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Automated glaucoma detection model based on 2-D discrete wavelet transform with ensemble learning approach

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Abstract
Glaucoma is a retinal disorder and ranks among the prevalent contributors to irreversible vision loss on a global scale. This study introduces an automated image processing technique for diagnosing glaucoma using digital fundus images. Timely identification of retinal diseases is pivotal in preventing vision deterioration and blindness. In this paper, we have proposed a new computer-aided diagnosis (CAD) model for glaucoma classification using fundus images. This method employed a two-dimensional discrete wavelet transform (2D-DWT) to extract features from fundus images. The dimension of the features has been decreased using principal component analysis (PCA) and linear discriminant analysis (LDA) to obtain more prominent features. Finally, the reduced set of features is applied to ensemble learning techniques by combining the XGboost (XGB), random forest (RF) and decision tree (DT) to classify glaucoma or healthy. Evaluation metrics like specificity, sensitivity, and accuracy serve as some of the statistical measures to assess the efficacy of these classification algorithms. Here, we have used two standard datasets, G1020 and ORIGA. From the experimental result, we observed that the proposed scheme obtained an accuracy of 91.95 % (G1020) and 92.97 % (ORIGA) datasets, superior to other state-of-the-art methods in classification results with a substantially reduced number of features. However, these challenges impede the models' performance and generalizability, thereby diminishing the reliability of their predictions.
Keywords: XGB, RF, PCA, LDA, Glaucoma Detection.

I. Introduction

Glaucoma is a retinal condition where the optic nerve sustains harm due to elevated intraocular pressure (IOP) within the eye. A fluid termed aqueous humor flows through the pupil and gets absorbed back into the bloodstream. In instances of glaucoma, this fluid's circulation becomes obstructed, leading to heightened intraocular pressure. Consequently, the optic nerve, responsible for delicate vision functions, incurs damage, ultimately affecting eyesight. Primarily impacting the inner region of the optic disk, the condition leads to an enlargement of the optic cup (OC), resulting in an elevated cup-to-disk ratio (CDR). This leads to a gradual reduction in the visual field for individuals affected by the condition. Following diabetic retinopathy, glaucoma ranks as the second most prevalent reason for global blindness. Unfortunately, glaucoma lacks a cure, and any vision loss incurred cannot be reversed. However, early detection makes it feasible to hinder additional vision deterioration through appropriate medical treatment and surgical interventions. Unlike numerous other medical conditions, glaucoma poses a significant and concerning challenge due to the absence of immediate signs and symptoms perceived by the patient [1]. By the time the patient becomes aware of these indications, irreversible damage to the retina has already occurred. Available data [1] suggests that over 2.2 million Americans are affected by glaucoma; regrettably, 50% remain oblivious to their condition. This predicament is exacerbated in developing nations across Asia and Africa, where a scarcity of trained ophthalmologists hinders timely glaucoma diagnosis.

Consequently, there arises a necessity to create efficient and automated computer-aided diagnosis (CAD) techniques for diagnosing such diseases. Certain studies have explored using computer vision techniques to detect glaucoma through digital fundus images. A method centred around image processing for identifying glaucoma was outlined in a previous study [2]. This involved examining and fusing various image-derived attributes to detect glaucoma indicators. Numerous research efforts involve segmenting the optic cup and disc within colour fundus images. This segmentation is crucial for calculating the CDR, aiding in detecting glaucoma indications. A method for segmenting the optic disc is introduced in a specific study [3]. This method leverages local image details around specific points of interest within a multi-dimensional feature space, showcasing resilience to variations around the optic disc vicinity. Machine learning (ML) has been used to tackle various tasks involving the analysis of medical images, demonstrating impressive speed and efficiency in optimizing processes across a wide range of diseases, such as breast cancer diagnosis [14-19], diabetes detection [20-21,26], etc. The machine learning techniques are also popular for natural language processing [27].

From the literature review indicates that a majority of the models have employed low-frequency sub-band coefficients from the Discrete Wavelet Transform (DWT) as the feature matrix to represent images. However, this approach becomes less effective when dealing with artefacts such as minor rotations and a limited image's luminosity. The directional information, crucial for improving performance, can be extracted from the high-frequency sub-bands rich in detail. Furthermore, most conventional methods have failed to adapt effectively to more extensive datasets. Based on our proposed model, we utilized the coefficients from a specific detail sub-band at level 3 of the 2D discrete wavelet transform to extract features from images of glaucoma-affected fundus images. In this context, we utilize feature reduction methods, including PCA and linear discriminant analysis (LDA), to decrease the number of dimensions in the feature set. Finally, the primary innovation presented in this paper revolves around the utilization of ensemble learning techniques, which incorporate machine learning classifiers like extreme gradient boosting (XGB), random forest (RF), and decision tree (DT) in the context of glaucoma detection has introduced in the following manner:

1. The central aim of integrating ensemble learning techniques into glaucoma detection is to increase the accuracy and reliability of the diagnostic techniques by combining the strengths of multiple classifiers, namely XGB, RF and DT.
2. This study seeks to create a robust and practical approach to identifying the presence of glaucoma.
3. The synergistic interaction among these classifiers is harnessed to tackle the intricacies of glaucoma diagnosis, ultimately aiming to provide a more precise and dependable means of early detection and intervention for this vision-threatening condition.

The remaining sections of the document are structured subsequently. In section 2, the emphasis is on related work. The proposed methodology is described in Section 3. Section 4 shows the experimental result and discussion. Finally, the conclusion and future scope are defined in Section 5.

II. Related Works

In current approaches for detecting glaucoma using feature-based classification, the entire fundus image or a retinal sub-image containing the optic disc is utilized to extract features. To extract and synthesize the techniques and features that have been notable progressions in the employment of machine learning (ML) approach for detecting and diagnosing glaucoma diseases. Yin et al. [4] proposed a new CAD model that examined four ocular conditions linked to an online platform through a cloud-based system and SVM for glaucoma classification. Islam et al. [5] have presented the CLACHE techniques to extract features from unequal datasets, which leads to avoiding overfitting issues. Maheswari et al. [6] have proposed a new model for diagnosing glaucoma based on empirical wavelet transform (EWT) that decomposes the images and correntropy features. They used the least-squares support vector machine (LS-SVM) classifier for classification. In [7], the authors have presented the variational model decomposition (VDM) method for image decomposition and used different features like Kapoor entropy, Renyi entropy, Yager entropy, feature dimension for extracting VDM components and LS-SVM used for classification purposes. Kausu et al. [8] have utilized dual-tree complex wavelet transform features and fuzzy c-means clustering techniques, and Otsu's thresholding is utilized for optic cup segmentation.

In [9], the authors have proposed optic disc localization and a non-parametric GIST descriptor that is used to reduce using locality sensitivity discriminant analysis (LSDA) through different feature selection and ranking schemes and classification. Parashar et al. [10] have proposed a new model for glaucoma diagnosis using wavelet analysis, which is used to decompose the fundus images into various modes, followed by extraction of FD and various types of entropies to capture and build a least square-SVM (LS-SVM) model using various kernel functions. In [11], a Computer-Aided Design (CAD) model utilizing machine learning techniques, specifically a Deep Sparse Autoencoder, was introduced. This model was created to acquire a blend of characteristics between deep and original features, potentially enhancing the overall efficiency of expressing high-level features. Additionally, the model incorporates L1 regularization to enhance the complementarity of deep features, particularly in scenarios with limited sample data. From the literature, it has been noted that machine learning holds a significant importance in various ensemble learning methods. This approach proves advantageous, particularly in the biomedical field, despite the limited availability of datasets. Nowadays, several existing models are based on ML-based approaches, but none of the papers focused on ensemble methods for glaucoma classification. Hence, our proposed work is based on ensemble learning, the combination of XGB, SVM and LR utilized for better classification results compared to other traditional models.

III. Proposed Methodology

The proposed model is based on four prime sections: feature extraction, feature normalization, feature dimensionality reduction and classification. Figure 1. shows the architecture using the proposed scheme's computer-aided diagnosis (CAD) model. Each section is described in detail.

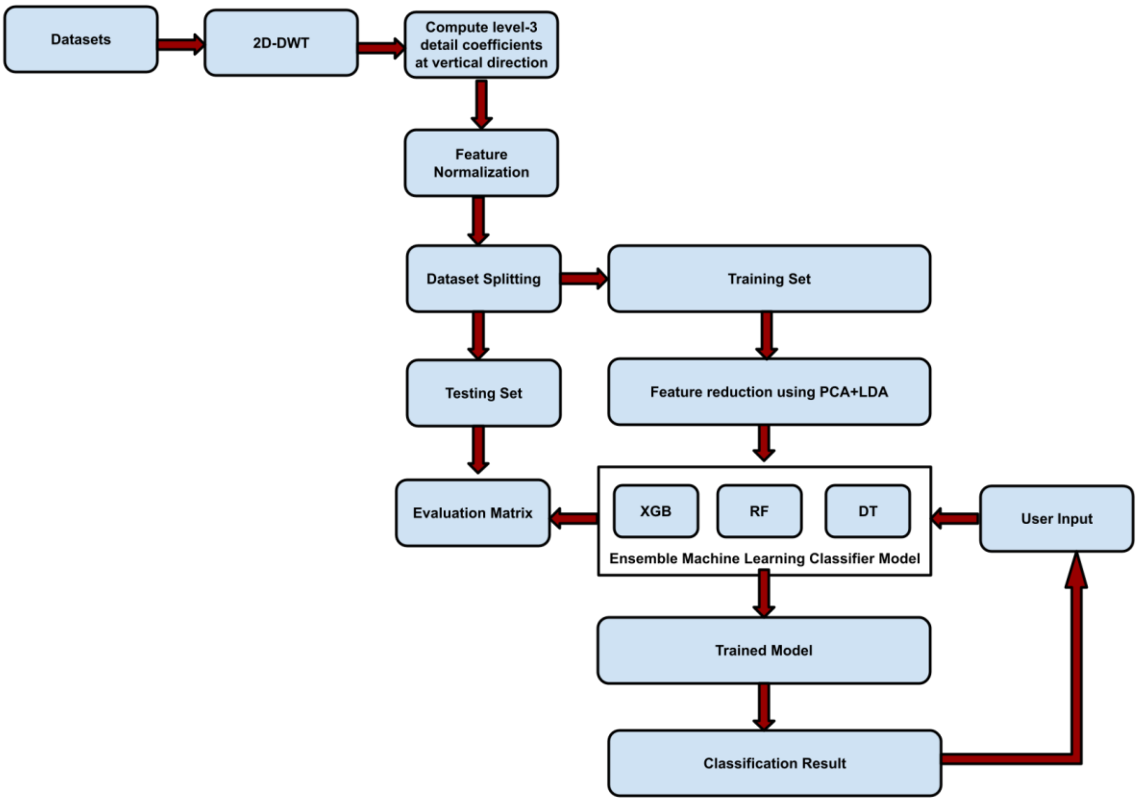

Figure 1: Proposed CAD model for glaucoma classification.

A. Feature Extraction

The initial phase of the deployed model involves assessing the 2D-discrete wavelet transform (2D-DWT) coefficients derived from retinal fundus images. The wavelet transform is a potent method for feature extraction thanks to its ability to analyze images across various levels of resolution [22]. The primary benefit of the wavelet lies in its capacity to furnish insights into both the time and frequency localization of an image, a crucial aspect for fundus image detection purposes. A 2D-DWT is applied by utilising both low-pass and high-pass filters and down sampling. In a list format, each level specifies four sub-band images (LL, LH, HL, HH). Among these, three sub-bands, LH (low-high), HL (high-low), and HH (high-high), represent the high-frequency components in the horizontal, vertical, and diagonal directions. Therefore, LL (low-low) is defined as a subset of the image (low-pass) component that is employed in the subsequent level of 2D discrete wavelet transform assessment [22]. Figure 2 shows the expansion of the wavelet decomposition technique to three distinct resolution levels for a typical glaucoma fundus image.

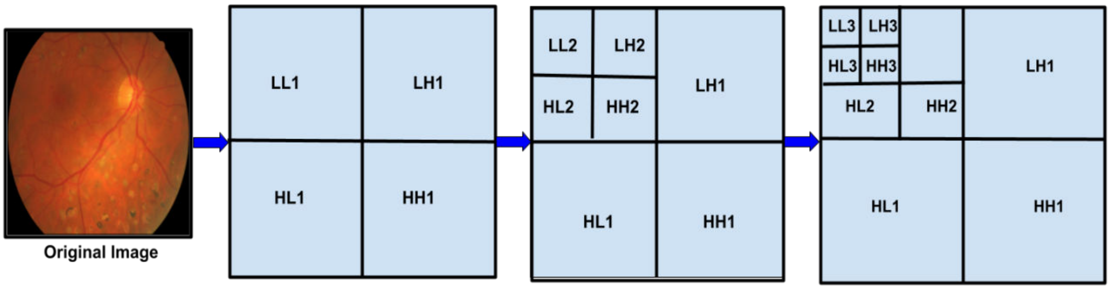

Figure 2. An average glaucoma fundus image alongside its wavelet breakdown into three different levels of resolution

This study used the Daubechies 4 wavelet's HL sub-band coefficients at level 3 (HL3) to generate features. To create a feature vector for each image, we organized the coefficients of the LH3 sub-band row-wise. After combining these vectors, a feature matrix F with dimensions P × Q (where P represents the total number of fundus images, and Q denotes the list of features) has been generated. This matrix serves as the input for the subsequent stage.

B. Feature Normalization

Based on numerous instances, classification performance is enhanced by normalizing characteristics. Before their PCA and LDA utilization, the derived features underwent normalization. The formula has normalized feature Z to Z_n.

$$Z_n = \frac{Z-\mu}{\sigma}$$
(1)

Here, In Equation 1, μ and σ are the averages and variability of the characteristics are appropriately adjusted. Subsequently, the standardized features are forwarded to the next stage.

C. Feature Dimensionality Reduction

We have noticed that when using only HL3 coefficients as features, it significantly augments the dimensions of the feature vector. To make the classification task manageable, it's necessary to significantly decrease the feature vector's dimensionality while retaining meaningful information. To achieve this, we employed two widely used methods, PCA and LDA, which help extract valuable features. PCA (principal component analysis) is a highly effective method extensively employed to reduce dimensions, extract features, and visualize data. It involves projecting data orthogonally onto a lower-dimensional linear space referred to as the principal subspace. This process aims to maximize the variance of the projected data [15]. Similarly, linear discriminant analysis (LDA) aims to find a projection that maximizes the distance between data samples from different classes while minimizing the distance between data samples within the same class. Our experiments reveal that using only LDA for feature reduction can lead to a singular within-scatter matrix. This situation arises when the size of the training dataset is less than the dimensionality of the original feature space, commonly known as the "small sample size" problem. To address this issue, we've implemented PCA as a preliminary step before applying LDA [16]. Initially, PCA is employed to reduce the dimensionality to P – 1. Next, LDA is employed to further reduce the dimensionality of the feature vector. This step creates a diminished feature matrix X with dimensions P × V, where V denotes the reduced feature set. This reduced X matrix and a class label vector Y that includes labels for all samples are subsequently inputted into the classifier.

D. Classification

In our proposed model, three machine learning classifiers have been combined and used to predict the binary classification problem. This technique is called ensemble learning. The ensemble learning technique is based on a heterogeneous nature because all the learners are different types of classifiers used by the same training data. Let's take one algorithm that is not fit for the model due to parameter constraints. We combine several classifiers like XGboost, random forest and decision tree to determine better-predicted accuracy. Ensemble learning is based on various learning techniques: Voting Ensemble, Weighted Average Ensemble, Stacking Ensemble, Bagging and Boosting techniques. In our proposed model, we have focused on the voting method. In a voting ensemble method, each base model, like Decision Tree, Random Forest, and XGBoost, makes predictions on the test data, and a majority vote determines the final prediction. The final prediction in a majority voting ensemble would be glaucoma or healthy.

Dataset Used:

In our proposed work, we have used two commonly used datasets comprising fundus images affected by Glaucoma. These datasets are called G1020 [12] and ORIGA [13]. The G1020 dataset comprises 1020 high-quality colour fundus images with a high level of detail. Among these images are 296 cases of Glaucoma and 724 cases of healthy eyes, each with annotations for glaucoma diagnosis. Similarly, the ORIGA dataset, established in 2010, is a significant resource for the research community. It encompasses 650 fundus images, with 168 showing glaucoma cases and 482 in Table 1. We have specified sample images from both datasets illustrated in Figure 3.

Table 1. Proposed Glaucoma Datasets sample split (Glaucoma Vs. Healthy)

Datasets	**Total Images**		**Training Images**		**Testing Images**	
	Glaucoma	**Healthy**	**Glaucoma**	**Healthy**	**Glaucoma**	**Healthy**
G1020	296	724	178	434	118	292
ORIGA	168	482	101	289	67	193

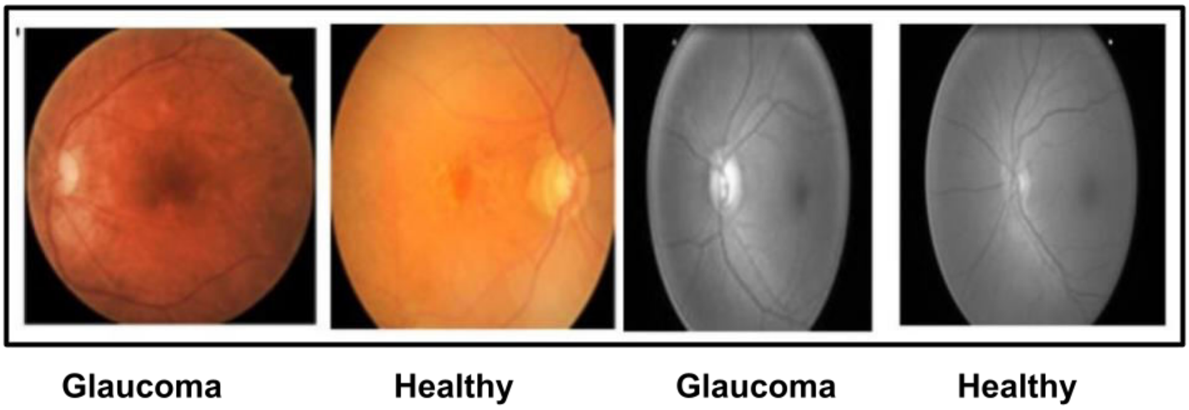

Figure 3. Sample images of both datasets (G1020 and ORIGA)

XG Boosting Algorithm:

It is an advanced version of Gradient Boosting algorithms. i.e., an assembling technique for sequential learning the difference between bagging and boosting. Bagging is a parallel assemble, meaning different models get trained one after another. So, the first order gets trained, then the second model, then the third model and then many models may combine to give a result. XGboost is nothing but an extension of gradient boosting. So, how gradient boost works based on glaucoma datasets. The prediction, the next model, will understand three things.

λ-Regularization parameters
r-Threshold that our auto proning of the tree and control our overfitting.
Eta- How first we want to coverage.
First, we have to noted down sum of residual.

$$Ss = \left(\frac{SR^2}{\#R^{+}\lambda}\right) \quad (2)$$

In Equation 2, Gama – when our Gama value is less, the split will happen; otherwise, the split will not happen. That is how our auto-pruning happens. How much our tree grows will depend on how much we gain by split and if that gain is within the range of the gain we intend to grow. If this is not satisfied, that break will not happen. Gama, if we give, we are prone to more aggressive and lower gain. It means we went prone with a less aggressive approach. By default, if we put, then the similarity score is one, which means that our tree is pruned to control our tree to overfit. It will increase our regularization parameter, and then we will take a more aggressive approach to prone our tree or control its overfit. How the prediction happens then simply tells us the sum of all the residuals divided by the number of residuals. It takes care of the outliers to some extent. If you increase the value, the impact of outliers on the prediction will come significantly. How aggressively prone our tree is used for how much we want to control the effect of an outlier in our data or how much we have to generalise the effect of extreme data points.
In the next part, New Prediction= Previous prediction + Learning rate (eta (0.3)) X output. That is the new prediction for the new residual value. The next model is trend. XGboost will reduce the residual and give us a final reassembled model, which is very close to the original observation. By using glaucoma datasets, we have to predict the accuracy analysis for training the model, which represents a tree structure, to find out whether our model is best fitted or not by implementing the procedure of XGBoost features and by applying its formula to avoid overfitting problems and find out the better result than other models used in machine learning algorithms. Tuning the hyperparameters of XGBoost for glaucoma classification in an ensemble learning setup is essential for achieving optimal performance. Identify the hyperparameters that are critical for glaucoma classification. Relevant hyperparameters might include max_depth, learning_rate, n_estimators, min_child_weight, subsample, and colsample_bytree, among others. Evaluate the ensemble's performance using the test dataset to assess its generalization ability and make sure you're not overfitting to the validation data.

Random forest:

It ranks among the pivotal classifiers within supervised machine learning, serving purposes in classification and regression tasks. The random forest constructs an ensemble of decision trees to tackle these problems, enhancing its predictive performance. A decision tree comprises branches, leaves, internal nodes, and siblings. A leaf node indicates the ultimate result, while internal nodes determine the choice of branch based on attributes, like whether someone's age qualifies them to vote. Multiple evaluators have been designated as 'n_estimators,' the maximum tree depth is set as 'max_depth,' the minimum number of splits is specified as 'min_sample_split,' the maximum number of instances is allocated as 'max_features,' and the maximum leaf node count is established as 'max_leaf_nodes.'. Hence, n_estimators is a hyperparameter

that indicates decision trees to be generated for the prediction. A significant number of decision trees is recommended for better prediction, which increases the execution time.
The Gini index is employed to construct a decision tree using the provided input datasets. The formula for calculating the Gini index is as follows:

$$Gini = 1 - \sum_{i=1}^{e}(pi)^2$$

(3)

In this context, we designate 'C' as the overall count of categories within the datasets, with 'C' set to 2. Within our datasets, eight occurrences exist, each associated with a single classification label. These labels can be either 1 (indicating the presence of glaucoma) or 0 (indicating the absence of glaucoma). Pi is the probability of selection of branches in the ith level for the next level of predicted result. In random forest (RF), many decision trees are in series. In glaucoma classification, the patient has glaucoma or is healthy. RF classifier is also used to handle missing data and maintain accuracy. We will not overfit the model, which applies to G1020 and ORIGA datasets. Then, we follow ensemble learning to combine different models. Here, RF classifiers with hundreds of estimators, for example, hundreds of decision trees. Then, we fit the model and predict the result. Then, we will train the training set and predict the X-test data to predict the outcomes. To evaluate the model, we use the scoring function.

Decision Tree Classifier:

It is also a supervised machine learning classifier that can classify the model. Such a classifier can solve rule-based problems and build the attributes set by applying the if-else pattern set by the Gini index. This approach is employed to make decisions at the internal node, leading to the subdivision of data into various samples for further branching in the tree.

$$Gini = 1 - \sum_{i=0}^{c}(Pi)^2 \quad (4)$$

$$Enytropy = -\sum_j p_j log_2 p_j$$

(5)

$$Miscclassification\ Error = 1 - maxp_j$$

(6)

All 32 features are arranged in a hierarchical arrangement using glaucoma datasets by a single Decision Tree classifier. Decision Tree, also called a flowchart. It is also called a classification tree that uses split conditions to predict a class label based on the provided input variables. The split process starts from the top node (root node), and, for each node, it checks whether input values recursively continue to the (left to right according to the supplied splitting condition (gini function). This process terminates when a leaf or terminal node is reached. Glaucoma datasets have analysed diagnostically whether a person has glaucoma or is healthy. For training, we will use rpart () from the report library. It includes glaucoma, which is predicted by all independent variables. While building the model, the Decision Tree classifier uses splitting criteria by two popular, i.e., “Gini” and “information gain”. The initial model and the “Gini” based model provide the same accuracy, as the report model provides the same result, as the report model “Gini” is the default splitting process. Then, the next step is to predict the class labels of the test data. Then, for predicting accuracy comparison of the models, we find that “Gini” based split and provide “information “based splitting for better accuracy.

IV. Experimental Result and Discussion

All the experiments have been conducted using the proposed computer-aided diagnosis (CAD) model implemented in MATLAB-R2018a. The experiments were performed on the PARAM Shavak – Supercomputer with an HPC system set up in a tabletop configuration. This system has an Intel(R) Xeon(R) Gold 5220R CPU running at 2.20GHz. It boasts a minimum of 2 multicore CPUs, each possessing at least 12 cores, along with one or two GPU accelerator cards, including the NVIDIA K40 accelerator card and NVIDIA P5000. The system offers a computing power of 3 Tera-Flops at its peak, complemented by 8 TB of storage and 64 GB of RAM. It comes pre-loaded with a parallel programming development environment and possesses computing power of 2 TF and above. Two standard datasets, G1020[12] and ORIGA [13], have been utilized throughout the experiments. The hyperparameters for the proposed model are shown in Table 2. Here, we have observed that our proposed model simulated with thirty-five features obtained better results in PCA +LDA on both datasets shown in Table 3 and the compassion between PCA and PCA +LDA visualized in Figure 3 - 4. The confusion matrix of both datasets, namely G1020 and ORIGA, is shown in Figure 5. Then, different classifiers' accuracy based on their training time compared with our proposed model is tabulated in Table 4. Our deployed model accuracy, sensitivity and specificity compared with other classifiers shown in Table 5 and visualized in Figure 6 (G1020) and Figure 7 (ORIGA) datasets. The performance analysis of our deployed CAD model with existing models has been compared in Table 6.

Table 2. Hyperparameter of the proposed model

Classifiers	Name	Parameters
XG Boost	Learning rate	0.3
	n_estimators	100
	scale_pos_weight	1
	Gamma	0
Random Forest	n_estimators	100
	criterion	Gini
	min_impurity_decrease	0
Decision Tree	criterion	Gini
	max_features	0,1
	min_samples_leaf	1
	min_sample_split	2

Table 3. Comparative analysis of proposed model with sample features

Proposed Method	**No. of Features**	**G1020**			**No. of Features**	**ORIGA**		
		Acc	**Sen**	**Spe**		**Acc**	**Sen**	**Spe**
2DDWT +PCA+XGB+RF+DT	40	91.24	82.35	94.86	40	92.19	90.48	92.75
2DDWT +PCA+LDA+XGB+RF+DT	**35**	**91.95**	**83.90**	**95.29**	**35**	**92.97**	**92.06**	**93.26**

*Acc - Accuracy, Sen – Sensitivity, Spe – Specificity

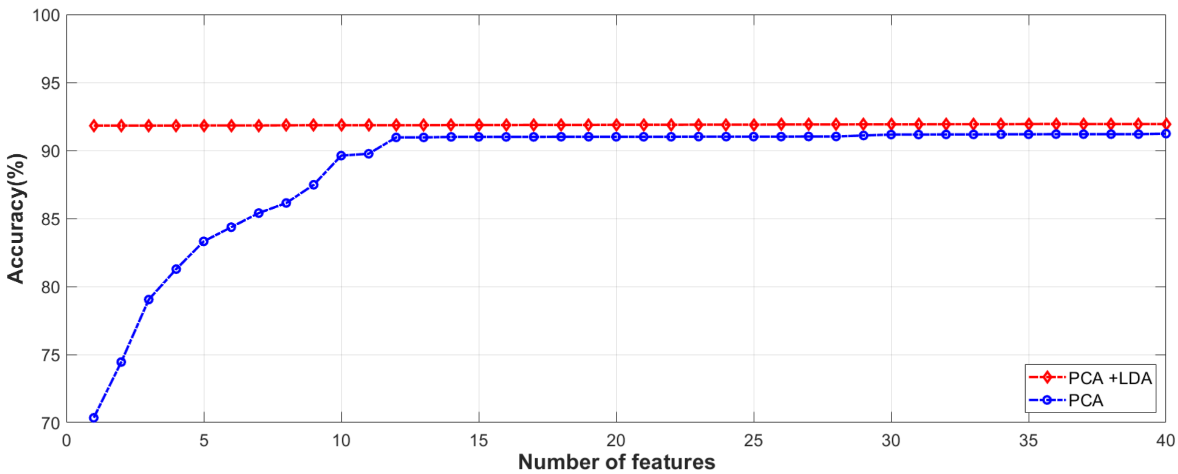

Figure 3. Classification accuracy obtained in G1020 dataset has examined with respect to the number of features

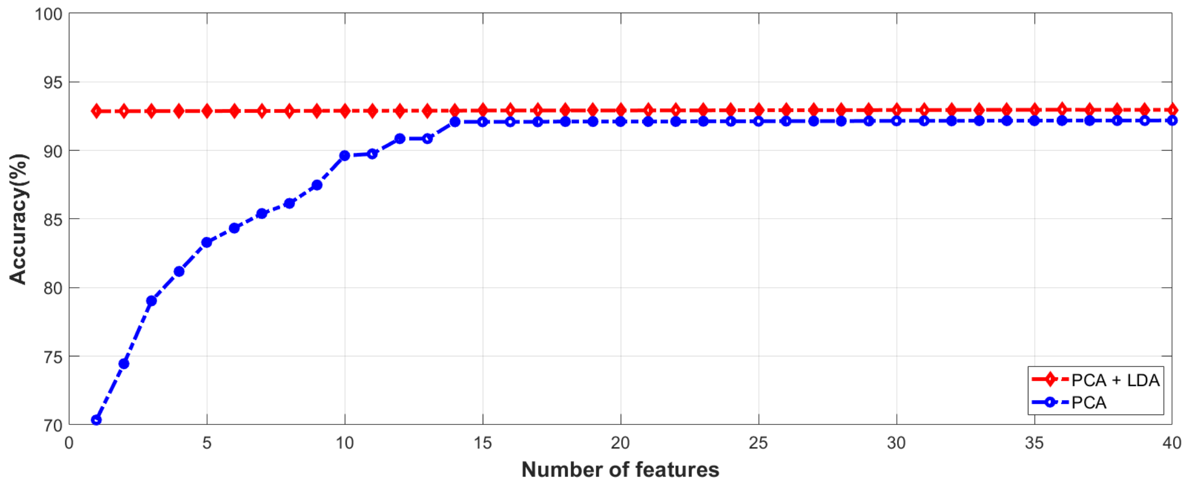

Figure 4. Classification accuracy obtained in ORIGA dataset has examined with respect to the number of features

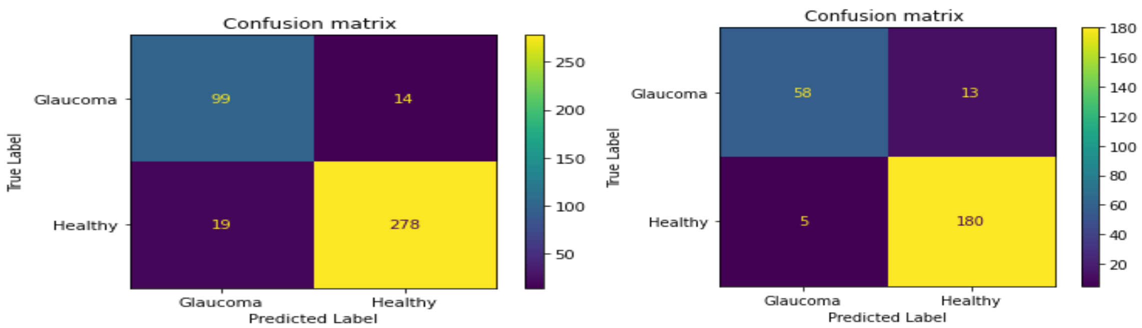

Figure 5. Confusion matrix obtained from G1020 and ORIGA dataset

Table 4. Comparative analysis (%) with different classifiers based on training time with G1020 and ORIGA datasets

Classifiers	G1020		ORIGA	
	Acc.	TT	Acc	TT
XGBoost	90.27	1125 sec	91.41	1028 sec
RF	90.75	1875 sec	90.63	1786 sec
DT	89.78	1996 sec	89.84	1877 sec
XGBoost + RF + DT	**91.95**	**1011 sec**	**92.97**	**1622 sec**

Acc- Accuracy, TT- Training Time

Table 5. Comparative analysis of proposed model with different Classifiers

Proposed Method	G1020			ORIGA		
	Acc	Sen	Spe	Acc	Sen	Spe
XGBoost	90.27	80.67	94.18	91.41	88.89	92.23
RF	90.75	81.52	94.52	90.63	87.38	91.71
DT	89.78	79.78	93.84	89.84	85.84	91.19
XGB+RF+DT (Proposed Model)	**91.95**	**83.90**	**95.29**	**92.97**	**92.06**	**93.26**

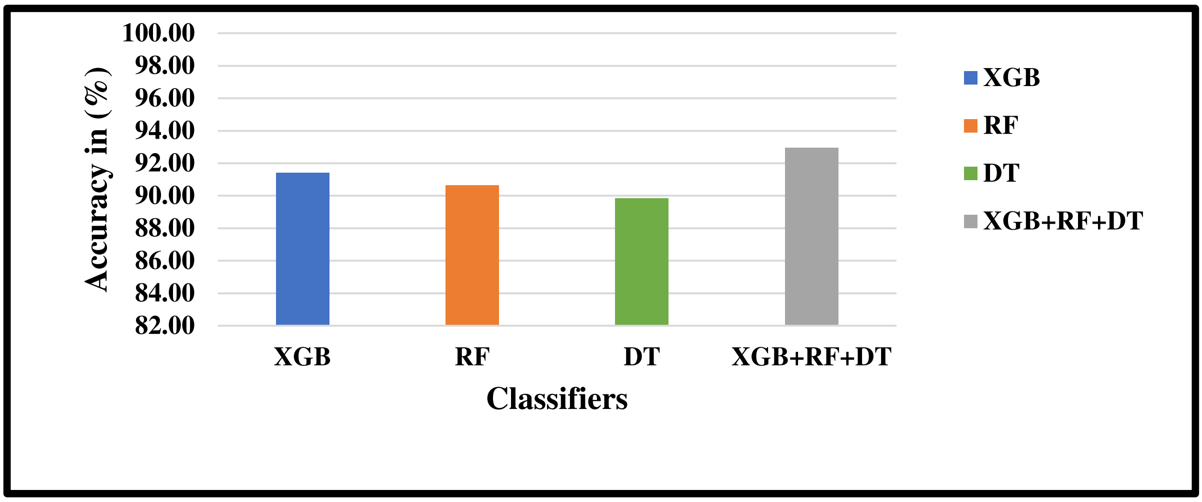

Figure 6. The classification accuracy obtained by different classifiers in G1020 dataset

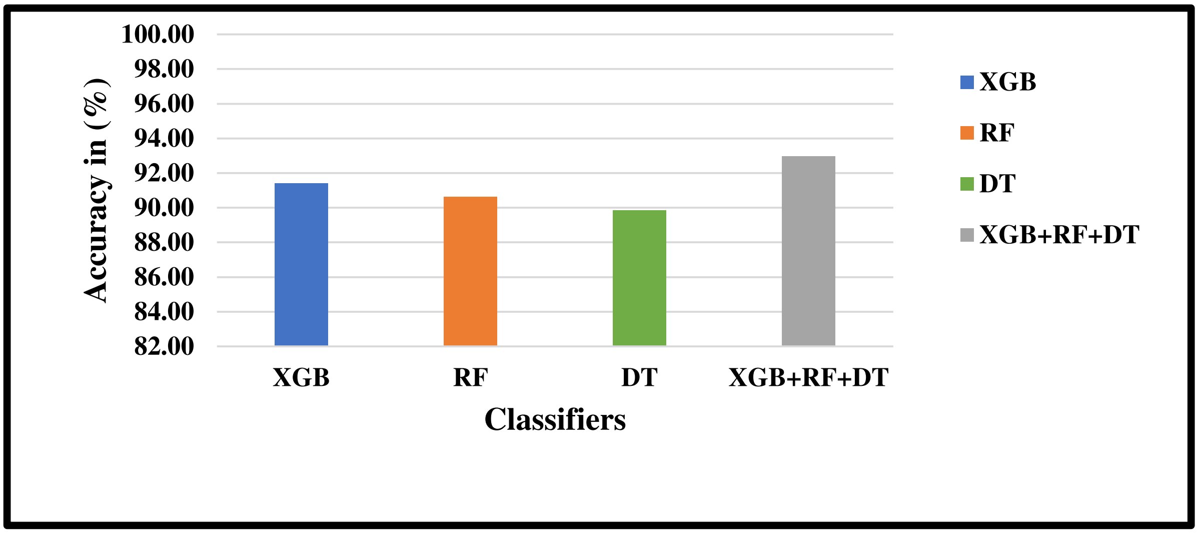

Figure 7. The classification accuracy obtained by different classifiers in ORIGA dataset

Table 6. performance analysis of proposed CAD model with existing models with G1020 and ORIGA datasets

Existing Methods	Accuracy (%)	
	Datasets	
	G1020	ORIGA
2D-FBSE-EWT [24]	---	91.01
SMOTE +RF [24]		78.30
SMOTE +RF [24]		82.80
HOG +SVM [25]	83.32	---
HOG + PNN [25]	87.92	---
HOG + RNN [25]	85.72	---
Proposed Model	**91.95**	**92.97**

A. Advantages and Disadvantages of Proposed Model

Ensemble learning in image processing has advantages and disadvantages, like in many other machine learning applications. Ensemble methods combine multiple machine learning models to improve overall performance. Here are some advantages and disadvantages of using ensemble learning in glaucoma detection.

- Ensemble methods often lead to higher accuracy compared to using a single model. By combining the predictions of multiple models, ensemble learning can reduce bias and variance, leading to more robust and accurate results.
- It helps to reduce overfitting by averaging or weighting the predictions of individual models. This makes the final model less sensitive to noise in the data.
- Ensembles are more robust to outliers and noisy data because they can "vote" or aggregate predictions from multiple models. Outliers are less likely to influence the final result significantly.
- Ensemble learning allows you to use different models or variations of the same model with different hyperparameters. This diversity can lead to better generalization and improved performance.
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Limitations:

- Ensembles are more complex than single models, which can make them harder to train, tune, and deploy. They require more computational resources and longer training times.
- Running multiple models in an ensemble can be computationally expensive, which may not be feasible in real-time or resource-constrained applications.
- While ensembles can sometimes reduce overfitting, they can also overfit if not correctly tuned. It's essential to avoid this issue and use techniques like cross-validation.
- Ensembles may require a more extensive and more diverse dataset to perform well. Ensemble methods may not provide significant benefits if the dataset is limited or biased.

V. Conclusions and Future Scope

In this work, we proposed an ensemble method, which is the combination of XGBoost, random forest (RF), and decision tree (DT) models for a wide range of machine learning tasks. It leads to improved predictive performance compared to individually using any of these models. The ensemble can leverage the strengths of each algorithm while mitigating its weaknesses. These three algorithms have different underlying mechanisms and are sensitive to different aspects of the data. This diversity in modelling approaches can enhance the overall generalization ability of the ensemble. Our proposed work focused on voting techniques to reduce the risk of overfitting associated with individual models. This is especially important when dealing with noisy or complex image data. The ensemble is likely to be more robust to outliers and data variations. Outliers or anomalies that might significantly affect one model are less likely to have a pronounced impact on the ensemble's predictions. Hence, individual models like Decision Trees are interpretable, but the ensemble as a whole may need to be more interpretable. However, you can still extract feature importance scores from Random Forest and XGBoost to gain insights into the importance of different image features. In future scopes, we plan to explore and optimize the hyperparameters of each model in the ensemble. Proper tuning is essential to achieving the best performance. Further extending the utility of investing in feature engineering to extract relevant features from image data, which could benefit significantly from informative features and focused on parallelization techniques and distributed computing frameworks to efficiently train and deploy the ensemble, especially when dealing with large-scale image datasets.

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