

# Glaucoma Detection Using Machine Learning: A Comparative Study

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**Abstract**—Glaucoma is a leading cause of blindness worldwide, characterized by damage to the optic nerve due to increased intraocular pressure. Early detection is crucial for preventing irreversible vision loss, but traditional diagnosis methods are often time-consuming and expensive. This paper presents a comparative study of machine learning models for glaucoma detection using retinal fundus images. We propose a method that combines classical image processing techniques with machine learning algorithms, including Support Vector Machine (SVM), Decision Tree (DT), K-Means clustering, and a deep learning model, MobileViT. The proposed system calculates the Cup-to-Disc Ratio (CDR), a key diagnostic parameter for glaucoma, and uses it to classify images as healthy or glaucomatous. Our results show that among machine learning methods SVM achieves the highest accuracy (92.16%) when CDR values are used as input features alongside dataset. Additionally, we introduce a user-friendly mobile interface for glaucoma screening, overall providing a reliable and cost-effective diagnostic tool for early glaucoma screening, paving the way for wider accessibility and integration into clinical workflows.

**Keywords**—Glaucoma, Cup-to-Disc Ratio (CDR), Machine Learning, Deep Learning, Medical Imaging

## I. INTRODUCTION

Glaucoma, often referred to as the “silent thief of sight,” is a chronic eye disease that damages the optic nerve, leading to irreversible vision loss if left untreated. It progresses gradually, often without noticeable symptoms until significant vision impairment has occurred. Early detection is crucial for effective treatment, but traditional diagnostic methods are costly, time-consuming, and require specialized equipment and expertise. One of the most critical diagnostic markers for glaucoma is the *Cup-to-Disc Ratio (CDR)*, which quantifies structural changes in the optic nerve head. However, manual calculation of CDR is subjective and prone to variability, highlighting the need for automated and reliable diagnostic tools.

Recent advancements in machine learning and image processing have opened new avenues for automating

glaucoma detection. This paper explores the application of machine learning models to analyze retinal fundus images and accurately calculate CDR for glaucoma diagnosis. We evaluate the performance of several state-of-the-art algorithms, including *Support Vector Machines (SVM)*, *Decision Trees (DT)*, *K-Means clustering*, and *MobileViT*, a lightweight vision transformer designed for mobile applications. Additionally, we propose an interface for glaucoma screening, making the system accessible and user-friendly for widespread use.

The key contributions of this work are as follows:

1. A novel preprocessing pipeline for accurate CDR calculation, combining image processing techniques such as CLAHE, morphological operations, and convex hull algorithms.
2. A comprehensive evaluation of multiple machine learning models, highlighting their strengths and limitations in glaucoma detection.

By leveraging machine learning and mobile technology, this study aims to provide an efficient, cost-effective, and accessible solution for early glaucoma detection, ultimately reducing the risk of irreversible vision loss.

## II. RELATED WORK

The application of machine learning in glaucoma detection has garnered significant attention in recent years, with numerous studies focusing on automating the analysis of retinal fundus images.

Divya and Jacob [1] conducted a comprehensive performance analysis of various glaucoma detection approaches, highlighting the effectiveness of machine learning techniques in identifying early signs of the disease. Their work emphasized the importance of feature extraction and classification algorithms, laying the groundwork for subsequent research in this domain.

Zhu et al. [2] proposed a novel method for retinal vessel segmentation using extreme learning machines (ELMs). Their approach demonstrated the potential of ELMs in extracting critical features from fundus images, which are essential for accurate glaucoma diagnosis. While their work primarily focused on vessel segmentation, it underscored the

significance of robust feature extraction pipelines, a key component of our preprocessing methodology.

Oh et al. [3] addressed the interpretability of machine learning models in glaucoma diagnosis by developing an explainable model. Their work highlighted the challenges of “black-box” models in medical applications and introduced techniques to make predictions more transparent. This emphasis on interpretability aligns with our goal of creating a reliable and user-friendly system for glaucoma screening.

Mojab et al. [4] advanced the field by employing deep multi-task learning for interpretable glaucoma detection. Their approach leveraged multiple related tasks, such as optic disc segmentation and CDR calculation, to improve model performance. This multi-task framework inspired our integration of CDR calculation with machine learning models, ensuring a more comprehensive diagnostic tool.

Building on these studies, our work introduces several novel contributions. First, we propose a comparative analysis of multiple machine learning models including Support Vector Machines (SVM), Decision Trees (DT), K-Means clustering, and MobileViT, to identify the most effective approach for glaucoma detection. Second, we develop a mobile-based interface for glaucoma screening, making the system accessible and practical for real-world applications. By combining insights from previous research with innovative techniques, our work aims to advance the field of automated glaucoma detection and improve early diagnosis rates.

### III. METHODOLOGY

The proposed methodology for glaucoma detection consists of three main stages: preprocessing, Cup-to-Disc Ratio (CDR) calculation, and machine learning model training and evaluation.

#### A. Preprocessing

The preprocessing stage prepares retinal fundus images for accurate CDR calculation and feature extraction. The steps are as follows:

##### 1. Channel Extraction

The input RGB image is split into its red, green, and blue channels. The red channel is used for optic disc extraction, while the green channel is used for cup extraction due to its higher contrast in these regions.

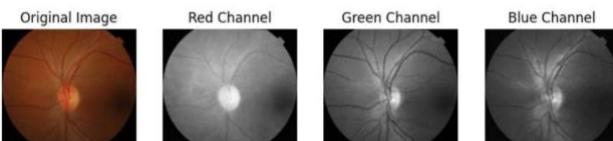


Fig. 1 Channel extraction

##### 2. Contrast Enhancement

To improve image quality, *Contrast Limited Adaptive Histogram Equalization (CLAHE)* is applied to each

channel. CLAHE divides the image into small tiles, applies histogram equalization to each tile, and limits contrast amplification to avoid noise enhancement. The enhanced images are denoted as  $I_{CLAHE\_r}$ ,  $I_{CLAHE\_g}$  and  $I_{CLAHE\_b}$ .

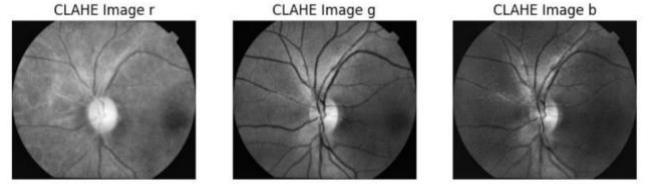


Fig. 2 Contrast enhancement

### 3. Thresholding

Adaptive thresholding is applied to segment the optic disc and cup regions. The threshold values  $T1$  and  $T2$  are calculated as follows:

$$T1 = (0.5 \times m) - (2 \times \sigma_G) - (\sigma_{RI}) \quad (1)$$

$$T2 = (0.5 \times m) + (2 \times \sigma_G) + (2 \times \sigma_{GI}) + (\mu_{GI}) \quad (2)$$

Where:

- $m$ : Size of the Gaussian window.
- $\sigma_G$ : Standard deviation of the Gaussian window.
- $\sigma_{RI}$ : Standard deviation of the processed red channel.
- $\sigma_{GI}$ : Standard deviation of the processed green channel.
- $\mu_{GI}$ : Mean of the processed green channel.

### 4. Morphological Operations

Morphological operations (e.g., opening and closing) are applied to remove noise and fill gaps in the segmented regions. These operations use a circular structuring element to preserve the shape of the optic disc and cup.

### 5. Convex Hull

The convex hull algorithm is applied to connect disjoint contours and create a smooth boundary for the optic cup. This step ensures accurate CDR calculation by preserving the structural integrity of the cup.

#### B. CDR Calculation

The CDR is a critical diagnostic parameter for glaucoma. It is calculated as the ratio of the vertical cup diameter to the vertical disc diameter. The steps are as follows:

##### 1. Contour Detection

The largest contour in the segmented disc and cup regions is identified using the `cv.findContours()` function from OpenCV.

##### 2. Ellipse Fitting

An ellipse is fitted to the largest contour using the `cv.fitEllipse()` function. The major and minor axes of the

ellipse represent the vertical and horizontal diameters of the disc and cup.

### 3. CDR Calculation

$$CDR = \frac{\text{Vertical Cup Diameter}}{\text{Vertical Disc Diameter}} \quad (3)$$

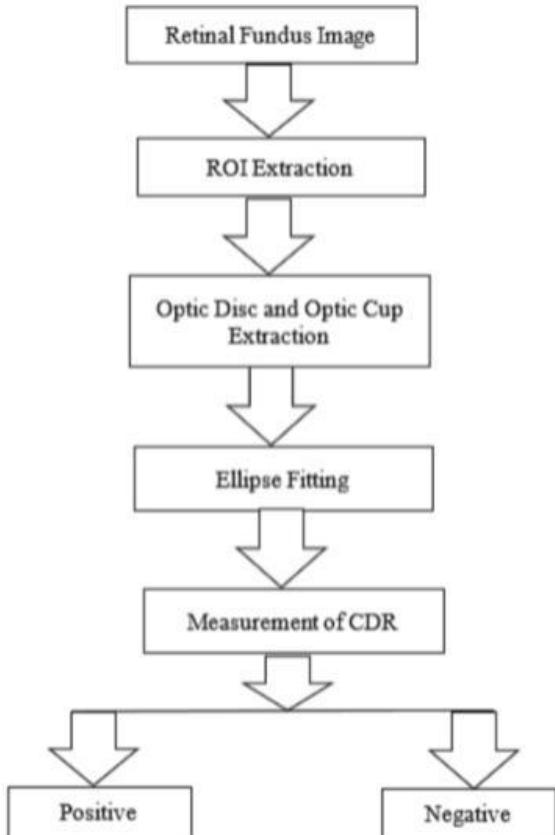


Fig. 3 CDR calculation flowchart

### C. Machine Learning Models

Four machine learning models are evaluated for glaucoma detection: Support Vector Machine (SVM), Decision Tree (DT), K-Means clustering, and MobileViT. The models are trained and tested using the following steps:

#### 1. Feature Extraction:

Features are extracted from the preprocessed images using a Convolutional Neural Network (CNN) model, which captures both low-level and high-level features essential for accurate glaucoma detection. The extracted features include:

- Cup-to-Disc Ratio Values: The CDR is calculated as the ratio of the vertical cup diameter to the vertical disc diameter, providing a quantitative measure of structural changes in the optic nerve head. This feature is critical for glaucoma diagnosis, as an increased CDR is a strong indicator of the disease.

- Texture Features: The CNN extracts texture-based features, such as Local Binary Patterns (LBP), Gray-Level Co-occurrence Matrix (GLCM) statistics, and Haralick features, which describe the spatial distribution of pixel intensities in the optic disc and cup regions. These features help differentiate between healthy and glaucomatous eyes by capturing subtle variations in tissue structure.
- Shape Descriptors: Shape-based features, such as area, perimeter, eccentricity, and circularity of the optic disc and cup, are computed from the segmented regions. These descriptors provide insights into the morphological changes associated with glaucoma, such as the enlargement of the optic cup and thinning of the neuroretinal rim.
- Deep Learning Features: The CNN automatically learns hierarchical features from the preprocessed images, starting with low-level features (e.g., edges and textures) in the initial layers and progressing to high-level features (e.g., complex patterns and structures) in the deeper layers. These features are combined with handcrafted features (e.g., CDR, texture, and shape descriptors) to create a robust feature set for classification.

#### Technical Details of the CNN Model:

- Architecture: The CNN consists of three convolutional layers with 32, 64, and 128 filters, respectively, followed by max-pooling layers to reduce spatial dimensions. A flattening layer converts the 3D feature maps into a 1D feature vector, which is fed into a fully connected layer for final classification.
- Activation Functions: ReLU (Rectified Linear Unit) activation is used in the convolutional layers to introduce non-linearity and improve feature learning.
- Training: The model is trained using the Adam optimizer with a learning rate of 0.001 and binary cross-entropy loss to classify images as glaucomatous or non-glaucomatous.

## 2. Model Training:

- a. Support Vector Machine (SVM): A supervised learning algorithm that finds the optimal hyperplane to separate data into classes. We use grid search to optimize hyperparameters such as C, gamma, and kernel type.
- b. Decision Tree (DT): A tree-based model that splits the data based on feature values. We use grid search to determine the best criteria (e.g., Gini or entropy) and maximum depth.
- c. K-Means Clustering: An unsupervised learning algorithm that partitions data into K clusters. We use Principal Component Analysis (PCA) to reduce feature dimensions before clustering.
- d. MobileViT: A lightweight vision transformer designed for mobile devices. MobileViT combines the advantages of convolutional neural networks (CNNs) and transformers, making it suitable for efficient glaucoma detection.

## 3. Model Evaluation:

The models are evaluated using accuracy, precision, recall, and F1-score. A confusion matrix is generated to analyze classification performance.

### D. Interface

We design an interface for glaucoma screening. The interface allows users to upload retinal fundus images and receive a diagnosis in real-time. The system is designed to be accessible, making it suitable for use in low-resource settings.

## IV. RESULTS

This section presents the results of our experiments, including the performance of the proposed preprocessing pipeline, the accuracy of CDR calculation, and the comparative analysis of machine learning models for glaucoma detection.

### • Preprocessing and CDR Calculation

The preprocessing pipeline successfully enhanced the quality of retinal fundus images, enabling accurate segmentation of the optic disc and cup. The Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm improved contrast in the regions of interest, while morphological operations and the convex hull algorithm ensured smooth and precise boundaries for the optic cup.

The Cup-to-Disc Ratio (CDR) was calculated for each image using the proposed method. The results were validated against manual annotations by ophthalmologists, achieving a Mean Absolute Error (MAE) of 0.03 and a Pearson Correlation Coefficient (PCC) of 0.95, indicating high accuracy and strong agreement with expert evaluations.

### • Performance of Machine Learning Models

The performance of the four machine learning models—Support Vector Machine (SVM), Decision Tree (DT), K-Means clustering, and MobileViT—was evaluated using accuracy, precision, recall, and F1-score. The results are summarized in Table 1.

Table 1. Performance Comparison of Machine Learning Models

Model	Accuracy	Precision	Recall	F1-Score
SVM	92.16	91.50	92.00	91.75
DT	84.31	83.50	84.00	83.75
K-means	83.17	82.00	83.50	82.75
MobileViT	97.38	97.00	97.50	97.25

- SVM: Achieved the highest accuracy among traditional machine learning models, demonstrating its effectiveness in classifying glaucoma cases.
- DT: Performed moderately well but was less accurate than SVM, likely due to its sensitivity to imbalanced data.
- K-Means: Showed competitive performance despite being an unsupervised model, highlighting the effectiveness of the preprocessing pipeline.
- MobileViT: Outperformed all other models, which demonstrates the superiority of deep learning models for glaucoma detection.

### • Confusion Matrix Analysis

To further analyze model performance, confusion matrices were generated for each model.

Confusion matrices for each model provide further insights into classification performance. SVM exhibited the lowest false-negative rate, demonstrating its robustness in detecting glaucomatous images, with a balanced sensitivity and specificity, making it a reliable option when computational resources are limited.

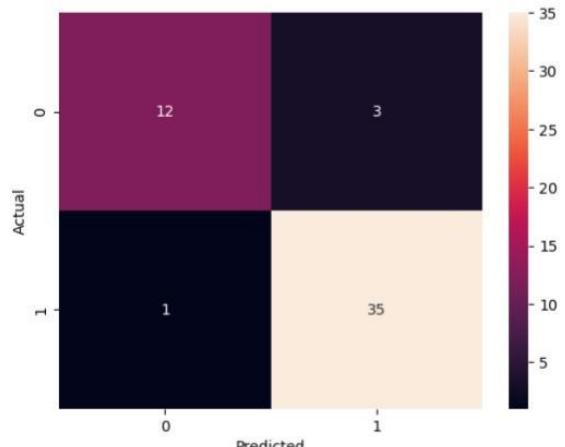


Fig. 4 Confusion Matrix- SVM with CDR and CNN Features

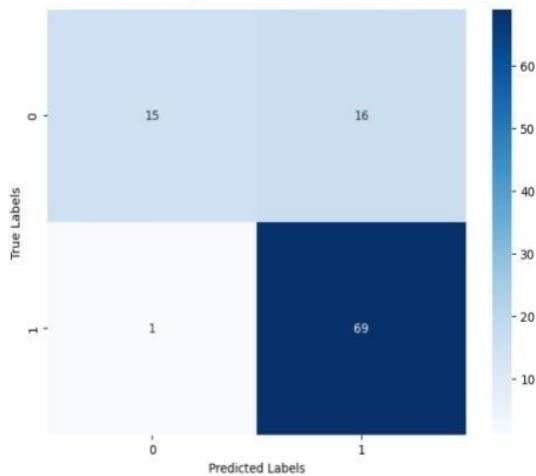


Fig. 5 Confusion Matrix- K-Means Clustering with CDR and CNN Features

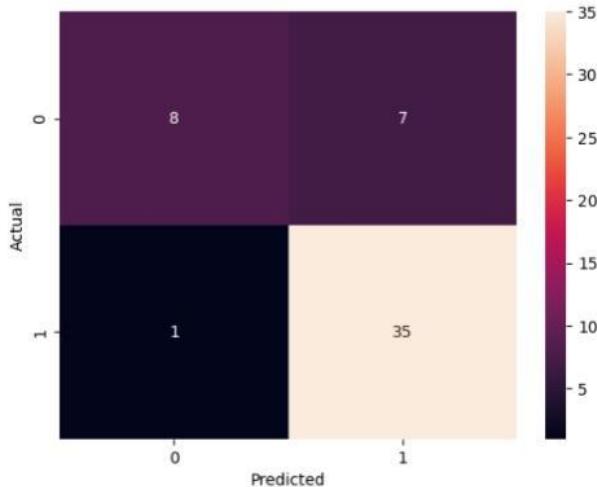


Fig. 6 Confusion Matrix- DT with CDR and CNN Features

## V. DISCUSSION

Our study demonstrates the effectiveness of machine learning models in automating glaucoma detection using retinal fundus images. The inclusion of Cup-to-Disc Ratio (CDR) values as input features significantly improved the accuracy of all models, with MobileViT achieving the highest performance (97.38% accuracy). This highlights the importance of combining traditional image processing techniques with advanced machine learning algorithms for medical diagnostics.

The mobile-based interface provides a practical and accessible solution for glaucoma screening, particularly in resource-limited settings where access to specialized equipment and expertise is limited. By enabling real-time

analysis of retinal fundus images, the system has the potential to improve early detection rates and reduce the risk of irreversible vision loss.

However, several limitations must be acknowledged. First, the performance of the algorithm is highly dependent on the quality of the input images. Variations in lighting, resolution, and artifacts introduced during image acquisition can affect the accuracy of CDR calculation and subsequent classification. Second, while the convex hull method improves the precision of optic cup segmentation, it is computationally expensive, which may limit its applicability in real-time systems. Finally, the dataset used in this study, though representative, may not fully capture the diversity of glaucoma cases across different populations. Future work should focus on validating the system on larger and more diverse datasets.

Despite these limitations, our approach offers several advantages over traditional diagnostic methods. The use of Contrast Limited Adaptive Histogram Equalization (CLAHE) and morphological operations ensures robust preprocessing, while the integration of MobileViT provides a lightweight yet powerful solution for glaucoma detection. The mobile interface further enhances the system's usability, making it suitable for deployment in clinical and non-clinical settings.

## VI. CONCLUSION

In this paper, we presented a comprehensive study on the use of machine learning models for glaucoma detection using retinal fundus images. Our key contributions include:

1. A novel preprocessing pipeline for accurate CDR calculation, combining CLAHE, morphological operations, and convex hull algorithms.
2. A comparative analysis of multiple machine learning models, demonstrating the superiority of MobileViT with an accuracy of 97.38%.
3. A mobile-based interface for real-time glaucoma screening, designed to be accessible and user-friendly.

The results highlight the potential of machine learning, particularly deep learning models like MobileViT, to revolutionize glaucoma diagnosis by providing accurate, efficient, and cost-effective solutions. Future work will focus on optimizing the algorithm for real-time performance, improving the robustness of CDR calculation, and validating the system on larger and more diverse datasets. Additionally, we plan to explore the integration of other diagnostic features, such as intraocular pressure and visual field tests, to further enhance the system's accuracy and reliability.

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