Comparative Study of Different Machine Learning Algorithms to Classify EEG Commands

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Abstract

Since electroencephalograms are non-invasive, inexpensive, and have high resolution, they are frequently used in diagnostic evaluations of a wide range of brain signals. However, manual EEG signal analysis can be exhausting and time-consuming. It takes a long time for physicians to become specialists in this field, and experts have low inter-rater agreement (IRA). To aid the last diagnosis and lessen the load, numerous Computer Aided Diagnostic (CAD) studies have looked into automating EEG interpretation. EEG signal classification provides an extra creative way of detecting emotions. Generic emotion recognition algorithms may face limitations and obstacles when restricting facial expression triggers and emotion masking. This study involves categorizing EEG data and evaluating the outcomes of several machine learning algorithms, such as Support Vector Machine (SVM), K-nearest Neighbor (KNN), Random Forest, Gradient Boosting, Logistic Regression, and Decision Trees. Grid search was also employed to reduce execution time for each of the machine learning models that were tested on the Spark cluster using hyperparameter tuning. This study used the Emotion Dataset, a multimodal dataset for classifying human affective states. Gradient Boosting outperformed other algorithms in terms of precision, recall, and F-Score, achieving 99.54%, 99.51%, and 99.52%, respectively, with an accuracy of 99.53%. According to the suggested model, several classification techniques are needed to differentiate between different emotional states, and gradient boosting is the most effective machine-learning technique. Current supervised classification techniques, including GBMs, are used to simulate a variety of typical machine-learning problems with high reliability. The recommended approach produced better accuracy and faster training speeds.

Keywords- Machine Learning, Electroencephalogram, Decision Tree, Logistic Regression, Random Forest, Gradient Boosting.

I. INTRODUCTION

The study of numerous elements and variables, such as the common sense emotions of happiness or rage with differing degrees, is necessary for emotion classification. These characteristics are second nature to humanity, making it difficult and expensive for facial recognition algorithms to detect them [1]. A common method for neuroimaging that monitors potential voltage changes caused by electrical impulses from firing neurons is the electroencephalogram (EEG). The scalp is used to detect the electrical impulses, and a device with a grid of electrodes records them. Delta band, theta band, alpha band, beta band, and gamma band are the five primary bands of EEG signals. Each of these spectra is typically connected to a specific activity, such as moving the fingers, sleeping, thinking actively, or solving problems. Brain-computer interfaces (BCI) employ EEG to enable non-contact communication between a human subject and a computer [2]. In the contemporary scientific research community, extensive EEG data analysis is a hot topic that scientists and economists have developed. The goal of this study is to apply Machine Learning algorithms to evaluate the similarly large dataset that is the brain wave signal to keep up with the pace of technology. In order, to reduce the burden on the physicians and help with the final diagnosis, various Computer Aided Diagnostic (CAD) research have explored automating the interpretation of EEG [3]. This facilitates the non-interventional detection and diagnosis of brain disorders. EEG is rapidly growing in popularity with the general public due to its extension into new industries outside of medicine, such as gaming, neuromarketing, and BCI, as well as its safety, simplicity, and affordable pricing [4]. Logistic Regression, SVM, KNN, and Decision Tree, along with the combination techniques: Boosting, F. Lotte, M. Congedo, A. Lcuyer, F. Lamarche, and B. Arnaldi reviewed Voting and stacking. The study offers recommendations for selecting algorithms when combined with the extracted features. [5]. An EEG-based BCI gadget senses the participant's brain activity and translates their intentions into commands without needing any peripheral nerves or muscles [6]. Brain functions are quickly processed into command sequences using BCI programs to do specialized tasks such as operating home appliances and wheelchairs, speech synthesizers, robotic arms, digital computers, and gaming apps [7].

The study above offers recommendations for selecting algorithms when combined with the extracted features. It will be possible to choose equipment that meets the requirements of the algorithms while also resolving issues with stability and limits. As a result, the employment of additional processing and identification algorithms is required before people may explore technology and put EEG to use. As a result, using additional processing and identification methods is a requirement before anyone can use technology and implement EEG [8].

This study concentrates on six machine learning methods in particular: Random Forest, KNN, Gradient Boosting, Logistic Regression, SVM, and Decision Tree. This research aims to apply a variety of machine learning algorithms and compare them based on minimum error, recall, precision, and f-measure, to further enhance the performance with dimensionality reduction and to obtain hidden information as suggested. In specific situations. As a result of this project, some of the technical advancements in computer science, following are:

- The methodology of workflows is easily repeatable.
- Determining the most appropriate categorization method to employ for each emotion
- Accuracy for each EEG data classification model.

The sections of the paper that follow discuss the detailed procedure of the study that was undertaken. Literature review is explained in the "Related Works" section. Methodology and algorithms are explained in section “The Methodology” section. The step-by-step implementation of the method and the utility of the subroutines are seen in the "adjusting parameters" section. The "Data" section contains descriptions of the datasets. The section “Evaluation Metrics” defines the recommended recall, precision, and F-score of the results. The section titled "Classification Algorithms Performance Results" details the outcomes of the experiments. The "Conclusion" section contains concluding observations.

II. RELATED WORK

I Recently, many efforts have been made by researchers to establish a practical method for identifying techniques to detect EEG. Studies are still being conducted in order to give the element of monitoring EEG situations. Present a series of studies connected to our strategy.

Hoang-Thuy-Tien Vo et al., [9]. Surveyed machine-learning algorithms and developing a model to meet the needs of electroencephalogram (EEG) signal classification. Eleven states, including those linked to eye behavior, facial expression, and thought signals, are captured using a self-written program. The Wavelet transform is utilized in the feature extraction phase of the signal processing process. The Wavelet method was used to determine the components of the feature matrix. This study provides information on both traditional machine-learning techniques like the Support Vector Machine (SVM) and the Bagged Tree (BT) as well as more recent ones like Deep Learning (DL), and Artificial Neural Network (ANN). To classify signals, four primar y algorithms are utilized. Results from the author's Amin algorithm using an SVM classifier showed 99.11% accuracy for coefficient approximations (A5) of low frequencies between 0 and 3.90 Hz. The device with 128 channels recorded an EEG dataset for one state (open eyes), and the SVM algorithm analyzed the data set up to 11 states recorded by the 5-channel device, despite its accuracy being only 72.7%. Emotive EPOC+ is used to capture EEG data using the ANN algorithm, which has 7 states, each with a single mental state. Results showed that the ANN classifier accurately predicted 75% of eye-opening, 85% of eye blinking, 90% of left eye blinking, 90% of right eye blinking, 100% of smiling, 90% of eye closing, and 47% of "push" thinking..

Vikrant Doma and Matin Pirouz, [10] analyzed epoch data from EEG sensor channels and comparing multiple machine learning techniques [namely Support Vector Machine (SVM), K-nearest neighbour, Linear Discriminant Analysis, Logistic Regression, and Decision Trees] for dimensionality reduction with and without principal component analysis (PCA). Grid search was also used to reduce execution time for each of the machine learning models that were evaluated over the Spark cluster by hyper parameter tuning. The DEAP Dataset, a multimodal dataset for the research of human affective states, was used in this work. The predictions were based on the labels assigned by the participants to each of the 40 one-minute music excerpts. Participants according to its level of arousal, valence, likeness or hate, dominance, and familiarity scored each movie. The time-segmented, 15-second intervals of epoch data were used to train the binary class classifiers separately for each of the four classes. The best segmentation performance was achieved using PCA with SVM, which produced an F1-score of 84.73% with 98.01% recall. Different classification models converge to higher accuracy and recall for each of the time segments and "a binary training class. The findings demonstrate the need for several classification models to categorize various emotional states.

Bhumireddy Venkata et al, [11] compared and recommended the top machine learning algorithms that can identify student perplexity when they are participating in MOOCs. To do this, initially employed five different machine-learning algorithms: decision tree, random forest, K Nearest Neighbour’s, and logistic regression. The performance parameters of accuracy, precision, and recall are used to compare the algorithms. Following the comparison, all algorithms were compared based on the confusion score. The finest machine learning algorithms with the best results were suggested. The finest machine learning algorithm put forth has a lot of potential for evaluating massive amounts of data to find confusion. The top method is Logistic Regression, which is then followed by Random Forest, Decision Tree, KNN, and SVM.

Rüya Akıncı et al, [12] focused on the classification of alpha waves from EEG signals to identify tiredness using performance analysis on 25 models of 8 different machine learning algorithms utilizing EEG signals in a dataset gathered from 20 different subjects. The classification accuracy and classification time were measured in the results. As a result, although the classification times are rather long, the Bagged Trees and Subspace k-Nearest Neighbour models outperformed the Tree algorithm methods in terms of classification accuracy. The use of tree algorithms yields the best results since it provide a classification accuracy that is more than sufficient in a shorter amount of time. The approach to be used should be determined by the criteria for accuracy and time for detecting drowsiness.

Pawan, Rohtash Dhiman, [13] provided an in-depth examination of four components of EEG signals in BCI systems: signal capture, signal pre-processing, feature extraction, and classification. For feature extraction in EEG-BCI systems, wavelet transform (WT), the most used time-frequency approach, and its upgraded variant, wavelet packet transform (WPT), are employed most frequently. Researchers were inspired by the advancement of artificial intelligence technology to identify motor imaging signals for BCI systems using machine learning (ML) and deep learning (DL) approaches. This literature review study examines over 220 research papers on ML and DL techniques for classifying EEG signals for BCI devices. Present issues are thoroughly addressed in order to pinpoint potential study areas for further exploration and recommendations for suitable feature extraction and classification methods are made. The study's findings, according to the authors, should aid in the development of an efficient EEG-BCI system by assisting researchers in discovering precise feature extraction, ML, and DL algorithms.

III. METHODOLOGY OF EEG CLASSIFY BY MACHINE LEARNING

This section introduces the proposed method for analyzing EEG in machine learning. The dataset can be formally described as D= {dataset of EEG}, where based on using six algorithms for machine learning: Random Forest, KNN, Gradient Boosting, Logistic Regression, SVM, and Decision Tree. Methods of machine learning The classification model is trained using Random Forest, KNN, Gradient Boosting, Logistic Regression, SVM, and Decision Tree. Utilizing training samples and testing samples, the classifiers were trained. All classifiers, including Random Forest, KNN, Gradient Boosting, Logistic Regression, SVM, and Decision Tree share the supervised type. Throughout the training phase, input and output are necessary. The general classification method is displayed in Figure (1). Datasets will be pre-processed using a search technique called (Grid search) before entering the processing phase, because of the inability to precisely forecast or determine the optimal method to choose these parameters because the parameters can include different solvers, the value of "k," gamma, kernel names, and more, each of which varies depending on the classification model being used. Then the data will be processed in machine learning by using Min-Max Scaler, and similarity measurements, then the post-processing data (apply Feature Extraction using Mutual Information, ANOVA, and Chi-Square), and finally the classification prediction of data.

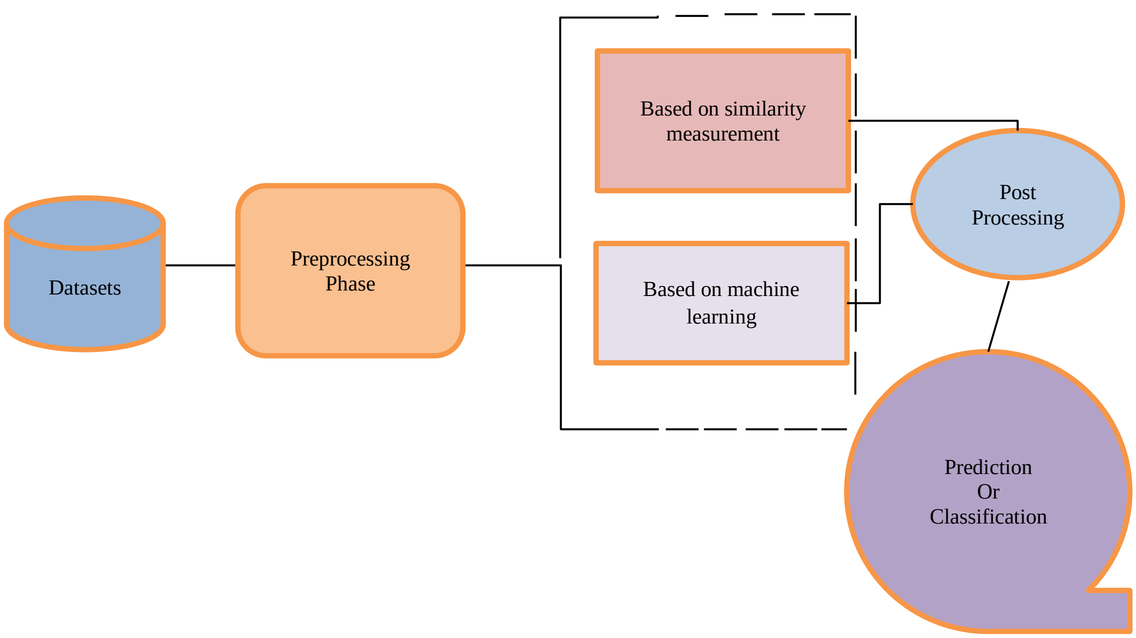


Figure (1): The General Classifiers of EEG Datasets.

A. Logistic regression

When there are only two classes and the input sample must belong to one of them, logistic regression is a statistical technique for predicting binary classes that are used widely in classification problems in the social sciences, medical fields, and natural language processing [14].

Because logistic regression employs a non-linear log transformation, it may cope with a wide range of relationships between dependent and independent variables. As a result, the associations between dependent and independent variables do not have to be linear. Large sample sizes are necessary for logistic regression in order to achieve good results and prevent overfitting and under fitting issues. Equation 1 explains how logistic regression is formulated mathematically [15].

$$p(X/D) = \frac{p\left(\frac{D}{X}\right)P(X)}{P(D)} \quad (1).$$

Where P denotes the probability, d is the overall degree, and X the degree of each member.

B. Support vector machine

One of the most reliable and accurate machine learning techniques is called a Support Vector Machine (SVM), which was first presented in the 1990s [16]. Classification and regression can be accomplished using SVM, which is renowned for its powerful generalization capabilities and simplicity in learning precise parameters. [17]. The SVM has a better chance of generalizing the issue, which is what statistical learning aims to do. To categorize the data point, an N-dimensional hyperplane must be found using the support vector machine technique. It is capable of handling both training and testing data. A set of training data that has been labelled as belonging to one of two classes is used in an SVM training to develop a model that assigns fresh samples to one of two classes. Your model is tested using the testing data, which were data that were not utilized for training. [18].

The SVM has two primary flaws. In the beginning, a change should be made to the SVM because it was initially created for binary-class classification. Second, with a vast scale of data, learning the SVM takes a lot of time [19]. There are three forms of SVM: linear, nonlinear, and regression. The proposed method made use of the linear SVM classifier.

C. Random Forest

In machine learning algorithms, the Random Forest is a supervised learning method. It has the capacity to be applied to both regression and classification. A collection of classifiers for tree structures make up Random Forest [20]. It is also the most adaptable and straightforward algorithm. Trees comprise a forest. A forest's strength is meant to be proportional to the amount of trees in it. The random forest generates decision trees using samples of data chosen at random, receives predictions from each tree, and decides which choice is the best. It also acts as a trustworthy gauge of the feature's worth. The decision trees generated in front of each other are connected to form a random forest [21].

A random forest is a collection of decision trees from distinct subsets of a given dataset. The average is used to improve prediction accuracy from that dataset [22]. Every tree has a category divide prediction, and the class with the highest votes becomes the subtree. Figure 2 depicts the main structure of the random forest.

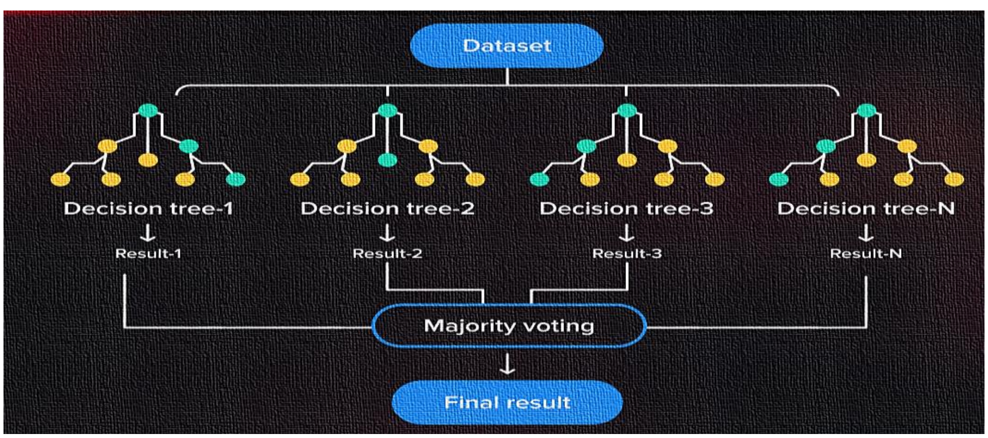


Figure 2. Structure of the Random Forest [22]

D. K- ⁻ nearest neighbor

When we use (KNN) for classification, the algorithm essentially provides a method to extract the majority vote that determines whether the observation belongs to a specific K-similar instance or not. The Euclidean distance is applied for this in any dimensional space. KNN is a non-parametric classification technique that labels previously unsampled points; therefore as the size of the data grows, its efficiency decreases [23]. As a result, the demand for a feature decomposition algorithm grows. Because the performance is entirely reliant on the value of k, the model was developed to test over a range of k values, which was accomplished through iterations above k-fold cross-validation from 0 to 5, where the values of k for KNN ranged from 2 to 50. Theoretically, it is difficult to choose a suitable value of k unless a thorough search is conducted using expensive techniques; hence, this methodology was proposed [24].

E. Gradient Boosting

A family of potent machine-learning techniques known as gradient-boosting machines has demonstrated significant effectiveness in a variety of real-world applications. They can be learned with regard to various loss functions, for example, and are extremely adaptable to the specific needs of the application. Gradient boosting machines, or just GBMs, use a learning process that sequentially fits new models to produce increasingly precise estimates of the response variable. The basic idea behind this technique is to build new base-learners that are maximally correlated with the negative gradient of the loss function, which is associated with the entire ensemble. The loss functions used can be chosen at random, but to provide a better understanding, if the learning process produced successive error fitting, the error function would be the traditional squared-error loss. In general, the researcher selects the loss function, with a wide range of loss functions derived thus far, and the option of developing one's own task-specific loss function. Because of their considerable versatility, GBMs can be tailored to any data-driven activity. It introduces a lot of variability into the model design, making selecting the best loss function a question of trial and error. However, boosting techniques are extremely simple to build, allowing for experimentation with various model designs [25].

F. Decision tree

A decision tree is a type of hierarchical class selection aid that makes use of a graph or model of choices and their conceivable outcomes that resemble a tree [26]. Coupled with accident outcomes, cost, and utility (i.e., bifurcation based on the choice made at each stage). A solution for class separation that solely employs conditional management statements is the decision tree. Every internal node of a decision tree could be a flowchart-like structure that reflects a "test" of an attribute (such being whether or not a coin flip results in heads or tails). When all attributes have been calculated, the choice is made, and each branch indicates the outcome of the check while each leaf node represents a category label. Classification rules are represented by the pathways from root to leaf. Decision Trees are built mostly on learning algorithms, which are among the most basic and widely used supervised learning procedures. Prophetical models are given more accuracy, stability, and simplicity using tree-based approaches. They map non-linear interactions far better than linear models do. They are flexible in identifying any conceivable drawback (classification or regression) at hand. Classification and Regression Trees (CART) are the abbreviation for classification algorithm decision tree [27].

IV. DATASET

The “Feeling Emotions dataset” is an EEG signal repository freely available, found at [10], for emotion analysis. This repository contains a multi-modal dataset that can be used for analyzing human brain states. 32 Biosemi data format files with 48 channels that were recorded at 512 Hz are included in the raw data collection. 11.2 GB of sampled EEG data in total. This area of study seeks to investigate how distinct brainwave patterns interact with various emotions, gain a better understanding of human emotional processes, and develop potential applications in emotion recognition and affective computing. Experimental Results of this section consist of evaluation metrics and the classification algorithm's performance. The dataset includes a pre-processing script in pickled Python or Matlab formats in addition to the raw data. Two arrays—one for data and the other for labels (arousal, liking, and dominance)—contain the subject information in this script. With the help of this data, classification methods can be used without concern for the preparation stage. The pre-processed version is used in this study to examine the initial accuracy of classic classification methods. EEG data collected from patients can be read using Python's pickle module.

A. Adjusting parameters of EEG

Several machine-learning algorithms are included in the Python module Sklearn. However, in some circumstances, we are unable to precisely forecast or determine the optimal method to choose these parameters because the parameters can include different solvers, the value of "k," gamma, kernel names, and more, each of which varies depending on the classification model being used. A thorough search technique called Grid search had to be used for this. In machine learning, Grid Search is a method for optimizing hyperparameter combinations to obtain the best fit for a given model. Hyperparameters are variables that the user sets before training, rather than the model learning, examples (regularization strength, and number of hidden layers). To implement a Grid Search, a grid of potential values for each hyperparameter is defined. For instance, would have a grid with eight different combinations to investigate if each of the three hyperparameters had two possible values. After that, Grid Search uses every possible combination of hyperparameters to train and assess a model, then chooses the model that performs the best. The following is the parameter-tweaking algorithm:

Algorithm 1: Adjusting parameters using grid search

```
1. # Load and Preprocess the Dataset
2. data = load_dataset("dataset.csv")
3. X, y = preprocess_data(data)
4. # Split Data into Training and Testing Sets
5. X_train, X_test, y_train, y_test = split_data(X, y)
6. # Data Preprocessing
7. X_train, X_test = preprocess_features(X_train, X_test)
8. # Choose a Classification Algorithm
9. model = LogisticRegression()
10. # Train the Classification Model
11. model.fit(X_train, y_train)
12. # Model Evaluation
13. y_pred = model.predict(X_test)
14. confusion_matrix = calculate_confusion_matrix(y_test, y_pred)
15. classification_report = calculate_classification_report(y_test, y_pred)
16. accuracy = calculate_accuracy(y_test, y_pred)
17. # Display the Results
18. display_results(confusion_matrix, classification_report, accuracy)
```

V. EVALUATION METRICS

The proposed model was evaluated using a well-known standard evaluation metrics namely, recall (R), Precision (P) and F-measure (F) as calculated in Equations [29]. All these metrics are calculated based on the confusion matrix.

$$R = \frac{TP}{TP+FN} \quad (2).$$

$$P = \frac{TP}{TP+FP} \quad (3).$$

$$F - measure = \frac{2*TP*TN}{TP+TN} \quad (4).$$

Where

TP is an actual value that is classified as a dataset of EEG.

TN is a false value classified as not a dataset of EEG.

FN is a false value classified as not a dataset of EEG.

FP is a false value student that is classified as a dataset of EEG.

A. *Classification Algorithms Performance Results*

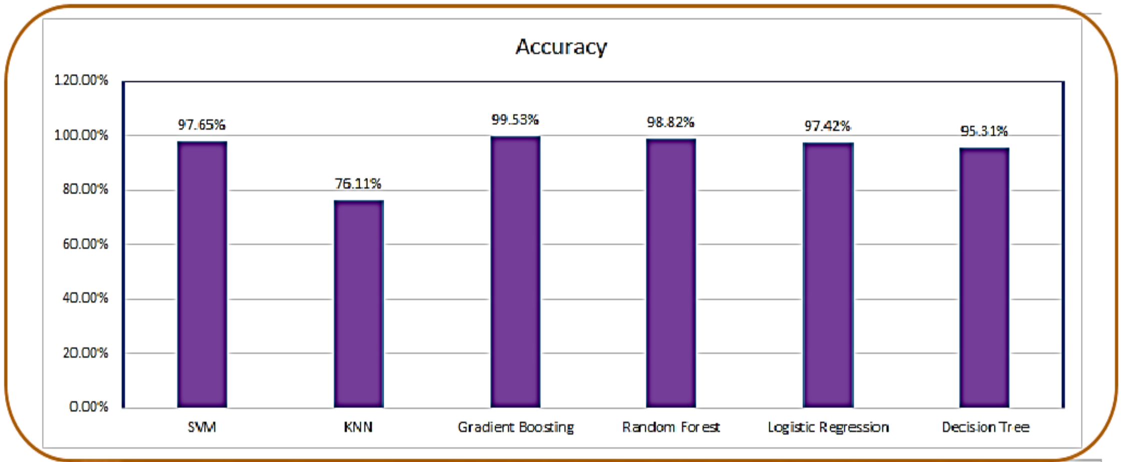
The results and comparisons of different classifiers after data training and testing are presented in this section. Many classifiers were used in the proposed model. Each classifier's results will be shown in graphs and tables for better understanding. Choosing a dataset that contains a dataset of EEG signal records.

Where a larger dataset can give better results. The cross-validation technique was used to train the classifiers. Cross-validation is a machine-learning model testing technique that involves training multiple models on subsets of the available input data and then assessing them on a separate subset of the data. 5-fold cross-validation was used in the proposed model. Table 1, and Figure 3 show the results of different classifiers used in the proposed model.

Table1: Evaluation metric values of the classifiers.

Model	Recall	Precision	F-Score	Accuracy
SVM	97.62%	97.62%	97.62%	97.65%
KNN	75.57%	75.09%	74.69%	76.11%
Gradient Boosting	99.54%	99.51%	99.52%	99.53%
Random Forest	98.78%	98.83%	98.80%	98.82%
Logistic Regression	97.36%	97.41%	97.37%	97.42%
Decision Tree	95.19%	95.33%	95.22%	95.31%

Evaluation metric values of the classifiers



	SVM	KNN	Gradient Boosting	Random Forest	Logistic Regression	Decision Tree
Recall	97.62%	75.57%	99.54%	98.78%	97.36%	95.19%
Precision	97.62%	75.09%	99.51%	98.83%	97.41%	95.33%
F-Score	97.62%	74.69%	99.52%	98.80%	97.37%	95.22%
Accuracy	97.65%	76.11%	99.53%	98.82%	97.42%	95.31%

Recall Precision F-Score Accuracy

The classification accuracies, recalls, precisions, and F-scores of 6 different machine-learning models are given in Table 1, and Figure 3. In the machine learning model in Table 1, 99.53% of the data was reserved for the accuracy of GBA, it is evident that GBA is the model that is the most accurate overall. The accuracy of random forest is 98.82%. The accuracies of SVM and Logistic Regression models are quite similar to one another (97.65%, and 97.42%). The KNN has the worst accuracy among them (76.11%). According to these results, the classification appears to be good.

VI. CONCLUSION

In conclusion, performance analysis and classification of a dataset that applied to 6 different machine learning algorithms using EEG signals in a dataset. Thus-obtained performance data were compared by means of classification accuracy and classification time. Accordingly, the Gradient Boosting Algorithm showed the optimal display in terms of both accuracy and classification time. The reasons for the good performance of GBA can be attributed to its simple classification logic, rapidity, less data cleaning required after creation, and no necessity for data pre-processing. In addition, since the missing values in the data will not significantly affect the formation of the GBA unlike other classification algorithms, the methodology serves high performance. The goal of the comparison analysis was to see if there was a correct mix of characteristics, parameters, and pre-processing approaches that might yield equivalent outcomes to more complex procedures. However, as the experiments showed, this might not always be the case. More advanced machine learning approaches based on digital signal processing techniques produce better outcomes. The findings, on the other hand, obtained a maximum of 99.52% F1-score with an execution time of 2 minutes for each binary class classification for the full 60 s trial, operating on a workstation with an Intel(R) i7 7700 CPU running at 2.81 GHz. the results demonstrate that Gradient Boosting is the models with the highest overall accuracy. The KNN has the worst accuracy among them. The random forest, and Logistic Regression models are quite similar to one another. SVM and Decision Tree are less than the accuracy of others.

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