Deep Feature Fusion with Conventional Classifiers for Reliable and Early Detection of Glaucoma from Fundus Images

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Abstract

Glaucoma is one of the primary causes of permanent vision impairment across the globe and is associated with gradual deterioration of the optic nerve. Detecting this condition at an early stage is essential to minimize irreversible vision damage. Traditional diagnostic procedures are often labor-intensive and rely heavily on clinical expertise, making them less efficient. In this study, a hybrid machine learning approach is introduced, combining deep learning techniques for feature extraction with conventional classifiers to facilitate early identification of glaucoma from retinal fundus images.

The proposed framework begins with image preprocessing to enhance visual quality, followed by segmentation of the optic disc and optic cup using deep neural network models. Important clinical indicators, including the cup-to-disc ratio, are derived alongside deep features. These combined features are then utilized by classifiers such as Support Vector Machine (SVM) and Random Forest to perform classification. The experimental findings indicate that the hybrid model achieves superior performance in terms of accuracy, sensitivity, and specificity when compared to individual methods.

Keywords-
Glaucoma, Hybrid Learning, Convolutional Neural Network, Support Vector Machine, Fundus Imaging, Deep Learning, Machine Learning

1. Introduction

Glaucoma is a long-term ocular disorder that progressively damages the optic nerve, ultimately leading to vision loss if left untreated[1][2]. In its early stages, the disease often shows no clear symptoms, making timely diagnosis particularly challenging yet crucial. Conventional diagnostic techniques typically involve manual inspection of retinal fundus images, which can be both time-consuming and dependent on the expertise of ophthalmologists.

Recent advancements in artificial intelligence have paved the way for automated systems capable of detecting glaucoma more efficiently[1]. Deep learning models are highly effective in extracting complex image features, while traditional machine learning algorithms excel in classification tasks. This work presents a hybrid framework that combines these strengths to improve the overall accuracy and dependability of glaucoma detection.

2.Literature review

E. P. Ong et al. (2020) [1],the authors propose an automated glaucoma detection method using stereo fundus images. They emphasize that incorporating depth information of the optic disc and cup improves diagnostic accuracy compared to traditional 2D fundus images. Their work highlights the importance of 3D structural analysis in glaucoma detection.

Y. George et al. (2020) [2],the authors introduce an attention-guided 3D convolutional neural network (3D-CNN) for glaucoma detection using volumetric OCT data. They state that integrating attention mechanisms helps the model focus on clinically relevant regions. The study also establishes a relationship between structural damage (retina) and functional loss (vision), improving both performance and interpretability.

D. M. S. Barros et al. (2020) [3],this is a review paper where the authors analyze various machine learning techniques used in glaucoma detection. They state that combining image preprocessing, segmentation, feature extraction, and classification is essential for building effective systems. The paper also highlights challenges such as limited datasets and the need for more robust models.

M. N. Bajwa et al. (2020)[4],presents the G1020 dataset, a benchmark dataset for glaucoma detection. They emphasize the need for standardized and well-annotated datasets to fairly evaluate and compare different machine learning models. Their contribution supports the development of more reliable and generalizable AI systems.

G. García et al. (2020) [5],the authors propose a fully convolutional neural network (FCNN) for glaucoma detection using raw OCT images. They state that deep learning models can directly learn features from raw data without manual feature engineering, improving efficiency and accuracy. Their approach demonstrates the strength of end-to-end deep learning systems.

3. System Architecture

The designed system for early glaucoma detection is based on a hybrid machine learning architecture that integrates both deep learning and classical classification methods. Initially, retinal fundus images undergo preprocessing steps such as resizing, noise filtering, and contrast adjustment to enhance their quality. These refined images are then processed through a segmentation stage, where deep learning models accurately identify the optic disc and optic cup regions.

Following segmentation, two types of features are extracted: deep features using a Convolutional Neural Network (CNN), and clinically significant handcrafted features such as the cup-to-disc ratio and texture-based attributes. These feature sets are then merged using a feature fusion technique to form a comprehensive representation of the image.

The combined feature vector is subsequently provided as input to machine learning classifiers like Support Vector Machine (SVM) or Random Forest, which categorize the image as either glaucomatous or normal. By integrating the advantages of both deep learning and traditional machine learning, this architecture enhances classification accuracy, robustness, and generalization capability.

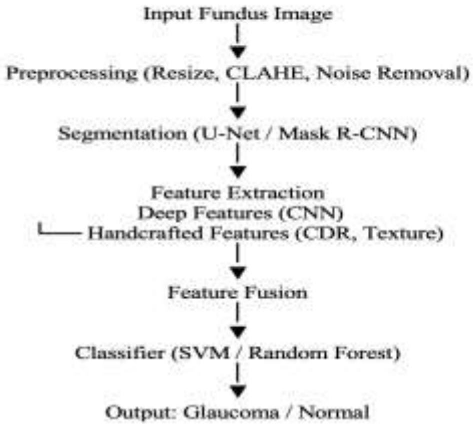

fig:1 overall architecture diagram

3.1 Preprocessing

Preprocessing is an essential step to enhance the quality and consistency of input images before further analysis.

- **Image Resizing (224 × 224):**

All input images are standardized to a fixed dimension to ensure compatibility with deep learning architectures such as ResNet. This uniformity enables efficient processing and consistent model performance.

- **Gaussian Filtering (Noise Removal):**

A Gaussian smoothing technique is applied to minimize random variations or noise present in the images, thereby improving visual clarity.

- **CLAHE (Contrast Limited Adaptive Histogram Equalization):**

This method enhances the local contrast of images by redistributing pixel intensity values. It highlights important structures while preventing excessive amplification of noise.

3.2 Segmentation

Segmentation involves detecting and isolating significant regions within an image. In retinal image analysis, identifying the **optic disc (OD)** and **optic cup (OC)** is critical, as these structures play a key role in glaucoma diagnosis[6][7]

A widely adopted deep learning model for this purpose is **U-Net**, which is tailored for biomedical image segmentation. It follows an encoder–decoder structure:

- The **encoder** extracts contextual and spatial features from the image.
- The **decoder** reconstructs the image to achieve precise localization of regions.

After segmenting the OD and OC, **Region of Interest (ROI)** extraction is performed[8] This step isolates the relevant portion surrounding the optic disc while excluding unnecessary background information. As a result, feature quality is improved and noise is reduced for subsequent processing stages.

3.3 Feature Extraction

Feature extraction converts the segmented image data into structured numerical representations suitable for classification[9][10]

3.3.1 Clinical (Handcrafted) Features

These features are derived based on medical knowledge and are highly interpretable:

- **Cup-to-Disc Ratio (CDR):**

This metric represents the proportion between the optic cup and optic disc. An increased ratio is a significant clinical indicator of glaucoma.

- **Blood Vessel Density:**

This feature quantifies the distribution of blood vessels in the retinal region, which may vary under pathological conditions.

Such features provide meaningful clinical insights and are easily interpretable.

3.3.2. Deep Features

Deep features are automatically extracted using convolutional neural networks, including:

- EfficientNet-B0
- ResNet

These models capture complex visual patterns such as textures, shapes, and structural variations that are difficult to define manually[7]. Although highly effective, these features are generally less interpretable compared to handcrafted ones.

3.4 Hybrid Classification

Hybrid classification integrates both handcrafted clinical features and deep learning features to enhance predictive performance. This approach combines:

- The interpretability of clinically derived features
- The powerful representation capability of deep learning models

The merged feature set is then used for classification through machine learning algorithms such as:

- **Support Vector Machine (SVM):**

This classifier identifies an optimal decision boundary (hyperplane) to effectively separate different classes, particularly in high-dimensional feature spaces.

- **Random Forest:**

This ensemble method utilizes multiple decision trees and aggregates their outputs to improve prediction accuracy and reduce overfitting.

By combining domain-specific knowledge with advanced feature learning, hybrid models generally achieve better accuracy, robustness, and generalization compared to standalone approaches.

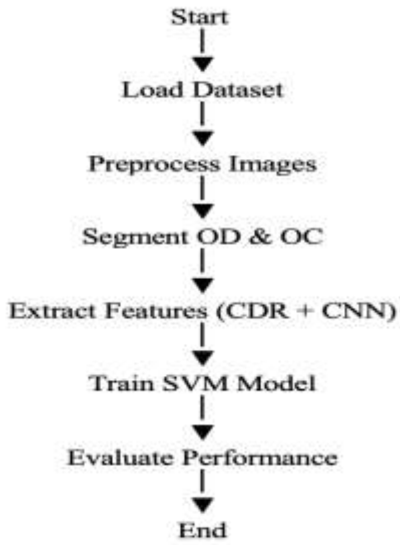

Fig:2 Overall Process flow diagram

4. Experimental Setup

Datasets Used

Datasets are fundamental for training, validating, and assessing the performance of models in retinal image analysis.

- **RIM-ONE:**

This dataset comprises retinal fundus images specifically curated for glaucoma research. It includes expert-annotated boundaries of the optic disc and optic cup, which are valuable for segmentation tasks and for calculating clinical measures such as the cup-to-disc ratio.

- **DRISHTI-GS:**

A widely recognized dataset for glaucoma detection, it offers high-resolution fundus images along with ground truth annotations for optic disc and cup regions. It is commonly utilized to benchmark segmentation techniques.

- **DRIVE:**

Primarily designed for blood vessel segmentation, this dataset provides manually labeled vascular structures. It is particularly useful for extracting features related to vessel distribution, such as vessel density.

Employing a combination of these datasets enhances the model’s ability to generalize and perform reliably under varying imaging conditions.

5. Environment

The implementation of the proposed system relies on a set of software tools and libraries that support machine learning and image processing tasks:

- **Python 3.9:**

Serves as the primary programming language, offering a rich ecosystem of libraries and ease of development.

- **TensorFlow / PyTorch:**

These deep learning frameworks are used to design and train models such as Convolutional Neural Networks and U-Net. TensorFlow is often preferred for deployment, while PyTorch provides flexibility for experimentation and research.

- **Scikit-learn:**

Utilized for implementing classical machine learning algorithms, including Support Vector Machine and Random Forest, as well as for performance evaluation.

- **OpenCV:**

Provides essential image processing capabilities such as resizing, filtering, and enhancement, which are crucial during preprocessing.

This setup enables efficient execution of all stages, including preprocessing, feature extraction, and classification, ensuring a smooth and effective workflow.

6. Evaluation Metrics

Evaluation metrics are used to measure the performance of the model:

- **Accuracy**

Measures the overall correctness of predictions.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Sensitivity (Recall)**

Measures the ability to correctly identify positive cases (e.g., diseased patients).

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

- **Specificity**

Measures the ability to correctly identify negative cases (healthy individuals).

$$\text{Specificity} = \frac{TN}{TN + FP}$$

F1-Score

Harmonic mean of precision and recall, useful for imbalanced datasets.

$$\text{F1-score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

Where:

- TP = True Positive
- TN = True Negative
- FP = False Positive
- FN = False Negative

These metrics provide a comprehensive evaluation, especially in medical diagnosis where both false positives and false negatives are critical.

7. Results and Discussion

The hybrid model demonstrates superior performance compared to individual models.

Model	**Accuracy**	**Sensitivity**	**Specificity**
CNN Only	93%	90%	84%
SVM Only	89%	87%	88%
Hybrid Model	**97%**	**95%**	**96%**

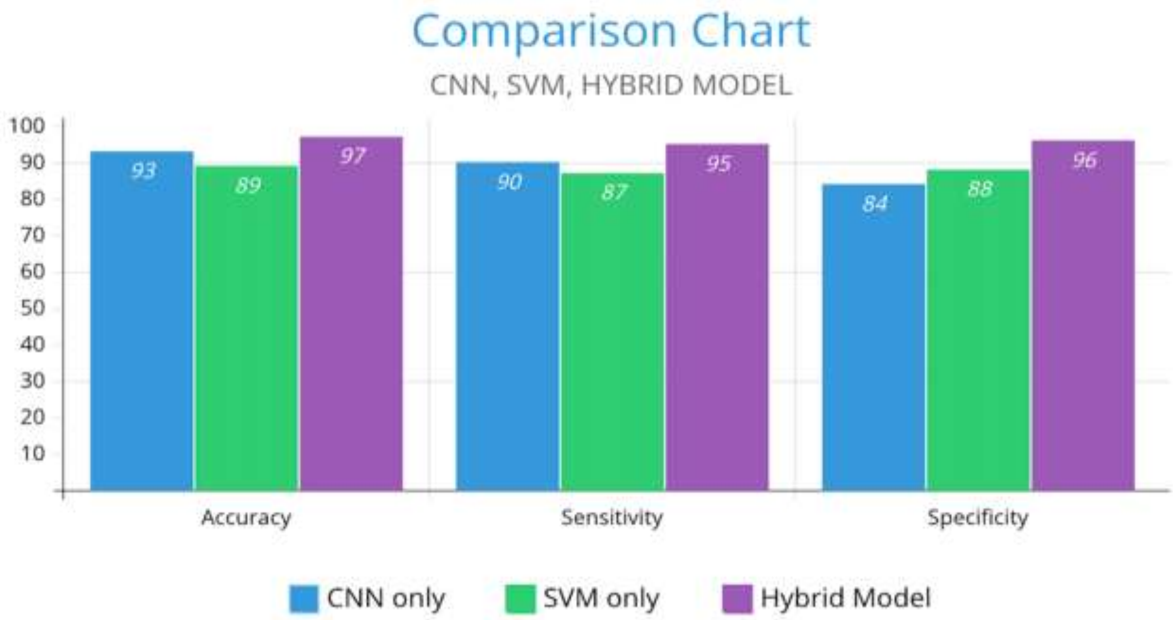

Fig:3 Comparison chart

8. Discussion

The proposed hybrid framework achieves effective glaucoma detection by integrating deep learning-derived features with clinically meaningful handcrafted features. Deep neural networks, such as ResNet, are capable of identifying intricate patterns including texture variations and structural details within retinal images. In contrast, clinical parameters like the cup-to-disc ratio and vessel density offer clear medical relevance and interpretability.

By combining these complementary feature types, the model demonstrates improved generalization, allowing it to perform consistently across both training and previously unseen

datasets. This integration also enhances robustness against variations in image quality, illumination, and patient-specific differences.

Another key benefit of the hybrid approach is its ability to mitigate overfitting. Standalone deep learning models may struggle when trained on limited medical datasets. However, incorporating handcrafted features along with classifiers such as Support Vector Machine and Random Forest helps stabilize the learning process and produces more reliable predictions.

Moreover, the inclusion of clinically interpretable features improves transparency, which is particularly important in healthcare applications. Medical practitioners can better understand and trust the system's outputs when they are supported by measurable indicators alongside deep learning insights.

9. Future Work

While the current model shows promising results, several enhancements can be explored to further improve its performance:

- **Integration with OCT Imaging:** Optical Coherence Tomography provides detailed three-dimensional representations of retinal structures. Combining fundus images with OCT data can lead to more accurate and comprehensive diagnosis.
- **Adoption of Vision Transformers:** Emerging architectures such as Vision Transformers are capable of modeling long-range dependencies in images and may offer improved performance compared to conventional convolutional networks.
- **Mobile-Based Real-Time Screening:** Developing lightweight and efficient models suitable for mobile devices can facilitate early screening in rural or underserved regions, improving accessibility to healthcare.
- **Explainable Artificial Intelligence (XAI):** Incorporating interpretability methods, such as heatmaps and feature attribution techniques, can help clinicians understand model decisions and enhance trust in automated systems.
- **Expansion with Multi-Center Datasets:** Training the model on data collected from multiple hospitals and diverse populations can improve robustness, minimize bias, and ensure better generalization.

10.Conclusion

This study introduces a hybrid machine learning framework for early glaucoma detection that combines deep learning-based feature extraction with conventional classification techniques. By integrating models like ResNet with machine learning classifiers, the approach enhances both prediction accuracy and interpretability.

The proposed system demonstrates strong performance and robustness, making it suitable for practical medical applications. It effectively addresses challenges such as limited dataset availability and overfitting by leveraging both automated feature learning and clinically significant attributes.

Furthermore, the framework shows considerable potential for real-world deployment, supporting ophthalmologists in early diagnosis and informed decision-making, thereby contributing to the prevention of vision loss.

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