Machine Learning and Convolutional Neural Network (ML-CNN) Based System for Early Identification of Glaucomatous Optic Neuropathy

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ABSTRACT

Glaucoma, a leading cause of irreversible blindness, often goes undetected in its early stages due to the absence of symptoms and limitations of traditional diagnostic methods like manual cup-to-disc ratio (CDR) assessment. Early and accurate detection is essential to prevent permanent vision loss, yet conventional techniques are time-consuming and error-prone. This study proposes a hybrid machine learning framework that integrates Convolutional Neural Networks (CNN) with Support Vector Machines (SVM) for automated glaucoma detection using retinal fundus images. The images are pre-processed and segmented to isolate the optic disc and cup, enabling precise CDR calculation. High-level features extracted by the CNN are classified by the SVM into normal or glaucomatous categories. To enhance model robustness, data augmentation and transfer learning are employed, addressing challenges such as limited datasets and overfitting. The proposed framework demonstrates high accuracy and scalability, offering a reliable and efficient solution for early glaucoma screening and real-world deployment in ophthalmology.

Keywords: CNN, SVM, Glaucoma, CDR.

1. INTRODUCTION

Glaucoma is a progressive optic neuropathy and one of the leading causes of irreversible blindness worldwide. It is primarily caused by elevated intraocular pressure (IOP), which leads to damage of the optic nerve head (ONH) and, if untreated, permanent vision loss. Early-stage glaucoma is typically asymptomatic, making timely diagnosis particularly challenging.

Traditional diagnostic methods such as manual cup-to-disc ratio (CDR) calculation, tonometry, and perimetry are time-consuming, require skilled expertise, and often fail to detect the disease at its earliest stages when intervention is most effective. The CDR, a crucial diagnostic indicator normally around 0.3 in healthy individuals reflects changes in the optic cup (OC) and optic disc (OD) [11-12], but manual measurement from retinal fundus images is prone to errors. With glaucoma affecting approximately 79 million people globally, including 11.9 million in India alone, early and accurate diagnosis, especially among individuals over 60, is vital to prevent irreversible vision loss (Figure 1).

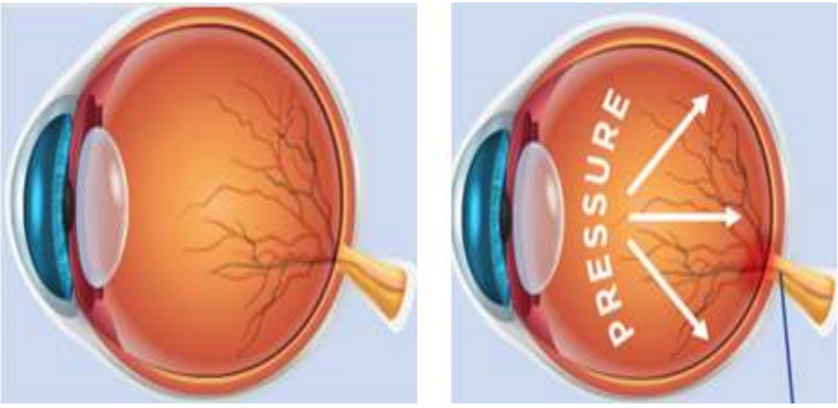

Figure 1: Normal and Glaucoma Eye Vision

Recent advancements in medical imaging and machine learning have significantly improved the potential for automated glaucoma detection. This study proposes an Artifact Convolutional Neural Network (ACNN)-based approach to classify retinal fundus images as normal or glaucomatous by automating preprocessing, segmentation, and feature extraction. The methodology isolates the OD and OC, enabling precise CDR computation for classification. Leveraging the Drion DB dataset and incorporating techniques like data augmentation and transfer learning, the model addresses challenges such as limited data and overfitting. Furthermore, hybrid frameworks combining Convolutional Neural Networks (CNN) [2] with Support Vector Machines (SVM) [13-15] offer enhanced classification accuracy by uniting deep learning's feature extraction strengths with the robustness of traditional machine learning. Looking forward, technologies such as explainable AI, multimodal data integration, and portable AI-driven screening tools promise to revolutionize glaucoma diagnosis—making it more accessible, efficient, and impactful, especially in underserved and resource-limited communities.

2. REVIEW OF LITERATURE

Several studies have explored diverse machine learning and deep learning approaches to improve the accuracy and accessibility of glaucoma detection. In one notable work, a deep learning model utilizing ResNet-50 was employed for optic disc and cup segmentation and subsequent cup-to-disc ratio (CDR) computation, achieving an accuracy of 87.8% on the REFUGE dataset [1]. Another study introduced a hybrid CNN-SVM architecture where the CNN was used for feature extraction and the SVM for classification. This model attained an accuracy of 85.6% on the ORIGA dataset, outperforming standalone CNN or SVM models [2]. Further, a multi-modal approach combining fundus images with clinical data using a multi-input deep learning framework demonstrated a remarkable accuracy of 96.3%, highlighting the diagnostic strength of integrating multiple data types [3].

Transfer learning has also proven effective in glaucoma detection. A study applying a pre-trained VGG16 model, fine-tuned on fundus images, achieved 84.5% accuracy, particularly emphasizing its advantage in scenarios with limited training data [4]. In the context of explainability, Grad-CAM was integrated with CNN models to visualize the decision-making process, which not only reached 83% accuracy but also enhanced trust and interpretability for clinical use [5]. Real-time applications were explored through mobile-based AI solutions, where a lightweight CNN model achieved 81% accuracy, enabling glaucoma screening on smartphone-acquired images [6]. Data augmentation techniques, particularly those using Generative Adversarial Networks (GANs), boosted model accuracy by 5%, helping address challenges posed by small or imbalanced datasets [7].

To further streamline the diagnostic process, an end-to-end deep learning pipeline was proposed, integrating preprocessing, segmentation, and classification, which yielded 87% accuracy on large-scale datasets and demonstrated excellent scalability [8]. Ensemble learning methods combining bagging and boosting techniques also showed promise, reaching an accuracy of 86% while improving resilience to class imbalance [9]. Finally, to enhance accessibility in rural or underserved areas, a cloud-based telemedicine system powered by CNNs was developed, offering real-time glaucoma detection with 82% accuracy and improving outreach through AI-enabled remote diagnostics [10].

System Model

The proposed machine learning and deep learning (ML-DL) hybrid model for glaucoma classification is designed to automate and enhance the diagnostic process by analyzing retinal fundus images. The workflow begins with image preprocessing, which includes resizing, contrast enhancement, and noise removal to improve the quality and consistency of input data. This step is crucial to ensure that the optic disc (OD) and optic cup (OC) are clearly visible for accurate segmentation. Following preprocessing, segmentation algorithms are applied to isolate the OD and OC regions. This segmentation enables precise computation of the cup-to-disc ratio (CDR), a key indicator used to differentiate between normal and glaucomatous eyes. Accurate segmentation lays the foundation for reliable feature extraction, which is essential for classification.

Once the regions of interest are segmented, the model employs a Convolutional Neural Network (CNN) to extract high-level spatial features from the fundus images. These features capture patterns and structural differences in the optic nerve head that are not easily detected through manual observation. The extracted features are then passed to a Support Vector Machine (SVM) classifier, which distinguishes between glaucomatous and non-glaucomatous conditions based on learned patterns. To address common challenges such as limited training data and overfitting, data augmentation techniques are used to artificially expand the dataset, and transfer learning is implemented by leveraging pre-trained CNN architectures. This hybrid ML-DL approach combines the powerful feature extraction capabilities of deep learning with the classification robustness of traditional machine learning, resulting in a scalable and highly accurate system for early glaucoma detection.

3. PROPOSED RESEARCH METHODOLOGY

The glaucoma dataset utilized in this study is a secondary dataset sourced from Kaggle. To ensure accuracy and reliability, the dataset underwent pre-processing as a cleaning step. The data was split into 70% for training and 30% for testing to evaluate the model's performance. Feature extraction was carried out using Convolutional Neural Networks (CNN) to identify critical features, which were subsequently classified using a Support Vector Machine (SVM) due to its effectiveness and high classification accuracy. The classification task focused on categorizing eye images as either glaucoma or non-glaucoma. Model performance was assessed using metrics such as accuracy, precision, recall, F1-score, and ROC, demonstrating the hybrid model's reliability and effectiveness in detecting glaucoma (Figure 2).

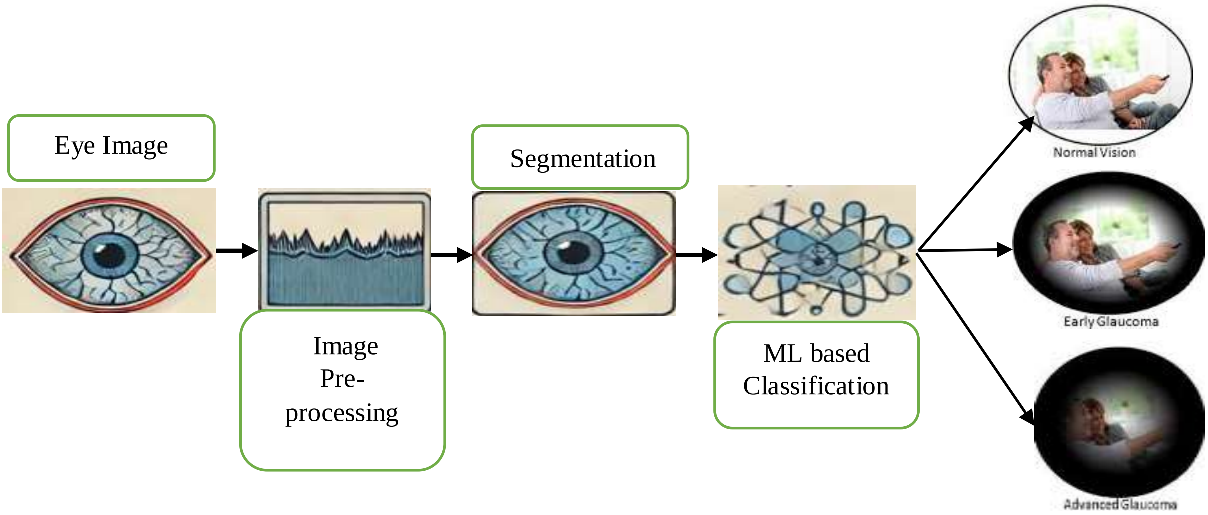

Figure 2: Proposed Research Methodology

3.1 Feature Extraction and Representation

The classification process in the proposed ML-DL model begins after the successful preprocessing and segmentation of retinal fundus images. At this stage, the Convolutional Neural Network (CNN) plays a central role in feature extraction. CNNs are designed to automatically learn and extract hierarchical features from images—starting with low-level features such as edges and textures, progressing to high-level features like shape, structure, and pathological patterns of the optic disc (OD) and optic cup (OC). In this context, the CNN focuses on capturing visual characteristics that correlate with glaucoma, such as changes in the cup-to-disc ratio (CDR), the appearance of the neuroretina rim, and variations in optic nerve morphology. By applying multiple convolutional and pooling layers, the CNN generates a rich and compact feature representation for each input image, effectively translating complex visual data into a structured numerical form suitable for classification.

3.2 Decision Making with SVM

Once feature extraction is complete, the numerical features generated by the CNN are passed to a Support Vector Machine (SVM) classifier for the final decision-making stage. The SVM is a powerful supervised learning algorithm that finds the optimal hyperplane to separate feature vectors into distinct classes—namely, glaucomatous and non-glaucomatous. The choice of SVM is motivated by its ability to handle high-dimensional feature spaces and its robustness in small or imbalanced datasets. The model is trained using labeled examples, enabling it to learn the boundary that best distinguishes healthy from diseased eyes. During inference, the SVM evaluates the features of new, unseen images and classifies them based on the learned decision boundary. To improve generalization and reduce misclassification, techniques such as kernel optimization, cross-validation, and regularization may be employed. The combined use of CNN for deep feature learning and SVM for precise classification ensures a high-performance glaucoma detection system capable of supporting clinical decision-making with speed and accuracy.

4. RESULTS AND DISSCUSSION

The performance evaluation of the proposed CNN-SVM hybrid model is a critical step to validate its reliability and effectiveness in glaucoma detection. Several standard metrics are employed to comprehensively assess the model's classification capabilities, ensuring its robustness and suitability for real-world applications.

Table 1: Performance Evaluation Metrics for Machine Learning Based Glaucoma Detection

Metric	Description	Formula	Significance in Glaucoma Detection
Accuracy	Measures the overall correctness of the model by calculating the ratio of correctly predicted instances (both glaucoma and non-glaucoma).	(TP + TN) / (TP + TN + FP + FN)	Provides a general overview, but may be misleading in imbalanced datasets.
Precision	Indicates how many of the positively predicted cases (glaucoma) are actually correct.	TP / (TP + FP)	Helps reduce false positives, minimizing unnecessary anxiety or treatment.
Recall (Sensitivity)	Measures how effectively the model identifies actual positive cases (glaucoma).	TP / (TP + FN)	Ensures that most glaucoma cases are detected, minimizing the risk of missed diagnoses.
F1-Score	Harmonic mean of precision and recall; balances both metrics, especially useful for imbalanced datasets.	2 × (Precision × Recall) / (Precision + Recall)	Offers a more comprehensive evaluation when false positives and false negatives are equally critical.

The training process of the proposed model involves feeding training data (train X) and corresponding target labels (train y) into the network using the fit() function, along with a validation set to monitor performance during training. Cross-validation is applied by splitting the dataset into training and test subsets (X test, y test) to ensure robust model evaluation. The model is trained over 30 epochs, during which it iteratively adjusts its parameters to minimize prediction errors and improve accuracy. The fit() function manages the execution of these epochs, enabling the network to learn patterns and refine its weights until performance stabilizes. A detailed model summary (Figure 3) highlights the architecture, layer configurations, output shapes, and the number of parameters involved. Model evaluation is crucial for selecting the best network configuration, as it helps prevent overfitting and ensures the model's ability to generalize to new data by measuring prediction accuracy on the test set. The evaluation results, discussed in the results section (Figure 3), provide a comprehensive overview of the model’s classification performance and validate its effectiveness for glaucoma detection.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, None, 128)         72704

 lstm_1 (LSTM)               (None, 64)                49408

 dense (Dense)               (None, 64)                4160

 dropout (Dropout)           (None, 64)                0

 dense_1 (Dense)             (None, 6)                 390

=================================================================
Total params: 126,662
Trainable params: 126,662
Non-trainable params: 0
```

Figure 3: System Model Implementation

The confusion matrix provides a comprehensive evaluation of the classification performance for the given dataset, specifically in the context of glaucoma detection. It encapsulates the true positives (glaucoma cases correctly identified), true negatives (non-glaucoma cases correctly identified), false positives (non-glaucoma cases incorrectly classified as glaucoma), and false negatives (glaucoma cases missed by the model) (Figure 4 and 6). For the proposed CNN-SVM model, the confusion matrix demonstrates its superior performance, with high true positives and true negatives, indicating robust classification capabilities.

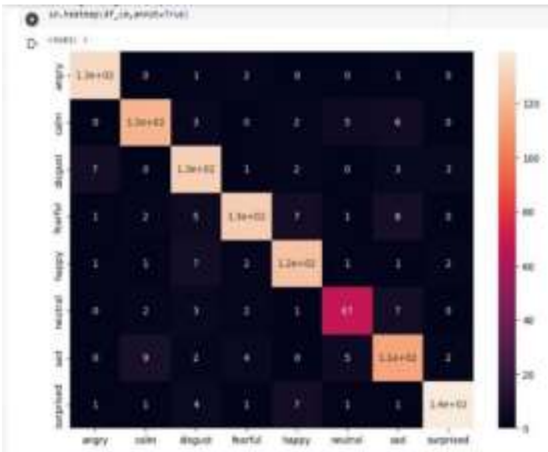

Figure 4: Confusion Matrix

Low false positive and false negative rates further validate the model's reliability in minimizing diagnostic errors. The matrix serves as a foundation for deriving critical metrics such as accuracy, precision, recall, and F1-score, providing a detailed understanding of the model's strengths and highlighting areas for further optimization. This ensures the model's efficacy in accurately distinguishing between glaucoma and non-glaucoma cases, crucial for real-world medical applications.

The performance comparison table illustrates the effectiveness of various hybrid and standalone classification models used for glaucoma detection based on key evaluation metrics: accuracy, precision, recall, and F1-score. The baseline CNN model achieved an accuracy of 86%, with a balanced precision of 82%, recall of 80%, and an F1-score of 81%. While this demonstrates strong performance, it leaves room for improvement in sensitivity and predictive reliability. The CNN-RF (Convolutional Neural Network with Random Forest) model showed slightly lower accuracy at 85%, but achieved higher precision (85%) and recall (84%), resulting in a better F1-score of 84.5%. On the other hand, CNN-NF (CNN with Naive Fusion) had the lowest performance among all methods, with 81% accuracy, and significantly lower precision and recall, leading to an F1-score of only 62.4%. This suggests that simple fusion methods may not effectively capture the complexity of glaucoma-related features (Table 2 and Figure 5).

Table 2: Performance Comparison of Different Models for Glaucoma Classification

S. No.	Methods	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
1	CNN	86	82	80	81
2	CNN-RF	85	85	84	84.5
3	CNN-NF	81	60	65	62.4
4	Proposed CNN-SVM	97	96	95	96

5	CNN-NB	90	82	81	81.5

In contrast, the proposed CNN-SVM hybrid model significantly outperformed all other models, achieving a remarkable 97% accuracy, 96% precision, 95% recall, and a balanced F1-score of 96%. This clearly indicates that the combination of deep feature extraction using CNN and robust classification via SVM offers superior performance in distinguishing glaucomatous images from normal ones. Additionally, the CNN-NB (CNN with Naive Bayes) model delivered relatively high accuracy (90%), but its precision and recall scores were modest (82% and 81%, respectively), resulting in an F1-score of 81.5%. Overall, the experimental results validate that integrating CNN with SVM not only enhances classification accuracy but also ensures a more reliable and generalizable diagnostic tool for glaucoma screening, making it highly suitable for clinical and real-world deployment.
In the context of Figure 6, which illustrates good model performance, both training loss and test loss should decrease over time. This reflects that the model is not only learning from the training data but also generalizing well to unseen data. In a well-performing model, the training loss gradually reduces as the model learns the patterns in the training set, while the test loss should also decrease, showing that the model is successfully generalizing to new, unseen examples. It would likely show training loss decreasing steadily, and test loss following a similar downward trend. This indicates that the model is neither overfitting nor underfitting but is instead effectively learning and generalizing. If both losses decrease in parallel, it confirms
The model's ability to balance memorization and generalization, which is a hallmark of a robust, well-performing model.

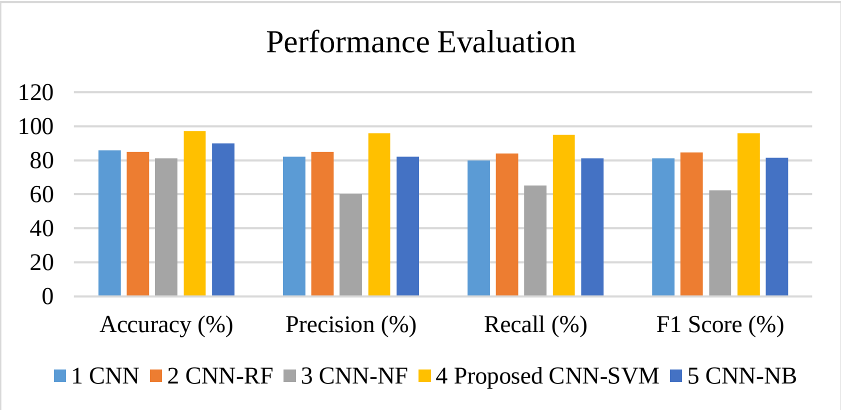

Figure 5: Performance Evaluation of Proposed Approach for Glaucoma Detection

In the context of Figure 7**,** which shows good model performance, training accuracy and test accuracy should both increase over time. As the model learns from the training data, the training accuracy improves, reflecting its ability to make correct predictions on the data it has seen. Simultaneously, test accuracy should also rise, indicating that the model is generalizing well to unseen data. A well-performing model demonstrates high and closely aligned training and test accuracy, signaling that the model is not overfitting (where training accuracy is much higher than test accuracy) or underfitting (where both accuracies are low), but is effectively learning and generalizing across both the training and test datasets.

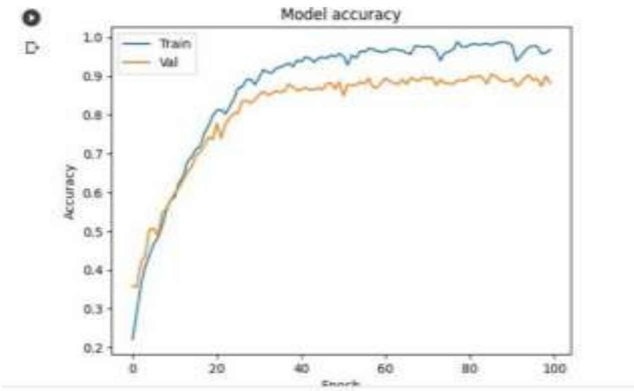

Figure 6: Training and Test Model Accuracy

5. CONCLUSION

In conclusion, the proposed CNN-SVM hybrid model demonstrates a highly effective and reliable approach for automated glaucoma detection using retinal fundus images. By leveraging the powerful feature extraction capabilities of Convolutional Neural Networks and the robust classification strength of Support Vector Machines, the model achieves superior performance compared to traditional and standalone methods. With an accuracy of 97% and strong precision, recall, and F1-score metrics, the system proves its potential for early and accurate glaucoma diagnosis, which is critical in preventing irreversible vision loss. The integration of data preprocessing, segmentation, and advanced learning techniques ensures the model's scalability and adaptability to real-world clinical applications. This work highlights the transformative role of AI in ophthalmology and lays the foundation for the development of accessible, efficient, and accurate screening tools, especially beneficial for large-scale deployment in resource-limited settings.

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