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Autism Diagnosis from EEG Signals through Machine Learning Algorithms and Convolutional Neural Networks

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ABSTRACT. A neurodevelopmental disorder recognized by insufficiency in social communication and repetitive behaviors is abbreviated as autism spectrum disorder (ASD). One of the most practical apparatus in diagnosing autism is the electroencephalography (EEG) signals, which represent the brain's function accurately. The recorded EEG of every individual contains sizeable data which is somewhat difficult to study and check visually. The main objective of machine learning algorithms is to train the machine in a manner that finally runs a diagnosis close to that of the human brain. The appropriate strategies for further exploitation of deep learning capabilities in the feature extraction block of autism diagnosis without applying the classical feature extraction methods are assessed in this article. For this purpose, a convolutional neural network (CNN) structure is involved in checking the available data for feature extraction. The five machine learning classifiers covering support vector machine (SVM), linear discriminant analysis (LDA), decision tree (DT), simple Bayes classification (GNB), and random forest (RF) are applied for classification. The accuracy percentages obtained through the SVM, LDA, DT, GNB, and RF classifiers are 100, 82, 80.5, 100 and 100%, respectively. This proposed method of convolutional neural networks for feature extraction and classification, by applying different machine learning methods yields high-accuracy similar if not better than its counterparts for autism diagnosis.

KEYWORDS: Autistic disorder, Convolutional Neural Network, Electroencephalography, Machine learning

1 INTRODUCTION

Autism is a type of nervous system developmental disorder that is diagnosed through insufficiency in social interactions and repetitive behaviors. If autism is diagnosed at its initiation, the child's social and verbal skills will improve [1]. Due to the essence of this subject, the machine learning algorithms have revealed remarkable performance in the autism diagnosis field, though, running more studies in this field is a must. The objective of machine learning (ML) is to apply data or expertise to solve problems. There exist many practical applications of machine learning, applicable in distinguishing and predicting diseases in clinical tests. With the advances made in medical technology, doctors can collect more detailed data on patients and apply machine learning algorithms in analyzing the high volume of data. Researchers have sought to diagnose this neurological disorder through electroencephalography (EEG) signals. Studies on autism where the EEG signal is applied have increased because of its high time resolution, relatively low cost, and the wide access of doctors to EEG signals [2].

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Due to the complexity of discriminating between two or more choices, and applying data systems, the artificial intelligence (AI) blocks in particular have become popular in decision-making-based disease treatments. AI is capable of configuring methods that can behave and react similarly to human intelligent conduct like simulating human thought processes and reasoning methods, understanding complex situations, successful response therein, and learning and having the ability to gain knowledge and reason to solve problems. Applying AI in medical sciences has made the prediction and diagnosis of brain diseases more accurate and thorough [3 and 4].

A method based on CNN for feature extraction and five machine learning algorithms for autism classification is proposed. This proposed feature extraction and classification method with different machine learning algorithms yields high-accuracy percentages corresponding to its counterparts in this field.

This article is organized as follows: the literature is reviewed in Sec. 2; the CNN algorithm is described in Sec. 3; the method is proposed in Sec. 4; the results and discussion is presented in Sec. 5 and the article is concluded in Sec. 6.

2 LITERATURE REVIEW

In the AI-based algorithms, where the input data consists of EEG signals in diagnosing autism the advantages and disadvantages of all proposed methods are assessed in [5]. The AI-based methods for analyzing autism are discussed in [5], where a brief description of autism and the current non-invasive method is applied to classify individuals with autism and without. New methods based on deep learning techniques are described through AI. In recent years, different objective measures have been proposed through the abnormalities in EEG signals and statistical analysis. Methods based on machine learning provide more flexibility and obtain better results in autism classification.

The articles where machine learning algorithms are applied and four steps of EEG data collection, pre-processing, feature extraction, and data classification prevail [6]. Likewise, the different methods and apparatus applied for pre-processing, feature extraction and selection, classification methods, and measures to assess the method strengths are analyzed. Moreover, a summary of autism disease classification current challenges and limitations, and future directions are discussed in [6].

To diagnose autism, machine learning, and deep learning networks are applied to classify normal and abnormal EEG waveforms, and CNN is applied for classification [7]. A transfer learning method is adopted to train pre-trained CNN, Google Net, and Squeeze Net in classifying individuals with autism and without control by applying EEG signals. The findings indicate that this method can contribute to classifying individuals with autism and without through EEG signals.

The effectiveness of different machine learning algorithms and pre-processing techniques for the classification of a medical dataset applied in predicting early autism traits in toddlers and adults is assessed in [8]. Complex machines and pre-processing are applied in many studies. Pre-processing steps, together with appropriate data coding and classification algorithms like logistic regression, K-Nearest Neighbors (KNN), and random forest, reveal comparable results compared to the existing methods. Researchers in [9] assessed the diagnosis of autism by applying the discrete wavelet transform (DWT), Shannon entropy (SE), and artificial neural network (ANN). An attempt is made in [10], to analyze and assess EEG signals in diagnosing autism spectrum disorder and epilepsy. Disease diagnosis is a challenging task that requires the efforts and expertise of physicians.

Through the advances made in the fields of signal processing and machine learning methods, computer-based systems can perform more complex tasks, like EEG signal analysis. According to [11 and 12], this analysis provides clues on brain conditions and damage, and the lately recorded signals are applied as a diagnostic tool for epilepsy and autism. The diagnosis of autism is assessed based on EEG through CNN, a well-known deep learning method for image analysis and classification in [13], where, first, the single EEG channel data are transformed into 2-D form by applying the Pearson's correlation coefficient and next, classified through CNN. A total of 43 articles on unsupervised machine learning algorithms' application for autism diagnosis are reviewed in [14], where the K-means clustering, hierarchical clustering, model-based clustering, and self-organizing maps prevail.

An attempt is made in [15] to diagnose autism by applying EEG and a 2-D deep CNN, where, the signals recorded from healthy and autistic individuals are presented as 2-D images with the channels as the width and the channel samples as the length. A 2-D deep CNN requires a relatively high count of data points to perform well in learning. In EEG-based studies, access to sufficient data is impossible, consequently, data augmentation is adopted where a combination generates new training data by selecting two sick or healthy individuals (both sick or both healthy) and combining their channels.

The EEG signals based on time-frequency space to distinguish autistic individuals from healthy is the theme in [16], where, the pre-processing operations, like filtering and normalization, are run on the EEG signals, and to convert the pre-processed signals into 2-D spectral images, a short-time Fourier transform is required to allow the machine learning and deep learning methods classify the yield images.

A lightweight hybrid deep feature extractor is proposed in [17] to obtain classification performance for automatic diagnosis of autism. The method was designed and tested by applying a big EEG dataset containing signals from both autistic patients and normal individuals. The objective of [18] is to diagnose autism through the fractal dimension and measure the complexity and dynamic changes in the brain. This method was checked on a blindfolded EEG database captured from two groups. Datasets of nine autistic and eight non-autistic children were recorded according to the international 10-20 system, each concluding 19 channels and digitized with a sampling rate of 256 Hz. Researchers in [19] sought to diagnose autism on an EEG set of 79 (46 people with autism and 33 healthy) individuals, by applying the least mean square error as a feature vector, next to K-nearest neighbor's multi-class classification algorithms, support vector machines, and simple Bayesian classification algorithms to classify autism and normal signals.

3 CNN ALGORITHM

CNN is defined as a type of network where a mathematical linear operation named convolution is run. This type of network is appropriate for data in the form of time series, image data, etc. This model divides complex concepts into simpler concepts until it obtains the basic and main concepts, which allows the model to decide on classification [20].

The three constituent main layers of the CNN structure are:

1) Convolution layer (CL): a layer applied to extract features by applying filter convolution in the input data. Point multiplication is made between the filter and the covered part of the input data to determine the result of applying the filter to the input, where, the filter slides on the input data and places its middle layer in each slide on each one of the input data layers.

2) Pooling layer (PL): the primary function of the pooling layer is to remove part of the features extracted in the former layers, to avoid excessive CNN structure complexity. The excessive complexity of the neural network allows the extraction of many features, which increases the neural network accuracy, while, the excessive increase in extracted features count increases the learning parameters, thus a timely learning process. The network is neutralized, and finally, due to the extraction of many features, the neural network may overfat. In general, this layer includes three: 1) maximum, 2) minimum, and 3) average pooling filters, each assigned to its spot. The maximum pooling filter selects the highest value by applying it to the outcome of the former layer in the area covered by the filter; the minimum pooling and average pooling filters have the same function as the maximum pooling filter, with the only difference that they select the lowest value and the average value covered by the filter, respectively.

3) Fully connected layer (FCL): This layer contains some neurons that have received the input from the former layer, and after being multiplied by the weight vector and applied in the activation function to each neuron, the corresponding output is calculated and sent to the next layer [21].

Deep and machine learning algorithms are widely applied, with similar applications, with the only difference that machine learning can function as a classifier by establishing correlation among features extracted by the user, clustering, and regression, but due to their hierarchical structure, deep learning models can extract feature automatically and apply them to similar tasks in machine learning through repetition and experience method. The repetition and experience method in deep learning requires a big data set in training the neural network to allow learning by the CNN method in the best way [22]. CNNs can learn local non-linear features and generate high-level features as a compound of low-level features [23]. For setting a practical CNN arrangement, this network should be able to excerpt a high volume of components and be limited to a diversity of features. CNNs vary in count of layers, beginning from shallow architectures designed with only one convolutional layer and ending in deep architectures with more than 1000 convolutional layers. CNNs have advantages and disadvantages compared to other machine learning models [24].

Being: 1) adapted for end-to-end learning, (i.e., learning from raw data without any elementary feature selection) and 2) being applicable in large-dimension datasets constitute the advantages of CNN.

Having: 1) incorrect prediction with high confidence, 2) requiring a high count of data for training, and 3) being difficult to interpret constitute the disadvantages of CNN.

Before interpreting the architecture of this proposed CNN, it is necessary to discuss how it fits EEG signals. CNN is applied here due to its ability to extract proper features automatically.

4 PROPOSED METHOD

The algorithms are divided into feature extraction and classification categories, Fig. (1). The data recorded by an EEG signal recording device with 129 channels are expressed in Fig. (2). Due to the high volume of channels in this study, 17 channels are selected to cover the skull area appropriately.
A bandpass filter is applied in the pre-processing stage, which is applied to remove the city electricity noise and very small fluctuations, thus, by applying this filter, frequencies below 0.5 Hz and above 50 Hz are removed.

To extract features, a CNN is proposed. Different machine learning methods, like the support vector machines, linear diagnostic analysis, decision trees, the simple Bayes clustering algorithm, and random forest are assessed to classify the data into two healthy and autistic classes.

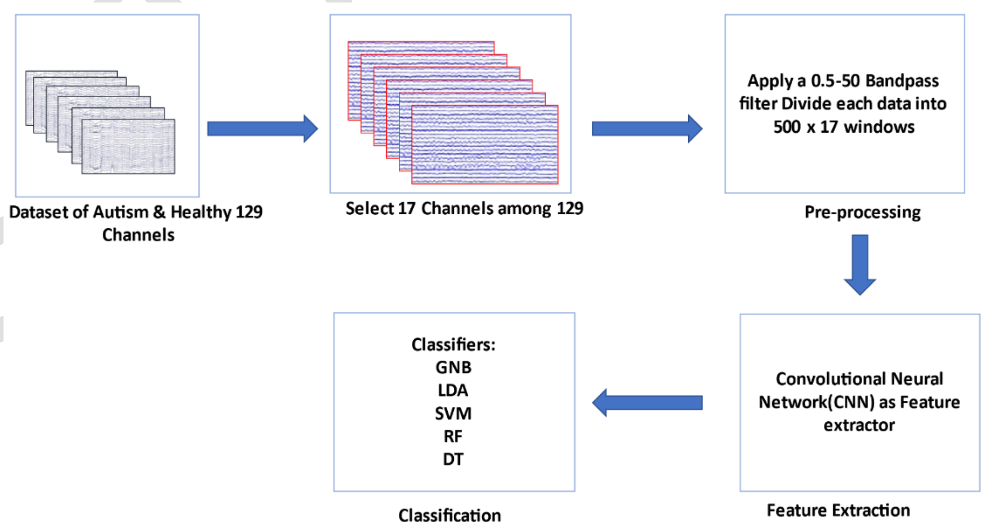

Figure 1: Block diagram of the proposed autism diagnosis system

4.1 Dataset

Data recording for the study of patients with autism based on EEG signals and distinguishing between healthy and autistic has a special process. Before data recording, the participants must be determined by experts. In such studies, individuals diagnosed with autism by a specialist should not be consuming a special drug that could affect the study process, and healthy individuals should be free of neurological disease or belong to a family without a history of neurological disease. The protocols for recording signals are of two general categories: 1) resting state, where, the subject is set on a chair, with eyes open or closed, free of any activity, and 2) where the subject in the same position must act according to the researchers' direction during signal recordation, like calculating a mathematical process, listening to ritual or soft music, tasting different flavors, etc.

The data are aggregated following the University of California's expert review board[2] guidelines [25].

The subjects consist of 10 individuals with autism and 9 without matched in terms of age and IQ. Children who have autism disorder are recognized by a California regional center. Clinical psychologists and child psychiatrist specialists verified autism disorder with certainty. EEG signals are recorded with 500 Hz frequency and a net geodesic of 129 channels. The protocol for recording this data set is that the subjects are watching a silent film where soap bubbles move. No sedatives are applied during the recording time or when the electrodes are placed on the head, at the subjects' normal state [26]. In this study, 17 channels out of 129 registered channels are applied to reduce the data volume. The proper channels are selected to cover the entire skull area. The manner of channel selection is shown in Fig. (2). Moreover, the data are pre-processed according to the filters applied in [27 and 28], followed by normalization.

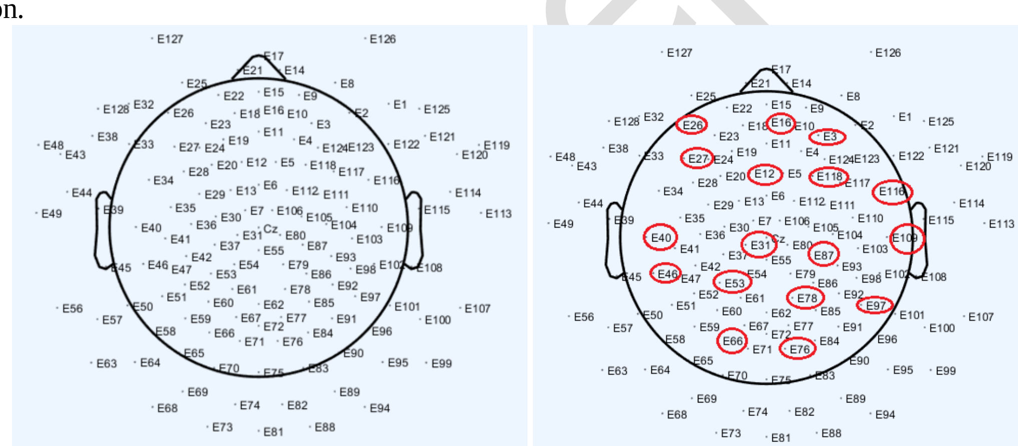

Figure 2: Selection of recording channels of EEG signals [20]

4.2 Feature extraction from EEG signal using CNN

The CNN algorithm is applied for feature extraction. This network can recognize the distinctive features of every subject and transfer them as input to the classifier automatically.
Although CNNs perform well on images, there exists a challenge with EEG signals. EEG signals consist of a dynamic time series of values measured by electrodes on the surface of the skull, and this requires CNN structures to be adapted for EEG signals. The input layer is considered as a 2-D array: 1) a width equivalent to the signal recording electrode counts and 2) a length equivalent to the count of the samples in the considered time interval. The received signals are considered as images with 522*17 dimensions. The arrangement of the neural network architecture in this study generally includes one input layer, five convolution layers, four maximum pooling layers, and one flat layer, Fig. (3). An activation function is

[2] https://datadryad.org/stash/dataset/doi:10.5061/dryad.2th78.

defined for each convolution in this neural network model, where, in the first layer of the first part, (i.e., the primary convolution layer), the linear activation function is applied. In the other convolution layers in the architecture of the neural network model, the exponential linear unit (ELU) activation function is applied. The CNN structure applied here for the feature extraction block is shown in Fig. (3). CNN prepares a feature vector of 360 sizes and transfers it to the classifier as input.

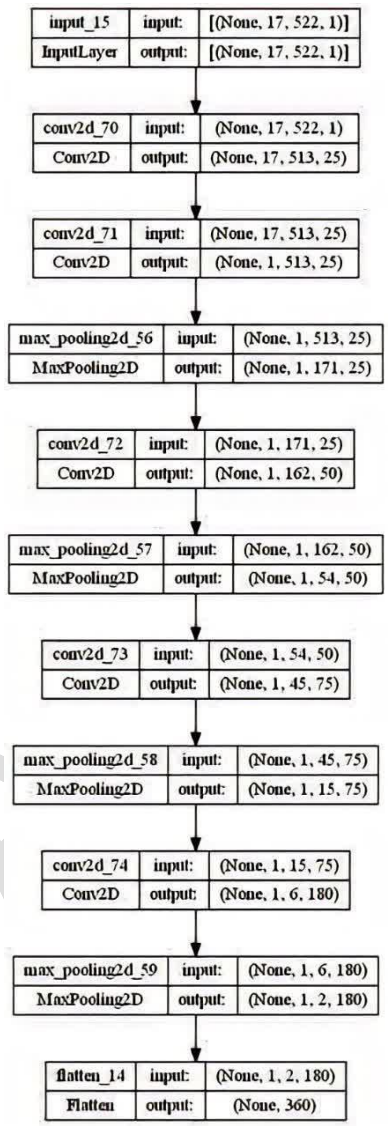

Figure 3: The CNN architecture that has been used for feature extraction

4.3 Classification algorithms

4.3.1 Support Vector Machine or SVM

One of the most popular classification algorithms is support vector machines applied in many scientific fields like speech processing, machine learning, activity recognition, etc. The basis of non-linear SVM involves fitting a non-linear kernel function to transfer the input data into a high-resolution space, which makes it easier to distinguish the data from the original input space [29 and 30]. The appropriate selection of kernels depends on the data type. The support vector machine supports binary classification, thus, if there is more than one class, it should be extended into multiple classes [31].

4.3.2 Linear Discriminant Analysis or LDA

The objective of LDA is to maximize the inter-group to intra-group dispersion ratio; consequently, it seeks to reduce the intra-group dispersion volume until this ratio reaches its maximum. In this process, different categories will evolve, which will have a small dispersion. The sum of intra-group dispersion for all categories will have the lowest volume [32].

4.3.3 Decision Tree or DT

A decision tree is a method in machine learning to develop, shape, or organize an algorithm. A DT algorithm is run to partition the features of the data set through a cost function. Before performing optimization and removing extra branches, this algorithm eliminates the unrelated features, thus, requiring a pruning operation to remove the extra branches. In the DT algorithm, parameters like the DT depth can be adjusted to avoid overfitting or overcomplicating as much as possible [33].

4.3.4 Random Forest or RF

Random forest is a supervised learning algorithm. This algorithm plants a forest randomly, which consists of a group of DIs. This algorithm is applied for classification and regression. As to classification, the RF forms DTs and provides output as a class that is the mode or mean of the original unique trees [33].

4.3.5 Gaussian Naïve Bayes or GNB

The likelihood function maximization method is adopted in GNB. It is based on the assumption of independence among features. Although the simple Bayes clustering technique has limited and accessible assumptions, it can solve real problems well. Simple classifiers require little training data to estimate the parameters required for classification [33].

5 RESULTS AND DISCUSSION

To train the neural network and test the performance and accuracy of the trained network, two sets of training and test data are required; consequently, two individuals with autism and two without are selected as the test subjects, and the remaining data is applied in training the neural network. In this process, a K-fold cross-validation algorithm is run to validate the result and to make the result obtained from the neural network trained on the test data more reliable, the K-FOLD algorithm is run. The cross-validation algorithm divides the data into K parts, where during K iterations, one of the K parts is considered as test data and other K-1 parts are considered the training data. The average evaluation result is considered as the final result. The cross-validation algorithm with K = 10 is applied for evaluation. The average results are calculated after 30 different runs on the data set.

In this study, first, the received input data enter the pre-processing phase, next, the convolutional neural network algorithm is run to extract features from the data, and then the output is transferred to the classification algorithms. The objective of this study is to extract features, train a model, and gain experience by applying a deep learning model from the trained data, next to generalizing the new data (test data).

A comparative summary of the classification of autistic and healthy individuals subject to available methods [10, 13, 15, 34, 35, 36] and this proposed method is provided in Table 1. Because EEG images are viewed as complex signals, physicians cannot distinguish between autism and healthy behavior through visual observation. This complexity demands that AI-based methods' intervention in diagnosing autism; consequently, the tables in [37] have reviewed machine and deep learning methods in feature extraction and classification stages to diagnose autism.

As observed in Table 1, the performance results of the five classification methods of the machine learning algorithm of this study are as follows: the accuracy of data classification with SVM methods is 100%, LDA is 82%, DT is 80.5%, GNB is 100%, and RF is 100%. Here, the analysis of SVM, GNB, and RF methods, by obtaining 100% overall accuracy, provided a better result in comparison with other classifications for autism diagnosis. By applying the convolutional neural networks for feature extraction more efficient features are generated for the three mentioned classifiers, with more accurate classification results. Moreover, the results are box-plotted as the accuracy percentages in Fig. (4).

Table 1: Comparison of the results of the proposed method and previous research

Classification Accuracy Percentage	**Classifier**	**Dataset**	**Feature Extractor**	**Year**	**Reference**
ANN = 91.05 KNN = 94.21 SVM = 92.63 LDA = 93.68	ANN, KNN, SVM, LDA	9 ASD & 10 healthy	DWT-SE (Wavelet + Entropy)	2018	[10]
100	Resnet (CNN)	14 ASD & 14 healthy	EEG data are used	2020	[13]
100	2D_DCNN	10 ASD & 9 healthy	EEG data are used	2022	[15]
98.88	CNN	20 ASD & 9 healthy	EEG data are used	2022	[34]
LSTM = 94 CNN = 92	LSTM CNN	14 ASD & 14 healthy	EEG data are used	2022	[35]
KNN= 72.77 SVM = 90.57	KNN SVM	34 ASD & 14 healthy	Linear and Nonlinear Features, MRMR, MI, IG, GA	2020	[36]
RF = 100 SVM= 100 GNB = 100 LDA = 82 DT = 80.5	RF, SVM GNB, LDA, DT	10 ASD & 9 healthy	CNN		The Proposed Method

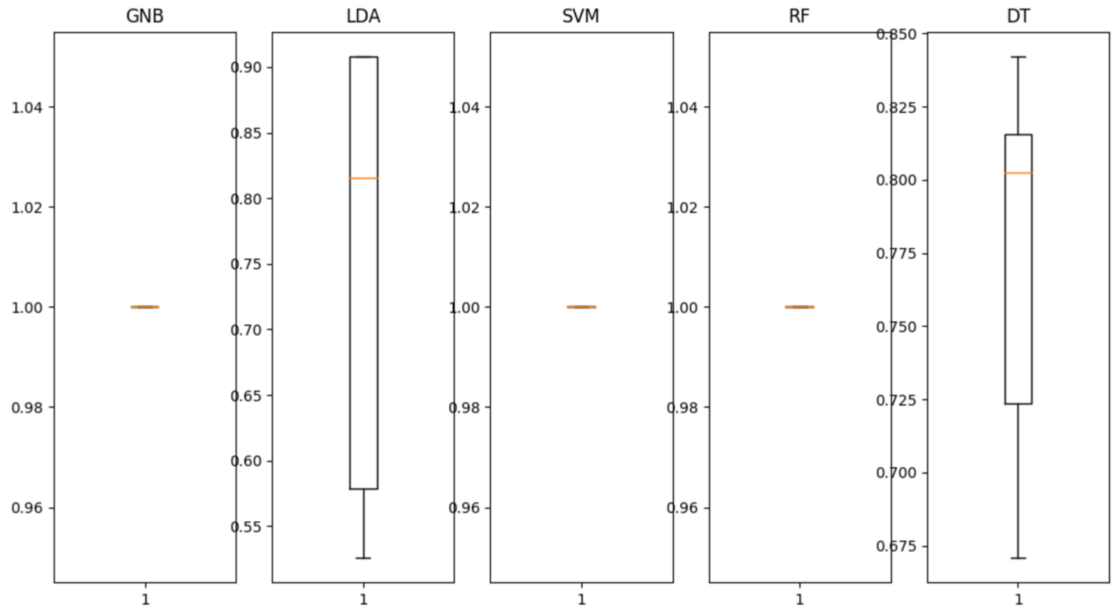

Figure 4: Comparison results of classifiers in the form of a box plot

6 CONCLUSION

The objective of this study is to diagnose autism through EEG signals, consequently, a method consisting of a convolutional neural network for feature extraction and five machine learning algorithms for data classification based on deep learning is proposed. According to the reviews, combining neural networks and machine learning algorithms as a collective method is an innovative approach in this field. The convolutional neural network algorithm applied in feature extraction and the combination of the mentioned methods for data classification are the most important findings of this study. These proposed methods are simulated and the results are of high-accuracy diagnosis of autism similar to their counterparts. Combining this method with other deep learning methods to increase accuracy percentage is considered a new proposal through future works.

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