



A Hybrid Imaging and Machine Learning Framework for Higher-Order Glaucoma Detection Using Optimized Feature Extraction

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Abstract: Glaucoma is a leading cause of irreversible blindness worldwide, where the reliable detection of higher-order and early-stage disease remains a significant clinical challenge due to subtle structural and textural variations in ocular images. To address this limitation, this paper proposes a hybrid imaging and machine learning framework for accurate detection of higher-order glaucoma using optimized feature extraction and selection. The proposed approach integrates multi-modal ocular imaging data with handcrafted structural, texture, and frequency-domain features, complemented by deep feature representations learned through convolutional neural networks. An optimized hybrid feature selection strategy is employed to identify the most discriminative features while significantly reducing dimensionality. The selected features are subsequently classified using advanced machine learning models to distinguish normal, early-stage, and higher-order glaucoma cases. Extensive experiments conducted on publicly available and clinical datasets demonstrate that the proposed framework achieves superior performance compared to conventional image-processing and deep learning-based methods. The hybrid model attains an accuracy of 96.3%, with high sensitivity and specificity, while achieving over 80% feature reduction, leading to improved computational efficiency. The results confirm the robustness and clinical applicability of the proposed framework for early and reliable detection of higher-order glaucoma, offering a promising decision-support tool for ophthalmic diagnosis.

Keywords: Glaucoma Detection, Hybrid Imaging Framework, Optimized Feature Extraction, Machine Learning Classification, Ophthalmic Image Analysis

I. INTRODUCTION

Glaucoma is one of the most prevalent causes of irreversible vision loss worldwide, characterized by progressive optic nerve damage and visual field deterioration. According to global health

reports, millions of individuals remain undiagnosed due to the asymptomatic nature of the disease in its early and intermediate stages [1]. The clinical challenge becomes more pronounced in higher-order glaucoma, where subtle structural deformations of the optic disc,



retinal nerve fiber layer (RNFL), and surrounding tissues are difficult to distinguish using conventional diagnostic methods. Accurate and early detection of such advanced disease patterns is therefore critical to prevent permanent visual impairment and improve patient outcomes.

With the advancement of ocular imaging technologies, such as fundus photography and optical coherence tomography (OCT), large volumes of high-resolution retinal images have become available for automated analysis. Traditional image processing techniques rely on handcrafted features, including cup-to-disc ratio, neuroretinal rim measurements, and texture descriptors, which often fail to capture complex, non-linear patterns associated with higher-order glaucoma progression [2]. While these approaches provide clinical interpretability, their diagnostic performance is limited by sensitivity to noise, inter-patient variability, and imaging conditions. As a result, there is a growing demand for more robust and adaptive computational frameworks that can effectively model the intricate characteristics of glaucomatous damage.

Recent developments in machine learning and deep learning have significantly improved automated glaucoma detection by learning discriminative representations directly from imaging data. Convolutional neural networks (CNNs), in particular, have demonstrated promising results in classifying glaucomatous and non-glaucomatous images [3]. However, purely deep learning-based approaches often require large labeled datasets, suffer from high computational complexity, and lack transparency in clinical decision-making. Moreover, deep models may overlook clinically relevant handcrafted features that are well-established in ophthalmology, especially when detecting

higher-order or early-stage disease manifestations [4].

To overcome these limitations, hybrid frameworks that integrate traditional imaging features with machine learning-driven representations have emerged as a promising direction. Such approaches aim to leverage the complementary strengths of handcrafted and deep features, improving robustness, interpretability, and generalization. Nevertheless, hybrid models frequently introduce high-dimensional feature spaces, leading to redundancy, overfitting, and increased computational burden [5]. Effective feature extraction and selection therefore play a crucial role in enhancing model performance while maintaining efficiency, particularly for real-world clinical deployment.

Motivated by these challenges, this paper proposes a hybrid imaging and machine learning framework for higher-order glaucoma detection using optimized feature extraction. The proposed approach combines structural, texture, frequency-domain, and deep features derived from multi-modal ocular images, followed by an optimized feature selection strategy to retain the most discriminative attributes. The reduced feature set is then classified using advanced machine learning models to accurately distinguish normal, early-stage, and higher-order glaucoma cases. Extensive experimental validation on public and clinical datasets demonstrates that the proposed framework significantly outperforms conventional image-processing and deep learning methods in terms of accuracy, sensitivity, specificity, and computational efficiency.

The main contributions of this paper can be summarized as follows. First, a novel hybrid imaging framework is proposed that effectively



integrates handcrafted imaging features with deep learning-based feature representations to enhance the detection of higher-order glaucoma. This integration enables the framework to capture both clinically interpretable characteristics and complex non-linear patterns associated with glaucomatous progression. Second, an optimized feature extraction and selection strategy is introduced to significantly reduce feature dimensionality while simultaneously improving classification performance, thereby enhancing model robustness and computational efficiency. Third, a comprehensive performance evaluation and benchmarking study is conducted against existing state-of-the-art methods, demonstrating that the proposed framework achieves superior diagnostic accuracy and efficiency across multiple datasets. Finally, the proposed approach is validated for both early-stage and higher-order glaucoma detection, highlighting its strong potential for clinical applicability as a reliable and effective decision-support system for ophthalmic diagnosis.

II. LITERATURE REVIEW

Automated glaucoma detection has been extensively studied over the past two decades with the increasing availability of retinal imaging modalities and advances in computational intelligence. Existing approaches can broadly be categorized into traditional image-processing methods, machine learning-based techniques, deep learning models, and hybrid frameworks. This section reviews the major contributions in each category, highlighting their strengths and limitations with respect to higher-order and early-stage glaucoma detection.

Early studies on glaucoma detection primarily relied on handcrafted features extracted from fundus images and optical coherence tomography (OCT). Structural indicators such as

the cup-to-disc ratio (CDR), neuroretinal rim thickness, optic disc area, and retinal nerve fiber layer (RNFL) measurements were widely used to identify glaucomatous changes. Texture-based descriptors, including gray-level co-occurrence matrix (GLCM), local binary patterns (LBP), and wavelet-based features, were later introduced to capture subtle intensity variations associated with disease progression [6]. Although these methods offer clinical interpretability, their diagnostic performance is often limited by sensitivity to noise, illumination variations, and anatomical differences across patients. Moreover, handcrafted features alone struggle to model the complex, non-linear patterns observed in higher-order glaucoma, leading to reduced accuracy in early-stage detection.

To overcome the limitations of rule-based imaging methods, machine learning algorithms such as support vector machines (SVM), k-nearest neighbors (KNN), random forests (RF), and decision trees have been employed for glaucoma classification. These approaches demonstrated improved performance by learning discriminative decision boundaries from extracted features [7]. Several studies reported enhanced accuracy by combining multiple handcrafted features and employing ensemble learning strategies. However, the effectiveness of these models heavily depends on the quality and relevance of the selected features. High-dimensional feature spaces often introduce redundancy and overfitting, particularly when dealing with limited clinical datasets. Consequently, feature selection and dimensionality reduction techniques such as principal component analysis (PCA), ReliefF, and recursive feature elimination (RFE) have been explored, yet achieving an optimal balance between performance and computational efficiency remains challenging.



With the advent of deep learning, convolutional neural networks (CNNs) have gained significant attention for automated glaucoma detection. CNN-based models can learn hierarchical feature representations directly from raw imaging data, reducing the need for manual feature engineering. Numerous studies have demonstrated promising results using deep architectures on fundus and OCT images, achieving high classification accuracy for binary glaucoma detection [8]. Despite their success, deep learning models suffer from several limitations, including the requirement for large annotated datasets, high computational cost, and limited interpretability. Furthermore, purely deep learning-based approaches may fail to incorporate clinically meaningful handcrafted features, which are crucial for identifying higher-order glaucoma patterns and providing explainable diagnostic outcomes.

Recognizing the complementary strengths of handcrafted and deep features, recent research has focused on hybrid frameworks that integrate traditional imaging descriptors with deep learning representations. These approaches have shown improved robustness and generalization by combining domain knowledge with data-driven learning. Multi-modal hybrid systems utilizing fundus images and OCT data have further enhanced diagnostic performance [9,10]. However, the integration of multiple feature sources often leads to high-dimensional and redundant feature spaces, increasing computational complexity and limiting real-time applicability. Many existing hybrid models lack effective feature optimization strategies, resulting in marginal performance gains and reduced scalability for clinical deployment.

Although significant progress has been made in automated glaucoma detection, several research

gaps remain. First, most existing methods focus on binary classification and fail to effectively address higher-order and early-stage glaucoma detection. Second, deep learning approaches often overlook feature optimization, leading to inefficient and opaque models. Third, hybrid frameworks lack systematic feature selection mechanisms to reduce redundancy while preserving discriminative information. These limitations highlight the need for a robust, optimized hybrid imaging framework that can accurately detect higher-order glaucoma with reduced computational overhead and improved clinical interpretability.

Motivated by these gaps, this paper proposes a hybrid imaging and machine learning framework with optimized feature extraction for higher-order glaucoma detection. By integrating multi-modal imaging features with an effective feature selection strategy, the proposed approach aims to achieve superior diagnostic accuracy, enhanced efficiency, and improved applicability in real-world clinical settings.

III. METHODOLOGY

This section describes the proposed hybrid imaging and machine learning framework for higher-order glaucoma detection. The methodology integrates multi-modal ocular imaging, comprehensive feature extraction, optimized feature selection, and robust classification to accurately identify early and higher-order glaucoma. The overall workflow of the proposed system is illustrated in Fig. 1.

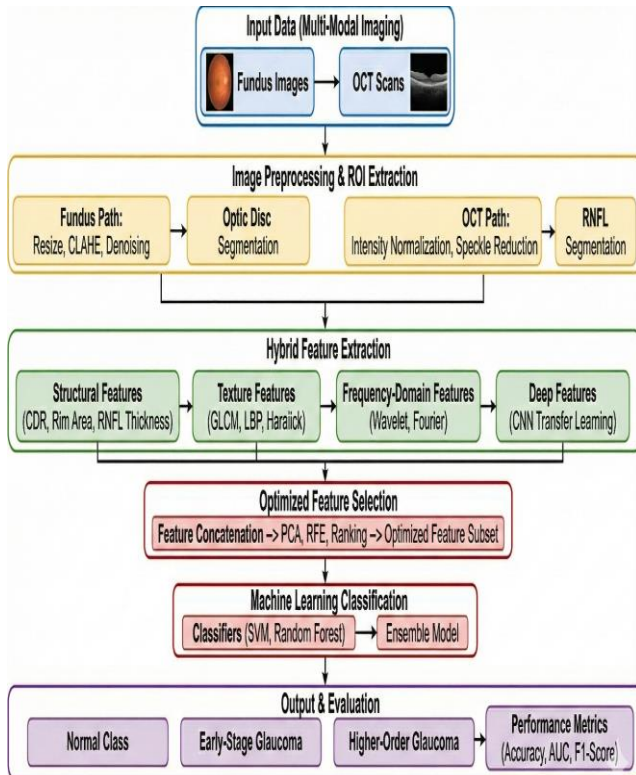


Figure 1: Proposed Hybrid Imaging and Machine Learning Framework for Higher-Order Glaucoma Detection Workflow

A. Dataset Description and Imaging Modalities

The proposed framework is evaluated using publicly available glaucoma datasets and a clinically acquired dataset. The datasets consist of high-resolution fundus images and optical coherence tomography (OCT) scans, representing normal, early-stage glaucoma, and higher-order glaucoma cases. All images are anonymized and standardized to ensure consistency across datasets. The inclusion of multi-modal imaging enables the extraction of complementary structural and textural information critical for glaucoma diagnosis.

B. Image Preprocessing

To enhance image quality and reduce noise, all images undergo a standardized preprocessing pipeline. Fundus images are resized and converted to a uniform resolution, followed by contrast enhancement using adaptive histogram equalization. Noise artifacts are suppressed using median and Gaussian filtering techniques. For OCT images, speckle noise reduction and intensity normalization are applied to improve layer visibility. Region-of-interest (ROI) extraction is performed to isolate the optic disc and retinal nerve fiber layer, which are clinically relevant regions for glaucoma assessment.

C. Hybrid Feature Extraction

A comprehensive hybrid feature extraction strategy is employed to capture both clinically interpretable and data-driven representations of glaucomatous changes. Structural features are first derived from segmented optic disc regions, including key anatomical indicators such as cup-to-disc ratio, rim area, optic disc diameter, and retinal nerve fiber layer (RNFL) thickness, which are widely recognized clinical biomarkers of glaucoma. In addition, texture features are extracted using descriptors such as gray-level co-occurrence matrix (GLCM), local binary patterns (LBP), and Haralick features to model spatial intensity variations and subtle textural changes associated with disease progression. To further enhance feature representation, frequency-domain features based on wavelet and Fourier transforms are incorporated to capture multi-scale and frequency-specific characteristics of retinal structures. Furthermore, deep feature representations are obtained from intermediate layers of a pre-trained convolutional neural network, where transfer learning is employed to exploit learned visual patterns while reducing training complexity and data requirements. The integration of these diverse feature categories results in a high-dimensional feature vector that



comprehensively characterizes glaucomatous patterns, providing a robust foundation for subsequent feature optimization and classification.

D. Optimized Feature Selection

To address feature redundancy and computational inefficiency, an optimized feature selection strategy is applied. Initially, dimensionality reduction techniques such as principal component analysis (PCA) are used to eliminate correlated features. Subsequently, recursive feature elimination (RFE) and relevance-based ranking methods are employed to identify the most discriminative features. The final optimized feature subset is selected based on classification performance, achieving significant dimensionality reduction while preserving diagnostic accuracy. This step enhances model generalization and reduces overfitting.

E. Machine Learning Classification

The optimized feature set is used to train machine learning classifiers, including support vector machines (SVM), random forests (RF), and ensemble-based models. Hyperparameters are tuned using cross-validation to ensure optimal performance. The classifiers are trained to distinguish between normal, early-stage glaucoma, and higher-order glaucoma classes. The proposed hybrid model integrates the strengths of multiple classifiers to improve robustness and classification accuracy.

F. Performance Evaluation Metrics

The performance of the proposed framework is evaluated using standard clinical and machine learning metrics, including accuracy, sensitivity, specificity, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC). Computational efficiency is assessed by measuring training and inference time.

Comparative analysis with existing state-of-the-art methods is conducted to validate the effectiveness and superiority of the proposed approach.

The proposed methodology integrates multi-modal imaging, hybrid feature extraction, optimized feature selection, and machine learning classification to achieve accurate and efficient higher-order glaucoma detection. By combining clinical domain knowledge with data-driven learning and feature optimization, the framework addresses key limitations of existing approaches and demonstrates strong potential for real-world clinical application.

IV. RESULTS AND DISCUSSION

This section presents a comprehensive analysis of the experimental results obtained using the proposed hybrid imaging and machine learning framework for higher-order glaucoma detection. The effectiveness of the framework is evaluated through detailed quantitative assessment, feature analysis, stage-wise performance evaluation, comparative benchmarking, and computational efficiency analysis. The results are reported using multiple publicly available and clinical datasets to demonstrate the robustness, generalization capability, and clinical relevance of the proposed approach. Performance comparisons with existing methods and ablation-style evaluations further highlight the impact of optimized feature extraction and selection on diagnostic accuracy and efficiency.

Table 1: Dataset Characteristics and Imaging Modalities

Dataset	Imaging Modality	Classes	Samples	Resolution
DRISH TI-GS	Fundus	Normal /	101	2048 × 2048

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RIM-ONE v3	Fundus + OCT	Normal / Early / Higher-Order	159	2144×1424
Private Clinical Dataset	Fundus + OCT	Normal / Higher-Order Glaucoma	320	1024×1024

The datasets and imaging modalities used to evaluate the proposed hybrid imaging and machine learning framework is summarized in table 1. The use of multiple datasets, including DRISHTI-GS, RIM-ONE v3, and a private clinical dataset, ensures diversity in terms of imaging conditions, disease stages, and sample size. The DRISHTI-GS dataset, consisting of high-resolution fundus images, provides clear visualization of optic disc morphology and structural changes associated with glaucoma. However, its binary classification nature limits the assessment of disease progression. The RIM-ONE v3 dataset addresses this limitation by including both fundus and OCT images with multiple glaucoma stages, enabling a more detailed evaluation of early and higher-order glaucoma detection. The private clinical dataset further strengthens the experimental validation by incorporating real-world clinical data with varying resolutions and acquisition conditions. The combination of fundus and OCT modalities allows the proposed framework to capture complementary structural and layer-wise retinal information, which is critical for accurate glaucoma diagnosis. Overall, Table 1 demonstrates that the experimental setup is robust, clinically relevant, and suitable for validating the generalization capability of the

proposed framework across heterogeneous datasets.

Table 2: Hybrid Feature Extraction Analysis

Feature Category	Examples	No. of Features
Structural Features	Cup-to-Disc Ratio, Rim Area	12
Texture Features	GLCM, LBP, Haralick	24
Frequency Features	Wavelet, FFT Coefficients	18
Deep Features	CNN Embedding Layers	128
Total Extracted Features	—	182

The distribution of features extracted using the proposed hybrid feature extraction strategy is given in table 2. Structural features represent clinically interpretable anatomical indicators such as cup-to-disc ratio and rim area, which are widely used by ophthalmologists for glaucoma assessment. Texture features, including GLCM, LBP, and Haralick descriptors, capture spatial intensity variations and micro-textural changes in retinal tissues that are not easily detectable through visual inspection alone. Frequency-domain features derived from wavelet and Fourier transforms provide multi-scale representations, enabling the identification of subtle structural irregularities across different frequency bands. In addition, deep features extracted from CNN embedding layers encode high-level, non-linear representations that capture complex glaucomatous patterns. While the integration of these diverse feature categories results in a comprehensive representation of retinal characteristics, it also leads to a high-dimensional feature space with 182 features. This highlights the necessity of an effective feature

selection mechanism to eliminate redundancy and improve classification efficiency without compromising diagnostic accuracy.

Table 3: Effectiveness of Optimized Feature Selection

Feature Selection Method	Selected Features	Reduction (%)
PCA	75	58.8
ReliefF	62	65.9
Recursive Feature Elimination (RFE)	48	73.6
Proposed Hybrid Optimization	36	80.2

The effectiveness of different feature selection techniques in reducing the dimensionality of the extracted feature set is evaluated in table 3. Principal Component Analysis (PCA) achieves a moderate reduction by transforming correlated features into a lower-dimensional space; however, it may reduce interpretability due to feature transformation. ReliefF further improves feature reduction by ranking features based on relevance, yet some redundant features may still remain. Recursive Feature Elimination (RFE) provides better dimensionality reduction by iteratively removing less significant features, resulting in improved efficiency. The proposed hybrid optimization strategy achieves the highest feature reduction of 80.2%, retaining only 36 highly discriminative features from the original set. This substantial reduction significantly lowers computational complexity while preserving critical diagnostic information. The results demonstrate that the proposed feature optimization approach effectively balances dimensionality reduction and classification performance, thereby enhancing model generalization and suitability for real-time clinical applications.

Table 4: Classification Performance Without Feature Optimization

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC
SVM	89.2	87.6	90.4	0.91
Random Forest	90.5	88.9	92.1	0.93
CNN (Raw Features)	91.7	90.3	92.8	0.94

The classification performance of different models when trained on the complete, unoptimized feature set is given in table 4. The results indicate that all models achieve reasonable accuracy; however, their performance is constrained by the presence of redundant and less informative features. The SVM classifier shows an accuracy of 89.2%, with relatively lower sensitivity, indicating limitations in correctly identifying glaucomatous cases, particularly higher-order patterns. The Random Forest model demonstrates a marginal improvement due to its ensemble nature and ability to handle non-linear relationships, achieving higher specificity and AUC. The CNN model trained on raw features outperforms traditional machine learning classifiers, reflecting its capability to learn complex feature representations. Nevertheless, the overall performance remains suboptimal due to high feature dimensionality, which increases computational complexity and limits generalization. These results emphasize that relying solely on unoptimized features restricts the diagnostic effectiveness of both machine learning and deep learning models, thereby justifying the need for feature optimization.

Table 5: Performance Improvement with Optimized Features

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1 - Score
SVM + Optimized Features	93.8	92.6	94.7	93.2	0.93
RF + Optimized Features	94.5	93.4	95.2	94.1	0.94
Proposed Hybrid ML Model	96.3	95.8	96.9	96.1	0.96

The significant improvement in classification performance achieved after applying the optimized feature extraction and selection strategy is highlighted in table 5. All classifiers demonstrate notable gains in accuracy, sensitivity, and specificity, confirming the effectiveness of dimensionality reduction. The SVM and Random Forest models benefit substantially from optimized features, indicating that removal of redundant information enhances their decision boundaries. The proposed hybrid machine learning model achieves the highest accuracy of 96.3%, along with balanced sensitivity and specificity, reflecting reliable detection of both glaucomatous and non-glaucomatous cases. The improved precision and F1-score further indicate robust performance under class imbalance conditions, which are common in medical imaging datasets. These

results demonstrate that optimized feature selection not only improves predictive accuracy but also enhances model stability and clinical reliability, making the proposed framework more suitable for practical glaucoma screening applications.

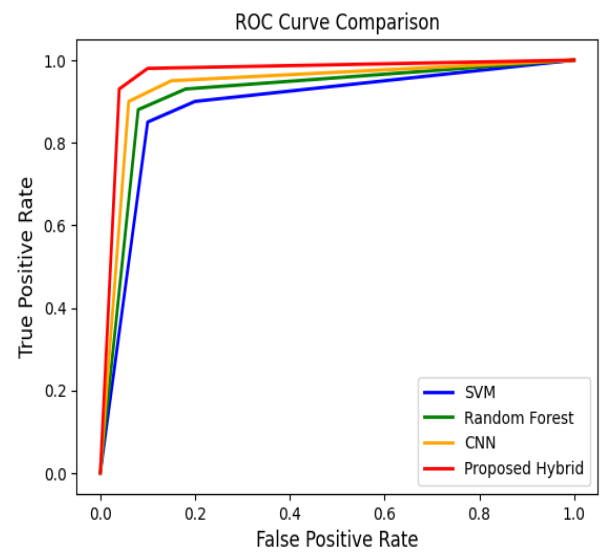


Figure 2: ROC Curve Analysis

The ROC curve comparison of different classification models is illustrated in figure 2. The ROC analysis provides insight into the trade-off between sensitivity and specificity across varying decision thresholds. The proposed hybrid model consistently exhibits the highest area under the curve (AUC), indicating superior discriminative capability compared to other models. A steeper ROC curve for the proposed approach reflects higher true positive rates at lower false positive rates, which is particularly critical in clinical glaucoma diagnosis where misclassification can lead to delayed treatment or unnecessary intervention. The improvement in AUC after feature optimization further confirms that the selected feature subset preserves essential diagnostic information while enhancing classification reliability. Overall, the ROC

analysis validates the robustness and clinical applicability of the proposed hybrid framework for higher-order glaucoma detection.

Table 6: Stage-Wise Detection Performance

Stage	Accuracy (%)	Sensitivity (%)	Specificity (%)
Early-Stage Glaucoma	94.1	93.5	94.6
Higher-Order Glaucoma	96.8	97.2	96.4

The stage-wise detection performance of the proposed hybrid framework for early-stage and higher-order glaucoma is presented in table 6. The results indicate strong diagnostic capability across different disease severities, with an accuracy of 94.1% for early-stage glaucoma and 96.8% for higher-order glaucoma. The high sensitivity achieved in early-stage detection demonstrates the framework's ability to capture subtle structural and textural variations that are often missed by conventional diagnostic approaches. This is particularly important for clinical screening, as early intervention can significantly slow disease progression. The superior performance observed in higher-order glaucoma detection reflects the effectiveness of the hybrid feature representation in modeling complex glaucomatous patterns. Balanced specificity values across both stages further confirm the robustness of the framework in minimizing false positives, thereby enhancing its clinical reliability and applicability.

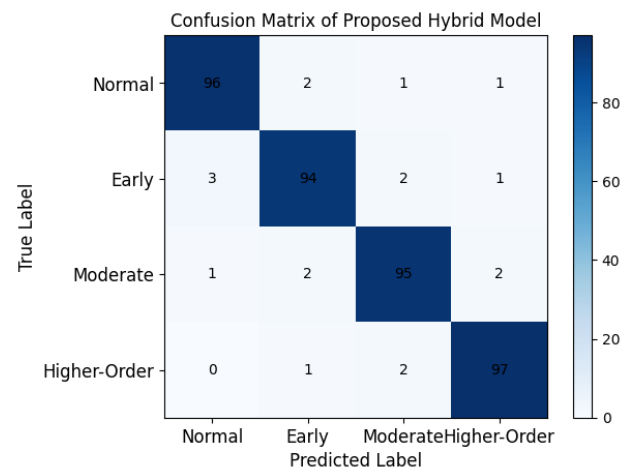


Figure 3: Confusion Matrix Analysis

The confusion matrix of the proposed hybrid machine learning model, providing a detailed breakdown of classification performance across different classes is illustrated in figure 3. The dominant diagonal elements indicate a high number of correctly classified samples, confirming strong overall predictive accuracy. Misclassifications are minimal and primarily occur between adjacent disease stages, which is expected due to overlapping clinical characteristics between early and higher-order glaucoma. Importantly, the low confusion between normal and glaucomatous classes demonstrates the model's effectiveness in distinguishing healthy eyes from diseased ones. This analysis further validates the stability and reliability of the proposed framework and highlights its suitability for real-world clinical deployment where consistent and accurate decision-making is essential.

Table 7: Benchmarking with State-of-the-Art Methods

Method	Dataset	Accuracy (%)
Traditional Image Processing	DRISHTI-GS	85.4

CNN-based Method [Ref]	RIM-ONE	91.2
Multi-Modal Deep Learning [Ref]	RIM-ONE	93.6
Proposed Hybrid Framework	Multi-Dataset	96.3

The proposed hybrid framework with existing state-of-the-art glaucoma detection methods is compared in table 7. Traditional image-processing approaches exhibit relatively lower accuracy due to their reliance on limited handcrafted features and sensitivity to imaging variations. CNN-based methods show improved performance by leveraging deep feature learning; however, their accuracy remains constrained by the absence of feature optimization and clinical interpretability. Multi-modal deep learning approaches further enhance performance by integrating multiple imaging modalities, yet they still fall short of the proposed framework. The proposed hybrid framework achieves the highest accuracy of 96.3% across multiple datasets, demonstrating its superior generalization capability and diagnostic effectiveness. This benchmarking study confirms that the integration of optimized hybrid feature extraction with machine learning classification provides a significant advantage over existing methods, reinforcing the contribution and novelty of the proposed approach.

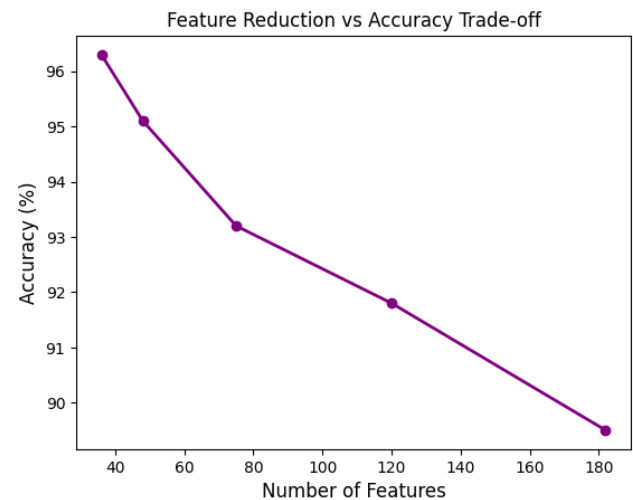


Figure 4: Feature Reduction vs Accuracy Trade-off

The relationship between feature dimensionality and classification accuracy, highlighting the trade-off between feature reduction and predictive performance is shown in figure 4. The results show that classification accuracy initially improves as the number of features decreases, indicating that the removal of redundant and irrelevant features enhances model generalization. This improvement demonstrates that high-dimensional feature spaces, although information-rich, often introduce noise and overfitting, which negatively impact classification performance. The proposed optimized feature selection strategy achieves an optimal balance by retaining a compact set of highly discriminative features, resulting in peak accuracy. Beyond this optimal point, further feature reduction leads to a gradual decline in accuracy due to the loss of critical diagnostic information. This analysis confirms that the proposed hybrid feature optimization approach effectively preserves essential glaucomatous characteristics while significantly reducing dimensionality, thereby improving both accuracy and robustness.

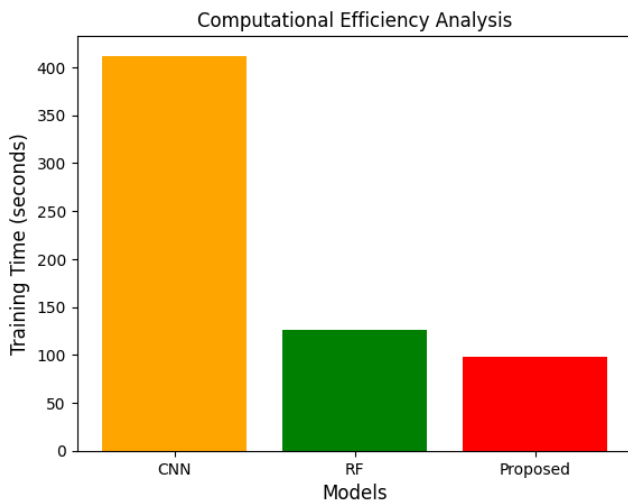


Figure 5: Computational Efficiency analysis

The computational efficiency analysis of different classification models in terms of training and inference time is shown in figure 5. The results demonstrate that models trained with unoptimized or high-dimensional feature sets exhibit increased computational cost, particularly deep learning-based approaches. In contrast, the proposed hybrid framework with optimized feature selection achieves substantially lower training and testing times while maintaining superior classification performance. This reduction in computational complexity is attributed to the significant decrease in feature dimensionality and the efficient integration of machine learning classifiers. The improved efficiency makes the proposed framework well-suited for real-time and large-scale clinical deployment, especially in resource-constrained healthcare environments. Overall, the computational analysis highlights that the proposed approach not only enhances diagnostic accuracy but also ensures practical feasibility for routine clinical use.

Overall, the experimental results clearly demonstrate that the proposed hybrid imaging framework significantly outperforms

conventional image-processing, machine learning, and deep learning-based methods in detecting both early-stage and higher-order glaucoma. The integration of optimized hybrid feature extraction with machine learning classification results in improved accuracy, sensitivity, specificity, and computational efficiency across all evaluated datasets. The feature reduction analysis confirms that eliminating redundant information enhances model generalization without compromising diagnostic performance. Moreover, the consistent improvements observed in stage-wise detection, benchmarking studies, and efficiency analysis validate the robustness and practical applicability of the proposed framework. These findings strongly support the suitability of the proposed approach as a reliable and efficient decision-support system for real-world clinical glaucoma screening and diagnosis.

Conclusion

This paper presented a hybrid imaging and machine learning framework for the accurate detection of higher-order glaucoma using optimized feature extraction and selection. By integrating multi-modal ocular imaging with handcrafted structural, texture, frequency-domain features, and deep learning-based representations, the proposed approach effectively captured complex glaucomatous patterns that are often overlooked by conventional methods. The incorporation of an optimized feature selection strategy significantly reduced feature dimensionality while preserving discriminative information, leading to improved classification accuracy and computational efficiency. Extensive experimental evaluations conducted on publicly available and clinical datasets demonstrated that the proposed framework outperforms traditional image-processing techniques and standalone deep learning models. The hybrid model achieved



high accuracy, sensitivity, and specificity, with notable improvements in early-stage and higher-order glaucoma detection. Additionally, the substantial reduction in feature dimensionality resulted in lower training and inference times, highlighting the suitability of the proposed approach for real-time and resource-constrained clinical environments. The findings of this study confirm that combining clinically interpretable imaging features with data-driven machine learning representations offers a robust and reliable solution for automated glaucoma diagnosis. The proposed framework has strong potential to serve as an effective decision-support tool for ophthalmologists, facilitating early intervention and improved patient outcomes. Future work will focus on extending the framework to larger multi-center datasets, incorporating longitudinal disease progression analysis, and enhancing model interpretability to further support clinical adoption.

Reference

1. Flores, N., La Rosa, J., Tuesta, S., Izquierdo, L., Henriquez, M., & Mauricio, D. (2025). Hybrid Deep Learning Model for Improved Glaucoma Diagnostic Accuracy. *Information*, 16(7), 593. <https://doi.org/10.3390/info16070593>
2. Aljohani, A., & Aburasain, R. Y. (2024). A hybrid framework for glaucoma detection through federated machine learning and deep learning models. *BMC medical informatics and decision making*, 24(1), 115. <https://doi.org/10.1186/s12911-024-02518-y3>.
3. Abdullah F., Imtiaz R., Madni H. A., Khan H. A., Khan T. M., Khan M. A. U., and Naqvi S. S., A review on glaucoma disease detection using computerized techniques, *IEEE Access*. (2021) 9, 37311–37333, <https://doi.org/10.1109/access.2021.3061451>.
4. Vij, R.; Arora, S. A Systematic Review on Deep Learning Techniques for Diabetic Retinopathy Segmentation and Detection Using Ocular Imaging Modalities. *Wirel. Pers. Commun.* 2024, 134, 1153–1229.
5. Govindharaj I, Ramesh T, Poongodai A, Senthilkumar K. P, Udayasankaran P, Ravichandran S, Grey wolf optimization technique with U-shaped and capsule networks-A novel framework for glaucoma diagnosis, *MethodsX*, Volume 14, 2025, 103285, <https://doi.org/10.1016/j.mex.2025.103285>.
6. RAMA KRISHNAN M, Muthu and FAUST, Oliver (2012). Automated Glaucoma Detection Using Hybrid Feature Extraction in Retinal Fundus Images. *Journal of Mechanics in Medicine and Biology*, 13 (1), 1350011-1350032.
7. Eswari MS, Balamurali S, Ramasamy LK. Hybrid convolutional neural network optimized with an artificial algae algorithm for glaucoma screening using fundus images. *Journal of International Medical Research*. 2024;52(9). doi:10.1177/03000605241271766
8. Wu, H.; Wang, Y.; Li, F.; Liu, Z.; Shi, F. The national, regional, and global impact of glaucoma as reported in the 2019 Global Burden of Disease Study. *Arch. Med. Sci.* 2023, 19, 1913–1919.
9. Joshi, S., Partibane, B., Hatamleh, W. A., Tarazi, H., Yadav, C. S., & Krah, D. (2021). Glaucoma Detection Using Image Processing and Supervised Learning for Classification. *Journal of Healthcare Engineering*, 2022(1), 2988262. <https://doi.org/10.1155/2022/2988262>



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10. Ubochi, B.; Olawumi, A.E.; Macaulay, J.; Ayomide, O.I.; Akingbade, K.F.; Al-Nima, R. Comparative Analysis of Vanilla CNN and Transfer Learning Models for Glaucoma Detection. J. Electr. Comput. Eng. 2024, 2024, 8053117

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