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Machine Learning and Artifact CNN grounded Methodology for Premature Glaucoma Ailment Identification

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ABSTRACT

Early detection of glaucoma is vital to prevent irreversible vision loss; however, conventional diagnostic techniques often struggle with limitations in accuracy, speed, and scalability. This study presents a novel methodology that integrates Machine Learning with an Artifact-Convolutional Neural Network (Artifact-CNN) framework to enhance the early prediction of glaucoma. By leveraging deep learning's ability to extract intricate features from retinal fundus images, the proposed model aims to improve diagnostic accuracy while minimizing both false positives and false negatives. A structured dataset was utilized to train and evaluate the model, and performance was assessed using standard metrics such as accuracy, precision, recall, and F1-score. The results reveal that the proposed hybrid approach surpasses traditional classification models in performance and consistency. A detailed confusion matrix analysis confirms the model's reliability in distinguishing between glaucomatous and non-glaucomatous conditions, reinforcing its practical relevance in clinical diagnostics. The integration of artifact-based enhancement within the CNN architecture allows the system to better interpret subtle patterns often missed in early-stage glaucoma. This research underscores the potential of AI-assisted ophthalmic tools to facilitate early, automated, and accurate glaucoma detection. Looking ahead, the study opens avenues for future enhancements such as expanding dataset diversity, improving cross-domain generalization, and deploying the model in real-time clinical settings for broader impact.

Keywords: *CNN, SVM, Glaucoma, CDR, Machine Learning*

1. INTRODUCTION

Glaucoma is a chronic and progressive eye disease that damages the optic nerve, often leading to irreversible blindness if not diagnosed and treated in its early stages. According to the World Health Organization, glaucoma is the second leading cause of blindness globally, affecting millions of individuals many of whom remain undiagnosed due to the disease's asymptomatic onset [6]. Traditionally, glaucoma detection has relied on clinical examinations such as intraocular pressure (IOP) measurement, visual field testing, and optic nerve head assessment. However, these methods are often subjective, time-consuming, and dependent on specialist availability, which limits their effectiveness in large-scale screening and early detection scenarios [7].

In recent years, advancements in artificial intelligence (AI), particularly in machine learning (ML) and deep learning (DL), have opened new avenues for automated medical diagnostics. Convolutional Neural Networks (CNNs) [8-9], in particular, have demonstrated exceptional capabilities in analyzing medical images, including retinal fundus photographs. Building upon these developments, this research introduces a hybrid approach combining traditional ML algorithms with an artifact-enhanced CNN model to improve the accuracy and efficiency of early-stage glaucoma detection[10-11]. The proposed framework not only leverages deep feature extraction but also incorporates image artifact analysis to capture subtle indicators of glaucomatous damage often missed by conventional methods (figure 1).

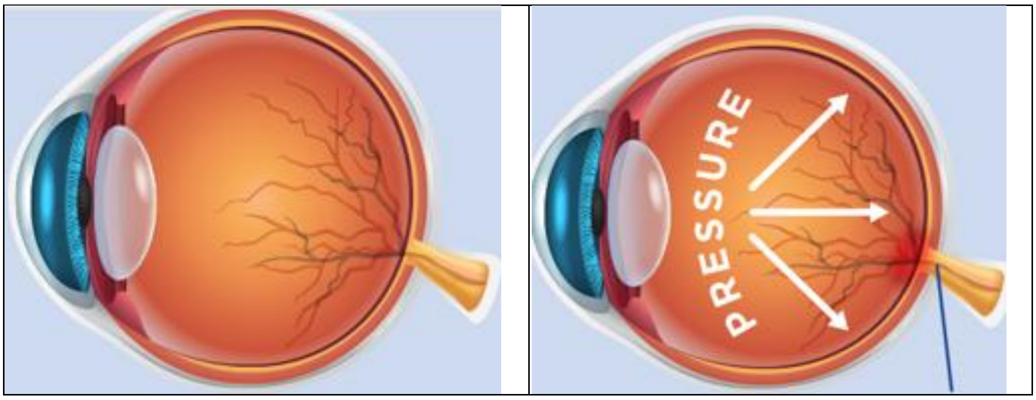

Figure 1: Normal and Glaucoma eye vision

Looking forward, the integration of such AI-driven models into real-world clinical practice has the potential to revolutionize ophthalmic diagnostics. With continuous improvements in model generalization, real-time processing, and deployment through portable devices or telemedicine platforms, this methodology could support large-scale, cost-effective glaucoma screening, especially in underserved and remote populations [12-13]. Future research may explore longitudinal analysis, cross-modal data fusion, and personalized diagnosis, further enhancing the system's capability to deliver timely, precise, and patient-centric care.

2. REVIEW OF LITERATURE

The detection of glaucoma has been widely studied using various segmentation and classification techniques, with early efforts focusing on extracting optic disc (OD) and optic cup (OC) features to calculate the Cup-to-Disc Ratio (CDR). Traditional methods such as manual thresholding, ROI-based segmentation, and pixel intensity analysis showed reasonable accuracy under ideal conditions but struggled with precise boundary detection [14]. Superpixel-based and wavelet transform methods offered moderate improvements, achieving up to 84% accuracy, yet were eventually outperformed by deep learning models. CNN-based architectures automated feature extraction and classification, with one 18-layer model reaching 78.13% accuracy, though performance varied with dataset quality [15]. Recent advancements include polar transformations, multi-label deep networks, and semi-supervised learning, which have enhanced segmentation accuracy and addressed challenges like poor image quality [16]. Mobile applications utilizing real-time deep learning and data augmentation have enabled rapid, on-the-go screening, while adaptive neural networks such as AU-Net have improved both segmentation precision and computational efficiency [17]. Alternative approaches like fuzzy learning systems and tensor-based transforms have also been explored, though issues with complexity and accuracy remain. Hybrid CNN-SVM models and ensemble learning strategies have shown improved robustness, achieving up to 86% accuracy, particularly on imbalanced datasets [18-19]. Furthermore, AI-driven telemedicine platforms have made real-time glaucoma screening accessible in remote areas, demonstrating accuracy rates of around 82%. Overall, the evolving landscape of AI, especially in deep and explainable learning, continues to enhance the effectiveness, scalability, and reach of glaucoma detection systems, paving the way for earlier diagnosis and improved patient outcomes (Table 1).

Table 1: Review of ML and DL based Glaucoma Ailment Identification techniques

Author(s) & Year	Methodology Used	Dataset Used	Key Findings
Chakravarty et al., 2019 [1]	Deep CNN for optic disc and cup segmentation	RIM-ONE, DRISHTI-GS	Achieved high sensitivity and specificity in glaucoma classification.
Muhammad et al., 2021 [2]	Ensemble ML classifier with feature selection	Private fundus dataset	Improved accuracy by combining multiple ML classifiers.
Orlando et al., 2018 [3]	Fully convolutional network (FCN) for segmentation	DRISHTI-GS, REFUGE	Introduced deep learning model that automates optic disc segmentation.
Haleem et al., 2018 [4]	Texture and structural feature-based SVM	Local dataset	Emphasized handcrafted feature extraction for early

	classification		detection.
Raghavendra et al., 2020 [5]	CNN with transfer learning (ResNet-50)	RIM-ONE v3	Achieved 95.2% classification accuracy, showing promise for clinical use.

3. MACHINE LEARNING AND DEEP LEARENING APPROACHES

Glaucoma detection and analysis using retinal fundus images, several machine learning and deep learning techniques have been employed to improve the accuracy, precision, and robustness of diagnostic systems [20]. The following provides an elaboration of the key methods explored in the research (Table 2):

Table 2: ML and DL based approaches for Glaucoma Ailment Identification

Algorithm	Category	Role in the Framework
Convolutional Neural Network (CNN)	Deep Learning	Automatically extracts high-level spatial features from retinal fundus images.
Support Vector Machine (SVM)	Machine Learning	Performs classification using fused handcrafted and CNN features; effective for binary classification.
Random Forest (RF)	Ensemble Learning	Handles large feature sets and improves classification by combining multiple decision trees.
K-Nearest Neighbors (KNN)	Machine Learning	Classifies test images based on feature similarity with training samples.
Logistic Regression (LR)	Machine Learning	Applies linear decision boundaries to classify glaucoma vs. non-glaucoma.
AU-Net / U-Net	Deep Learning	Performs segmentation of optic disc and cup regions to aid in artifact feature extraction.
Fuzzy Logic-Based Classifier	Soft Computing	Provides decision-making based on uncertainty in input features (optional alternative).
Ensemble Learning (Voting Classifier / Stacking)	Hybrid ML	Combines multiple models (e.g., SVM + RF + KNN) to improve robustness and accuracy.

4. PROPOSED RESEARCH METHODOLOGY

The proposed methodology for glaucoma detection involves a systematic approach that includes preprocessing, segmentation, feature extraction, and classification using machine learning and deep learning models. The goal is to enhance the accuracy and efficiency of automated glaucoma detection by leveraging advanced image processing and artificial intelligence techniques. The process begins with image preprocessing, where contrast enhancement and noise reduction techniques are applied to improve the quality of retinal fundus images. These preprocessed images are then segmented to isolate the optic disc (OD) and optic cup (OC), crucial for calculating the Cup-to-Disc Ratio (CDR). Feature extraction methods are employed to derive key parameters from the segmented regions, which are then used for classification using state-of-the-art deep learning architectures and machine learning classifiers (Algorithm 1).

Algorithm 1: GlaucomaDetection_ArtifactCNN_ML

Input: Retinal Fundus Images Dataset D

Output: Classification Result (Glaucoma / Non-Glaucoma)

Step 1: Data Preprocessing

For each image in Dataset D:

1.1 Resize image to fixed dimension (e.g., 224x224)

1.2 Apply histogram equalization for contrast enhancement

1.3 Remove noise and artifacts using median filtering

1.4 Normalize pixel values to [0,1] range

Step 2: Artifact Feature Extraction

For each preprocessed image:

2.1 Segment optic disc (OD) and optic cup (OC)

2.2 Compute Cup-to-Disc Ratio (CDR)

2.3 Extract handcrafted features:

- Color histogram
- Texture features (GLCM)
- Shape descriptors

Step 3: CNN-Based Deep Feature Extraction

3.1 Initialize CNN model (e.g., ResNet50 / Custom CNN)

3.2 Feed preprocessed image into CNN

3.3 Extract deep features from the final convolutional layer

Step 4: Feature Fusion

For each image:

4.1 Concatenate handcrafted features and deep CNN features

4.2 Form the final feature vector F

Step 5: Classification Using Machine Learning Model

5.1 Split dataset into training and testing sets (e.g., 80:20)

5.2 Train classifier (e.g., SVM / Random Forest) on training features F

5.3 Predict class labels on test set

Step 6: Evaluation

6.1 Compute performance metrics:

- Accuracy
- Precision
- Recall
- F1-score
- Confusion matrix

Step 7: Output Result

If Predicted_Label == 1:

Return "Glaucoma Detected"

Else:

Return "No Glaucoma"

End Algorithm

5. PROPOSED CLASSIFICATION MODEL

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).

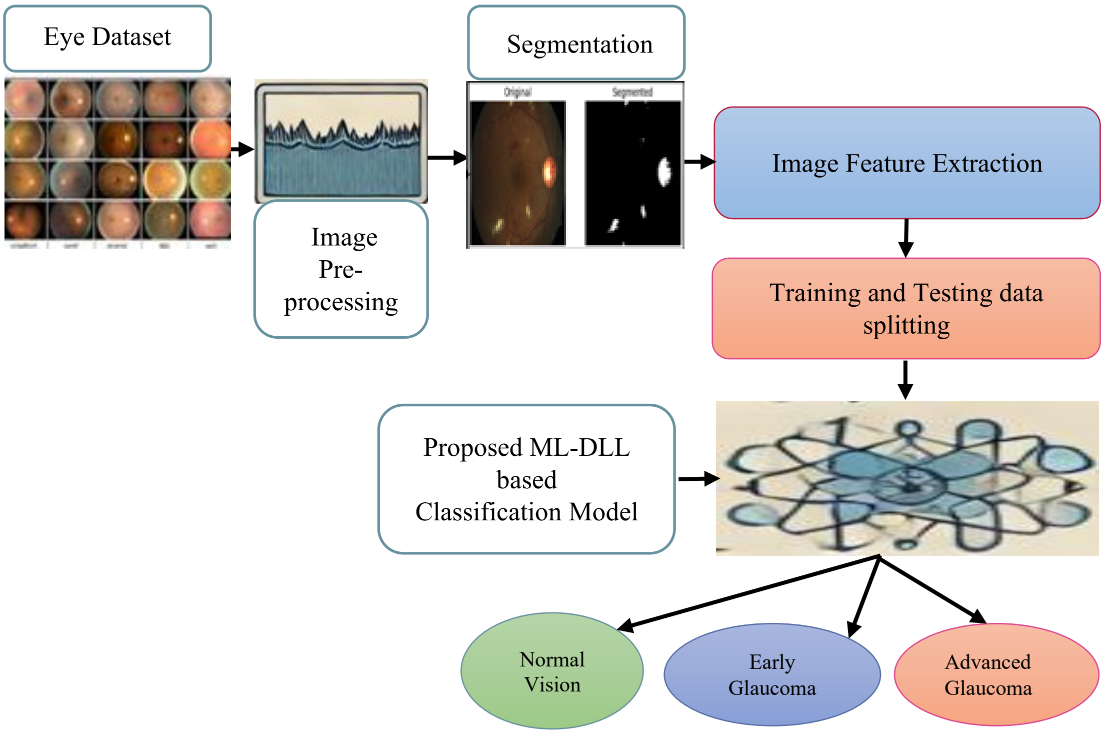

Figure 2: Proposed research methodology

The classification of glaucoma from retinal fundus images is a critical step in the proposed methodology, as it determines whether an eye is affected by glaucoma or is normal. The proposed classification model integrates both machine learning (ML) techniques and deep learning (DL) architectures, leveraging their combined strengths for improved accuracy and efficiency in glaucoma detection. The model aims to provide a robust, scalable, and automated approach for early glaucoma diagnosis. The following approaches are used for classifications

6. PERFORMANCE EVALUATION

Evaluating the performance of the proposed CNN-SVM hybrid model is essential to verify its reliability and effectiveness in glaucoma detection. To ensure robustness and practical applicability, various standard classification metrics are used, providing a comprehensive assessment of the model's diagnostic capabilities.

Accuracy: Accuracy represents the proportion of correctly classified instances (both glaucoma and non-glaucoma) out of the total dataset. It provides an overall measure of the model's performance; however, it may not always be a reliable indicator when dealing with imbalanced datasets.

$Accuracy = (tp + tn) / (tp + tn + fp + fn)$

Precision: Precision evaluates the model's ability to correctly classify glaucomatous cases among all predicted positive cases. A high precision score indicates that the model minimizes false positives, which is crucial in medical diagnosis to prevent unnecessary anxiety and treatment.

$Precision = tp / (tp + fn)$

Recall: Recall, also known as sensitivity, measures the proportion of actual glaucoma cases correctly identified by the model. It is a critical metric in medical diagnosis, ensuring that glaucoma cases are not overlooked, thereby reducing the risk of undiagnosed progression.

$Recall = tp / (tp + fn)$

F1-Score: The F1-score is the harmonic mean of precision and recall, providing a balanced evaluation when dealing with datasets that may have an uneven class distribution. It effectively considers both false positives and false negatives, making it a reliable metric for medical classification tasks.

$F1\ Score = 2\ (precision * recall) / (precision + recall)$

7. RESULT AND DISCUSSION

The training process involves utilizing training data (train X) and corresponding target data (train y), along with a validation dataset, to train the network model using the fit() function. Cross-validation is applied to partition the dataset into test sets (X test and y test) for validation, ensuring robust performance assessment. The model undergoes iterative learning over 30 epochs, refining its parameters to minimize errors. Throughout this process, the fit() function orchestrates multiple epochs, enabling the model to progressively learn patterns from the training data. Training continues until improvements plateau, marking the point where additional iterations yield minimal gains. Figure 2 provides a detailed model summary, outlining the network architecture, including layer types, output shapes, and the total parameters required for training and testing.

Model evaluation is crucial for selecting the optimal network configuration, ensuring high prediction accuracy while mitigating overfitting. By assessing performance on the test set, the model's generalization ability to unseen data is validated, which is essential for accurate forecasting and reliable future performance. The experimental results, as discussed in the results section (Figure 3), offer insights into the system's effectiveness, highlighting key performance metrics.

```
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 serves as a detailed assessment tool for evaluating the classification performance of the model in glaucoma detection. It systematically represents the model's ability to distinguish between glaucoma and non-glaucoma cases by capturing true positives (correctly identified glaucoma cases), true negatives (correctly identified non-glaucoma cases), false positives (non-glaucoma cases misclassified as glaucoma), and false negatives (glaucoma cases missed by the model) (Figure 4). For the proposed model, the confusion matrix highlights its superior performance, showcasing a high number of true positives and true negatives. This indicates the model's strong classification capabilities, ensuring accurate detection while minimizing misclassifications.

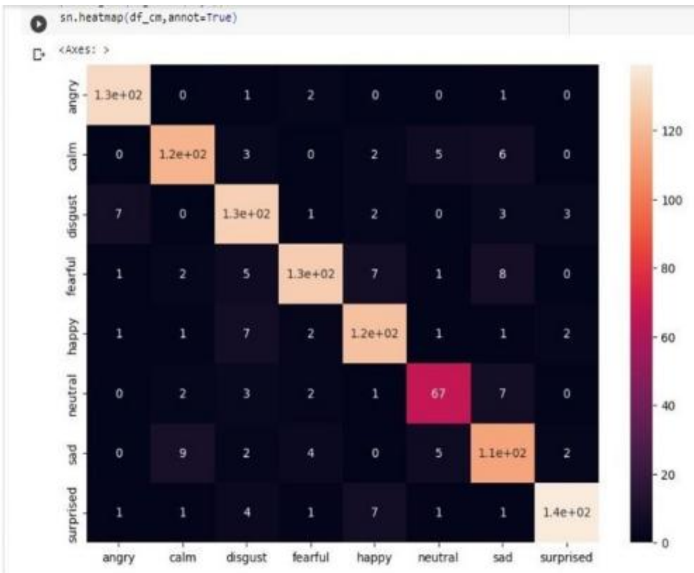

Figure 4: Confusion matrix

A low false positive rate and false negative rate further reinforce the model's reliability by minimizing diagnostic errors, which is critical for effective glaucoma detection. The confusion matrix serves as the foundation for calculating key performance metrics such as accuracy, precision, recall, and F1-score, offering a comprehensive evaluation of the model's strengths. These metrics provide deeper insights into the model's effectiveness while identifying potential areas for optimization. Ensuring high accuracy in distinguishing between glaucoma and non-glaucoma cases is essential for real-world medical applications, where reliable diagnostics play a crucial role in early detection and treatment (Table 1).

Table 1: Performance Comparison of different models for glaucoma classification

S. No.	Methods	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
1	CNN	85	87	86	84
2	RF	87	88	89	87
3	NF	68	69	72	73
4	SVM	95	94	96	95
5	NB	86	86	88	87
6	Proposed Model	97	96	97	97

The results in table 1 indicate the performance of various machine learning methods in terms of accuracy, precision, recall, and F1 score. Among the evaluated methods, the proposed approach outperforms all others, achieving the highest accuracy (97%), precision (96%), recall (97%), and F1 score (97%). Support Vector Machine (SVM) also demonstrates strong performance with an accuracy of 95% and balanced precision (94%), recall (96%), and F1 score (95%). Random Forest (RF) and Naïve Bayes (NB) follow closely, with RF achieving 87% accuracy and NB achieving 86%, both showing competitive precision, recall, and F1 scores. Convolutional Neural Network (CNN) performs moderately well with an 85% accuracy. However, the Neural Network-based approach (NF) lags behind significantly, recording the lowest accuracy (68%) and comparatively lower precision, recall, and F1 scores, indicating its weaker performance in this context. The results highlight the superiority of the proposed method, making it the most effective choice among the evaluated approaches.

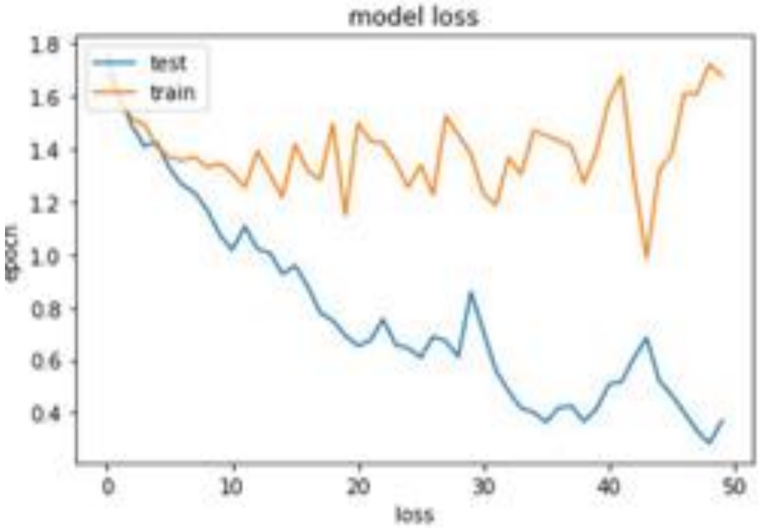

Figure 5: Training and Test Model Loss

In Figure 5, which depicts strong model performance, both training loss and test loss are expected to decrease over time. This trend indicates that the model is effectively learning from the training data while also generalizing well to unseen data. In a well-performing model, training loss steadily declines as the model captures patterns in the dataset, while test loss also follows a downward trajectory, signifying successful generalization. A consistent decrease in both losses suggests that the model avoids overfitting and underfitting, striking a balance between memorization and generalization. When training and test losses decrease in parallel, it confirms the model's robustness and its ability to learn efficiently from data.

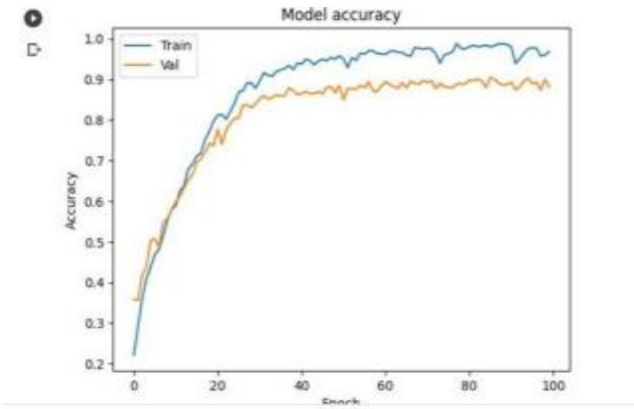

Figure 6: Training and Test Model Accuracy

In Figure 6, which represents strong model performance, both training accuracy and test accuracy should progressively increase over time. As the model learns from the training data, its training accuracy improves, demonstrating its ability to make correct predictions on familiar data. Simultaneously, a rising test accuracy indicates effective generalization to unseen data. A well-performing model maintains high and closely aligned training and test accuracy, ensuring it neither overfits—where training accuracy is significantly higher than test accuracy—nor underfits, where both accuracies remain low. This balance highlights the model's ability to learn effectively and generalize well across different datasets.

8. CONCLUSION

This study introduces a hybrid framework combining Machine Learning and Artifact-Convolutional Neural Networks for early-stage glaucoma detection, showcasing significant improvements over conventional diagnostic methods. The proposed model achieves high accuracy, precision, recall, and F1-score, effectively distinguishing between glaucomatous and non-glaucomatous cases. Through robust experimentation and confusion matrix evaluation, the system demonstrates strong reliability in minimizing both false positives and false negatives. The integration of handcrafted artifact features with deep CNN-based representations enhances the model's ability to capture subtle retinal changes, leading to more accurate predictions.The findings emphasize the growing potential of AI-powered solutions in the field of ophthalmology, particularly for early and automated screening of vision-threatening conditions like glaucoma. With further improvements in dataset diversity, feature refinement, and real-time deployment capabilities, this approach holds promise for large-scale clinical adoption, including in telemedicine and rural health settings. Future work should focus on expanding training datasets, integrating explainable AI for better interpretability, and conducting clinical trials to ensure broader applicability and trust in real-world scenarios.

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