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Web-Based Hybrid Deep Learning and Machine Learning System for Automated Glaucoma Detection from fundus images

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ABSTRACT: Glaucoma is one of the leading causes of permanent vision loss worldwide, and early detection plays a critical role in preventing severe damage. However, traditional screening methods require expert analysis of retinal fundus images, To address this proposed system presents an automated glaucoma detection system that combines deep learning and machine learning techniques within a practical web-based framework. The proposed system begins by validating whether the uploaded image is a proper retinal fundus image using structural and intensity-based checks. Once validated, the image is resized and preprocessed then passed into a pre-trained EfficientNetB0 model to extract meaningful visual features. These features are further refined using scaling and Principal Component Analysis (PCA). For classification, a hybrid approach is adopted by combining Support Vector Machine (SVM) and Random Forest classifiers. The final prediction is obtained by averaging the probability outputs of both models, which improves stability and reduces misclassification. In addition to this, the Cup-to-Disc Ratio (CDR) is estimated. The system was evaluated using a EyePACS-AIROGS-light-V2 fundus image dataset and achieved an accuracy of 84.5% along with an AUC score of 0.92, indicating reliable performance. The integration of this model into a web application enables real-time screening and report generation, making it a practical tool for early glaucoma detection.

KEYWORDS: Glaucoma Detection, Fundus Image Analysis, EfficientNetB0, Machine Learning, Support Vector Machine, Random Forest, Hybrid Classification, Principal Component Analysis, Cup-to-Disc Ratio (CDR), Medical Image Processing.

I. INTRODUCTION

Glaucoma is a progressive eye disorder that damages the optic nerve and is one of the leading causes of irreversible blindness across the world. The condition develops slowly and often shows no noticeable symptoms in its early stages, which makes timely diagnosis difficult. Because of this, glaucoma is commonly referred to as the “silent thief of sight.” According to global health reports, the number of people affected by glaucoma is steadily increasing, highlighting the importance of early detection and continuous monitoring to prevent permanent vision loss [7].

In clinical practice, glaucoma is diagnosed using several methods, including intraocular pressure measurement, visual field analysis, and retinal fundus examination. Among these, fundus imaging is widely used because it provides a clear view of the optic disc and surrounding retinal structures. One of the key indicators used by ophthalmologists is the cup-to-disc ratio (CDR), which represents the relationship between the optic cup and optic disc. An increase in this ratio is often associated with glaucoma progression. However, accurate estimation of CDR typically requires manual inspection, which can be time-consuming and dependent on the expertise of the clinician [5].

With the advancement of artificial intelligence, automated analysis of retinal images has become an active area of research. Deep learning techniques, especially Convolutional Neural Networks (CNNs), have demonstrated strong capability in extracting complex visual features from medical images. These models have been successfully applied to various ophthalmic conditions, including glaucoma detection, and have shown improved performance compared to traditional methods [1], [11]. Many existing systems rely on segmentation of the optic disc and optic cup regions before classification. While effective, such approaches often involve multiple processing stages and may increase computational complexity [6]. Many existing systems do not include input validation, which may lead to incorrect predictions when non-retinal or poor-quality images are provided."

To address these challenges, machine learning algorithms such as Support Vector Machine (SVM) and Random Forest have been widely used for classification tasks due to their efficiency and ability to handle high-dimensional feature spaces [12], [13]. However, using a single classifier may not always provide consistent results across different datasets. Combining multiple models through a hybrid approach can improve overall prediction performance and reduce the impact of individual model limitations.

In this work, a glaucoma detection system is developed by integrating deep learning-based feature extraction with a hybrid machine learning classification framework. EfficientNetB0 is employed to extract meaningful features from retinal fundus images, followed by Principal Component Analysis (PCA) to reduce feature dimensionality and improve processing efficiency. A hybrid classification strategy combining SVM and Random Forest is then used to generate the final prediction.

In addition, a retinal image validation mechanism is incorporated to ensure that only valid fundus images are processed by the system. A Cup-to-Disc Ratio (CDR) estimation is also included as a supporting parameter to assist in clinical interpretation. The entire system is implemented as a web-based application, allowing users to upload images, perform automated analysis, and generate diagnostic reports in real time.The primary contributions of this work are as followrs :

- Development of a hybrid glaucoma detection framework combining EfficientNetB0, SVM, and Random Forest
- Implementation of a retinal image validation technique to improve input reliability
- Inclusion of CDR-based analysis as a supporting diagnostic factor .
- Deployment of a web-based system for real-time glaucoma screening and report generation

II. RELATED WORK

The growing integration of artificial intelligence and deep learning into ophthalmology has accelerated research into automated glaucoma detection from fundus images. A considerable body of work has emerged targeting the identification of structural abnormalities in the optic disc and optic cup as key diagnostic indicators.

Cheng et al. [5] proposed a superpixel-based method for segmenting the optic disc and optic cup to compute the cup-to-disc ratio (CDR) for glaucoma detection. Their approach showed promising results; however, it required precise segmentation, which increases computational complexity and processing time. Similarly, Fu et al. [6] introduced a deep learning framework for joint optic disc and cup segmentation using multi-label networks, achieving improved segmentation accuracy but with higher model complexity.

Raghavendra et al. [7] developed a deep learning-based glaucoma detection system using convolutional neural networks (CNNs), which demonstrated good classification performance. Mahapatra et al. [8] also explored CNN-based approaches for automated glaucoma detection, highlighting the effectiveness of deep feature extraction in medical image analysis. However, most CNN-based models rely heavily on large datasets and computational resources.

To improve detection performance, ensemble learning methods have been widely used. Fu et al. [9] proposed a disc-aware ensemble network that combines multiple models to enhance glaucoma screening accuracy. Chen et al. [10] presented an automatic feature learning approach using deep learning techniques, which reduced the need for manual feature engineering. Li et al. [11] further demonstrated the effectiveness of deep learning systems in clinical settings for detecting glaucomatous optic neuropathy.

Apart from deep learning methods, traditional machine learning algorithms such as Support Vector Machine (SVM) and Random Forest have been applied for classification tasks. Cortes and Vapnik [12] introduced SVM as a powerful classifier for high-dimensional data, while Breiman [13] proposed Random Forest as an ensemble learning method that improves prediction stability. These models are computationally efficient and can perform well with properly extracted features.

Despite these advancements, many existing approaches either rely on complex segmentation techniques or use single-model classification, which may not provide consistent performance across different datasets. In addition, most systems do not include mechanisms to validate input images, which can lead to incorrect predictions when non-retinal images are processed.

To address these limitations, the proposed work combines deep learning-based feature extraction with a hybrid machine learning approach for glaucoma detection. By integrating EfficientNetB0, SVM, and Random Forest, along with retinal validation and CDR-based support, the system aims to provide a more efficient and reliable solution for real-time glaucoma screening.

Author	Method	Description	Limitation
Cheng et al. [5]	Superpixel Segmentation	Computes CDR using optic disc and cup segmentation	Requires precise segmentation and high computation
Fu et al. [6]	Multi-label CNN	Deep learning-based joint segmentation of optic disc and cup	Complex model and high training cost
Raghavendra et al. [7]	CNN Classification	Uses deep features for glaucoma classification	Requires large dataset
Proposed Method	Hybrid ML + CNN	EfficientNet feature extraction with SVM and RF classification	Reduced complexity with improved stability

Table. 2.1 Comparison Table

III. PROPOSED SYSTEM

The proposed system is designed to automatically detect glaucoma from retinal fundus images using a combination of deep learning and machine learning techniques. The system follows a structured pipeline that includes retinal image validation, preprocessing, feature extraction using EfficientNetB0, dimensionality reduction using Principal Component Analysis (PCA), and classification using a hybrid model consisting of Support Vector Machine (SVM) and Random Forest. In addition, the Cup-to-Disc Ratio (CDR) is computed as a supporting clinical parameter. The final output of the system provides the predicted class along with confidence and CDR value, ensuring reliable and efficient glaucoma detection.

A. System Overview

The proposed system is designed as a structured pipeline to perform automated glaucoma detection from retinal fundus images. The overall workflow of the system is illustrated in Fig. 3.1. The process begins with the input of a retinal image, which is first subjected to a validation stage to ensure that it is a valid fundus image suitable for analysis. This step helps in avoiding incorrect predictions caused by irrelevant or low-quality images.

After validation, the image undergoes preprocessing, where it is resized to a fixed dimension, converted into the appropriate color format, and normalized. These operations standardize the input data and prepare it for feature extraction. The preprocessed image is then passed through the EfficientNetB0 model, which extracts deep features representing important structural patterns in the retina.

The extracted features are further processed using feature scaling and Principal Component Analysis (PCA) to reduce dimensionality and improve computational efficiency. The reduced feature vector is then provided to two classifiers,

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Support Vector Machine (SVM) and Random Forest, which independently generate probability scores for classification. These outputs are combined using a hybrid approach to obtain the final prediction.

In addition, the Cup-to-Disc Ratio (CDR) is calculated as a clinical parameter to support the decision-making process. The final output of the system includes the predicted class label (glaucoma or normal), along with the confidence score and CDR value. This integrated workflow ensures accurate and reliable glaucoma detection.

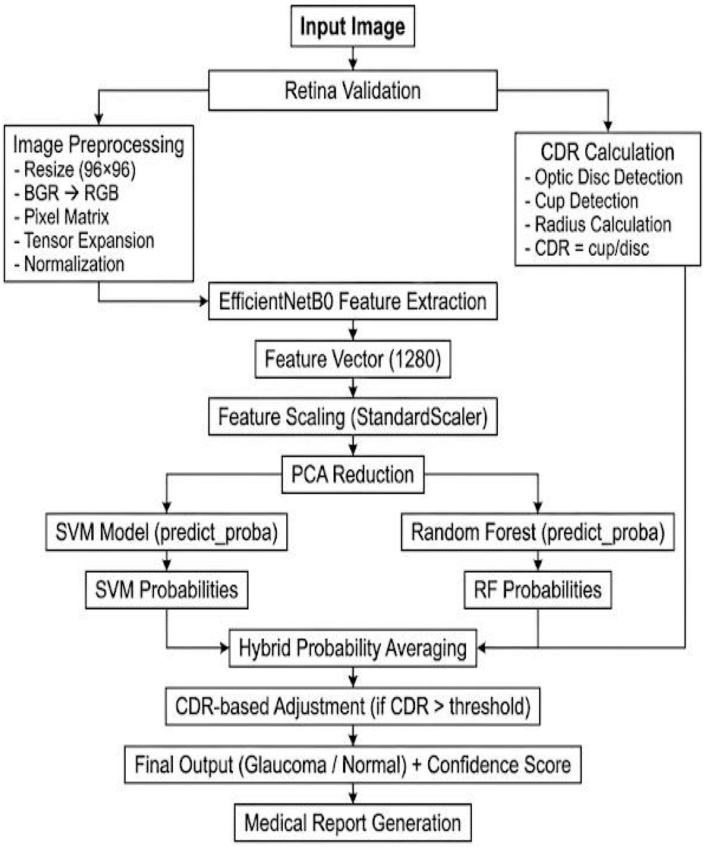

Fig. 3.1 Block Diagram of Proposed System.

B. Retina Validation

Before processing, the system checks whether the uploaded image is a valid retinal fundus image. This is important because wrong or unclear images can lead to incorrect predictions.The validation is done using a few simple checks. First, the image resolution is verified to make sure it is not too small. Then, the color distribution is checked, where retinal images usually show higher intensity in the red channel compared to others. The brightness pattern is also analyzed by comparing the center and border regions, since the center of a fundus image is generally brighter. Finally, the system tries to detect the optic disc using circular detection. If these conditions are satisfied, the image is considered valid and passed to the next stage.

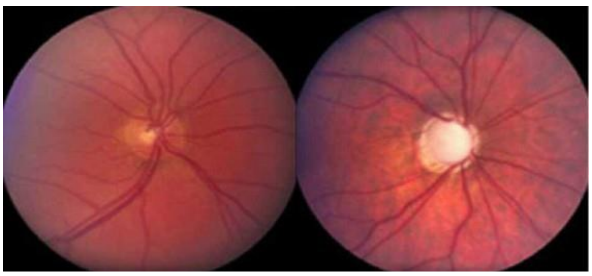

Fig. 3.2 Fundus images for Healthy(Left) and Glaucomatous eye(Right)

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C. Image Preprocessing

After validation, the input image is preprocessed to ensure that it is consistent and suitable for further analysis. Since images can vary in size, the first step is to resize the image to a fixed dimension (96×96). This helps in maintaining uniformity and allows the model to process all images in the same format. The image is then converted from BGR to RGB format, as deep learning models expect images in RGB. After this, the image is represented in the form of a matrix where each pixel contains three values corresponding to red, green, and blue channels. This matrix representation allows the image to be processed numerically by the model.

$$I \in R^{(H \times W \times 3)}$$

Eqn. 3.1

Next, the image is expanded into a tensor by adding an extra dimension. This step is required because deep learning models expect input in batch format. Finally, normalization is applied using EfficientNet preprocessing, which adjusts the pixel values based on the model's expectations. These preprocessing steps ensure that the image is properly prepared for feature extraction.

D.Feature Extraction

EfficientNetB0 is a convolutional neural network model designed for image feature extraction with high efficiency and accuracy. Which uses a balanced scaling approach to improve performance while keeping the number of parameters low. This makes it suitable for medical image analysis where both accuracy and computational efficiency are important.

In this work, EfficientNetB0 is used as a feature extractor rather than a classifier. The final classification layer of the model is removed, and the network is used to extract meaningful features from the retinal fundus image. This approach helps in capturing important visual patterns related to glaucoma without performing direct classification.The preprocessed image is passed through the model, where multiple convolutional layers analyze the image at different levels. The initial layers detect basic features such as edges and color variations, shapes, textures while deeper layers capture complex patterns such as changes in the optic disc and their thickness and surrounding regions. These learned features are important for distinguishing between normal and glaucomatous eyes. In this work EfficientNet learns:

- Optic disc boundary
- Cup enlargement
- Brightness variations
- Blood vessel patterns
- Texture changes in retina

The output of this stage is a feature vector that represents the image in a numerical form. It can be expressed as:

$$F = [f_1, f_2, f_3, \ldots, f_n]$$

Eqn. 3.2

where each value corresponds to a learned feature, and n denotes the number of extracted features. These features are then used as input for further processing and classification. In this work the feature vector size is approximately 1280.

E. Feature Scaling and Dimensionality Reduction

After feature extraction, the obtained feature vector contains a large number of values, and these values may vary in scale. To ensure that all features contribute equally during classification, feature scaling is applied.In this work, StandardScaler is used to normalize the feature values. It transforms the features by subtracting the mean and dividing by the standard deviation. This helps in bringing all feature values to a similar range, which improves the performance of machine learning models such as SVM.

The scaling process can be expressed as:

$$X' = (X - \mu) / \sigma$$

Eqn. 3.3

where μ represents the mean and σ represents the standard deviation of the feature values.

After scaling, Principal Component Analysis (PCA) is applied to reduce the dimensionality of the feature vector. Since the extracted features are high-dimensional, PCA helps in reducing the number of features while preserving the most important information. It transforms the original features into a new set of components that capture maximum variance in the data. The transformation can be represented as:

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$$Z = XW$$

Eqn. 3.4

where X is the input feature matrix, W is the matrix of principal components, and Z is the transformed feature vector.This process reduces computational complexity and improves the efficiency of the classification stage without significantly affecting accuracy. And this the correct form for the classifications.

F. Hybrid Classification Model

After feature scaling and dimensionality reduction, the processed feature vector is used as input for classification. In this work, a hybrid classification approach is adopted by combining Support Vector Machine (SVM) and Random Forest (RF) models.

Support Vector Machine (SVM) is a supervised learning algorithm that classifies data by finding an optimal boundary that separates different classes. In this system, the input feature vector is mapped into a high-dimensional space, where SVM determines the best decision boundary that distinguishes between normal and glaucomatous images. The decision function of SVM is given by:

$$f(x) = w \cdot x + b$$

Eqn. 3.5

where x represents the feature vector, w is the weight vector, and b is the bias term. Based on this function, the model predicts the probability of the image belonging to each class.

Random Forest is an ensemble learning algorithm that consists of multiple decision trees. Each tree is trained on different subsets of the data and makes its own prediction based on the input features. The final prediction is obtained by combining the outputs of all trees, which improves robustness and reduces overfitting. In the proposed system, the feature vector obtained after PCA is given as input to both SVM and Random Forest models. Each model independently generates probability scores for the classes (glaucoma or normal). These probability outputs represent how confident each model is about its prediction.

To improve classification performance, the outputs of both models are combined using a hybrid approach. The final probability is calculated by averaging the probabilities obtained from SVM and Random Forest:

$$P\_final = (P\_SVM + P\_RF) / 2$$

Eqn. 3.6

The class with the highest probability is selected as the final prediction. This approach leverages the strengths of both models, where SVM provides strong decision boundaries and Random Forest improves stability through ensemble learning. As a result, the hybrid model produces more reliable predictions compared to individual models.

G. CDR Calculation

In addition to classification, the system computes the Cup-to-Disc Ratio (CDR), which is an important clinical parameter used in glaucoma detection. The CDR represents the ratio between the optic cup and the optic disc and is widely used to assess structural changes in the retina.

In many existing methods, optic disc and optic cup regions are obtained through explicit segmentation techniques, which require complex processing and higher computational cost. In contrast, the proposed system does not rely on explicit segmentation for classification. Instead, deep features are automatically learned using EfficientNetB0, allowing the model to capture relevant retinal structures implicitly.

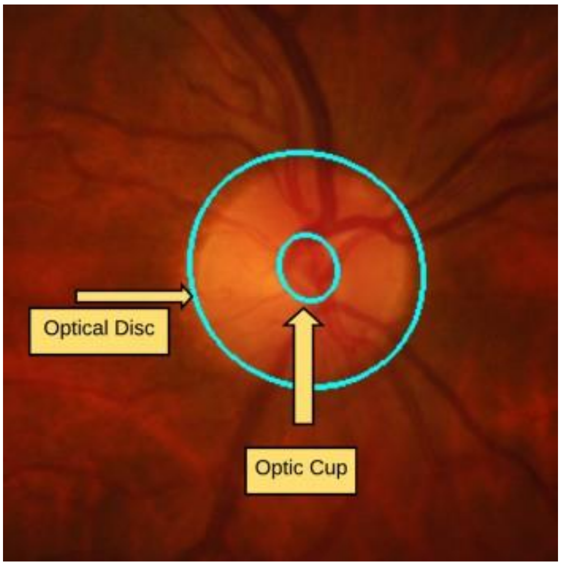

Fig. 3.3 Optic disc and optic cup regions used for CDR calculation

However, to provide clinical interpretability, CDR is computed as an additional parameter. The optic disc is detected using circular detection methods, and the optic cup region is estimated using intensity-based thresholding and contour detection. The radii of both regions are then used to calculate the CDR as:
CDR = Optic Cup Radius /Optic Disc Radius

Eqn. 3.7

A higher CDR value generally indicates a higher likelihood of glaucoma detection due to enlargement of the optic cup. In the proposed system, the computed CDR is not used as the primary classifier but as a supporting factor to refine the hybrid model prediction. When the CDR value exceeds a predefined threshold, a slight adjustment is applied to the averaged probability, improving sensitivity in detecting glaucomatous cases.This approach combines implicit feature learning with explicit clinical measurement, providing both accuracy and interpretability without relying entirely on segmentation-based methods.

IV. DATASET

The dataset used in this work is the EyePACS-AIROGS-light-V2 dataset, which is a standardized retinal fundus image dataset designed for glaucoma classification. The dataset contains high-quality fundus images categorized into two classes: referable glaucoma and non-referable glaucoma. These images are preprocessed and organized to support machine learning applications.[8]. The dataset is divided into training, validation, and testing sets to ensure proper evaluation of the model. The training set is used to learn feature representations, while the validation and test sets are used to evaluate the performance of the system. All images are color fundus images and are suitable for automated glaucoma detection. In addition to this dataset, several studies in the literature commonly use datasets such as DRISHTI-GS for glaucoma analysis. These datasets focus on optic disc and cup segmentation. However, in this work, the model is trained using a classification-based approach without relying on explicit segmentation.

Dataset Split	Glaucoma	Normal	Total
Training	4000	4000	8000
Validation	385	385	770
Testing	385	385	770

Table 4.1 Dataset Distribution

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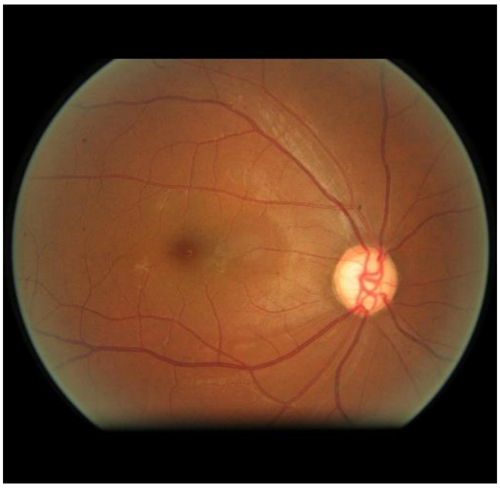

Fig. 4.1 Glaucoma fundus image from Dataset

Fig. 4.2 Normal fundus image from Dataset

V. RESULT AND DISCUSSION

A. Evaluation Metrics

The performance of the proposed glaucoma detection system is evaluated using the test dataset. The evaluation is carried out using standard classification metrics such as accuracy, precision, recall, and F1-score, which provide a comprehensive understanding of the model's performance.

Accuracy represents the overall correctness of the model and is defined as:

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

Eqn 5.1

Precision measures how many of the predicted glaucoma cases are actually correct:

$$\text{Precision} = TP / (TP + FP)$$

Eqn 5.2

Recall represents the ability of the model to correctly identify glaucoma cases:

$$\text{Recall} = TP / (TP + FN)$$

Eqn 5.3

F1-score is the harmonic mean of precision and recall:

$$\text{F1-score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$$

Eqn 5.4

These metrics provide a comprehensive evaluation of the classification performance.

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B. Model Performance

The performance of the individual models and the hybrid model is shown in Table 5.1. It can be observed that the hybrid model achieves better accuracy compared to SVM and Random Forest individually. This improvement is due to the combination of probability outputs from both models, which enhances stability and reduces misclassification.

Modal	Accuracy(%)
SVM	83.9
Rabdom Forest	80.0
Hybrid Model	84.5

Table 5.1 Model Performance Comparison

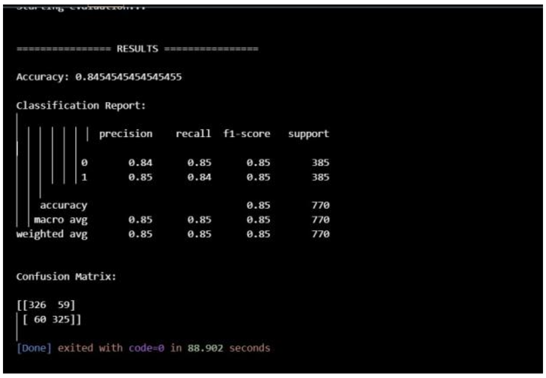

Fig. 5.1 Training Output for model accuracy

C. Confusion Matrix

The confusion matrix of the hybrid model is shown in Fig. 5.2. It provides detailed information about correct and incorrect predictions. The model shows balanced performance in both glaucoma and normal classes, with most samples correctly classified.

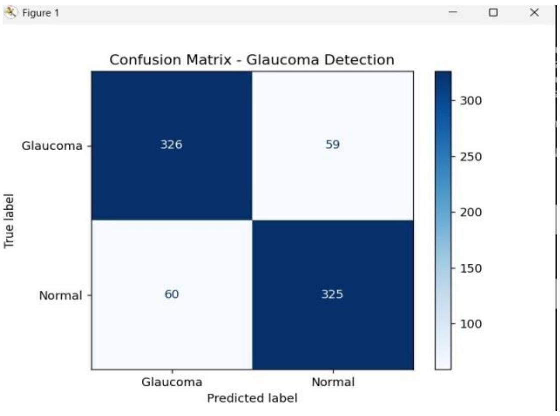

Fig. 5.2 Confusion Matrix for Hybrid Model

D. ROC Curve Analysis

The ROC curve of the proposed model is shown in Fig. 5.3. It represents the trade-off between true positive rate and false positive rate. The obtained AUC value of 0.92 indicates that the model has strong capability in distinguishing between glaucoma and normal cases.

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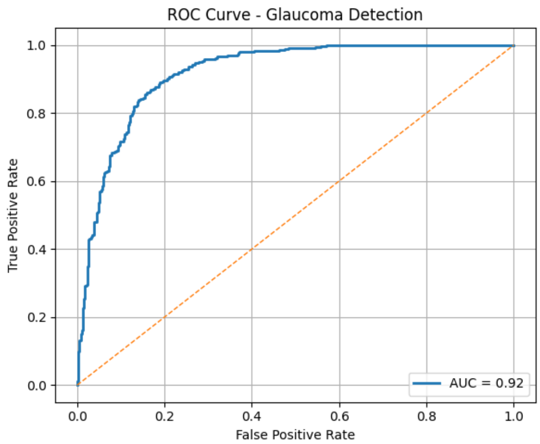

Fig. 5.3 ROC Curve Analysis

E. Web Application Implementation and Ouput

The proposed glaucoma detection system is implemented as a web-based application to provide an easy and interactive interface for users. The application begins with a user registration and login system, where user details are securely stored in a database. Once logged in, the user is directed to the home page, from which they can access the detection module. This ensures that each user's activity and prediction history can be managed effectively.

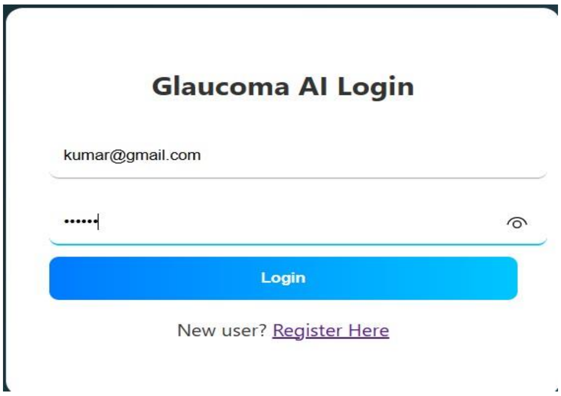

Fig. 5.4 Website Login

In the detection module, the user uploads a retinal fundus image, which is first validated to ensure that it is a proper retinal image. After validation, the image is processed through the complete pipeline including preprocessing, feature extraction using EfficientNetB0, dimensionality reduction, and hybrid classification using SVM and Random Forest. The system then displays the prediction result as glaucoma or normal along with the confidence score and the calculated CDR value. If glaucoma is detected, an additional risk assessment questionnaire is presented to gather further information.

The application is developed using Flask as the backend framework, with HTML, CSS, and JavaScript used for the frontend interface. The system integrates deep learning and machine learning models using libraries such as TensorFlow, OpenCV, and scikit-learn. Additionally, a medical report is generated in PDF format using ReportLab, which includes the prediction results, confidence level, and CDR value. This web-based implementation makes the system practical for real-time glaucoma screening and user-friendly interaction.

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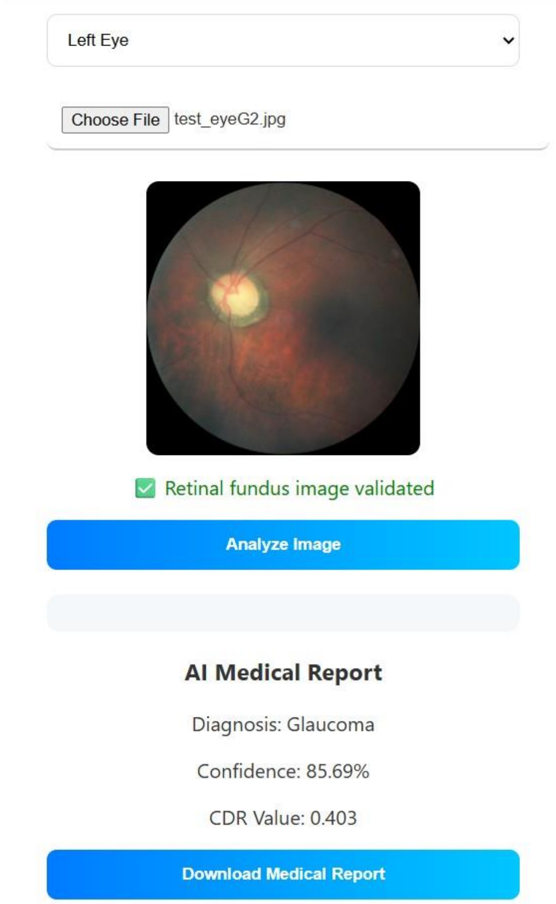
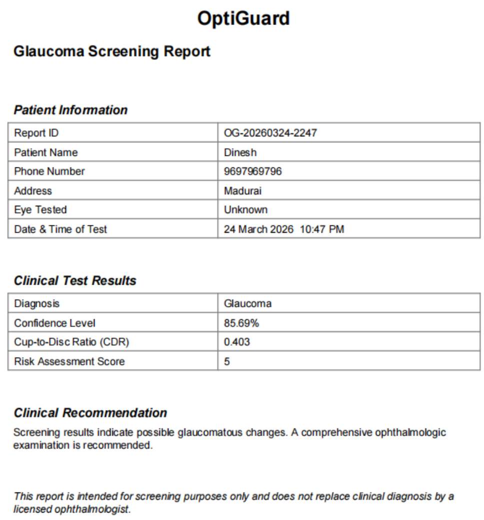


Fig. 5.5 Output of Glaucoma Detection in Website

A medical report is generated automatically, which includes key diagnostic details such as prediction result, confidence level, and CDR measurement and patient Details with prediction information including date and time. It also shows the left of right eye. This report can be used for further clinical reference.



OptiGuard

Glaucoma Screening Report

Patient Information

Report ID	OG-20260324-2247
Patient Name	Dinesh
Phone Number	9697969796
Address	Madurai
Eye Tested	Unknown
Date & Time of Test	24 March 2026 10:47 PM

Clinical Test Results

Diagnosis	Glaucoma
Confidence Level	85.69%
Cup-to-Disc Ratio (CDR)	0.403
Risk Assessment Score	5

Clinical Recommendation

Screening results indicate possible glaucomatous changes. A comprehensive ophthalmologic examination is recommended.

This report is intended for screening purposes only and does not replace clinical diagnosis by a licensed ophthalmologist.

Fig. 5.6 Generated Medical Report

VI. CONCLUSION

The proposed system presents an efficient approach for automated glaucoma detection using retinal fundus images. By combining deep learning-based feature extraction with machine learning classification, the system is able to achieve reliable performance. EfficientNetB0 is used to extract meaningful features, which are further processed using feature scaling and PCA before classification.A hybrid model combining Support Vector Machine and Random Forest is implemented to improve prediction accuracy and stability. In addition, the inclusion of Cup-to-Disc Ratio (CDR) provides a clinical perspective to support the model's decision. The system achieved an accuracy of 84.5% along with balanced precision, recall, and F1-score, demonstrating its effectiveness.The integration of the model into a web-based application enables real-time glaucoma screening and user-friendly interaction. Overall, the proposed system provides a practical and scalable solution for early glaucoma detection.

VII. FUTURE WORK

Although the proposed system provides promising results, there are several areas for improvement. Future work can focus on improving accuracy by using larger and more diverse datasets. Advanced deep learning models and ensemble techniques can also be explored to enhance performance.

In addition, incorporating segmentation-based methods for optic disc and cup detection may further improve clinical interpretability. The system can also be extended to detect multiple eye diseases using a unified framework. Further improvements can be made by enhancing the web application with better visualization and real-time feedback. Integration with clinical systems can also be considered for practical deployment in healthcare environments.

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