A Comprehensive Survey on Automated Glaucoma Detection Using Image Processing and Machine Learning Techniques

Shiveta Pandita
M.tech Scholar
Computer Science & Engineering
Lakshmi Narain College of Technology,Bhopal
Shivetapandita047@gmail.com

Dr. Pushpendra Singh Tomar
Associate Professor
Computer Science & Engineering
Lakshmi Narain College of Technology,Bhopal
pushpendrarat@lnct.ac.in

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Abstract: Glaucoma is a progressive optic neuropathy that causes irreversible vision loss and is considered one of the leading causes of blindness worldwide. Early diagnosis of glaucoma is essential to prevent permanent damage to the optic nerve and preserve visual function. However, manual examination of retinal fundus images is time-consuming, subjective, and highly dependent on expert ophthalmologists. Consequently, automated glaucoma detection systems based on image processing, machine learning, and deep learning have gained significant attention in recent years. This survey paper presents a comprehensive review of existing glaucoma detection methodologies using retinal fundus images. The study covers traditional image processing approaches, wavelet-based feature extraction techniques, decomposition models, texture and statistical feature analysis, machine learning classifiers, and recent deep learning frameworks. Furthermore, the paper discusses preprocessing methods, feature fusion strategies, dimensionality reduction techniques, and classification models used for glaucoma diagnosis. A comparative analysis of existing techniques is also presented to identify their advantages, limitations, and research gaps. The review highlights that hybrid frameworks combining multi-resolution analysis and machine learning provide an effective balance between accuracy and computational efficiency. Finally, future research directions toward robust, efficient, and clinically deployable glaucoma detection systems are discussed.

Keywords: Glaucoma Detection, Fundus Images, Machine Learning, Deep Learning, Discrete Wavelet Transform, Feature Extraction, Medical Image Processing, Retinal Image Analysis.

1. INTRODUCTION

Glaucoma is a chronic eye disorder characterized by progressive damage to the optic nerve, resulting in irreversible vision loss if left untreated. It is one of the major causes of blindness globally and affects millions of people worldwide. According to epidemiological studies, the number of glaucoma patients is expected to increase significantly in the coming decades due to aging populations and rising visual health issues [5]. The disease gradually damages retinal ganglion cells and optic nerve fibers, causing peripheral vision loss that eventually progresses to complete blindness.

One of the major challenges associated with glaucoma is that it often remains asymptomatic during its early stages. Many patients do not realize the presence of the disease until substantial vision impairment has already occurred. Traditional clinical diagnosis relies on manual examination methods such as tonometry, optical coherence tomography (OCT), visual field testing, and retinal fundus imaging [6]. Among these, retinal fundus imaging is widely preferred because it is non-invasive, cost-effective, and capable of revealing structural abnormalities in the optic nerve head region.

The increasing demand for large-scale glaucoma screening has motivated researchers to develop automated computer-aided diagnosis systems capable of assisting ophthalmologists in accurate and early disease detection. Automated glaucoma diagnosis systems aim to analyze retinal fundus images, extract discriminative features, and classify images into glaucomatous or normal categories using computational intelligence techniques. Over the past decade, substantial research has been conducted using image processing, machine learning, and deep learning approaches for glaucoma detection [1], [7].

Traditional glaucoma detection approaches primarily relied on handcrafted features extracted from retinal images. These methods focused on texture descriptors, wavelet transforms, statistical features, and morphological analysis of the optic disc and cup regions [11], [12]. Although these techniques achieved moderate performance, their effectiveness depended heavily on feature engineering and preprocessing quality.

Recent advancements in deep learning have introduced convolutional neural networks (CNNs), transfer learning, and hybrid architectures capable of automatically learning hierarchical image representations [1], [3], [4]. Deep learning models have demonstrated improved diagnostic accuracy; however, they often require large annotated datasets and significant computational resources. This limitation restricts their deployment in real-time and low-resource healthcare environments.

In addition to deep learning methods, wavelet-based and decomposition-based techniques have gained considerable attention due to their ability to capture both spatial and frequency-domain characteristics of retinal images. Techniques such as Discrete Wavelet Transform (DWT), Variational Mode Decomposition (VMD), Empirical Wavelet Transform (EWT), and Bidimensional Empirical Mode Decomposition (BEMD) have shown promising performance in glaucoma diagnosis [9], [12], [16]. These methods effectively represent structural and textural variations in retinal images while maintaining lower computational complexity.

This survey paper provides a detailed review of existing glaucoma detection methodologies based on retinal image analysis. The study categorizes different approaches into preprocessing methods, feature extraction techniques, machine learning classifiers, and deep learning frameworks. Furthermore, a comparative analysis of major research contributions is presented along with research gaps and future research directions.

2. OVERVIEW OF GLAUCOMA

Glaucoma is a group of progressive optic neuropathies associated with degeneration of retinal ganglion cells and optic nerve fibers. The disease causes structural damage to the optic nerve head and corresponding visual field defects. Elevated intraocular pressure (IOP) is considered one of the primary risk factors, although glaucoma can also occur in patients with normal IOP levels [5]. Glaucoma can be categorized into several major types:

A. Primary Open-Angle Glaucoma: Primary Open-Angle Glaucoma (POAG) is the most common type of glaucoma. It progresses gradually and is usually asymptomatic in its early stages. The drainage angle remains open, but the outflow of aqueous humor becomes inefficient, causing increased intraocular pressure.

B. Angle-Closure Glaucoma: Angle-Closure Glaucoma occurs when the drainage angle between the iris and cornea becomes blocked, resulting in sudden elevation of intraocular pressure. This condition requires immediate medical attention.

C. Normal-Tension Glaucoma: In this type of glaucoma, optic nerve damage occurs even when intraocular pressure remains within normal range. Genetic factors and reduced blood flow are believed to contribute to the disease.

D. Secondary Glaucoma: Secondary glaucoma develops due to trauma, inflammation, prolonged steroid use, or other medical conditions.

E. Congenital Glaucoma: Congenital glaucoma is a rare form present at birth due to developmental abnormalities in the eye.

2.1 Risk Factors

Several factors increase the risk of glaucoma development:

- Elevated intraocular pressure
- Aging
- Family history
- Diabetes and hypertension
- Myopia
- Prolonged corticosteroid usage

2.2 Importance of Early Detection

Glaucoma-related vision loss is irreversible; therefore, early diagnosis is critically important. Automated glaucoma detection systems can significantly improve screening efficiency, reduce clinical workload, and assist in early diagnosis, especially in rural and resource-limited regions [7], [23].

3. RETINAL FUNDUS IMAGE ANALYSIS

Retinal fundus imaging plays an important role in automated glaucoma detection systems because it provides detailed visualization of retinal blood vessels, optic disc, optic cup, and surrounding tissues. Structural changes in the optic nerve head region serve as key indicators of glaucoma progression.

The optic disc is a bright circular region where retinal nerve fibers exit the eye. In glaucomatous conditions, enlargement of the optic cup and thinning of the neuroretinal rim are commonly observed. Therefore, many automated systems focus on optic disc segmentation and cup-to-disc ratio analysis.

Retinal image analysis generally involves several stages:

1. Image acquisition
2. Preprocessing
3. Region of interest extraction
4. Feature extraction
5. Feature selection
6. Classification
7. Performance evaluation

Each stage contributes significantly to the overall diagnostic performance of glaucoma detection systems.

4. IMAGE PREPROCESSING TECHNIQUES

Image preprocessing is an essential step in glaucoma detection systems because retinal images often contain noise, illumination variations, and low contrast. Effective preprocessing improves feature extraction quality and enhances classification performance.

Contrast Enhancement: Contrast enhancement techniques improve visibility of retinal structures such as the optic disc and blood vessels. Contrast Limited Adaptive Histogram Equalization (CLAHE) is one of the most widely used preprocessing methods in retinal image analysis [29]. CLAHE enhances local contrast while preventing excessive noise amplification.

Noise Removal: Noise removal techniques such as Gaussian filtering and median filtering are commonly applied to eliminate unwanted artifacts from retinal images.

Image Normalization: Normalization adjusts pixel intensity distributions and ensures consistency among images captured from different devices.

Region of Interest Extraction: Region of Interest (ROI) extraction focuses analysis on clinically important regions such as the optic nerve head. ROI extraction reduces computational complexity and eliminates irrelevant background information.

5. FEATURE EXTRACTION TECHNIQUES FOR GLAUCOMA DETECTION

Feature extraction is one of the most important stages in automated glaucoma diagnosis systems. The extracted features should effectively represent structural and textural characteristics associated with glaucomatous changes.

Statistical Feature Extraction: Statistical features describe intensity distributions and image variations. Commonly used statistical features include:

- Mean
- Variance
- Standard deviation
- Skewness
- Kurtosis
- Entropy

These features are computationally efficient and provide useful information regarding retinal texture patterns.

Texture-Based Feature Extraction: Texture features are highly effective for identifying structural variations caused by glaucoma. Gray-Level Co-occurrence Matrix (GLCM)-based features such as contrast, correlation, energy, and homogeneity are widely used in retinal image analysis [25]. Sonti and Dhuli [23] demonstrated that combining texture and shape-based features significantly improves glaucoma classification accuracy.

Wavelet-Based Feature Extraction: Wavelet transforms are extensively used because they provide multi-resolution image analysis capabilities. Discrete Wavelet Transform (DWT) decomposes an image into multiple sub-bands containing approximation and detail information. DWT effectively captures both spatial and frequency-domain characteristics [11], [12]. Kirar et al. [11] utilized RGB channel decomposition combined with DWT to improve feature representation for glaucoma diagnosis. Their method demonstrated improved classification accuracy compared to conventional approaches. Kirar and Agrawal [17] further combined DWT with histogram-based feature extraction and achieved reliable glaucoma detection performance. Wavelet packet decomposition extends DWT by decomposing both approximation and detail components. Raja and Gangatharan [19] proposed an automated glaucoma diagnosis framework using wavelet packet decomposition with optimal sub-band selection. Raja and Gangatharan [18] introduced hyper-analytic wavelet transforms for glaucoma detection and reported improved feature representation compared to conventional wavelet techniques. Variational Mode Decomposition (VMD) is an advanced signal decomposition technique capable of extracting intrinsic mode functions from retinal images. Agrawal et al. [13] proposed a quasi-bivariate VMD-based glaucoma detection system that achieved improved feature representation and classification performance. An iterative VMD for automated glaucoma diagnosis and demonstrated higher stability and robustness. Empirical Wavelet Transform (EWT) adaptively decomposes images into meaningful frequency bands. Maheshwari et al. [16] combined EWT with corr-entropy-based feature extraction and achieved strong noise robustness and high classification accuracy. Bidimensional Empirical Mode Decomposition (BEMD) techniques have also been used for retinal image analysis. Jianjia and Yan [30] proposed a BEMD-based image fusion method capable of preserving important structural information. The texture analysis using BEMD and demonstrated improved characterization of nonlinear image patterns.

6. MACHINE LEARNING APPROACHES

Machine learning techniques play a major role in automated glaucoma diagnosis systems. These methods classify retinal images based on extracted features. Support Vector Machine (SVM) is one of the most widely used classifiers for glaucoma detection because of its effectiveness in high-dimensional feature spaces. SVM classifiers provide strong generalization capability and perform effectively even with limited datasets. K-Nearest Neighbor (KNN) is a simple non-parametric classifier that classifies images based on similarity measures. Random Forest classifiers use multiple decision trees to improve classification robustness and reduce overfitting. Hybrid machine learning models combine multiple feature extraction techniques and classifiers to improve diagnostic accuracy.

7. DEEP LEARNING APPROACHES

Deep learning techniques have revolutionized medical image analysis by automatically learning hierarchical image representations. Convolutional Neural Networks (CNNs) are extensively used for glaucoma detection because they automatically learn discriminative image features. David et al. [7] proposed an ensemble CNN model that achieved higher accuracy compared to standalone CNN architectures. Transfer learning reduces the need for large annotated datasets by utilizing pre-trained deep learning models. Pin et al. [8] compared several transfer learning architectures including VGG, ResNet, and Inception models. Their results indicated that ResNet-based architectures achieved superior performance. Bowd and Belghith et al. [1] proposed an autoencoder-based region-of-interest framework specifically designed for glaucoma detection in myopic eyes. Wiharto et al. [3] introduced an EfficientNet-LSTM hybrid model capable of extracting spatial and contextual image features. Xavier and Fanax [4] proposed ODM Net, which combines DenseNet and MobileNet architectures with heuristic optimization for efficient glaucoma detection. Devecioglu et al. [26] introduced Self-ONNs for real-time glaucoma detection and demonstrated improved computational efficiency and accuracy. Singh et al. [27] proposed a hybrid framework combining handcrafted features with deep learning representations to improve robustness and diagnostic accuracy.

8. COMPARATIVE ANALYSIS OF EXISTING METHODS

Table 1 presents a comparative summary of major glaucoma detection approaches.

Table 1: A Comparative Summary of Major Glaucoma Detection Approaches.

Ref	Technique	Major Contribution
[1]	Autoencoder-based ROI + Deep Learning	Improved localization and reduced false positives
[2]	Neural Network	Early-stage glaucoma detection
[3]	EfficientNet + LSTM	Improved contextual feature learning
[4]	ODM Net	High accuracy with reduced complexity
[7]	Ensemble CNN	Improved robustness
[9]	SS-QB-VMD	Enhanced feature representation
[11]	RGB + DWT	Multi-resolution analysis
[12]	DWT + EWT	Improved sensitivity and specificity
[16]	EWT + Corr-entropy	Noise robustness
[18]	Hyper-Analytic Wavelet	Better feature extraction
[23]	Shape + Texture Features	Improved hybrid feature representation
[25]	GLCM Texture Features	Effective texture analysis
[26]	Self-ONNs	Real-time capability
[27]	Hybrid CNN + Handcrafted Features	Enhanced robustness
[29]	CLAHE	Improved image contrast

The comparative analysis indicates that deep learning models generally achieve higher accuracy because of their ability to learn complex image representations automatically. However, these methods require extensive training data and computational resources. In contrast, wavelet-based and decomposition-based techniques provide computational efficiency while maintaining satisfactory performance. Hybrid frameworks combining multi-resolution feature extraction and machine learning classification demonstrate a practical balance between performance and complexity.

9. CHALLENGES IN AUTOMATED GLAUCOMA DETECTION

Despite significant advancements, several challenges remain in automated glaucoma diagnosis systems.

Limited Dataset Availability: Deep learning models require large annotated datasets, which are difficult to obtain due to privacy concerns and expert labeling requirements.

Image Quality Variations: Retinal images often suffer from illumination variations, blur, and noise, affecting feature extraction and classification performance.

High Computational Complexity: Advanced deep learning models require powerful computational hardware and large memory resources.

Feature Redundancy: Decomposition-based methods generate large numbers of features, leading to redundancy and increased computational cost.

Early-Stage Glaucoma Detection: Detecting early-stage glaucoma remains difficult because structural changes are often subtle and difficult to distinguish.

Lack of Standardized Evaluation: Different studies use different datasets and evaluation protocols, making direct performance comparison challenging.

10. RESEARCH GAPS

Based on the reviewed literature, several important research gaps are identified:

- Dependence of deep learning methods on large datasets [1], [3]
- High computational complexity in advanced deep learning models [4], [26]
- Limited capability of handcrafted features to capture nonlinear patterns [11], [25]
- Feature redundancy in decomposition-based approaches [9], [32]
- Insufficient use of feature fusion strategies [12], [23]
- Sensitivity to image quality variations [29]
- Limited emphasis on early glaucoma detection [2]
- Lack of standardized benchmark datasets

These gaps indicate the necessity for efficient hybrid frameworks capable of combining multi-resolution analysis, feature fusion, dimensionality reduction, and robust classification.

11. FUTURE RESEARCH DIRECTIONS

Future glaucoma detection research should focus on:

- Development of lightweight deep learning architectures
- Multi-modal retinal image analysis
- Explainable artificial intelligence for clinical interpretation
- Federated learning for privacy-preserving diagnosis
- Integration of handcrafted and deep features
- Real-time glaucoma screening systems
- Early-stage glaucoma detection models
- Standardized datasets and benchmarking protocols

The integration of machine learning with advanced image processing techniques is expected to significantly improve the reliability and accessibility of glaucoma diagnosis systems.

12. CONCLUSION

This survey paper presented a comprehensive review of automated glaucoma detection techniques based on retinal fundus image analysis. Various methodologies including preprocessing approaches, statistical feature extraction, texture analysis, wavelet transforms, decomposition models, machine learning algorithms, and deep learning frameworks were critically analyzed. The review demonstrates that wavelet-based and decomposition-based approaches effectively capture multi-resolution image characteristics while maintaining computational efficiency. Deep learning models achieve superior performance by automatically learning hierarchical image representations; however, their dependence on large datasets and computational resources limits practical deployment. Hybrid frameworks combining feature extraction, feature fusion, dimensionality reduction, and machine learning classification provide a promising balance between accuracy and computational complexity. The analysis also identified several research gaps including feature redundancy, limited dataset availability, and challenges in early-stage glaucoma detection. Overall, automated glaucoma detection systems have shown significant progress and possess strong potential for assisting ophthalmologists in early disease diagnosis. Future research should focus on developing efficient, interpretable, and clinically deployable frameworks capable of delivering accurate and reliable glaucoma screening in real-world healthcare environments.

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