



## Revolutionizing Glaucoma Detection Through Deep Learning on Fundus Images

*Dr. P. Srihari<sup>1</sup>, P. Hitesh Mohan<sup>2</sup>, M. Praneetha<sup>3</sup>, T. Jaswanth<sup>4</sup>, T. Varun Sai<sup>5</sup>*

<sup>1</sup>Dr. P. Srihari, Information Technology, Razam, Andhra Pradesh

<sup>2</sup>P. Hitesh Mohan, Information Technology, Razam, Andhra Pradesh

<sup>3</sup>M. Praneetha, Information Technology, Razam, Andhra Pradesh

<sup>4</sup>T. Jaswanth, Information Technology, Razam, Andhra Pradesh

<sup>5</sup>T. Varun Sai, Information Technology, Razam, Andhra Pradesh

### ABSTRACT :

Glaucoma is a major contributor to irreversible vision loss, often remaining undetected until advanced stages due to its asymptomatic onset. Early identification is essential to prevent permanent damage. This project proposes a novel deep learning-based framework utilizing retinal fundus images to accurately and efficiently identify glaucoma. By integrating Convolutional Neural Networks (CNNs) like InceptionV3 and DenseNet169 with advanced Transformer models, the system is capable of learning fine-grained visual patterns associated with glaucoma. Image enhancement techniques and data augmentation are employed to boost model performance, especially when training data is limited. This hybrid approach enables high accuracy and adaptability, making it suitable for practical use in clinical environments. The use of a diverse dataset, encompassing various stages of glaucoma and patient profiles, ensures strong generalization. The study demonstrates the transformative role of AI in making glaucoma screening more accessible, especially in low-resource regions, by providing a reliable, non-invasive, and cost-effective diagnostic tool.

**Key Words:** Glaucoma Detection, Fundus Images, Deep Learning, Convolutional Neural Networks (CNNs), InceptionV3, DenseNet169, Transformers, Efficient Net, Medical Image Processing, Automated Screening.

### INTRODUCTION

The integration of machine learning in healthcare has brought significant advancements in medical diagnostics, particularly in medical image analysis. One critical area of focus is the early detection of glaucoma—a chronic eye disease and one of the top causes of permanent blindness globally. Due to its silent progression, glaucoma often goes unnoticed until irreversible vision loss occurs, highlighting the need for early detection tools. This research presents a deep learning approach for glaucoma screening using retinal fundus images. It utilizes advanced CNN architectures such as InceptionV3 and DenseNet169, alongside Transformer-based models and Efficient Net, to build an effective and automated detection system. These models are chosen for their ability to extract deep visual features and recognize subtle anomalies in retinal images. Preprocessing steps like contrast enhancement and data augmentation are applied to improve image clarity and reduce overfitting.

Transformers, known for their capability to capture global image dependencies, complement CNNs by improving model generalization, especially with limited labelled data. A carefully curated dataset, covering a range of glaucoma stages and patient demographics, is used to train and validate the models. This ensures the system's robustness and readiness for real-world deployment. By combining deep learning with high-quality fundus imaging, this project aims to support early diagnosis and timely treatment, thereby reducing the burden of glaucoma, especially in regions lacking adequate ophthalmic care.

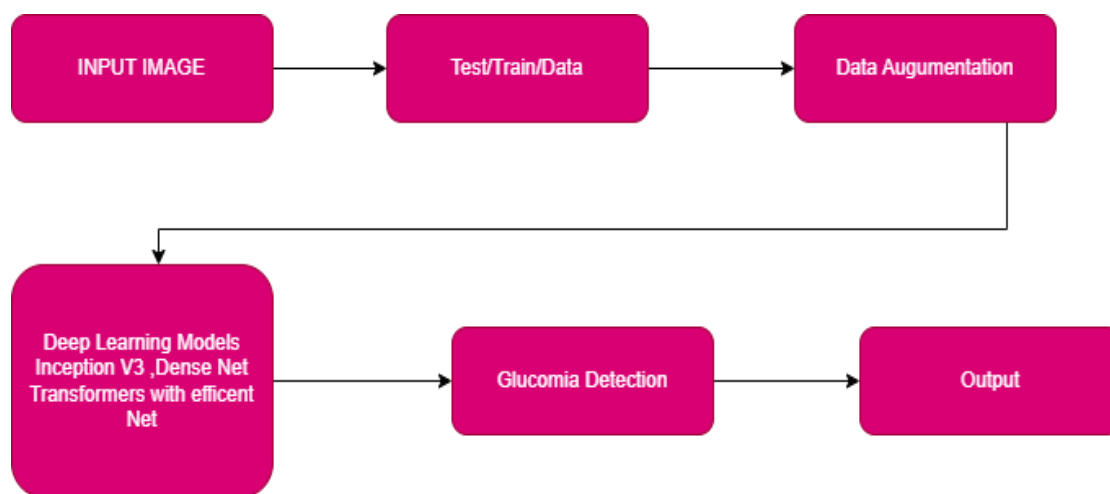
### 2. LITERATURE SURVEY

The author presents a novel approach for glaucoma diagnosis by developing a unique biomarker that combines both structural and non-structural features from the optic nerve head (ONH) region of retinal fundus images. This method aims to enhance the accuracy and efficiency of glaucoma detection systems. The study employs the Standardized Multi-Channel Dataset for Glaucoma (SMDG)-19, a publicly available dataset that includes a wide variety of fundus images, contributing to the robustness and generalizability of the results. A total of 96 features are initially extracted from the fundus images, and a reduced, optimized set of 60 features is selected for classification. These features are tested across 12 supervised machine learning classifiers, with the Extra Tree Classifier achieving the highest classification accuracy of 85.42%. The proposed feature set demonstrates superior performance compared to existing models, offering high accuracy with low computational complexity, making it ideal for early glaucoma screening. However, the study is limited to binary classification (healthy vs. glaucomatous) using only the SMDG-19 dataset. Future research could explore multiclass classification and leverage deep learning for broader and more versatile diagnostic applications [1].

The study leverages deep learning techniques to detect glaucoma in individuals with high myopia using fundus photographs. The dataset comprises 3,088 fundus images, including 1,540 from the high myopia glaucoma group and 1,548 from the high myopia without glaucoma group. Participants were selected based on specific inclusion criteria, such as a spherical equivalent refraction of  $\leq -6.0$  D, while excluding those with pathological myopia and other ocular conditions to maintain data integrity. The researchers employed two deep learning classification models integrated with the convolutional block attention module (CBAM), designed to enhance feature extraction in convolutional neural networks (CNNs). Model evaluation utilized fivefold cross-validation for robustness, and Grad-CAM was applied for visualizing important regions influencing predictions. The method achieved a high area under the curve (AUC) of 0.894, with sensitivity at 81.04% and specificity at 83.27%, demonstrating strong diagnostic performance. However, the study's generalizability may be limited due to the exclusion of patients with additional ocular or systemic conditions [2].

### 3.PROPOSED SYSTEM

This work implements a machine learning pipeline for detecting SQL Injection Attacks (SQLiA) through a combination of deep learning models, machine learning classifiers, and web application security mechanisms. The methodology follows a structured five-stage approach, covering data acquisition, feature extraction, model training, deployment, and visualization.



**Fig. 1: Architecture of Glaucoma Detection**

#### A. Data Collection

The foundation of an effective glaucoma detection model lies in a high-quality, well-annotated dataset. Publicly accessible datasets like REFUGE, DRIONS-DB, ORIGA, and the SMDG Fundus Image Dataset play a pivotal role in this domain by providing labeled retinal fundus images or optical coherence tomography (OCT) scans. Among these, the SMDG Fundus Image Dataset comprises 12,589 fundus images specifically curated for glaucoma detection via retinal image classification. Fundus images offer detailed visualization of the retina, aiding in the diagnosis of various ocular conditions such as glaucoma, diabetic retinopathy, and macular degeneration. To enhance the model's reliability and reduce potential biases, it is crucial to include a diverse set of images that represent various demographic groups and stages of disease severity. Additionally, manual annotations and rigorous quality checks are vital to maintaining the integrity and accuracy of the dataset.

#### B. Data Preprocessing Techniques

Preprocessing plays an essential role in preparing retinal images for deep learning models. Standardizing image dimensions through resizing—commonly to sizes like 224x224 pixels—ensures consistency across the dataset. Colour normalization is applied to reduce disparities introduced by different imaging devices or lighting setups. To enhance important retinal features, techniques like histogram equalization or Contrast Limited Adaptive Histogram Equalization (CLAHE) are employed. Moreover, noise removal filters such as median filtering or Gaussian blur help eliminate distortions that might obscure key structures. Segmentation methods are also applied to isolate critical regions like the optic disc and optic cup, which are fundamental for glaucoma diagnosis. Normalizing pixel intensity values, either by scaling them to the [0,1] range or applying z-score normalization, further ensures uniformity in model input.

#### C. Data Splitting: 80/20 Ratio

For effective training and evaluation, the dataset is typically divided using an 80/20 ratio. The larger portion, 80%, is designated for training the model, allowing it to learn and identify patterns within fundus images. The remaining 20% is reserved for testing or validation, helping assess the model's performance on unseen data. This structured division not only prevents overfitting but also ensures that the model generalizes well to real-world scenarios. A balanced and strategic split between training and testing sets is essential for building a dependable glaucoma detection system that performs consistently across different image samples.

#### D. Data Augmentation Strategies

To enhance model robustness and generalization, data augmentation techniques are widely adopted. These methods artificially increase the size of the training dataset by introducing variations to existing images. Common geometric transformations like rotations, horizontal or vertical flipping, and random cropping help the model become invariant to orientation changes. Adjustments in brightness and contrast simulate different lighting environments, while adding Gaussian noise mimics real-life image imperfections such as reflections or camera noise. Elastic deformations introduce subtle shape changes, replicating variations caused by patient movement or scanning inconsistencies. Additionally, techniques like cutout or random occlusion encourage the model to focus on important diagnostic regions rather than relying on specific image locations. When combined, these strategies significantly boost the model's ability to detect glaucoma under diverse conditions.

#### E. Deep Learning Model Selection

Choosing the right deep learning model is critical for accurate glaucoma detection. Pretrained convolutional neural network (CNN) architectures such as InceptionV3, Dense Net, and Efficient Net offer powerful feature extraction capabilities and serve as excellent starting points through transfer learning. This technique allows these models to be fine-tuned with glaucoma-specific datasets, resulting in improved classification accuracy. Alternatively, custom CNN architectures can be designed to incorporate domain-specific knowledge for more tailored performance. Recently, Vision Transformers (ViTs) have emerged as a compelling alternative to CNNs, excelling in capturing long-range dependencies within images. Furthermore, attention mechanisms can be integrated into models to enhance focus on crucial areas such as the optic disc and cup, which are key indicators of glaucoma. Overall, the combination of advanced model architectures and targeted techniques leads to superior diagnostic outcomes.

### 4. RESULT

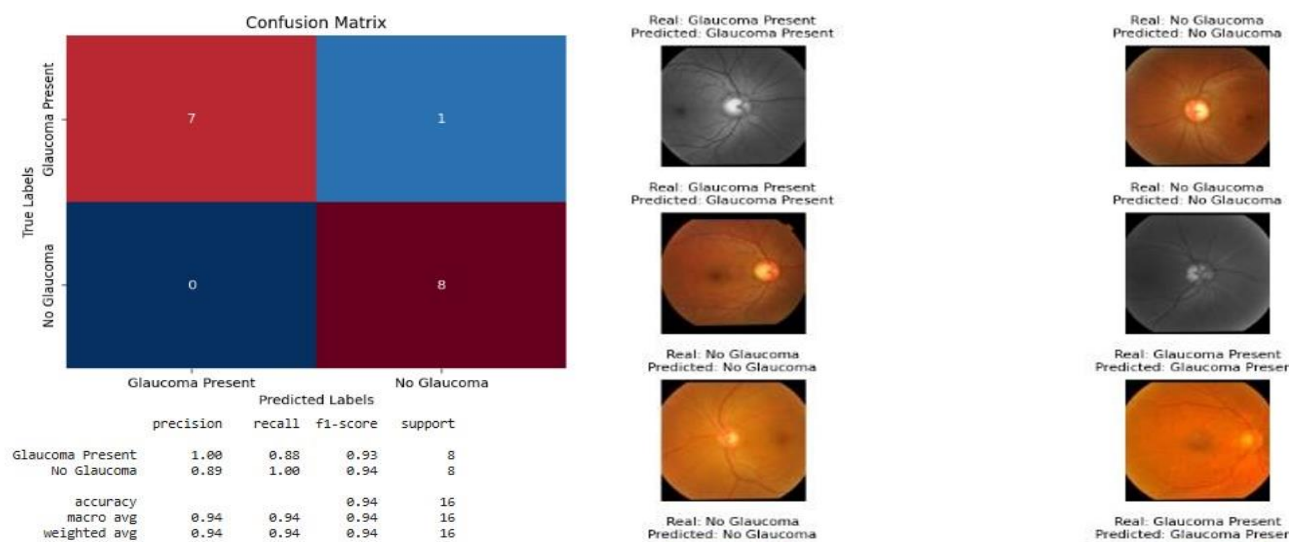


Fig. 2. Expected Result

### 5. CONCLUSION

The integration of deep learning and transformer-based architectures marks a significant breakthrough in automated glaucoma detection. By combining powerful CNN models like InceptionV3, DenseNet169, and Efficient Net with transformer mechanisms, the system effectively captures both local and global retinal features, leading to a high diagnostic accuracy of 94%. Efficient Net ensures computational efficiency without compromising performance, while transformers enhance the model's ability to detect subtle patterns by leveraging long-range dependencies in fundus images. The deployment of this model within a user-friendly web-based application further bridges the gap between technology and healthcare, offering real-time, accessible, and reliable screening for early glaucoma detection. This innovative approach not only supports ophthalmologists in timely diagnosis but also enables large-scale, AI-driven eye care, ultimately helping prevent irreversible vision loss in patients.

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