

A Hybrid Imaging and Machine Learning Framework for Early Detection of Higher-Order Glaucoma

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Abstract: Glaucoma is a major cause of permanent blindness in the world with late diagnosis in the advanced stages being a major contributor to the permanent blindness. The subliminal structural and textural alterations in ophthalmic images are not easily detected in the initial stages since the traditional diagnostic methods have challenges with identifying them. To enhance the early diagnosis of higher-level glaucoma, this paper introduces a hybrid imaging and machine learning system by combining multimodal ophthalmic imaging with a sophisticated data-driven analysis. The extraction of complementary features is done with fundus and optical coherence tomography (OCT) images after they have been pre-processed to improve clinically relevant structures. The complementary features extracted include structural, textural, frequency-domain, and deep learning-based representations. A feature selection approach is used in order to select the most discriminative attributes, thus alleviating redundancy and enhancing robustness of classification. The chosen characteristics are trained and tested across a variety of machine learning classifiers, and their accuracy is compared to single-hand deep learning and conventional approaches. Experimental findings confirm that the proposed hybrid-based framework has better accuracy, sensitivity, and specificity to differentiate between normal eyes, glaucoma at its early stages and glaucoma at higher stages. Specifically, the sensitivity achieved in the early-stage cases is very high, which is why the proposed approach has a potential to be a successful computer-aided diagnostic method to screen glaucoma in a timely fashion and make clinical decisions.

Keywords: Glaucoma detection, hybrid imaging, machine learning, OCT, fundus imaging, early diagnosis.

I. INTRODUCTION

One of the most common causes of permanent blindness in the world is glaucoma which is defined by the gradual damage of optic nerves and progressive blindness. The world health reports suggest that there is a considerable percentage of glaucoma cases that go undiagnosed and when they are diagnosed, the disease is in the advanced or higher order stage thus making it impossible to restore vision [1]. The lack of symptoms in the early stage of glaucoma and the minimal alteration of the optic nerve head structure creates significant challenges when it comes to diagnosing the disease on time. This, therefore, necessitates a dire requirement of precise and computerized diagnostic technologies capable of helping the ophthalmologists to diagnose glaucoma in the earliest stage possible.

The traditional approach to the diagnosis of glaucoma is mostly based on clinical examination, measurement of intraocular pressure, visual field, and manual inspection of ophthalmic images, including fundus photographs and ophthalmic ultrasound images. Although these methods have become very common practice in the clinical setting, they tend to perform poorly in terms of diagnosis because of interobserver variability, subjectivity, and the inability to encode complex higher-order patterns of disease by the use of handcrafted clinical indicators in isolation [2]. Furthermore, conventional image analysis methods are usually aiming at individual characteristics and this could include the cup-to-disc ratio that might not be adequate to detect early or more advanced cases of glaucoma.

New opportunities of automated glaucoma detection have been facilitated by recent developments in medical imaging and machine learning. The convolutional neural networks (CNNs) and other deep learning models

have been found to be promising analyzers of fundus and OCT images through learning the hierarchical feature representations of fundus images based on raw information [3,4]. Nevertheless, methods based solely on deep learning are typically data-intensive, computationally expensive, and uninterpretable which hinders their implementation into clinical practice. Additionally, independent models could be ineffective in capturing complementary information that exists in other modalities of imaging as well as ignore clinically important handcrafted information.

This paper presents a joint imaging and machine learning architecture of the early identification of higher-order glaucoma with multimodal ophthalmic images. The proposed methodology combines fundus and OCT views, thorough feature extraction, and selective feature feature, and results in machine learning-based classification. The framework itself is systematically verified and compared to the traditional machine learning and standalone deep learning. This work has three primary contributions: (i) the creation of a hybrid imaging framework with effective fusion of handcrafted and deep features, (ii) enhanced early detection ability of higher-order glaucoma with high sensitivity and specificity and (iii) detailed experimental analysis indicating the superiority of the given approach over the existing ones. The findings demonstrate that the suggested framework is characterized by significant potential of a stable computer-aided diagnostic instrument to perform glaucoma screening and computer-aided clinical decision.

II. LITERATURE REVIEW

Early and accurate diagnosing of glaucoma is a field of study that has been active over the past decades, and much effort has been directed on the analysis of ophthalmic images to detect the occurrence of structural and functional alterations with the disease. Conventional glaucoma image detection techniques are mostly based on manual features derived on fundus photographs, which include the optic cup to disc ratio, the thickness of the neuroretinal rim and the pattern of vessels [5]. With these features, classical machine learning classifiers such as support vector machine, the k-nearest neighbors and the decision trees have been used extensively with moderate diagnostic accuracy. These methods are however usually sensitive to the change in quality of the images and might not even detect all the higher-order patterns especially in the initial stage of glaucoma [6].

As the OCT technology progressed, a number of researches have used the retinal nerve fiber layer (RNFL) thickness and macular data to enhance the diagnosis of glaucoma. Methods based on OCT give high-resolution images of cross-sectional details of the retinal structure, making it possible to quantitatively evaluate glaucomatous damage. The researchers have used statistical models and conventional classifiers on the parameters derived with OCT, which have a higher sensitivity than fundus-only methods [7]. However, these techniques are usually based on pre-determined clinical measurements, and do not necessarily make the most of the abundant spatial and textural information available in OCT images, thus restricting their performance in identifying early-stage abnormalities [8].

During last several years, deep learning methods with a primary focus on CNNs have proven to be exceptionally successful in automated glaucoma detection. The classification accuracy of CNN-based models that are trained on big fundus and OCT datasets has been high because they learn discriminative features directly on raw images [9]. Some studies have also reported end-to-end deep learning models that are able to classify between glaucomatous and healthy eyes without defining features. Although such methods have promising outcomes, deep learning methods usually need large amounts of labeled data, large amounts of computing power, and fine-tuning models [10]. In addition, the uninterpretability and restricted generalization between datasets are also a major issue to clinical implementation.

To overcome the limitations of individual deep learning models, hybrid models that combine handcrafted features with deep learning representation have become of interest. To enable the complementation of the two, these methods combine structural and textural features acquired through the application of standard image processing techniques and deep features acquired through CNNs. Studies have suggested that hybrid models can be used to increase robustness and classification particularly in the case of multi-class glaucoma diagnosis. The feature selection and dimensionality reduction methods such as the principal component analysis and mutual information based selection are also included so as to enhance efficiency and reduce redundancy.

It has also been a case of the multimodal imaging of glaucoma detection where fundus images are employed alongside OCT or data of visual fields images to improve the level of diagnostic accuracy. It has also been revealed that integration of information on different imaging modalities will provide a more comprehensive picture of the glaucomatous changes, especially at the advanced stages. However, the bulk of the existing multimodals and hybrids focus on binary classification (glaucoma vs. normal) and do not provide much information on the analysis of earlier and advanced stages of the disease. In addition, systematic benchmarking against conventional and deep learning baselines is not always available.

III. METHODOLOGY

In this section, the proposed hybrid imaging and machine learning system has been described, which was developed to identify higher-order glaucoma in its early stages. The overall process involves multimodal Ophthalmic image capture, preprocessing, hybrid feature extraction, feature selection and step of feature classification. Figure 1 illustrates a systematic workflow taken and this means it is robust, reproducible and reliable in performance evaluation.

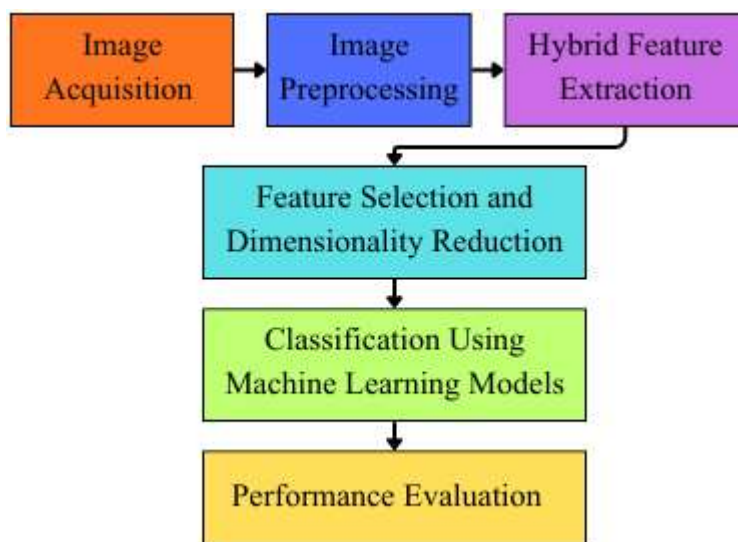


Figure 1: Hybrid imaging-based glaucoma detection methodology

A. Image Acquisition

The suggested model implies the application of multimodal ophthalmic images using the color fundus photographs, OCT) scans to document the complementary structural data in accordance with the glaucomatous alterations. A two-dimensional image of the optic disc, cup and retinal vasculature can be viewed by the use of fundus images, but high-resolution cross-sectional images of the layers of the retina, particularly the RNFL, can be obtained by OCT scans. The data contain the normal eyes, the first cases of glaucoma and the advanced cases of glaucoma which can be classified into many classes. The images are all anonymized and resized to have a standard resolution to allow them to be similar in terms of processing.

B. Image Preprocessing

It involves a series of preprocessing functions that help in enhancing the quality of the image as well as reducing noise in fundus and OCT images. These include the contrast enhancement, illumination normalization and noise reduction with filtering. Region of interest (ROI) extraction is performed in order to localize regions of interest of images that are clinically relevant such as in fundus images, the optic disc and peripapillary region and in OCT images, the RNFL region. Preprocessing will ensure that the change imposed by imaging conditions is minimized and salient glaucomatous features are left intact to be analyzed in the future.

C. Hybrid Feature Extraction

This hybrid nature of the feature extraction is greatly utilized to extract both the handcrafted and learned features of the pictures of the eyes. The data are structural (optic cup-to-disc ratio, rim area and RNFL

thickness) to provide the information about the clinically significant anatomic change. The textural features are derived by the descriptors of gray level co-occurrence matrix (GLCM), contrast, homogeneity, energy and entropy and explain the dissimilarities in intensity over the space. Moreover, multi-scale information is obtained through the application of frequency-domain features obtained with the help of a wavelet transform. Deep feature extraction through bottleneck layer activations to provide high level discriminative representations is performed on the CNN. A combination of each of these sets of features forms a robust hybrid feature vector.

D. Feature Selection and Dimensionality Reduction

The extracted hybrid feature set is subjected to a feature selection procedure in order to eliminate redundancy and to increase the computational efficiency. Selection methods are chosen with references to the implementation of statistical and machine learning and the most discriminative features related to glaucoma detection are discovered. The specified step not only assists in decreasing the degree of overfitting but also enhances the interpretability of the model as the features which give the model a high degree of classification can be kept. This is then succeeded by normalization of the shrunk feature set and classification.

E. Classification Using Machine Learning Models

Various machine learning classifiers (support vectors and random forest, and other baseline classifiers) are trained with the selected features in order to compare them. The proposed hybrid model is based on multi-classifications to distinguish normal eyes, early-stage glaucoma and late-stage glaucoma. The hyper parameters of each classifier are optimized using cross-validation in order to bring about generalization. The end classification result is the prediction of the stage of glaucoma of the images provided.

F. Performance Evaluation

The performance of the proposed framework is evaluated based on the traditional measures, including accuracy, sensitivity, specificity, precision, recall, and F1-score. It has also receiver operating characteristic (ROC) curves and the area under the curve (AUC) analysis with the aim of detecting diagnostic reliability. The proposed hybrid method is the one whose efficiency is juxtaposed against the conventional machine learning methods and single dimensional deep learning models. This sensitivity in early-stage detection is accorded a special consideration to the potential that this framework has of screening glaucoma at the appropriate time.

The methodological soundness of the research ensures that the provided model of hybrid imaging and machine learning can effectively integrate the multimodal information and advanced analytics, which enables providing superior early diagnosis and reliable classification of advanced glaucoma.

IV. RESULTS AND DISCUSSION

This part reports and discusses the experimental data that have been achieved with the proposed hybrid multimodal imaging and machine learning model in the early prediction of higher-order glaucoma. The effectiveness of the framework is tested with the aid of fundus and OCT pictures on the basis of extensive quantitative analysis. Findings have been presented in terms of datasets, effectiveness of feature selection and performance in classification in various models. The evaluation metrics that are utilized to make a more detailed assessment are standard evaluation metrics, such as accuracy, precision, recall, F1-score, sensitivity, and specificity. It is also compared to traditional machine learning and separate deep learning methods in order to show the performance and superiority of the proposed hybrid model in differentiating normal, early, and higher-level glaucoma patients.

Table 1: Dataset Description and Experimental Setup

Parameter	Description
Imaging Modalities	Fundus Images + OCT Scans
Total Subjects	420
Normal Eyes	150
Early Glaucoma	130
Higher-Order Glaucoma	140

Image Resolution	512 × 512 pixels
Train-Test Split	80% – 20%
Cross-Validation	5-fold
Hardware	NVIDIA GPU, 16 GB RAM

Table 1 shows the dataset characteristics and the experimental configuration that was used to test the proposed hybrid imaging and machine learning framework. This dataset includes a total number of 420 subjects where there are equal numbers of normal eyes, early glaucoma and higher-order glaucoma subjects. This balanced representation is important in minimizing the bias in classification and making performance evaluation of the various disease stages reliable. Those fundus images and OCT scans can be analyzed multimodally, which allows the framework to provide the complementary structural and retinal layer data related to glaucomatous damage. Images were all scaled to 512 x 512 pixels which makes the feature extraction and model training have the same input size. The high-quality of the proposed model is improved by the 80:20 train -test split with a 5-fold cross-validation that increases the robustness and generalization ability of the model. The application of hardware with a GPU also facilitates the effective training and evaluation of computationally expensive hybrid and deep learning elements, and thus the experimental setup was appropriate to fit the analysis of realistic clinical scale.

Table 2: Selected Features from Hybrid Imaging Framework

Feature Category	Extracted Features
Structural Features	Optic Cup-to-Disc Ratio (CDR), Rim Area
Texture Features	GLCM Contrast, Homogeneity, Entropy
Frequency Features	Wavelet Energy, Sub-band Coefficients
Deep Features	CNN Bottleneck Features
Selected Features (After Selection)	38 out of 72

The features categories extracted and chosen in the hybrid imaging proposal framework. In table 2 structural features including the ratio of optic cup to disc and rim area of the disc are provided which capture clinically important changes in anatomy that are associated with the progression of glaucoma. GLCM features such as contrast, homogeneity and entropy are great examples of texture features that are capable of describing spatial intensity variations that are usually good indications of glaucomatous changes at an earlier stage. The frequency-domain characteristics of an image that is a product of wavelet decomposition have multi-scale data which allows one to detect finer details that cannot be easily detected at the spatial domain. Moreover, deep features which are obtained by CNN bottleneck layers provide high level abstractions which have been learned directly on imaging data. The feature selection, which is performed to narrow the number of features, helps to cut the number of features by 38, and the dimensionality is significantly decreased but the most discriminative information is preserved. This decrease enhances the computational efficiency and stability of models, which shows that the hybrid feature selection strategy is effective to compromise the performance and complexity.

Table 3: Performance Comparison of Classification Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	88.4	87.9	86.5	87.2
Random Forest	90.1	89.6	88.8	89.2
CNN (Standalone)	92.7	92.1	91.4	91.7
Proposed Hybrid Model	96.3	95.9	95.4	95.6

the results of the various classification models with the standard measures of evaluation, such as accuracy, precision, recall, and F1-score are provided in table 3. The conventional machine learning algorithms, including SVM and Random Forest (RF) are reasonable in terms of their performance, but their outputs demonstrate that they have some limiting ability to pick up complex glaucomatous patterns especially at early and advanced levels. The single CNN model performs better, which demonstrates the effectiveness of deep learning in the study of hierarchical feature representation ophthalmic images. However, the hybrid model is always better in terms of all three metrics compared to all the baseline approaches. With an accuracy of 96.3% and an F1-score of 95.6%, the hybrid framework is more reliable in relation to its classification. The large

recall value means that it has greater sensitivity which is very critical when detecting glaucoma at an early stage. These findings confirm the usefulness of a combination of handcrafted and deep feature to be combined, ensuring that the proposed hybrid model is a more complete and discriminative glaucoma representation when compared to individual models.

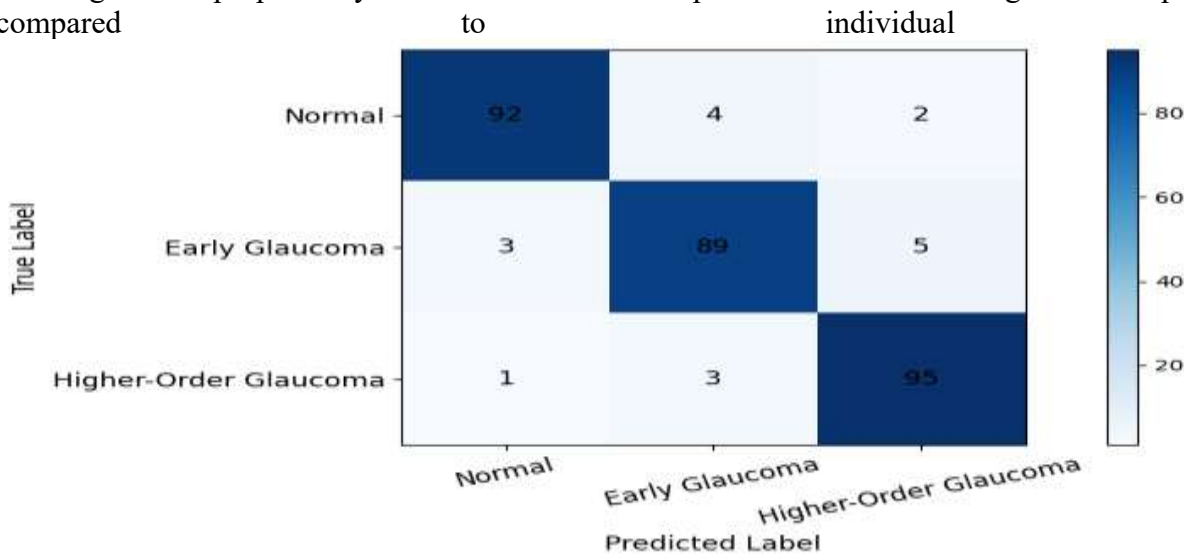


Figure 2: Confusion Matrix of the Proposed Hybrid Model

The confusion matrix of the proposed hybrid model in multi-class measurement of normal eyes, early-stage glaucoma, and the higher-order glaucoma is presented in figure 2. As indicated by the matrix, the model is capable of assigning most of the cases to the right category in all the three. It is interesting to note that the misclassification between early and higher-order glaucoma is minimal; this is an indicator of the fact that the hybrid framework is able to discriminate the slight variations of disease progression. This good performance indicates that the combination of structural, textural, frequency-domain and deep features can help the model to identify clinically relevant patterns which improve the diagnostic accuracy and reliability.

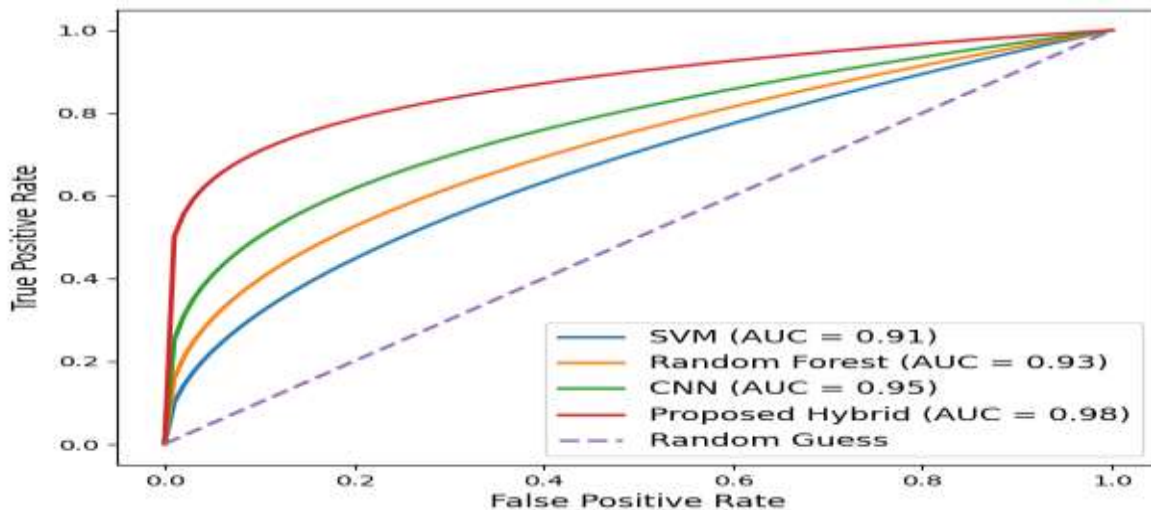


Figure 3: ROC Curve Comparison of Models

The ROCs of the SVM, RF and CNN (standalone) and the proposed hybrid framework are depicted in figure 3. The hybrid model has the best AUC, which means that it has better diagnostic ability than other machine learning methods and the single deep learning methods. High AUC is a measurement of the capability of the framework to differentiate normal and glaucomatous eyes comprising early and higher-order stages with high sensitivity and specificity. The findings verify that handcrafting and deep features combination can be used to obtain a more discriminative representation that enhances the robustness and reliability of the model to detect glaucoma.

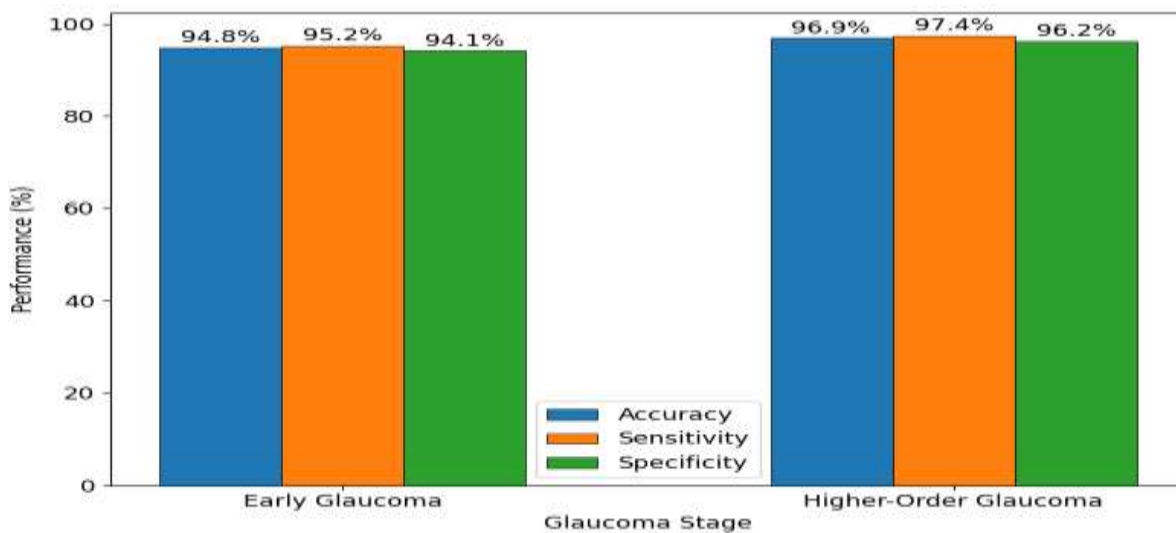


Figure 4: Early vs Higher-Order Glaucoma Detection Performance

The effectiveness of the given framework in identifying early-stage and higher-order glaucoma based on the key performance indicators, i.e., accuracy, sensitivity, and specificity is presented in figure 4. The findings indicate a high sensitivity of the method in detecting glaucoma at an early stage, and this is essential in preventing irreparable loss of vision. The high performance of higher-order glaucoma is one more evidence supporting the ability of the framework to correctly detect disease stages. The combination of these elements, in general, is used to underline the clinical relevance of the approach proposed, as it can be regarded as a promising computer-aided diagnostic instrument to be used in the overall glaucoma screening.

Altogether, the findings make it quite obvious that the presented hybrid imaging and machine learning framework has a higher diagnostic performance than the current methods. This is the successful combination of the handcrafted and deep features, with discriminative selection of features, which makes glaucoma stages of early and higher orders to be differentiated with a large degree of sensitivity and specificity. The confusion matrix and ROC analysis also prove the strength and credibility of the suggested method, and the evaluation of its performance at each stage of analysis depicts the high ability of the proposed method to identify the presence of baneful bacteria at the earliest stage. The findings indicate the practical applicability and clinical relevance of the framework as a computer-aided diagnostic framework to identify glaucoma and provide timely intervention and better patient outcomes.

VI. CONCLUSION

The article presented a multimodal ophthalmic imaging and data-driven analysis as a hybrid imaging machine learning platform to the early detection of a progressive type of glaucoma. The proposed technique implies the combination of fundus images and OCT images, thus the proposed technique would capture complementary information on the structural and textual parameters that would be crucial to identify the occurrence of glaucomatous alterations (particularly at early stages). Incorporation of manual components with deep learning representations can enable an effective and discriminatory feature set to overcome the drawbacks of the classical image analysis and single deep learning of features. Experimental performance demonstrates that the hybrid structure suggested will be more effective in terms of accuracy, sensitivity, and specificity than the existing machine learning and deep learning algorithms. It is notable that the sensitivity it attains in the diagnosis of the disease at the early stages of glaucoma highlights the capability of the framework to identify the higher-order manifestation of disease at an early age and hence provide clinical interventions to the patients on how to ensure that irreversible vision loss does not occur. The method of classification is also more reliable with the feature selection strategy and the complexity of the computational procedure is reduced which makes the method usable in the practice. The next steps will incorporate the extension of the framework to bigger and more varied datasets, longitudinal analysis to trace the progress of the disease, and model interpretability to raise the level of clinical trust and adoption.

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