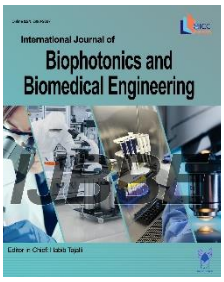

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A Hybrid Model Based on Deep XGBOOST for Creating a Stable Network and Classifying Cancer Tumor Images Using Ensemble Learning (Cono-XGBoost)

Amir Asil[1], Hamed Alipour-Banaei[2,*], Shahram Mojtahedzadeh[1], Hasan Asil[3]

[1] *Department of Electrical Engineering, Aza. C., Islamic Azad University, Azarshahr, Iran*
[2] *Department of Electronics, Ta.C., Islamic Azad University, Tabriz, Iran*
[3] *Department of Computer Engineering, Aza. C., Islamic Azad University, Azarshahr, Iran*

***Corresponding author:** ha.alipour@iau.ac.ir

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Abstract

Ensemble learning is expanding and is employed in solving various problems. Network stabilization and incremental network learning (enhancing weak learners) are some benefits that can be pursued in this type of learning. Moreover, the application of ensemble learning in medical science has also increased with the advancement of machine learning, which is used in various aspects of this field, such as diagnosis, treatment, and prevention. Machine learning in medical image processing has significantly developed over the past few years. The classification of medical images, including the detection of cancer tumors, fractures, masses, etc., has been among these research endeavors. This study aimed to utilize the development of the XGBOOST method to propose a technique for reducing the error rate in the classification of cancer tumor images. In addition to error reduction, another goal pursued in this model is network stabilization to enhance the effectiveness of identifying various images. The research, evaluated on different datasets, shows a 2% reduction in error compared to previous methods. This technique can potentially be used in the future to classify other topics.

Keywords: Deep Learning; XGBoost; Classification; Image Processing; Brain Tumor

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1. Introduction

Machine learning-based issues are divided into three categories based on the type of dataset: supervised, semi-supervised, and unsupervised, with various applications depending on the available datasets [1]. In supervised methods, datasets include labeled data where, in addition to the input, the outcome is also identified with a label. Thus, the supervised approach can be used in various classification issues [2].

Automatic image classification is a method that assigns an image to one of the pre-defined classes. Automated image classification is used in engineering and medical fields to analyze and examine relevant images [3]. Naturally, reducing the error rate is a notable point in solving medical issues based on deep learning, given the sensitivities in the medical field [4].

To date, various techniques in machine learning have been presented for image classification. Hybrid methods are common techniques in machine learning [5]. These methods combine different predictions, striving to present better and more accurate results in problem-solving [6]. Hybrid or ensemble machine learning models are machine learning methods in which several models, known as weak learners or base models, are trained to solve a problem and are combined for better results. When correctly combined, weak models can create more accurate or stable models [7].

Selecting algorithms is crucial in machine learning models to achieve good results. Model selection depends on many variables in the problem, such as the amount of data, data dimensions, and distribution hypothesis. Creating a model with low bias and variance is two essential and desirable features, although these two are often in opposite directions in most cases [8]. In hybrid machine learning methods, base models are combined as building components to create more complex models. Often, these models do not perform well because of high bias or variance. Hybrid classification uses a combination of multiple classifiers. Each of these classifiers builds its model on the data and stores this model [9]. Finally, a vote is taken among these classifiers for the final classification, and the class that gets the most votes is considered the final class. Each classifier builds a model on the training data so that it can understand the differences between different classes. Hybrid classifiers, however, instead of building a model themselves, use the models built by the other classifiers and determine which class to choose for the current sample by voting [10,11].

Among the essentials of these methods are bagging, boosting, and mixtures. Bagging is a hybrid method that uses random subsets of the training set to generate hypotheses for its combinations independently. For each classifier, a training set is generated by randomly drawing with replacement N examples, where N is the size of the original training set. [12] In the resampling process, many of the original examples may be repeated in the resulting training set. Each independent classifier is generated in combination with a different random sample from the training set. Because bagging resamples the training set with replacement, each example can be sampled multiple times. Examples that are not sampled are kept as the test set, called Out-Of-Bag (OOB), and are used to evaluate the generated classification model [13,14].

Berryman showed that the bagging algorithm is efficient for "unstable" learning algorithms, where small changes in the training set lead to large changes in the predictions [15]. Berryman claimed that neural networks and decision trees are examples of unstable learning algorithms. Boosting is a general method for improving the performance of weak classifiers, such as classification rules or decision trees. It works by repeatedly running a linear learner on weighted training samples. After the various classifications, the resulting classifiers are combined into a final composite classifier, which often performs better than a single classifier. Each of these algorithms has sub-algorithms that have been developed to improve, and one of these algorithms is multi-class classification [16].

Multi-class classification is the task of classifying samples into more than two classes. The goal of supervised multi-class classification algorithms is to assign a class label to each input sample. Most boosting algorithms are originally designed to solve binary classification problems. Two main approaches have been proposed to solve the multi-class classification problem. The first approach is to use general techniques to apply binary methods to multi-class problems. This technique often works by decomposing the original multi-class classification problem into several binary sub-problems and then applying the binary learning algorithm to each of them. Examples of this approach include one-versus-all, one-versus-one, and error-correcting output code. The second approach is to directly create a multi-class boosting algorithm. Several methods, such as SAMME and ..., have been proposed for multi-class boosting [17].

AdaBoost (adaptive boosting) is one of the first boosting algorithms, introduced by Brund and Shapiro. The main idea behind the boosting algorithm is to give more weight to examples that have been incorrectly classified by the hypotheses that have been made so far. The weights of the data are updated at each iteration based on the classification errors. Examples that have been incorrectly classified by previous classifiers have more weight than correctly classified examples. As a result, the learner focuses on difficult examples in subsequent iterations. Finally, the combination of weights of different classifiers becomes the final classification model [17]. Other algorithms developed in this area include DAdaBoosting, XGBoost, and… methods [18].

The general boosting approach is to provide better results by combining weak learners. Boosting is classified by allocating weights to training samples. Boosting is a general method to improve the performance of weak classifiers, such as classification rules or decision trees [19].

Figure 1 shows different versions of this ensemble boosting method.

Stronger solutions have been presented for problem-solving upon developing the boosting method and its combination with other methods. One of these solutions is XGBoost, a combination of boosting and gradient methods. XGBoost has a very high prediction power, making it the best option for accuracy in various events because it has a linear model and a tree-learning algorithm. This algorithm is almost ten times faster than existing gradient boosting algorithms, which include different objective functions, regression, classification, and ranking. One of the most interesting points about XGBoost is that it is also known as a technique for regulated boosting, which helps reduce large models [20]. This algorithm predicts more accurately and efficiently than simple decision trees by using objective functions and complex optimization methods. XGBoost has become one of the most popular machine learning algorithms due to these outstanding features. Among the features of this method are the following [20,21]:

1.1. High accuracy

By optimizing decision trees and using advanced techniques, XGBoost provides excellent prediction capabilities. This is especially important for solving complex problems with incomplete or noisy data.

1.2. Computational efficiency

By using parallel processing and optimization techniques, XGBoost can run efficiently even on large data sets. This feature makes XGBoost suitable for processing large data sets and real-time analytics.

1.3. Flexibility

XGBoost has a wide range of tunable parameters that allow it to be customized for different types of data and problems. This flexibility makes XGBoost a versatile tool for solving a wide range of machine-learning problems.

1.4. Handling incomplete data

One of the common challenges in data analysis is the presence of incomplete or missing data. Equipped with advanced techniques for handling incomplete data, XGBoost intelligently handles this data and prevents it from negatively affecting prediction accuracy.

1.5. Pruning Decision Trees

Decision trees tend to become too complex as the number of nodes increases, which leads to the phenomenon of overfitting. This phenomenon occurs when the model over fits the training data and, as a result, performs poorly on new data. XGBoost eliminates unnecessary nodes by using the decision tree pruning technique, thus preventing overfitting.

1.6. Regularization

Regularization is one of the important techniques in machine learning that is used to prevent overfitting and improve the generalizability of the model. XGBoost uses different types of regularization to maintain a balance between the flexibility and accuracy of the model.

XGBoost is a versatile algorithm that is capable of working with different types of data, including numerical data, ordinal categories, and categorical data. This feature makes XGBoost suitable for a wide range of applications in different fields. The introduction of this article provided explanations about the application of machine learning in medical science, then described one of the machine learning techniques, namely ensemble learning, and then talked about the boosting family (as one of the ensemble learning) and its advanced method, Xgboost. Considering the presented discussions, this research aims to develop and combine the XGBoost method with deep convolutional learning to present a stable network for classifying cancer tumor images. The goal of presenting this model is to stabilize the network while reducing errors in various classifications of medical images. [1]

2. Research literature

The use of machine learning in medicine is continuously developing, with its application in solving various problems [12]. These networks have endeavored to optimize methods through diverse approaches. On the other hand, Deep Belief Networks (DBNs) also offer significant advantages and have been utilized for various problem-solving applications. A similar issue was the classification of social networks using a Neural Network DBN based on the genetic algorithm [13]. Another work introduced a new method for pre-training neural networks based on deep Boltzmann machines to enhance training speed and accuracy in phoneme recognition. Furthermore, deep neural networks were applied in medical image recognition [14].

Another study utilized deep learning to identify the number of segments in brain images and for the automatic segmentation of normal and abnormal MRI brain images. The objective of this project was automatic image segmentation, where the number of image segments is determined based on their entropy, thereby improving the accuracy of segmentation [15, 16]. In another study, Lee et al. trained a custom Convolutional Neural Network (CNN) to classify lung image segments [17]. This model comprises only one layer for extracting deep features [18].

In another research, a CNN was trained by ImageNet to identify various types of pathologies in chest X-ray images. Optimal accuracy was achieved by combining features extracted from the CNN with manual features. Shin et al. [19, 20] discussed why transfer learning could be beneficial in addressing medical images. Additionally, the results were validated in the diagnosis of chest lymph node (LN) and the classification of Interstitial Lung Disease (ILD) [21]. Another article presented spectral clustering-based segmentation for images, where this method could be used as preprocessing for more advanced applications like image retrieval, tracking, and object recognition [22].

The related projects include active contours and deformable models in segmenting MRI medical images. Other research in this domain includes presenting a new algorithm for automatically segmenting medical MRI and CT images [23]. Image segmentation using a convex form model based on the region is another study in the medical field. Another project involved the c-means algorithm used in medical image segmentation [18]. Semantic classification of medical images in a hierarchical structure based on unsupervised clustering is among other research in this area.

In recent years, ensemble methods have gained more attention, and Boosting is one of these ensemble algorithms [24]. The principal idea is to create a strong learner from a combination of weak learners. Several algorithms have been developed based on this algorithm, including Adaboosting, XGBoost, and others that assign more weight to samples that are incorrectly classified. XGBoost was initially started as a research project by Tianqi Chen as part of the distributed machine learning team [16]. Initially, this project was configured as a terminal program using a configuration file. Following its victory in the Higgs Machine Learning Challenge, XGBoost has been widely used in the Kaggle community for numerous research purposes [23,5].

Considering the reviews, various research has been conducted on medical image processing, but most of these methods have focused on reducing the error rate. This research aimed to present a model focusing on network stability in medical image processing. This model combines the XGBOOST method and deep convolutional learning with a transfer layer.

3. The proposed algorithm

This study aims to present a new method for classifying medical images. The main structure of the proposed method is based on boosting, which is based on weak learning. Boosting improves learning by repeating weak learning and updating weights. In the proposed method, stronger learners are combined and classified instead of weaker learners.

The proposed method intends to improve image classification and reduce errors by combining the boosting method and basic learning based on deep learning.

The boosting method, based on the ensemble method, tries to strengthen weak learners. The new version uses the XGBoost method to improve the base algorithm and approach the answer in less time. The solution of this algorithm was based on the gradient.

As the algorithm indicates, it boasts numerous advantages, such as improved outcomes, scalability, and reduced learning time. Given the complexity and size of medical images, the proposed research integrates this method with deep learning techniques to develop a more stable network for medical imaging than the aforementioned method. This study aims to enhance this algorithm by employing deep foundational learning.

The proposed ensemble method comprises four components: the training set, base learner, generator, and blender. The different sections of the proposed method include:

- Training Set: A collection of labelled samples utilized for training. The training set for this project consists of mammography data of cancerous masses. Some data will be used for training and some for testing.
- Base Learner: A foundational learning algorithm employed for training the set, which will use deep learners for classification. The utilized learning algorithm is a convolution. The convolution in use incorporates two convolution functions for each classification, aimed at greater convergence. Additionally, the convolution function's policy is based on reducing the error rate in learning.
- Generator: This component is used for creating various classifiers. Different classifiers are generated at each stage of the bagging method.
- Blender: This section is used for combining classification methods. Various methods for combining classifiers have been presented. Majority voting is one of the commonly used methods. Majority voting is akin to unweighted averaging.

However, majority voting counts votes for predicted labels from base learners and makes a final prediction using the label with the most votes instead of averaging output probabilities. Majority voting can take an unweighted average using the label of base learners and select the label with the highest value. A weakness of majority voting is the loss of information since it only utilizes the predicted label. Figure 2 displays the overall structure of the proposed algorithm.

Suppose the training data sets (x_1, c_1), (x_2, c_2), (x_3, c_3), etc., where the input $X_i \in Rp$ and the output ci are qualitative or quantitative, but it is assumed that they are in the set {1,2,3...k}. K is the number of classification classes, and the training data are independent. Classification aims to find C(x) based on training data. With a new input x, a class label of {1, . . ., K} can be obtained.

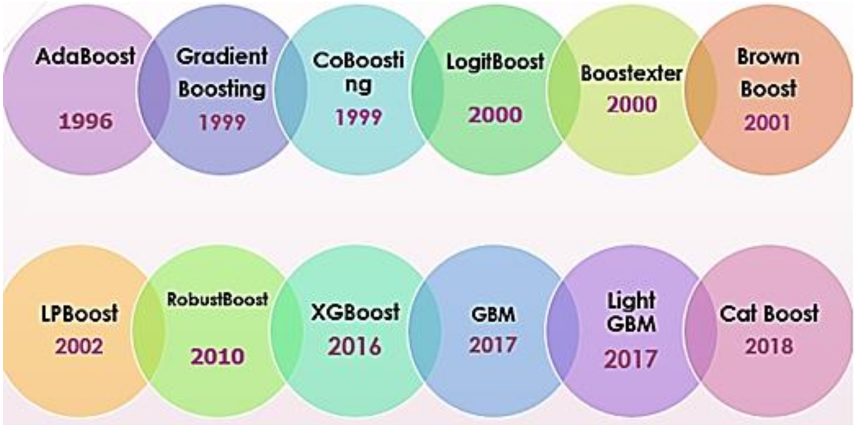

Figure 1. Different generations of boosting model

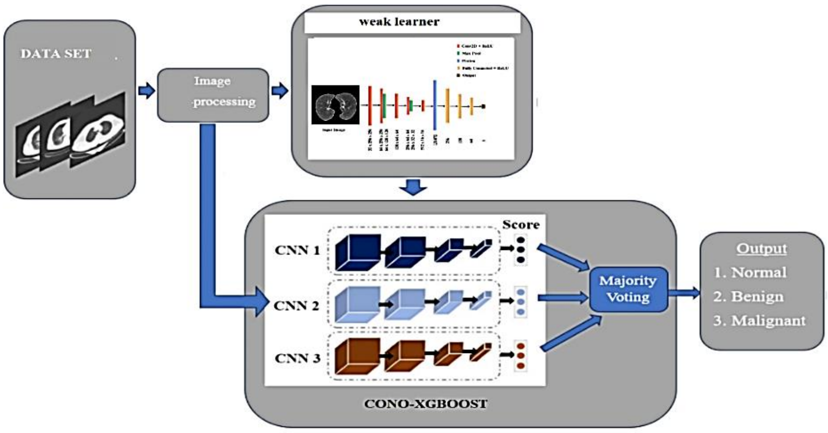

Figure 2. Proposed structure of the ensemble method by replacing the weak learner with a deep learner

Algorithm 1. Cono-XGBoost

1. Initialize the observation weights $w_i = 1/n \quad i = 1, 2, \ldots, n$.
2. For m = 1 to M:

(a) Fit a classifier $T^{(m)}(x)$ to the training data using weights w_i.

(b) Compute

$$err^{(m)} = \sum_{n}^{i=1} w_i \prod(c_i \neq t^{(m)}(x_i)) / \sum_{n}^{1=1} w_i$$

$$\alpha^{(m)} = log \frac{1 - err^{(m)}}{err^{(m)}}$$

(C) Set

$$w_i \leftarrow w_i' + (w_i . \exp\left(\alpha^m . \prod\left(c_i \neq t^{(m)}(x_i)\right)\right) + \log(k - 1))/2$$

w_i' *is weight CNN &transfer in week leaner.*

for i = 1, 2,…, n.

1. Output C(x) (e)

Re-normalize By Compute w_i.

$$C(x) = \arg\max_k \sum_{m=1}^{M} \alpha^{(m)} \prod_i (T^{(m)}(x) = k))$$

Figure 3. Proposed algorithm with a deep learner

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In this method, the procedure is repeated utilizing XGBOOST, and subsequently, the classifier is predicted based on the combination of weak learners. Initially, the weights of the samples are equal, which are then updated in each iteration and subsequent classifications. The number of iterations typically ranges from 500 to 2000 in learning, although this can vary depending on the size of the images. Each stage's score is considered a coefficient and multiplied by the classifier; ultimately, these classifiers are linearly combined. Figure 3 shows the proposed composite algorithm [5].

The general structure of this algorithm has three main parts: initializing weights, an iterative loop for training weak classifiers, and calculating the final output. The key point here is that the algorithm uses a "two-layer approach of transfer and convolution" for weak learning, which refers to the processing of features. Of course, it is necessary to explain that this network (weak learner) can be changed based on the type of problem. Our main approach in this research is to use strong learners instead of weak learners in solving problems, in which we used convolution for image classification.

One of the most important conditions, as shown in Figure 3, is that the error of each weak classifier is theoretically less than 1/2, because this is the basic condition for the convergence of boosting algorithms. Finally, the final output is calculated by summing the votes of all learners.

The steps of implementing the algorithm are as follows, based on Figure 4:

Initializing weights: Initially, all data samples in the training set are assigned the same weight equal to 1/n

Iteration to build weak models (m step):

Training a classifier: A weak classifier model (T(x)) is trained using the training data and considering the current weights of the samples.

Calculating error and importance factor: After training the model, its error is calculated. This error (err) indicates which samples the model misidentified (with higher weights). Then, an important factor (α) is calculated for this model. The lower the model's error, the higher its importance factor. This factor determines how much weight the opinion of this weak model will have in the final vote.

Updating weights: In this key step, the weights of the samples are reset. The weights of the samples that are misclassified by the current model are increased. This makes the algorithm focus more on the harder samples (previously misclassified) in the next iteration.

Merge and Final Conclusion: After building M weak models, all models are applied to classify a new data (x). Then, a weighted voting is performed. Each weak model votes with its own importance coefficient (α). Finally, the class that gets the highest total votes is selected as the final prediction (C(x)).

Figure 4 shows the structure of the weak learner. This structure is taken from previous work [29]. Two-layer approach: It is mentioned that a “two-layer convolution and transfer approach” is used for weak learning. This architecture refers to the preprocessing technique within each weak model that can enable the extraction of more complex features.

Low error: According to the theory behind this algorithm, the error (err) of each weak classifier should be less than 50%. This is a fundamental condition for the correct functioning of boosting algorithms.

Cono-XGBoost is a clever combination based on the XGBoost mechanism and an innovative strategy for weak learning, aiming at an accurate and robust model for classification applications.

As indicated in the proposed ensemble algorithm, a dual-layer transfer and convolution approach was utilized for weak learning. According to the theory, the error rate (err(m)) in each weak classification of XGBOOST is less than 1/2 [8]. When the number of categories is 'k', the probability of error becomes (K−1)/K. The XGBoost method becomes less effective when the error rate exceeds 1/2. Therefore, the weak learners in the proposed method were enhanced to address this issue. This approach is designed for classifying multi-class problems.

4. Comparison of Results

The proposed approach was implemented using Python libraries and compared with other methods to evaluate the research method. This research used CT scan images of lung tumors (NCCD) for evaluation.

In this study, we presented a result of our work in the field of image processing and tumor detection. Our main goal is to create a stable network to make the model reliable in sensitive sciences, especially medicine. In fact, we are looking for a new hybrid method to replace weak learners with a more stable network for data. The goal of this report is to present one of the research results. If we want to elaborate, the images used in nccd are images from the IQ-OTH/NCCD - Lung Cancer Dataset with 1190 CT scan images from 110 patients.

This dataset comprises 1190 large images. The classification of these images falls into three categories: diagnosed as malignant, diagnosed as benign, and normal. Figure 5 exhibits an example of a normal image.

The results of this experiment, based on the number of repetitions, are shown in Table 1, which shows the error rate for the three methods. As shown in Table 1, the error rate decreases with increased repetitions.

On the other hand, the network moved faster towards stability in the proposed method. Figure 6 demonstrates the AUC and Loss rates with the two-layer convolution method. Figure 8 shows the evaluation results of the proposed method. Compared to the previous two methods, this method has improved significantly in error rate and moved towards stability after learning.

As shown in Figure 9, the error rate related to different methods decreases with an increase in the number of repetitions, though the rate of decrease varies depending on the method. Given the nature of the chosen method, a relative stability in the number of repetitions is observed post-training. Moreover, this method shows a reduction in error rate compared to other methods.

Table 1. Comparison of error rate based on algorithms and number of iterations

No.	Data type	convolution	XGBoost	Cono-XGBoost
1	ducational data	2.91	0.42	0.31
2	test data	22.83	2.8	0.33

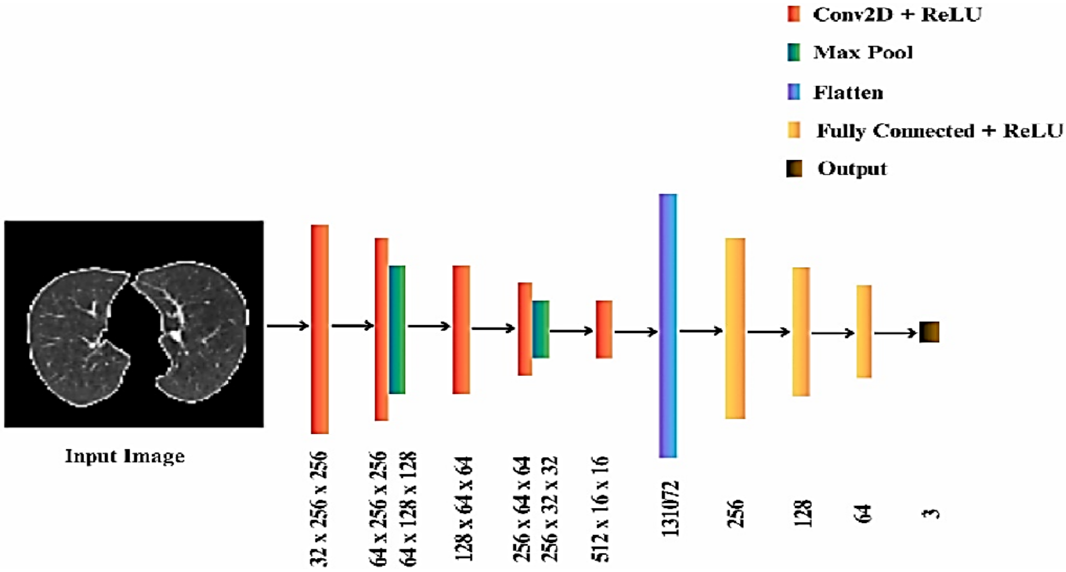

Figure 4. Weak learner structure

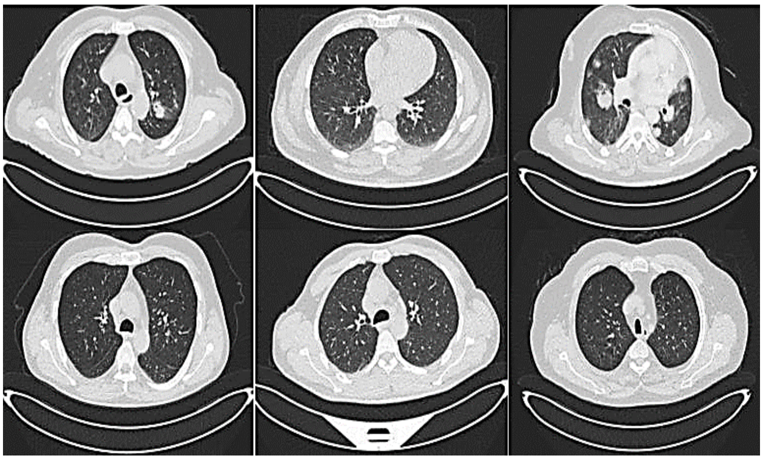

Figure 5. Example of a IQ-OTH/NCCD image

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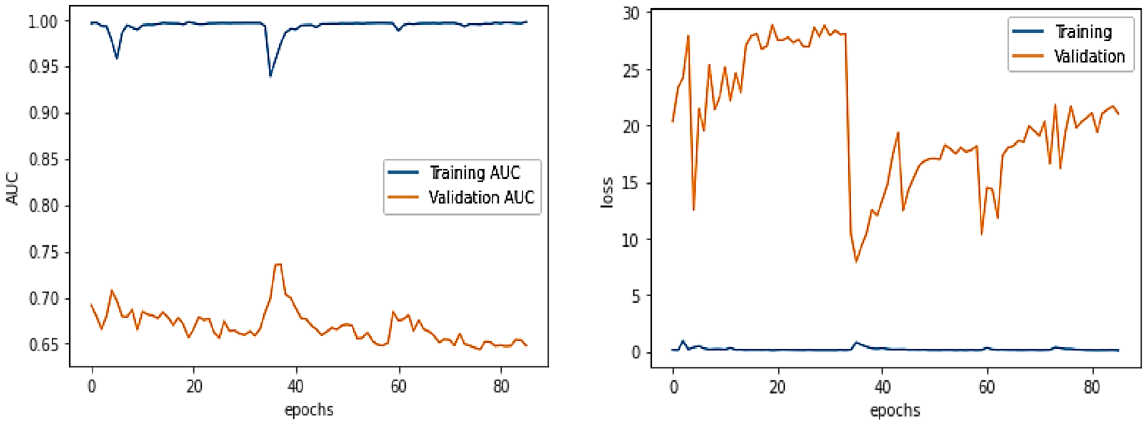

Figure 6. AUC and LOSS rate on a dataset with a convolution algorithm

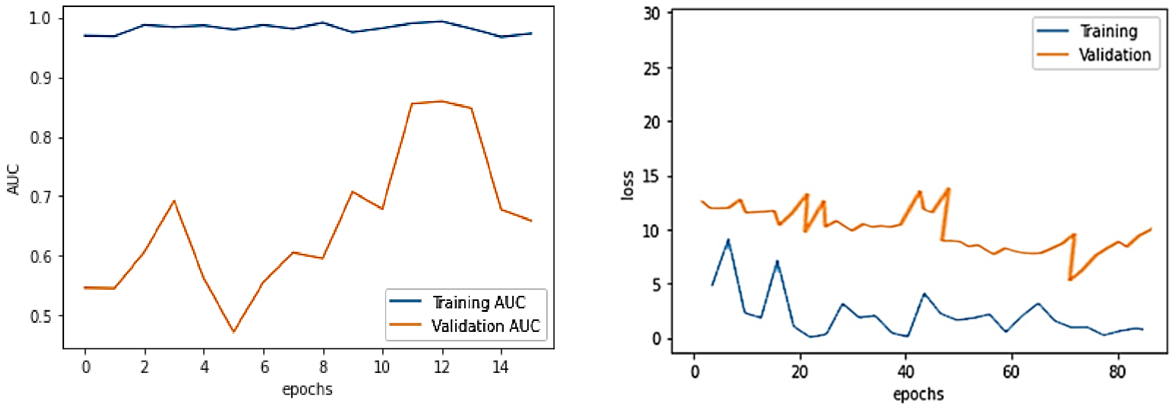

Figure 7. AUC and LOSS rate on a dataset with the XGBoost algorithm

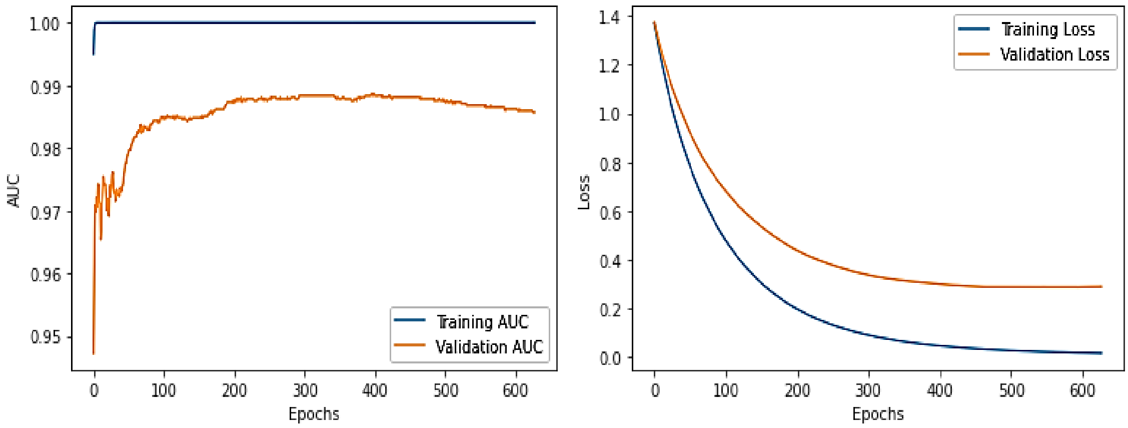

Figure 8. AUC and LOSS rate on the dataset with the proposed algorithm

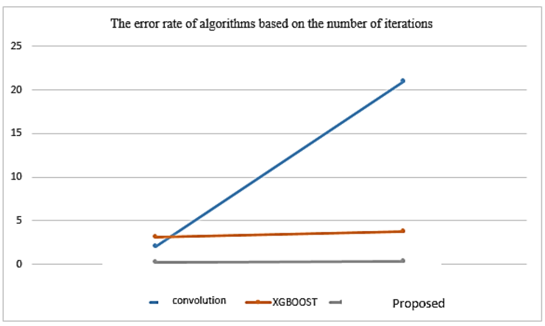

Figure 9. The error rate of algorithms based on the number of iterations

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5. Conclusion

Various methods were employed for the classification of medical images. The primary objective of these methods was to reduce the error rate due to the sensitivity of medical science. Various techniques were used, such as convolution with different layers, Deep Belief Networks (DBN), recurrent networks, etc. Over the past years, efforts based on ensemble learning have been made to strengthen weak learners and provide better results. Combining ensemble methods and deep learning (using convolution and transfer layers), this research strived to reduce the error rate while stabilizing the network. The findings of this study indicated that the proposed method has a lower error rate than the convolution and XGBOOST methods, showing a 2% reduction. The proposed algorithm tries to increase the accuracy of medical image evaluation by deepening weak learners. Another problem in this approach is that due to the combination of characteristics of the combined methods, this method avoids overfitting the network. With the proposed method, the path to using stronger learners and the result of the combined evaluation were beneficial. One of the tasks that can be developed in the future with the help of the proposed method is the use of different heterogeneous combined learners in the evaluation of medical images, so that the image can be evaluated based on different perspectives. In this evaluation, naturally, considering the evaluation results of weak learners, a combiner is decided for the final result. In the future, with the development of this model, this method can also be employed in other fields.

Authors Contribution
All authors have contributed equally to prepare the paper.

Availability of data and materials
The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Conflict of interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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