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A Novel Weighted Ensemble Approach Integrating LightGBM for Glaucoma Severity Classification on Retinal Fundus Images

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***Abstract* - Over several decades, machine learning has developed into a valuable approach for learning complex patterns from medical image data. This study introduces a novel weighted ensemble machine learning framework with LightGBM for glaucoma severity classification using retinal fundus images. The proposed framework applies suitable pre-processing and feature extraction to obtain informative image representations, which are subsequently provided to a set of complementary machine learning classifiers. Instead of depending on the decision of a single classifier, the proposed method combines their outputs using a weighted ensemble strategy that assigns different contributions to individual models based on their predictive behaviour. LightGBM is integrated into the ensemble to enhance the learning of nonlinear feature relationships and improve the final decision process. The combined predictions are used to distinguish different glaucoma severity categories from retinal fundus images. The proposed framework emphasizes the integration of enhanced classifier with weighted decision fusion, and LightGBM to manipulate the individual classification models effectively. In our approach unified learning strategy provides a structured and flexible approach for automated glaucoma severity classification and demonstrates the potential of ensemble-based machine learning for retinal image analysis respectively.**

Keywords: Glaucoma Severity Classification, Machine Learning, Weighted Ensemble Learning, LightGBM, Retinal Fundus Images, Feature Extraction, Classification, Decision Fusion, Automated Diagnosis.

I. INTRODUCTION

The main focus on our research based on analysing complex patterns in medical images and supporting automated classification. In retinal image analysis, different learning models have been explored to identify glaucoma-related patterns and reduce dependence on manual assessment [1], [2]. Deep learning architectures, particularly Convolutional Neural Networks, have shown the capability to learn representative features from fundus images and support automated retinal classification [3], [4]. The feature learning, segmentation techniques have been used to focus the analysis on relevant anatomical regions, for being hybrid and ensemble models have been investigated to utilize the strengths of different learning strategies with evaluation [5]. Ensemble learning is particularly useful when individual classifiers produce different decision boundaries, as combining their outputs can provide a more comprehensive representation of the underlying data patterns. Recent studies have examined CNN ensembles and other hybrid learning frameworks for retinal image analysis [8] and demonstrating the potential of combining multiple predictive models [6], [7]. Nevertheless, conventional ensemble methods generally treat the contributions of individual classifiers similarly or use fixed combination rules, which may not fully exploit differences in their predictive behaviour. To address this limitation, the present study develops a weighted ensemble machine learning approach integrating LightGBM for glaucoma severity classification. The proposed work emphasizes adaptive combination of multiple classifiers and the use of LightGBM for learning complex nonlinear relationships, providing a machine learning-oriented framework for distinguishing severity categories from retinal fundus images respectively.

II. LITERATURE REVIEW

The research studies have demonstrated the increasing application of machine learning and deep learning for automated analysis of retinal fundus images. CNN-based approaches have shown the ability to learn discriminative retinal representations and support automated glaucoma assessment [2]. Different deep learning architectures have subsequently been investigated to improve feature learning and classification from fundus photographs [3]. Segmentation-based methods have also been explored to isolate the optic disc and optic cup, providing clinically relevant regions for subsequent classification [5]. Comparative investigations of

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CNN architectures have emphasized the importance of appropriate feature-learning models for retinal image analysis [7]. Ensemble learning has gained attention because combining multiple predictive models can exploit complementary decision patterns and reduce dependence on an individual classifier [8], [9]. A deep learning ensemble developed specifically for glaucoma staging demonstrated the feasibility of distinguishing unaffected, early-stage, and late-stage cases using multiple CNN models [10]. Other studies have investigated hybrid CNN frameworks and ensemble strategies for glaucoma detection using different retinal datasets [12]. Machine learning classifiers such as Random Forest, Support Vector Machine, and other heterogeneous classifiers have also been incorporated into automated glaucoma systems [15]. Dynamic ensemble selection further demonstrated the benefit of selecting suitable classifiers according to individual samples rather than applying a fixed classifier to the complete dataset [16]. Recent approaches have expanded ensemble-based retinal analysis through multiple CNN architectures, attention mechanisms, and integrated segmentation-classification frameworks [17]. The literature review indicates that combining diverse learning models can provide a stronger classification framework than relying on a single learner. Nevertheless, weighted ensemble learning integrating LightGBM specifically for glaucoma severity classification remains comparatively less explored. Therefore, the proposed study focuses on weighted decision integration with LightGBM to learn complex relationships among complementary classifier outputs and support severity-based retinal fundus classification [20]

III. PROBLEM STATEMENT

- **Limited severity classification:** Major research work focus on glaucoma detection rather than detailed severity classification.
- **Single-model dependency:** Machine learning classifiers require diverse retinal feature patterns effectively.
- **Fixed ensemble decisions:** Conventional ensemble methods to mandate similar or predefined importance to different classifiers.
- **Limited LightGBM integration:** The combination of weighted ensemble learning and LightGBM for glaucoma severity classification remains insufficiently explored.

IV. ABOUT THE DATASET

The research work involved and generate a proposed system with three retinal fundus image datasets: DRIVE, REFUGE, and Chákṣu, providing diverse image characteristics and glaucoma-related information for machine learning-based classification. DRIVE contains 40 RGB fundus images with field-of-view and retinal-vessel annotations. REFUGE consists of 1,200 RGB fundus images with glaucoma labels and optic disc/cup annotations. Chákṣu contains 1,345 RGB fundus images with ophthalmologist-based glaucoma annotations and structural attributes such as optic disc area, optic cup area, VCDR, HCDR, and ACDR. These datasets provide complementary image features and clinical annotations for training and evaluating the proposed weighted ensemble machine learning framework with LightGBM for glaucoma severity classification respectively.

V. PROPOSED METHODOLOGY

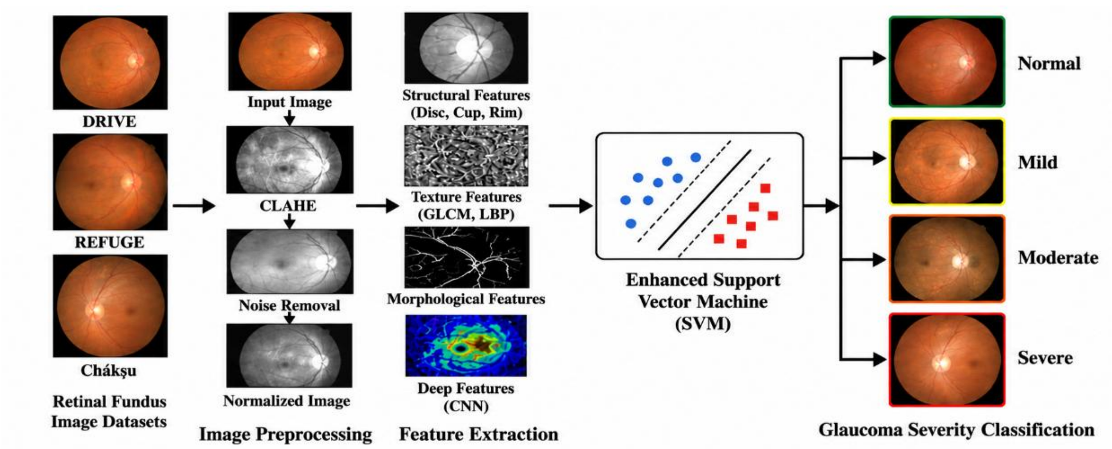

Figure 1: Glaucoma severity classification using weighted ensemble machine learning

The framework begins with retinal fundus images obtained from the DRIVE, REFUGE, and Chákṣu datasets. The input images undergo pre-processing using Contrast Limited Adaptive Histogram Equalization noise removal, and image normalization to improve the quality and consistency of the retinal data. Relevant information is then obtained through

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feature extraction including structural features related to the optic disc, optic cup, and neuroretinal rim, texture features such as GLCM and LBP, morphological features, and deep features extracted using CNN.

The extracted feature representations are supplied to an Enhanced Support Vector Machine for machine learning-based classification. The classifier analyses the learned feature patterns and assigns the retinal fundus image to the corresponding glaucoma severity category: Normal, Mild, Moderate, or Severe respectively. The evaluation integrates image pre-processing, feature extraction, and enhanced machine learning classification into a unified framework for automated glaucoma severity assessment respectively.

Algorithm: Proposed weighted ensembling approach integrating with Light BGM for Glaucoma Severity Classification

Steps involved in this research

Input: Retinal fundus image datasets $D = \{\text{DRIVE, REFUGE, Chákṣu}\}$
Output: Glaucoma severity class Y

1. Dataset Acquisition and Image Preprocessing

$$I(x, y, c), \quad c \in \{R, G, B\} \tag{1}$$

$$I_N(x, y) = \frac{I(x, y) - I_{\min}}{I_{\max} - I_{\min}} \tag{2}$$

$$I_C(x, y) = \text{CLAHE}(I_N(x, y)) \tag{3}$$

$$I_P(x, y) = \text{Preprocess}(I_C(x, y)) \tag{4}$$

where I represents the input retinal fundus image, I_N is the normalized image, and I_C is the contrast-enhanced image.

2. Feature Extraction

$$F_s = \text{Structural}(I_P) \tag{5}$$

$$F_t = \text{Texture}(I_P) \tag{6}$$

$$F_m = \text{Morphological}(I_P) \tag{7}$$

$$F_d = \text{CNN}(I_P; \theta) \tag{8}$$

$$F = [F_s, F_t, F_m, F_d] \tag{9}$$

where F_s, F_t, F_m, and F_d represent structural, texture, morphological, and deep features, respectively.

3. Multiple Machine Learning Classification

$$P_i = C_i(F), \quad i = 1, 2, \ldots, n \tag{10}$$

where C_i represents the individual machine learning classifiers and P_i denotes their predicted class probabilities.

4. Performance-Based Weight Assignment

$$w_i = \frac{M_i}{\sum_{j=1}^{n} M_j} \tag{11}$$

$$\sum_{i=1}^{n} w_i = 1 \tag{12}$$

where M_i represents the selected validation performance measure of classifier C_i and w_i denotes its normalized weight.

5. Weighted Ensemble Decision Formation

$$P_E = \sum_{i=1}^{n} w_i P_i \tag{13}$$

$$F_E = [F, P_E] \tag{14}$$

where P_E is the weighted prediction vector and F_E is the enhanced ensemble feature set.

6. LightGBM-Based Final Classification

$$\hat{Y} = \text{LightGBM}(F_E; \Theta) \tag{15}$$

$$\hat{Y} \in \{0, 1, 2, 3\} \tag{16}$$

where

$$0 = \text{Normal}, \quad 1 = \text{Mild}, \quad 2 = \text{Moderate}, \quad 3 = \text{Severe} \tag{17}$$

The proposed methodology begins with the acquisition of retinal fundus images from the DRIVE, REFUGE, and Chákṣu datasets**,** followed by image normalization to maintain consistent intensity and representation. Contrast Limited Adaptive Histogram Equalization is applied to improve local contrast and enhance the visibility of relevant retinal structures, followed by noise removal and image pre-processing. The processed images are then used to extract structural, texture, morphological, and CNN-based deep features to construct a comprehensive feature representation. These extracted features are provided to multiple machine learning classifiers to generate individual prediction probabilities. A performance-based weighting mechanism is then applied to assign suitable weights to the classifier outputs according to their predictive contribution. The weighted predictions are combined to form an enhanced ensemble

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representation. The representation is subsequently provided to LightGBM, which learns nonlinear relationships between the extracted features and ensemble predictions respectively and the proposed model classifies the retinal fundus images into four glaucoma severity categories such as Normal, Mild, Moderate, and Severe efficiently.

VI. RESULTS & DISCUSSIONS

Table 1: Precision rate on proposed weighted ensembling approach integrating with Light BGM for Glaucoma Severity Classification

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.

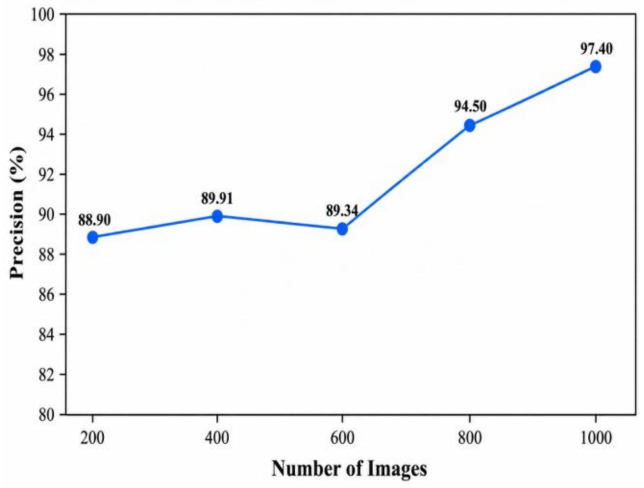

Figure 2: Precision rate on proposed weighted ensembling approach integrating with Light BGM for Glaucoma Severity Classification

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 Proposed weighted ensembling approach integrating with Light BGM for Glaucoma Severity Classification

No of Images	F1-SCORE in %
200	89.25
400	89.59
600	90.48
800	92.90
1000	97.30

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

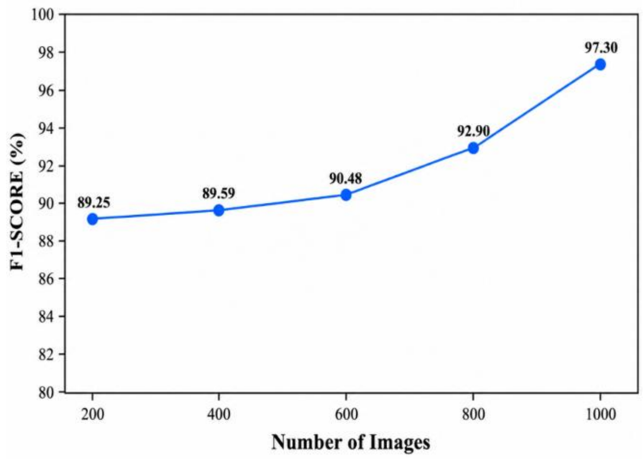

Figure 3: F1-Score on Proposed weighted ensembling approach integrating with Light BGM for Glaucoma Severity Classification

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

Table 3: Recall on proposed weighted ensembling approach integrating with Light BGM for Glaucoma Severity Classification

No of Images	Recall in %
200	89.31
400	92.55
600	94.03

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No of Images	Recall in %
800	94.52
1000	97.20

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

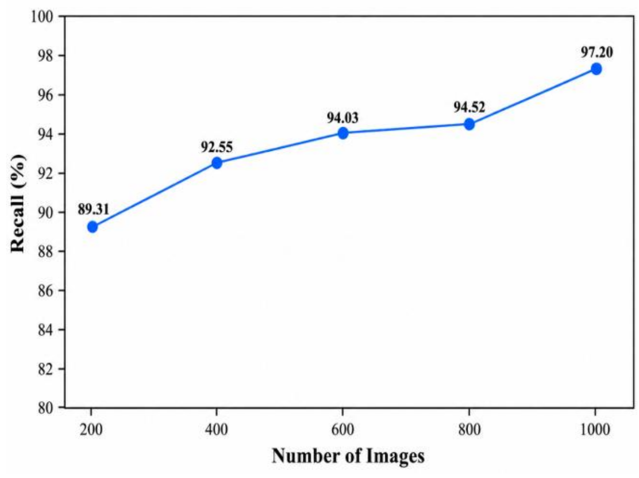

Figure 4: Recall on Proposed weighted ensembling approach integrating with Light BGM for Glaucoma Severity Classification

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 proposed weighted ensembling approach integrating with Light BGM for Glaucoma Severity Classification

No of Images	Accuracy in %
200	89.90
400	90.50
600	94.50
800	95.32
1000	97.80

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

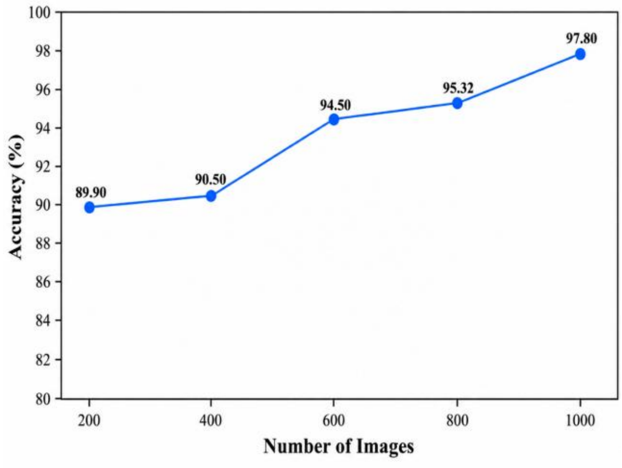

Figure 5: Accuracy on Proposed weighted ensembling approach integrating with Light BGM for Glaucoma Severity Classification

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 proposed weighted ensemble machine learning approach integrating LightGBMprovides an efficient framework for automated glaucoma prediction and severity classification using retinal fundus images. The integration of pre-processing and diverse feature extraction techniques enables the model to identify meaningful retinal characteristics for classification. The weighted ensemble mechanism combines the contributions of multiple learning models, while LightGBM enhances the final decision process by learning complex relationships within the feature space. The proposed framework supports the classification of glaucoma into different severity levels, including normal, mild, moderate, and severe categories. The results demonstrate the effectiveness of the proposed learning strategy across different image dataset sizes. Hence, the approach provides a promising computational framework for early glaucoma prediction and automated severity classification and can support efficient retinal image-based assessment respectively.

REFERENCES

[1] M. N. Bajwa *et.al.*, "Two-stage framework for optic disc localization and glaucoma classification in retinal fundus images using deep learning," *BMC Medical Informatics and Decision Making*, vol. 19, Art. no. 136, 2019.

[2] S. Phan *et.al.* "Evaluation of deep convolutional neural networks for glaucoma detection," *Japanese Journal of Ophthalmology*, vol. 63, pp. 276–283, 2019.

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[3] R. Hemelings *et al.*, "Accurate prediction of glaucoma from colour fundus images with a convolutional neural network that relies on active and transfer learning," *Acta Ophthalmologica*, vol. 98, no. 1, pp. e94–e100, 2020.

[4] K. Hashimoto *et. al.* "Glaucoma diagnosis with machine learning based on optical coherence tomography and color fundus images," *Journal of Healthcare Engineering*, vol. 2019, Art. no. 4061313, 2019.

[5] Sonia Phene *et al.* "Deep learning and glaucoma specialists: The relative importance of optic disc features to predict glaucoma referral in fundus photographs," *Ophthalmology*, vol. 126, no. 12, pp. 1627–1639, 2019.

[6] J. M. L. *et al.*, "Predicting glaucoma before onset using deep learning," *Ophthalmology Glaucoma*, vol. 3, no. 4, pp. 262–268, 2020.

[7] A.J. Thompson *et al.*, "Human versus machine: Comparing a deep learning algorithm to human gradings for detecting glaucoma on fundus photographs," *American Journal of Ophthalmology*, vol. 211, pp. 123–131, 2020.

[8] S. Ajitha *et. al.* "Identification of glaucoma from fundus images using deep learning techniques," *Indian Journal of Ophthalmology*, vol. 69, no. 10, pp. 2702–2709, 2021.

[9] R. Shinde *et. al.* "Glaucoma detection in retinal fundus images using U-Net and supervised machine learning algorithms," *Intelligence-Based Medicine*, vol. 5, Art. no. 100038, 2021.

[10] O. C. Devecioglu *et. al.* "Real-time glaucoma detection from digital fundus images using Self-ONNs," *IEEE Access*, vol. 9, pp. 140031–140041, 2021.

[11] W. T. Song *et. al.* "A statistical robust glaucoma detection framework combining Retinex, CNN, and DOE using fundus images," *IEEE Access*, vol. 9, pp. 103772–103783, 2021.

[12] H. Cho *et. al.* "Deep learning ensemble method for classifying glaucoma stages using fundus photographs and convolutional neural networks," *Current Eye Research*, vol. 46, no. 10, pp. 1516–1524, 2021.

[13] M. Alghamdi *et. al.* "A comparative study of deep learning models for diagnosing glaucoma from fundus images," *IEEE Access*, vol. 9, pp. 23894–23906, 2021.

[14] P. Shanmugam *et. al.* "An automatic recognition of glaucoma in fundus images using deep learning and random forest classifier," *Applied Soft Computing*, vol. 109, Art. no. 107512, 2021.

[15] V. Sunanthini, *et. al.* "Comparison of CNN algorithms for feature extraction on fundus images to detect glaucoma," *Journal of Healthcare Engineering*, vol. 2022, Art. no. 7873300, 2022.

[16] P. Venkatesh Ramesh *et. al.* "Utilizing human intelligence in artificial intelligence for detecting glaucomatous fundus images using human-in-the-loop machine learning," *Indian Journal of Ophthalmology*, vol. 70, no. 4, pp. 1131–1138, 2022.

[17] S. N. Sangeethaa *et. al.* "Presumptive discerning of the severity level of glaucoma through clinical fundus images using hybrid PolyNet," *Biomedical Signal Processing and Control*, vol. 81, Art. no. 104347, 2023.

[18] S. Pathan, *et. al.* "An automated classification framework for glaucoma detection in fundus images using ensemble of dynamic selection methods," *Progress in Artificial Intelligence*, vol. 12, pp. 287–301, 2023.

[19] K. Sonti *et. al.* "A new convolution neural network model 'KR-NET' for retinal fundus glaucoma classification," *Optik*, vol. 283, Art. no. 170861, 2023.

[20] G. D'Souza *et. al.* "AlterNet-K: A small and compact model for the detection of glaucoma," *Biomedical Engineering Letters*, vol. 14, pp. 23–33, 2024.

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