

# An Efficient Glaucoma Prediction Using an Optimized CNN and XGBoost with Attention-Based Deep Learning Framework

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**Abstract:** Over the Decade, The machine learning incorporated on image classification has gained increasing attention for extracting discriminative patterns from retinal fundus images and supporting automated glaucoma severity analysis respectively. The several studies have explored convolutional neural networks, feature extraction, support vector machines, Random Forest, and ensemble learning strategies for glaucoma classification. The study proposes a novel weighted ensemble machine learning framework integrating LightGBM for glaucoma severity classification. The proposed framework begins with preprocessing of retinal fundus images using contrast enhancement, normalization, and noise reduction. Multiple feature representations, including structural, texture, morphological, and CNN-based deep features, are generated to capture complementary characteristics of the input images. The features are provided to multiple machine learning classifiers to obtain individual class-probability predictions respectively. A performance-based weighted ensemble mechanism is needed to assign differentiated weights to the classifier outputs according to their predictive contribution. Providing an enhanced computational framework for automated glaucoma severity classification respectively.

**Keywords:** XGBoost, Glaucoma Severity Classification, Retinal Fundus Images, Feature Extraction, Deep Features, Decision Fusion, CNN, Classification.

## I. INTRODUCTION

Machine learning has become an important computational technique for analysing complex image patterns and developing automated classification systems. In retinal fundus image analysis, Convolutional Neural Networks have demonstrated their ability to learn representative features directly from images and identify glaucoma-related patterns [1]. Transfer learning and optimized deep learning architectures have further improved feature representation by adapting learned models to retinal image characteristics [5]–[7]. Conventional machine learning classifiers have also been combined with extracted deep features to strengthen classification performance [8]. Among these methods, XGBoost provides an effective tree-based learning mechanism for modelling nonlinear relationships and handling complex feature interactions. At the same time, attention-based deep learning can guide the network toward more informative image regions, allowing relevant retinal characteristics to receive greater importance during feature learning. Ensemble and hybrid approaches reported in recent studies demonstrate the potential of integrating complementary learning techniques for glaucoma prediction [15]. Nevertheless, the joint utilization of an

optimized CNN, attention-based feature learning, and XGBoost within a unified computational framework requires further investigation. Therefore, this study proposes an efficient glaucoma prediction framework using an optimized CNN and XGBoost with attention-based deep learning. The proposed approach emphasizes optimized feature learning, attention-guided representation, and machine learning-based decision making to develop an efficient and robust computational model for automated glaucoma prediction respectively.

## II. LITERATURE REVIEW

The research primarily focused on effective approach for automated glaucoma analysis using retinal fundus images. Early studies demonstrated the capability of CNN-based models to learn discriminative retinal representations for glaucoma detection and classification [4]. Transfer learning and deep CNN architectures were subsequently explored to improve feature representation and reduce the dependence on manually engineered features [7]. Several studies incorporated machine learning classifiers with extracted retinal features, demonstrating the usefulness of combining learned representations with

conventional classification techniques [9]. Ensemble-based approaches further improved the utilization of complementary feature patterns by combining multiple learning models rather than depending on a single classifier [12]. CNN architecture comparisons and hybrid learning strategies have also highlighted the importance of model selection and feature representation in retinal image classification [15]. Attention mechanisms have emerged as an important development because they enable CNN models to emphasize discriminative spatial regions and relevant retinal structures. An attention-based CNN demonstrated the usefulness of directing feature learning toward informative regions in fundus images [16]. More recent attention-based frameworks have incorporated retinal vessel and optic-disc information with CNN models, while multi-scale and dual-attention mechanisms have been investigated to capture fine-grained retinal patterns. Multi-stage glaucoma classification has also received attention through CNN-based ensemble and specialized deep learning approaches [19]. Despite these developments, the combined use of an optimized CNN, attention-based feature learning, and XGBoost within a unified glaucoma prediction framework remains comparatively less explored. Therefore, the proposed study focuses on optimizing CNN feature extraction, incorporating attention to emphasize relevant retinal representations, and employing XGBoost classifier to establish an efficient computational framework for glaucoma prediction respectively.

### III. PROBLEM STATEMENT

- Conventional CNN models consistently face challenges in capturing subtle and complex retinal image patterns required for accurate glaucoma prediction.
- CNN-based feature extraction generates high-dimensional representations, which can increase computational complexity and affect classification efficiency.
- The approaches provide limited emphasis on the most informative retinal regions, affecting the quality of discriminative feature learning.
- The integration of optimized CNN features with XGBoost for effective glaucoma classification remains an area requiring further investigation.
- Therefore, an efficient attention-based framework integrating optimized CNN and XGBoost is required to enhance feature extraction and improve glaucoma prediction from retinal fundus images.

### IV. ABOUT THE DATASET

The dataset used in our research consists of 1,345 RGB retinal fundus images, including 1,009 training images and 336 test images, collected using different fundus imaging devices. The dataset contains several image-level and structural attributes relevant to glaucoma prediction, including optic disc area, optic cup area, neuroretinal rim area, vertical cup-to-disc ratio, horizontal cup-to-disc ratio, and area cup-to-disc ratio. The images are annotated by ophthalmologists for optic disc and optic cup regions, along with glaucoma-related decisions respectively. These attributes provide both visual and structural information that can support deep feature extraction and machine learning-based classification. In the proposed framework, the retinal images and associated structural characteristics are utilized for attention-based feature learning through the optimized CNN inherited with XGBoost to improve the efficiency of glaucoma prediction.

### V. PROPOSED METHODOLOGY

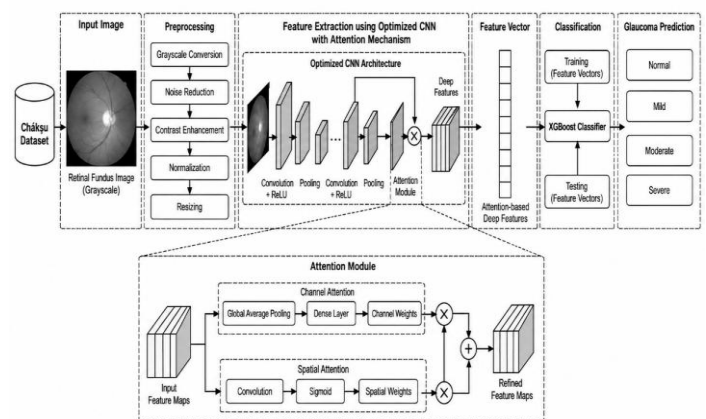


Figure 1: Attention-Based Optimized CNN with XGBoost Framework for Glaucoma Prediction

#### Steps involved in this research

The sequential procedure of the proposed Attention-Based Optimized CNN–XGBoost framework for glaucoma prediction. The process begins with the Chákṣu retinal fundus image dataset, including the available structural attributes such as optic disc area, optic cup area, neuroretinal rim area, VCDR, HCDR, and ACDR. The input images are initially perform preprocessing operations including resizing, noise reduction, contrast

enhancement, normalization, and grayscale conversion to obtain a standardized representation. The preprocessed images are then processed through the optimized CNN, where convolution, ReLU activation, and pooling operations generate hierarchical feature maps. An attention mechanism is subsequently applied through channel and spatial attention to assign greater importance to informative feature representations and produce

refined deep features. These attention-based features are combined with the available structural features to form an integrated feature vector. Feature optimization is then performed to retain the relevant information for classification. Therefore, the optimized feature representation is supplied to the XGBoost classifier generates the glaucoma prediction as Normal, Mild, Moderate, or Severe respectively.

**Input** : Chákşu retinal fundus image dataset  $D$

**Output** : Predicted glaucoma class  $Y \in \{\text{Normal, Mild, Moderate, Severe}\}$

# 1. Start

## 2. Load Dataset

Load the Chákşu dataset  $D$  containing retinal fundus images and structural attributes (optic disc area, optic cup area, neuroretinal rim area, VCDR, HCDR, ACDR).

## 3. For each retinal fundus image $I \in D$ do

### 4. Image Preprocessing

Resize the image, remove noise, enhance contrast, normalize pixel intensity values, and convert to grayscale.

$$I_p = G(N(C(R(I)))) \quad (1)$$

where  $R(\cdot)$  is resizing,  $C(\cdot)$  is contrast enhancement,  $N(\cdot)$  is noise reduction, and  $G(\cdot)$  is grayscale conversion.

### 5. Feature Extraction using Optimized CNN

Apply convolution, activation (ReLU), and pooling operations in an optimized CNN to obtain hierarchical feature maps.

$$F_c = \text{ReLU}(W_c * I_p + b_c) \quad (2)$$

$$F_p = \text{Pool}(F_c) \quad (3)$$

$$F_h = \text{OptimizedCNN}(I_p) \quad (4)$$

### 6. Attention Mechanism

Apply channel attention to emphasize informative feature channels and spatial attention to highlight important spatial regions, and obtain refined feature maps.

$$F_{ch} = F_h \otimes A_{ch} \quad (5)$$

$$F_{sp} = F_{ch} \otimes A_{sp} \quad (6)$$

$$F_a = F_{ch} + F_{sp} \quad (7)$$

### 7. Feature Representation

Generate deep feature vector from the attention-based CNN, extract structural features from the Chákşu dataset, and combine both feature sets.

$$F_d = \text{Flatten}(F_a) \quad (8)$$

$$F_s = [\text{ODA, OCA, NRA, VCDR, HCDR, ACDR}] \quad (9)$$

$$F = [F_d | F_s] \quad (10)$$

### 8. Feature Optimization

Apply feature optimization to obtain the relevant feature subset.

$$F_o = \text{Optimize}(F) \quad (11)$$

### 9. Classification using XGBoost

Provide the optimized feature vector to the XGBoost classifier.

$$Y = \text{XGBoost}(F_o) \quad (12)$$

10. Assign the predicted class  $Y \in \{\text{Normal, Mild, Moderate, Severe}\}$ .

11. End For

12. Stop

## VI. RESULTS & DISCUSSIONS

Table 1: Precision rate on Attention based optimized CNN-XGBoost for Glaucoma Prediction

| No of Images | Precision in % |
|--------------|----------------|
| 200          | 88.90          |
| 400          | 89.91          |
| 600          | 89.34          |
| 800          | 94.50          |
| 1000         | 97.40          |

The above table represents the precision performance of the proposed approach for different numbers of images. The precision varies across the dataset sizes respectively.

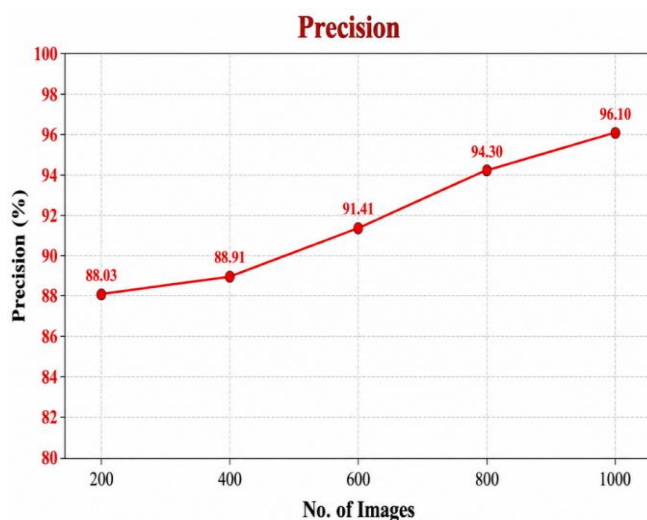


Figure 2: Precision rate on Attention based optimized CNN-XGBoost for Glaucoma Prediction

The above figure represents the performance evaluation of the proposed approach using different numbers of images. The graph illustrates the variation in precision across different dataset sizes respectively.

Table 2: F1-Score on Attention based optimized CNN-XGBoost for Glaucoma Prediction

| No of Images | F1-SCORE in % |
|--------------|---------------|
| 200          | 87.25         |
| 400          | 88.43         |
| 600          | 89.81         |
| 800          | 92.50         |
| 1000         | 95.95         |

The above table represents the F1-Score performance of the proposed approach for different numbers of images. The F1-Score varies across the dataset sizes respectively.

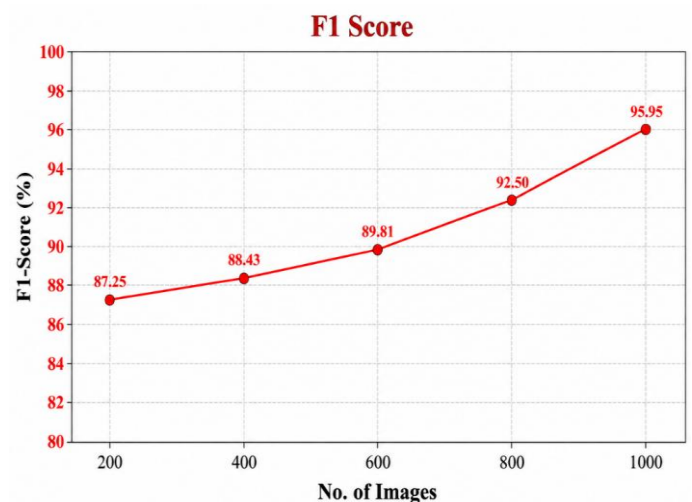


Figure 3: F1-Score on Attention based optimized CNN-XGBoost for Glaucoma Prediction

The above figure represents the performance evaluation of the proposed approach using different numbers of images. The graph illustrates the variation in F1-Score across different dataset sizes respectively.

**Table 3: Recall on Attention based optimized CNN-XGBoost for Glaucoma Prediction**

| No of Images | Recall in % |
|--------------|-------------|
| 200          | 87.42       |
| 400          | 88.50       |
| 600          | 90.12       |
| 800          | 91.63       |
| 1000         | 94.20       |

The above table represents the Recall performance of the proposed approach for different numbers of images. The Recall varies across the dataset sizes respectively.

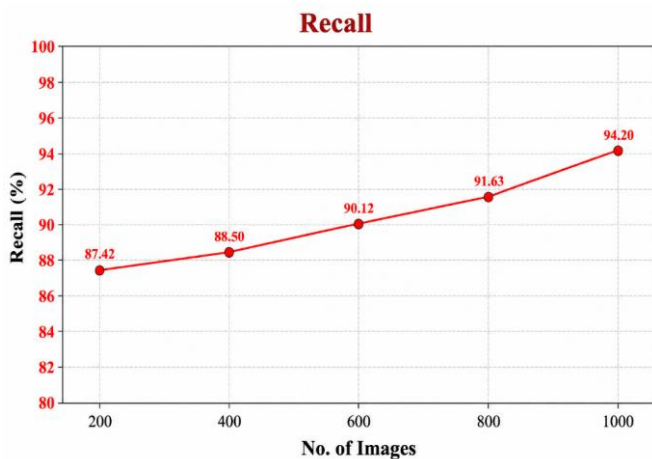


**Figure 4: Recall on Attention based optimized CNN-XGBoost for Glaucoma Prediction**

The above figure represents the performance evaluation of the proposed approach using different numbers of images. The graph illustrates the variation in Recall across different dataset sizes respectively.

**Table 4: Accuracy on Attention based optimized CNN-XGBoost for Glaucoma Prediction**

| No of Images | Accuracy in % |
|--------------|---------------|
| 200          | 89.33         |
| 400          | 90.21         |
| 600          | 93.40         |
| 800          | 95.32         |
| 1000         | 96.40         |

The above table represents the Accuracy performance of the proposed approach for different numbers of images. The Accuracy varies across the dataset sizes respectively.

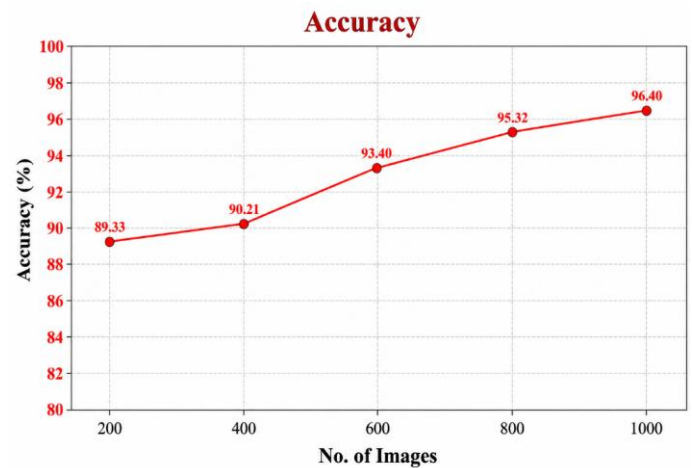


**Figure 5: Accuracy on Attention based optimized CNN-XgBoost for Glaucoma Prediction**

The above figure represents the performance evaluation of the proposed approach using different numbers of images. The graph illustrates the variation in Accuracy across different dataset sizes respectively.

## VII. CONCLUSION

The enhanced Attention-Based Optimized CNN-XGBoost framework provides an efficient approach for automated

glaucoma prediction. The optimized CNN extracts hierarchical and discriminative retinal image features effectively. The attention mechanism enhances relevant feature representations by focusing on informative retinal regions. Structural features are integrated with deep features to provide a comprehensive feature representation. Feature optimization further retains the relevant information for subsequent classification. XGBoost effectively learns nonlinear relationships from the optimized feature set. The proposed framework demonstrates improved performance as the number of input images increases. Thus, the integrated approach provides an enhanced alternative to traditional machine learning-based glaucoma prediction methods respectively.

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