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Proceeding Paper

Automated Glaucoma Detection in Fundus Images Using Comprehensive Feature Extraction and Advanced Classification Techniques †

Vijaya Kumar Velpula [1], Jyothisri Vadlamudi [2], Purna Prakash Kasaraneni [3] and Yellapragada Venkata Pavan Kumar [4,*]

[1] Department of Electronics and Communication Engineering, MLR Institute of Technology, Hyderabad, Telangana, India; vijaykumarv@mlrit.ac.in
[2] Electronics and Communication Engineering, Malla Reddy Engineering College, Hyderabad 500100, Telangana, India; jyothisriv@mrec.ac.in
[3] Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram 522502, Andhra Pradesh, India; kpurnaprakash@kluniversity.in
[4] School of Electronics Engineering, VIT-AP University, Amaravati 522237, Andhra Pradesh, India
* Correspondence: pavankumar.yv@vitap.ac.in; Tel.: +91-863-2370155

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Abstract: Glaucoma, a primary cause of irreversible blindness, necessitates early detection to prevent significant vision loss. In the literature, fundus imaging is identified as a key tool in diagnosing glaucoma, which captures detailed retina images. However, manual analysis of these images can be time-consuming and subjective. Thus, this paper presents an automated system for glaucoma detection using fundus images, combining diverse feature extraction methods with advanced classifiers, specifically Support Vector Machine (SVM) and AdaBoost. The pre-processing step incorporates Image Enhancement via Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance image quality and feature extraction. This work investigates individual features such as Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), Chip Histogram Features, and Gray Level Co-occurrence Matrix (GLCM), as well as their various combinations, including HOG + LBP + Chip Histogram + GLCM, HOG + LBP + Chip Histogram, and others. These features are utilized with SVM and Adaboost classifiers to improve classification performance. For validation, the ACRIMA dataset, a public fundus image collection comprising 369 glaucoma-affected and 309 normal images is used in this work, with 80% of the data allocated for training and 20% for testing. The results of the proposed study show that different feature sets yield varying accuracies with SVM and Adaboost classifiers. For instance, the combination of LBP + Chip Histogram achieved the highest accuracy of 99.29% with Adaboost, while the same combination yielded 65.25% accuracy with SVM. The individual feature LBP alone achieved 97.87% with Adaboost and 98.58% with SVM. Furthermore, the combination of GLCM + LBP provided 98.58% accuracy with Adaboost and 97.87% with SVM. The results demonstrate that CLAHE and combined feature sets significantly enhance detection accuracy, providing a reliable tool for early and precise glaucoma diagnosis, thus facilitating timely intervention and improved patient outcomes.

Keywords: AdaBoost; Chip Histogram; fundus image; GLCM; glaucoma; HOG; LBP; SVM

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1. Introduction

Glaucoma is a leading cause of vision loss globally. It is a neurodegenerative eye condition that develops due to increased intraocular pressure within the eye. Glaucoma is the second most common cause of blindness globally and can result in total vision loss if it is not detected and treated promptly. It is a condition that results from damage to the optic nerves, which are responsible for transferring visual signals from the retina to the brain [1]. When the optic nerves are impaired, the brain cannot process visual information correctly. This damage is frequently produced by elevated pressure within the eye. Early detection of glaucoma is crucial, as regular eye exams and timely treatment can help prevent further vision loss. While treatment can preserve existing vision, it cannot restore damaged nerve tissue. If diagnosed at an advanced stage, the disease may lead to significant, irreversible damage to the optic nerve, potentially resulting in central vision loss and blindness. Hence, early diagnosis is a key to manage the condition effectively [2,3]. Preventing vision loss from glaucoma relies on early detection and proper treatment, making diagnosing the condition in its early stages essential. Traditional diagnostic techniques in medical practice rely on instruments such as corneal pachymetry, goniolenses, tonometers, Optical Coherence Tomography (OCT), Scanning Laser Polarimetry (SLP), and Scanning Laser Ophthalmoscopes (SLO), but their manual operation often proves time-consuming.

Color fundus imaging allows for the analysis of key eye structures, including the optic disc, macula and retina. It is a cost-effective technique compared to previous imaging methods. These tools operate using optical and mechanical principles, but they have limitations, including being labor-intensive, less accurate, and challenging for diagnosing early-stage glaucoma. Additionally, due to the shortage of skilled ophthalmologists, manually screening all potential glaucoma patients is difficult. As a result, computerized methods are essential for more efficient, accurate, and reliable early diagnosis of glaucoma. In recent years, machine learning (ML) and deep learning (DL) techniques have been applied in various applications such as medical image classification and segmentation, smart energy, etc., [4–7]. While traditional ML methods offer quick results, they rely on structured data and require manual feature extraction, which can introduce errors due to human oversight.

2. Related Work

Glaucoma is an eye condition characterized by increased intraocular pressure, which can be categorized into two types: open-angle glaucoma and closed-angle glaucoma. This pressure increase is primarily due to flow restriction of aqueous humor within the eye. Various tests are conducted to diagnose the disease. A deformable model was developed in [8] to outline fluid-filled regions in the retina. The method includes these phases: first, input image is denoised utilizing Gaussian filtering to minimize speckle noise, then an edge map is created and normalized for further processing. A novel network, referred to as self-ONNs, was introduced in [9] for analyzing fundus images in glaucoma detection. GoogleNet, pre-trained on a large dataset, was employed for the early detection of glaucoma. A two-stage approach was introduced, starting with cropping an image to focus on region of interest (ROI), followed by using a pre-trained neural network to diagnose glaucoma [10]. A new glaucoma detection approach uses QB-VMD [11] to decompose retinal images, followed by PHOG and Haralick texture feature extraction. This method leverages both shape and texture features for diagnosis. This paper [12] utilized an adapted version of GoogLeNet. The methodology consists of two stages: (1) identifying region of interest (ROI) and (2) classifying the image. In this study, five ImageNet-trained models were utilized for automated glaucoma assessment from fundus images [13]. Deep features are extracted with a new CNN [14] model and used for classification with traditional machine learning methods, including Adaboost, k-Nearest Neighbors (kNN), Random Forest (RF), Multilayer Perceptron (MLP), Support Vector Machines (SVM), and Naive Bayes (NB). This paper introduced a comprehensive deep learning model for detecting glaucoma from fundus images [15]. This study introduced CoG-NET [16], a deep learning network designed for glaucoma prediction. This paper proposed [17] an explainable AI model for automatic glaucoma detection using pre-trained CNNs to obtain features and machine learning classifiers to categorize images. Performance evaluation involves selecting optimal CNN and classifier parameters. Further, this method is proposed in [18] to first obtain optic disc from fundus images utilizing image segmentation. Glaucoma diagnosis is then performed by applying deep learning networks to the segmented optic disc images.

A technique was proposed in [19] to apply RGB channel weighting for processing fundus images in glaucoma classification. However, this method only led to slight improvements in the efficiency of glaucoma diagnosis.

A novel combination of HOG, LBP, GLCM, and Chip Histogram features is used for glaucoma detection, enhancing texture and shape representation in fundus images. A comparison of Adaboost and SVM shows Adaboost achieves superior accuracy, especially with the HOG, LBP, and Chip Histogram combination. This hybrid approach improves glaucoma detection effectively.

3. Materials and Methods

This section provides a detailed overview of dataset, experimental setup & methodology for detection of glaucoma in fundus images.

3.1. Dataset

In this work, ACRIMA [13] fundus image dataset is used, comprising 705 images, including 396 glaucomatous and 309 normal cases, collected from patients at FISABIO Oftalmología Médica in Valencia, Spain. These images, centered on the optic disc and taken after pupil dilation, were captured using Topcon TRC retinal camera by a 35° visual range. Images with artifacts or poor contrast were discarded. Two glaucoma experts, each with 8 years of experience, annotated images without additional clinical information. Released in March 2019, the ACRIMA dataset is widely used for glaucoma classification tasks, though it lacks optic disc and cup segmentation data. Figure 1 compares, retinal image of an individual diagnosed with glaucoma and that of normal.

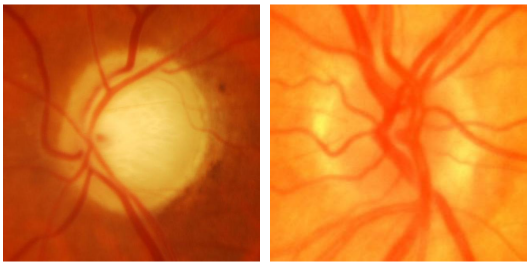


Figure 1. (**Left**) Glaucoma affected Image; (**Right**) Normal Image.

3.2. Methodology

Figure 2 shows workflow of the proposed method for glaucoma detection and it can be briefly outlined in the below sub-sections.

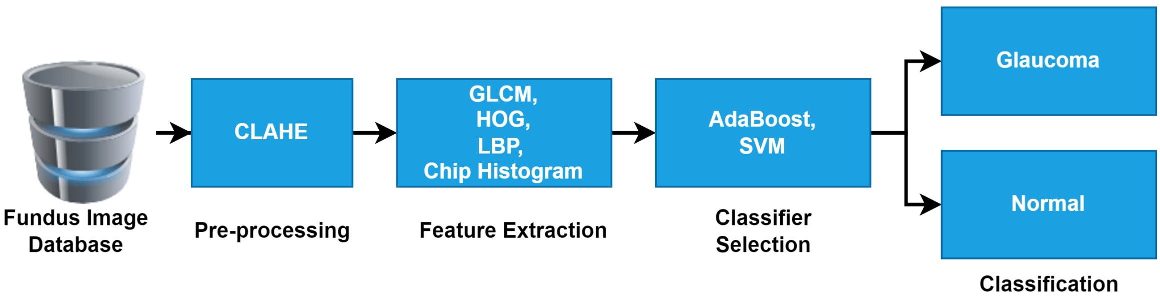


Figure 2. Workflow of the proposed method for detection of glaucoma in fundus images.

3.2.1. Input Fundus Images

The system uses fundus images as input from the ACRIMA dataset, which includes 396 glaucoma-affected and 309 normal images.

3.2.2. Pre-Processing

The CLAHE preprocessing method was utilized to improve image quality and contrast, preparing the images for effective feature extraction. CLAHE was chosen because it enhances local contrast in fundus images, making subtle features, such as texture variations around the optic disc, more distinguishable, which is crucial for accurate glaucoma detection.

3.2.3. Feature Extraction

Various feature extraction methods are used, both individually and in combinations, to capture significant image features such as GLCM, HOG, LBP, and Chip Histogram.

GLCM is a feature extraction method that captures second-order texture information by analyzing the spatial relationship between pixel intensities in an image. In glaucoma detection, texture features such as those derived from GLCM can be crucial for identifying subtle changes in the retinal structure. HOG is a feature extraction method that focuses on capturing edge directions and shapes in an image by computing the gradient orientation histograms. HOG is often used in computer vision tasks, especially for detecting objects or shapes, which makes it a useful feature extraction method for glaucoma detection where structural changes in the optic nerve head are critical. LBP is a texture-based feature extraction method that focuses on capturing local texture information by comparing pixel intensities in a local neighborhood. It is particularly effective for identifying patterns in texture variations, which are critical in detecting structural changes in the optic nerve head for glaucoma diagnosis. Chip Histogram is a feature extraction method that summarizes pixel intensity distributions in localized regions or “chips” of the image. This method focuses on capturing intensity variations in specific areas of the fundus images, which can be informative in identifying regions affected by glaucoma. These features were evaluated individually and in various combinations (e.g., LBP + Chip Histogram, GLCM + LBP) to assess their impact on classification performance.

3.2.4. Classification

For classification, two advanced classifiers: SVM and AdaBoost are chosen. SVM is selected due to its strong theoretical foundation and effectiveness in handling high-dimensional feature spaces, making it a common choice in medical image classification. It works by finding the optimal hyperplane that maximally separates the data points belonging to different classes. SVM is effective in high-dimensional spaces and is particularly useful when the number of dimensions exceeds the number of samples, which makes it ideal for complex image classification tasks such as glaucoma detection. AdaBoost is an ensemble learning algorithm that combines multiple weak classifiers to form a strong classifier. The algorithm adjusts the weights of incorrectly classified instances, forcing subsequent classifiers to focus on these harder cases. AdaBoost is particularly useful when the base classifiers (or weak learners) are simple and prone to errors individually but perform well when combined. AdaBoost was chosen for its ability to create a strong ensemble classifier by focusing iteratively on misclassified samples. AdaBoost’s strength in handling complex and non-linear data distributions made it a valuable addition, particularly for feature sets that might introduce complexity or noise.

3.2.5. Training and Testing

The dataset is split into 80% for training and 20% for testing. The system is trained using different feature sets to observe how various combinations affect classification performance. In the training phase, both classifiers are trained on the extracted features. The SVM classifier was trained using the different extracted features. SVM attempts to find the optimal hyperplane that separates glaucoma and healthy samples in the feature space. The classifier is trained using both individual and combined feature sets. The AdaBoost classifier was trained with the same features. It works by combining multiple weak classifiers, iteratively focusing on misclassified instances to improve overall classification accuracy. AdaBoost adapts to the training data, particularly targeting more difficult-toclassify images as the training progresses. After training, the trained models are tested on the remaining 20% of the dataset (testing set) to evaluate their ability to generalize to new, unseen data. Each feature set is evaluated with both classifiers (SVM and AdaBoost) to assess performance, using accuracy as the primary metric.

4. Results

The effectiveness of the proposed automated glaucoma detection system is evaluated utilizing various feature extraction methods and their combinations, classified with both SVM and AdaBoost classifiers. Table 1 illustrates the outcomes of the proposed method that demonstrate effectiveness of different feature sets and highlights the significant variations in classifier performance depending on the feature combination.

Table 1. The performance of each feature and combination of features, showing the differences between the SVM and AdaBoost classifiers.

Feature Combination	AdaBoost (%)	SVM (%)	Feature Combination	AdaBoost (%)	SVM (%)
Individual			**Combination of Three**		
1	78.72	82.98	1+2+3	**95.04**	**84.4**
2	84.4	82.98	1+2+4	88.65	56.74
3	**97.87**	**98.58**	1+3+4	**99.29**	65.25
4	52.48	56.03	2+3+4	94.33	56.74
Combination of Two			**Combination of Three**		
1+2	82.98	86.52	1+2+3+4	95.04	56.74
1+3	**98.58**	**97.87**			
1+4	79.43	58.87			
2+3	**93.62**	**84.4**			
2+4	85.82	56.74			
3+4	**99.29**	65.25			

* 1—GLCM, 2—HOG, 3—LBP and 4—Chip Histogram

4.1. Individual Feature Performance

From Table 1, LBP alone provided strong results with both classifiers, reaching 97.87% with AdaBoost and 98.58% with SVM. This indicates that LBP is a robust feature for detecting glaucoma-related texture changes in fundus images. Chip Histogram alone produced lower accuracy than the other three feature sets.

4.2. Feature Combination Performance

4.2.1. LBP + Chip Histogram (3+4):

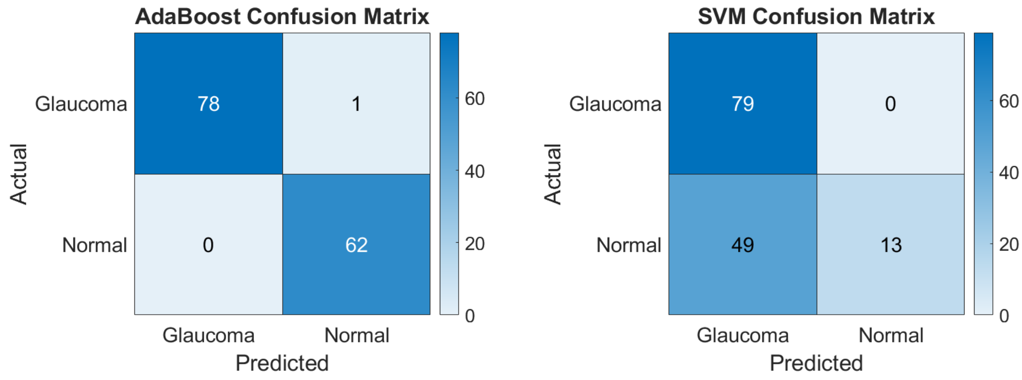
This combination yielded the highest accuracy with the AdaBoost classifier, achieving a remarkable 99.29%. However, the same feature set performed poorly with SVM, yielding only 65.25% accuracy. The disparity suggests that the non-linear complexity of this feature set was better handled by AdaBoost's ensemble method, while SVM struggled with separability in the high-dimensional space. Figure 3 presents the confusion matrices for LBP + Chip Histogram features combination.

4.2.2. GLCM + LBP (1+3):

This feature combination achieved a balanced performance with both classifiers, resulting in 98.58% accuracy with AdaBoost and 97.87% accuracy with SVM. The similarity in performance suggests that these features provided a well-structured representation of the image data that both classifiers could handle effectively. Figure 4 presents the confusion matrices for GLCM + LBP features combination.

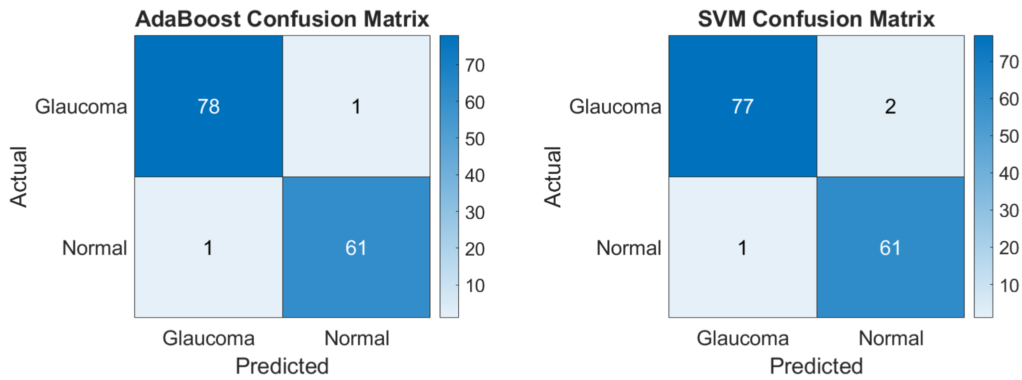
4.2.3. GLCM + LBP + Chip Histogram (1+3+4):

For the combination of GLCM, LBP, and Chip Histogram (1+3+4), AdaBoost yielded the highest accuracy of 99.29%, but SVM only achieved 65.25%, showing that ADB handles this feature set much better than SVM. Figure 5 presents the confusion matrices for the GLCM + LBP + Chip Histogram features combination.



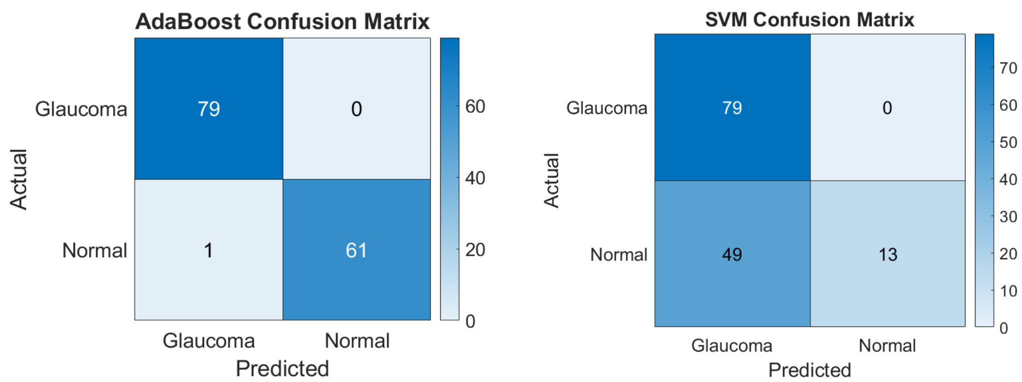
(**a**) Adaboost (**b**) SVM

Figure 3. Confusion Matrices of Adaboost and SVM for LBP + Chip Histogram.



(**a**) Adaboost (**b**) SVM

Figure 4. Confusion Matrices of Adaboost and SVM for GLCM + LBP.



(**a**) Adaboost (**b**) SVM

Figure 5. Confusion Matrices of Adaboost and SVM for GLCM + LBP + Chip Histogram.

Table 2 provides a comparative analysis of various state-of-the-art methods for glaucoma detection from fundus images, highlighting their respective accuracies. Methods such as the Adapted GoogLeNet (Cerentini et al., 2017) achieved an accuracy of 86.4%, while Claro et al. (2019) using a pre-trained GoogleNet on a large dataset obtained 95.31% accuracy. Devecioglu et al. (2021) proposed Self-ONNs, which achieved 94.5% accuracy, while Juneja et al. (2022) introduced CoG-NET, reaching 95.3%. The proposed method using Adaboost with a combination of HOG, LBP, and Chip Histogram features resulted in the highest accuracy of 99.29%, outperforming other methods. The SVM classifier also showed strong performance with 97.87% accuracy when using GLCM and LBP feature combinations, although it performed lower (65.25%) when combined with HOG, LBP, and Chip Histogram features. This comparison shows the effectiveness of the proposed method, especially when leveraging Adaboost, which surpasses previous works in terms of accuracy for glaucoma detection.

Table 2. Comparison of proposed method results with some state of the art methods.

Author(s)	Year	Method	Accuracy (%)
Cerentini et al. [12]	2017	Adapted GoogLeNet	86.4
Claro et al. [10]	2019	GoogleNet	95.31
Diaz-Pinto et al. [13]	2019	ImageNet- (VGG16, VGG19, etc.)	70.21
Devecioglu et al. [9]	2021	Self-ONNs	94.5
Juneja et al. [16]	2022	CoG-NET	95.3
Sonti et al. [11]	2022	QB-VMD, PHOG, and Haralick texture features	96.7
Oguz et al. [14]	2024	CNN + traditional ML methods (Adaboost, SVM, etc.)	92.96
Velpula et al. [17]	2024	Explainable AI model (CNN + ML classifiers)	98.03
Proposed Method (Adaboost)	2024	HOG + LBP + Chip Histogram features GLCM + LBP features	**99.29** **98.58**
Proposed Method (SVM)	2024	HOG + LBP + Chip Histogram features GLCM + LBP features	**65.25** **97.87**

5. Conclusions

In conclusion, this study presents an effective automated system for glaucoma detection using fundus images by integrating various feature extraction methods with advanced classifiers. The application of CLAHE for image enhancement significantly improved feature visibility, which, in combination with diverse feature extraction techniques, contributed to the system's overall performance. The results demonstrate that different combinations of features have a significant impact on classification accuracy. Specifically, the combination of LBP + Chip Histogram achieved the highest accuracy with AdaBoost, while other feature sets such as GLCM + LBP also delivered strong performance across both classifiers. AdaBoost consistently outperformed SVM in handling complex feature combinations, highlighting its robustness for this application. The proposed method, with its high accuracy rates, offers a reliable tool for early glaucoma diagnosis, which is crucial for preventing irreversible vision loss and improving patient outcomes.

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Abbreviations

The following abbreviations are used in this manuscript:

CLAHE	Contrast Limited Adaptive Histogram Equalization
CNN	convolutional neural network
OCT	Optical Coherence Tomography
DL	Deep Learning
GLCM	Gray Level Co-occurrence Matrix
HOG	Oriented Gradients
LBP	Local Binary Patterns
ML	Machine Learning
SLO	Scanning Laser Ophthalmoscopes
SLP	Scanning Laser Polarimetry
SVM	Support Vector Machine

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