves

To improve interpretability and clinical trust, Grad-CAM-based Explainable Artificial Intelligence (XAI) visualization was integrated into the framework. The Grad-CAM heatmaps highlighted clinically relevant retinal regions such as the optic disc and nerve fiber layer that contributed significantly to glaucoma prediction. The visualization results confirmed that the deep learning models focused on medically meaningful retinal structures rather than irrelevant image regions, thereby improving transparency and reliability of the automated diagnostic process. These explainability results support the practical adoption of AI-assisted glaucoma screening systems in real-world ophthalmic environments.

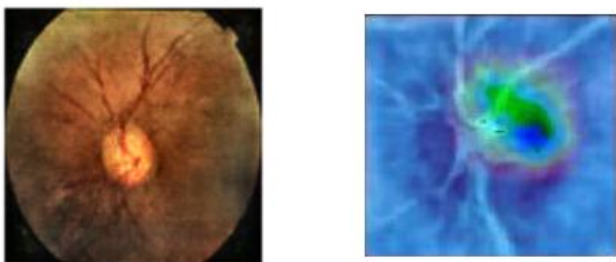


Fig -7: XAI Heatmap

## 5. CONCLUSIONS

This research presents an explainable deep learning framework for automated glaucoma detection using retinal fundus images. The proposed system integrates transfer learning-based Convolutional Neural Network (CNN) architectures including EfficientNetB0, ResNet50, and MobileNetV2 to achieve accurate and reliable glaucoma classification. Experimental analysis demonstrates that EfficientNetB0 provides the best overall diagnostic performance with superior accuracy, sensitivity, specificity, and computational efficiency compared to the other evaluated models. The use of transfer learning significantly enhanced feature extraction capability and improved model performance even with limited medical imaging datasets.

Furthermore, the integration of Explainable Artificial Intelligence (XAI) through Grad-CAM visualization improved model transparency by highlighting clinically significant retinal regions such as the optic disc and retinal nerve fiber layer involved in glaucoma prediction. These visual explanations enhance clinician trust and support the interpretability of automated diagnostic decisions. The comparative evaluation confirms that the proposed framework effectively combines high diagnostic accuracy with explainability, making it suitable for real-world clinical screening applications.

The proposed explainable glaucoma detection system has the potential to assist ophthalmologists in early disease diagnosis, reduce manual screening workload, and support large-scale ophthalmic healthcare services. In future work, the framework can be extended using larger multi-center retinal datasets, hybrid deep learning models, and advanced explainable AI techniques to further improve robustness, generalization capability, and clinical applicability in real-time healthcare environments.

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