Analyzing electroencephalogram signals with machine learning to comprehend online learning media

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ABSTRACT

In E-learning, evaluating students' comprehension of lecture video content is significant. The surge in online platform usage due to the pandemic has been remarkable, but the pressing issue is that learning outcomes still need to match the growth. Addressing this, a scientific system that gauges the comprehensibility of lecture videos becomes crucial for the effective design of future courses. This research paper is based on a cognitive approach utilizing EEG signals to determine student's level of comprehension. The study involves the design, evaluation, and comparison of multiple machines learning models, aiming to contribute to developing an efficient learning system. Fifteen distinct machine learning (ML) classifiers were implemented, among them AdaBoost (ADA), gradient boosting (GBC), extreme gradient boosting (XGboost), extra trees (ET), random forest (RF), light gradient boosting machine (light gum), and decision tree (DT) algorithms standouts. The DT exhibited exceptional performance across metrics such as area under the curve (AUC), accuracy, recall, F1 score, Kappa, precision, and matthews correlation coefficient (MCC). It achieved nearly 1.0 in these metrics while taking a short training time of only 1.7 seconds. This reveals its potential as an efficient classifier for electroencephalography (EEG) datasets and highlights its viability for practical implementation.

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1. INTRODUCTION

The education landscape has undergone a profound transformation in the aftermath of the pandemic. The prominence of information and communication technology (ICT) tools alongside online learning methodologies has garnered its significance, resulting in an exponential growth of online education within the academic domain [1]. However, a noticeable variance has emerged in achieving desired learning outcomes. Remarkably, the era of coronavirus disease 2019 (COVID-19)-induced online learning showcased student performance in the course that was either at the same level as or surpassing pre-pandemic levels [2]. Leveraging online learning platforms has enhanced students' academic accomplishments and overall satisfaction. Additionally, the role of online discussions has proven highly advantageous for students' learning experiences. This paradigm shift offers various advantages, including the flexibility for individuals to learn from any location, at any time, and their own pace. Nevertheless, ascertaining whether learners genuinely grasp the subject matter is a significant hurdle. Engaging in online classes without a genuine understanding of the concepts can be counterproductive, wasting both the educator's and the learner's time. To address this challenge, a concerted effort has been made to assess whether learners have comprehended a lesson, employing a scientific methodology involving electroencephalography (EEG) data.

This test employs minuscule metallic chip-based electrodes affixed to the scalp's surface to measure the brain's electrical activity. This test capitalizes on the fact that brain cells communicate through electrical impulses around the clock, maintaining activity even during sleep. EEG records the crimped lines representing their communication patterns as these cells remain constantly active. EEG serves multiple purposes, including diagnosing epilepsy and various brain-related disorders. Assessing brain waves identifies abnormal neural activity that might indicate underlying issues. When analyzed across multiple contexts, these recorded patterns offer insights, enabling informed conclusions. The EmotivEPOC is a sophisticated multi-channel wireless neuro-headset designed to provide high-resolution insights into brain activity. The EPOC is ingeniously engineered to capture and interpret the brain's electrical impulses by comprising a remarkable fourteen-sensor array and two reference rubber comfort pads. This cutting-edge technology lets the headset discern and decode a user's thoughts, emotions, and facial expressions in real-time. The headset's intricate configuration involves a network of sensors strategically positioned across the scalp, each poised to detect specific neural signals. The two reference rubber comfort pads also serve as benchmarks, accurately interpreting the recorded brain activity. These pads create a stable baseline against which the signals from the sensors can be compared and analyzed. The resulting data is a dynamic representation of the user's cognitive and emotional processes. It offers a deeper understanding of how the brain functions during various activities, emotional states, and mental tasks [3]. This technology holds immense promise across diverse domains, from cognitive research to human-computer interaction, allowing for the development of applications that can respond to users' mental states and intentions.

Scholars from diverse fields have undertaken research, elucidating their methodologies for analyzing EEG data. Their meticulous approach involved collecting and preparing datasets while addressing challenges such as noise elimination, data irregularities, and EEG signal intricacies. Additionally, they integrated machine learning (ML) and deep learning techniques into their classification methodologies to derive desired insights from the datasets. An experiment involving ten volunteers [4] aimed to investigate a specific aspect or phenomenon using EmotivEPOC+headsets to collect experimental electroencephalographic data. The proposed methodology, which employed a common biological signal processing technique, encompassed steps like typical geometric layout, feature extraction through band power analysis, and comprehensive evaluation of various classification techniques. These techniques included linear discriminant analysis, k-nearest neighbors (KNN), support vector machine (SVM) with linear and radial basis functions, random forests, and artificial neural networks. Furthermore, a ML approach utilizing EEG is suggested for assessing sleep quality, offering advantages over the traditional polysomnography (PSG) method. By focusing on three sleep stages instead of five, this method can provide more accurate sleep quality predictions while enhancing user experience by requiring fewer body sensors during sleep. The authors developed an innovative automatic sleep-staging system combining multi-class SVM classification with a decision tree technique, leveraging quantitative data extracted from EEG signals [5].

Drawing from cognitive load theory, the authors introduced a system to capture and categorize a user's mental state while viewing web videos through a commercial EEG device. They have implemented various normalization algorithms to analyze the EEG signals collected from the device, experimenting with different temporal window lengths. Furthermore, they have recommended using multiple supervised learning techniques for training and evaluating classifiers, followed by assessing classification accuracy. The study's results demonstrate the proposed method's effectiveness in handling EEG data, exhibiting superior accuracy, precision, and recall rates in classifier training compared to prior studies [6]. Learner monitoring has become increasingly vital for present and future generations in innovative education due to its significant educational advantages. Bandura's social cognitive theory underscores the importance of self-efficacy as a critical aspect of learner monitoring, yet establishing a reliable evaluation methodology poses challenges. To offer a more precise and objective analysis of the three levels of academic self-efficacy, the authors advocate for an approach centered on long short-term memory (LSTM) networks and EEG signal analysis, departing from conventional subjective evaluation methods. EEG signals and scholastic self-efficacy scores were initially recorded from 39 students who completed three challenging school assignments. The authors then applied pass-band filters and baseline drift reduction techniques to the EEG data for analysis [7].

The proposed method exploits the relationship between the EEG task and the user's program, employing a dry-type sensor and multiple electrodes in the EEG setup to gather data from specific locations. Variations in EEG activity within the prefrontal cortex among individuals are noted. To address these variances, the authors devised a component vector for the input modality of the self-organizing map (SOM).

This inputs vector for the SOM comprises the obtained EEG character vector and a human feature vector representing individual characteristics assessed through ego analysis using psychological tests. During preprocessing, the EEG character vector is selected by computing the time average for each frequency band [8].

In a study by Kopparapu *et al.* [9], the influence of different learning platforms on iPad mobile devices was investigated, focusing on program enhancement using the TGAM chip. Poikonen *et al.* [10] explored student attentiveness variations when utilizing three learning platforms: text-based, visual with text, and audiovisual content. Results indicated that students using the text-based platform exhibited the highest concentration levels, with no significant deviation in attentiveness observed across different media formats. However, when students utilized the audiovisual medium for learning, notable differences in concentration levels between proactive and contemplative students were observed. The audiovisual medium has the potential to influence students' attentiveness towards various learning methodologies. Central nervous-based interfaces (CNSIs) represent a continuously advancing area of research that concentrates on motor processes and is pivotal for understanding cognitive capabilities. A significant aspect involves utilizing EEG data to classify information processing during visual tasks. A new technique has been introduced in this context, employing an inter-feed-forward neural network to accurately classify left and right-hand motions [11], [12]. This method offers a promising avenue within CNSIs for efficiently categorizing motor processes using EEG data.

Shaw and Patra [13] introduced a novel approach in the form of a flipped recommender system. Their methodology was grounded in unsupervised learning techniques, specifically clusters-based analysis. In a distinct vein, Alyuz *et al.* [14] proposed a three-parameter analysis encompassing video source attributes, contextual performance metrics, and mouse-related actions during the learning phase. Meshulam *et al.* [15] investigated learning from the perspective of neural alignment. They leveraged alignment data to predict students' final examination performance and to uncover patterns that revealed insights into conceptual learning. In 2014, Brinton *et al.* [16] delved into the intricacies of massive online open courses (MOOCs). Their exploration spanned statistical examination to generative models, enhancing our understanding of social dynamics within these platforms. A unique perspective emerged through [17], who utilized social media and readership metrics to categorize biology preprints.

The realm of cognitive processes is found in the author's work [18], as they explore the disruptive role of mind-wandering in event perception. Ramírez-Moreno *et al.* [19] engaged with EEG signals from university-level students, while Huang *et al.* [20] introduced a technique focused on analyzing knot-tying tasks within a surgical context. Examining online learning and collaboration, Bernard and Rubalcava [21] comprehensively discussed essential components, challenges, and potential future directions. Similarly, Easton [22] compared students and instructors within an open and distance learning environment, noting similarities to traditional classroom teaching methods. Investigations into students' attention levels yielded intriguing insights. Liu *et al.* [23] scrutinized students' attention spans throughout lectures to gauge their learning outcomes. Ke *et al.* [24] introduced a nonlinear parameter-based system for studying attention levels across various scenarios: attention mode, not-in-attention mode, and rest mode. Peng *et al.* [25] delved into states of mind and the depth of attention through EEG data analysis. Delorme [26] analysis centered on optimized preprocessing pipelines and applying models to the well-known open-source EEG platform. These studies collectively contributed to the understanding and assessment of diverse learning activities.

2. METHOD

An innovative online learning assessment system is introduced to gauge the extent of a student's comprehension derived from a lecture video, leveraging EEG signal data analysis. This system is designed to go beyond conventional metrics and delve into the nuanced aspects of a student's learning experience, aiming to provide a more comprehensive evaluation. This cutting-edge approach incorporates neurophysiological data to gain deeper insights into the cognitive processes during the learning experience. The online learning assessment system, enriched with EEG signal data analysis, goes beyond traditional evaluation methods by tapping into the intricate neural activities associated with learning. By monitoring brainwave patterns during the engagement with lecture videos, the system aims to discern levels of attention, comprehension, and cognitive load. This neuroscientific perspective enables a more nuanced understanding of the student's learning journey, providing educators with valuable information about the cognitive mechanisms underlying knowledge absorption. This approach enhances the precision of the assessment and contributes to the broader field of educational technology by bridging the gap between neuroscience and online learning. It aligns with the contemporary need for adaptive and personalized education. It offers a novel dimension to the evaluation process that fosters a more comprehensive understanding of a student's learning outcomes from lecture videos.

The principal components of this system encompass a repository for video lectures, a learning environment equipped with an EEG setup, a component dedicated to the training and selection of an ML model, and a predictive module. The system's architecture is visually depicted in Figure 1. The repository is curated to offer diverse subjects, facilitating comprehensive assessment across different fields of study. The learning environment is enhanced by an EEG setup, allowing the monitoring of brain activity while a student engages with the online lecture. By capturing the brain's electrical signals, this setup offers insights into cognitive responses, helping discern engagement, comprehension, and attention levels. The system's heart comprises a dedicated component responsible for training ML models and selecting the most suitable one. The algorithms are trained on the EEG data collected during learning sessions. The predictive module predicts the degree to which the student has grasped the lecture content using the selected best model.

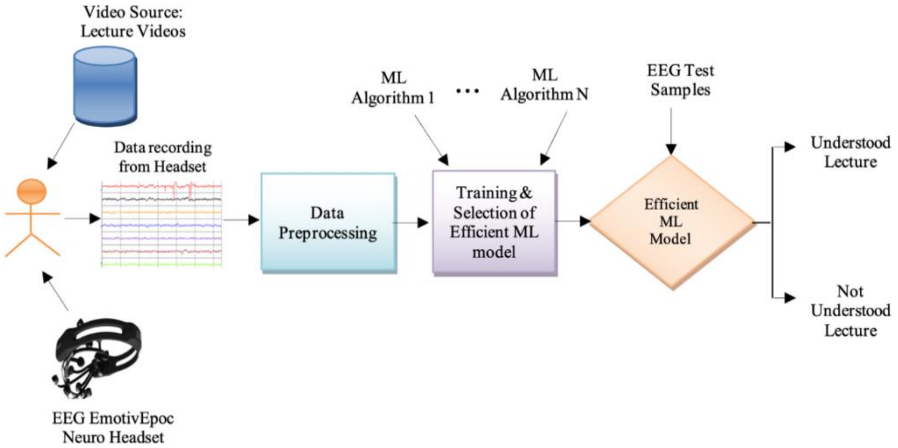

Figure 1. EEG-based online learning prediction framework

2.1. The overall system works in the following three phases

- Learning environment setup: the EEG headset employed in the experiment is the EmotivEpoc_X-14 channel. Students are provided with a series of lecture videos sourced from the video repository. Students wear the sensor-equipped headset during this phase and view an online lecture video.
- Data acquisition: the EEG headset records data by capturing brain waves and EEG signals through its sensors. While students are engrossed in the video content, the headset collects data that is subsequently useful for evaluating their online learning engagement.
- Efficient ML prophecy model: an efficient model is designated to assess the student's learning performance. The selection of this model hinges upon an exhaustive assessment of the performance of numerous classification algorithms across the dataset. Post-evaluation, the most proficient model is chosen. This model is then employed to predict the outcomes of student learning activity using test EEG samples. The model undertakes binary classification, wherein outcomes are categorized as 0 (indicating non-comprehension of the lecture) and 1 (indicating comprehension of the lecture).

2.2. Application of ML algorithms

In the pursuit of developing a highly efficient predictive model for gauging student understanding of online lecture videos through EEG data analysis, a meticulous exploration involving fifteen distinct ML classification algorithms is undertaken. The algorithms encompass a diverse range of methodologies, including AdaBoost (ADA), gradient boosting (GBC), extreme gradient boosting (XGBOOST), light gradient boosting machine (LIGHTGBM), extra trees (ET), random forest (RF), decision tree (DT), KNN, logistic regression (LR), linear discrinant analysis (LDA), RIDGE, Naïve Bayes (NB), dummy, SVM, and quadratic discriminant analysis (QDA), as outlined in Table 1. Applying this varied set of algorithms reflects a comprehensive evaluation strategy to identify the most effective ML algorithm for constructing the predictive model. Rigorous analysis under various performance metrics, including accuracy, Matthews correlation coefficient (MCC), area under the curve (AUC), Kappa, precision, recall, and F1 score, assesses each algorithm's strengths and weaknesses. Subsequently, the top two optimal algorithms are selected for further discussion, shedding light on their specific performance attributes and training time that position them as the most suitable candidates for integration into the proposed system.

Table 1. Performance analysis of the top 15 ML algorithms

	Model (classifier)	Accuracy	ACC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
ADA	AdaBoost	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	21.6480
GBC	Gradient boosting	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	108.216
XGBOOST	Extreme gradient boosting (XGB)	1.0000	1.0000	1.0000	1.0000	1.0000	0.9999	0.9999	23.4680
LIGHTGBM	Light GB machine	1.0000	1.0000	0.9999	1.0000	1.0000	0.9999	0.9999	3.1160
ET	Extra trees	0.9999	1.0000	0.9999	1.0000	0.9999	0.9998	0.9998	3.9580
RF	Random forest	0.9998	1.0000	0.9998	0.9999	0.9999	0.9994	0.9994	24.1570
DT	Decision tree	0.9986	0.9975	0.9993	0.9989	0.9991	0.9957	0.9957	1.7000
KNN	K neighbours	0.9506	0.9769	0.9736	0.9641	0.9689	0.8490	0.8493	4.0620
LR	Logistic regression	0.9100	0.8995	0.9772	0.9147	0.9449	0.7004	0.7122	7.6810
LDA	Linear discriminant analysis	0.8734	0.9221	0.9520	0.8945	0.9224	0.5814	0.5899	1.3330
RIDGE	Ridge	0.8711	0.0000	0.9730	0.8772	0.9226	0.5427	0.5702	0.5060
NB	Naïve Bayes	0.8386	0.6837	0.9814	0.8409	0.9057	0.3678	0.4297	0.3480
DUMMY	Dummy	0.7899	0.5000	1.0000	0.7899	0.8826	0.0000	0.0000	0.6520
SVM	SVM-linear Kernel	0.7793	0.0000	0.8455	0.8883	0.8227	0.3938	0.4515	4.2080
QDA	Quadratic discriminant analysis	0.7261	0.9595	0.6590	0.9913	0.7910	0.4376	0.5213	0.8790

2.2.1. Ada boost algorithm

The terminology "adaptive boosting" is derived from its distinctive feature of dynamically assigning weights to each instance within the dataset. This technique operates on the fundamental principle that learning evolves progressively throughout its iterations. Starting from the second learner in the sequence, each subsequent learner learns from its predecessor, progressively enhancing learners through the algorithm's iterative application. This sequential learning process transforms initially weak learners into stronger ones over time. One noteworthy characteristic of adaptive boosting is its diminished susceptibility to overfitting, a common challenge in ML. This resilience is attributed to its unique mechanism of emphasizing previously misclassified instances, thereby directing the subsequent learners to focus on the areas of difficulty in the dataset. Adaptive boosting achieves more favorable outcomes by elevating the performance of these initially weaker learners through successive iterations and mitigates the risk of overfitting. The ability to adapt and improve iteratively makes adaptive boosting a potent ensemble learning method, particularly effective in scenarios involving complex datasets or varied patterns, as seen in EEG data analysis. Its iterative learning process, emphasizing previously misclassified instances, proves valuable in capturing intricate relationships within EEG signals, making it a robust choice for accurate predictions in neurophysiological data analysis.

Algorithm 1. Ada boost

Step1: Create the 1^{st}Base Learner with minimum GI

$$Gini\ Index(GI) = 1 - (\sum_{k=1}^{m} .\ \ P_k\ )^2$$

Step2: Calculate Overall Error (OE)

OE= ∑ error in classified records for given sample weights

Step3: Calculate the Stump Performance using α

$$\alpha = \frac{1}{2} ln\ ln(1 - OE)/OE$$

Step4: Update Weights for wrongly classified records

New_Sample_Wt = Sample_Wt X e^ (Stump Performance)

Step5: Create a New Dataset using normalized weights

Step6: Repeat the algorithm until all features used as root node once

2.3. Decision tree algorithm

Decision trees are a powerful tool in constructing a hierarchical structure of nodes that encapsulate rules crucial for decision-making processes. This structure involves internal nodes representing features or attributes, branches illustrating regulations based on these features, and leaves denoting the ultimate outcomes or decisions. The iterative data division process within the training set is pivotal in crafting this tree structure, with the division persisting until the tree reaches its maximum depth or satisfies the minimum required sample count, acting as the stopping criteria for the tree-building process. The attractiveness of decision trees lies in their capability to generate comprehensible and interpretable rules, eliminating the need for extensive data preprocessing. The iterative nature of data division allows decision trees to adeptly capture intricate relationships and patterns inherent in the dataset, making them especially well-suited for decision-making scenarios.

3. RESULTS AND DISCUSSION

This section delineates the experimental configuration, providing details on the hardware, software, and procedures involved. It introduces appropriate performance metrics tailored for evaluating the success rate of the classification task and outlines the fair model evaluation process utilized. The results encompass a thorough presentation, incorporating raw data, visual representations, and interpretations across all considered performance metrics to evaluate the proposed model meticulously. The subsequent analysis compares these findings with existing literature, benchmarks, or studies, highlighting the superiority of the proposed model. This comprehensive approach ensures a lucid comprehension of the experiment's methodology, results, and their significance within the field.

3.1. Experimental setup

The development of a proficient model takes place in the Jupyter Notebook environment, utilizing Google Colab. This platform provides a space for seamless model development, experimentation, and analysis. Various Python libraries are enlisted to support this effort, with notable mentions such as NumPy and Pandas, aiding in effective data manipulation and processing. Moreover, the incorporation of Pycaret, a versatile ML library, enhances the efficiency of the model-building process by providing a plethora of tools to automate different stages of the pipeline. However, the crux of the model's efficacy is vested in the classification module, which stands as a cornerstone of this project. This module encapsulates a comprehensive suite of eighteen distinct algorithms tailored explicitly for classification tasks. These algorithms span from traditional methods to advanced ensemble techniques.

3.2. Performance metrics

In assessing the model's performance in ML, the following crucial classification metrics are utilized as benchmarks to measure effectiveness and accuracy in handling classification tasks. These selected metrics offer insights into diverse aspects of the model's performance, such as its ability to accurately identify and categorize different classes.

Accuracy(A): it compares the proportion of properly classified instances to all the instances as given in (1), where α: true positive, β: true negative, γ: false positive, Ω: false negative.

$$A = \frac{\alpha + \beta}{\alpha + \beta + \gamma + \Omega} \quad (1)$$

Precision (P): it is 1.0 for an elite model. This occurs when γ in (2) becomes zero.

$$P = \frac{\alpha}{\alpha + \gamma} \quad (2)$$

Recall (R): its decent score is 1.0, this occurs when Ω in (3) becomes zero.

$$R = \frac{\alpha}{\alpha + \Omega} \quad (3)$$

F1-score (F): it is 1.0 for the ideal case, which occurs when P and R become one in (4).

$$F = 2 * \frac{P * R}{P + R} \quad (4)$$

AUC-ROC (AUC): it measures the ability of a classifier to separate instances between the classes, which given in (5).

$$AUC = \int \frac{\alpha}{(\alpha + \Omega)} d\left(\frac{\gamma}{\gamma + \beta}\right) \quad (5)$$

Kappa (K): it measures inter-rater level of agreement, its formula is given in (6), where P_{obs}: agreement probability, P_{hyp}: random agreement probability:

$$K = \frac{P_{obs - P_{hyp}}}{1 - P_{hyp}} \quad (6)$$

MCC: calculate or quantify the discrepancy between the actual versus predicted values as given in (7).

$$MCC = \frac{\alpha * \beta - \gamma * \Omega}{\sqrt{(\alpha + \gamma)(\alpha + \Omega)(\beta + \gamma)(\beta + \Omega)}} \quad (7)$$

3.3. Results discussion

The model evaluation process uses StratifiedKFold cross validator with a 70-30 train-test split to ensure a fair and unbiased assessment. Seven metrics and training time are analyzed using fifteen different ML classifiers to choose an efficient model displayed in Table 1. It is noticed that seven algorithms (ADA, GBC, XGBOOST, LIGHTGBM, ET, RF, DT) exhibited nearly 1.0 accuracy but with varied training time. Its remarkable accuracy was obtained over a large dataset with 68,831 samples and 87 features. Next, these algorithms are analyzed over other vital metrics, which are AUC, precision, recall, Kappa, F1, and MCC; it is observed that all these seven classifiers reported outstanding performance. DT has taken less time, i.e., 1.7 seconds for training. Hence, it is considered an efficient model. It is further analyzed over ten times and predicts a test sample. Next, the decision boundary of target classes is studied, depicted in Figure 2. Only a little disturbance was noticed when reporting the best classifying performance. The classifier performance is compared in the training and testing phases, and both training and validation curves are much closer, as shown in Figure 3.

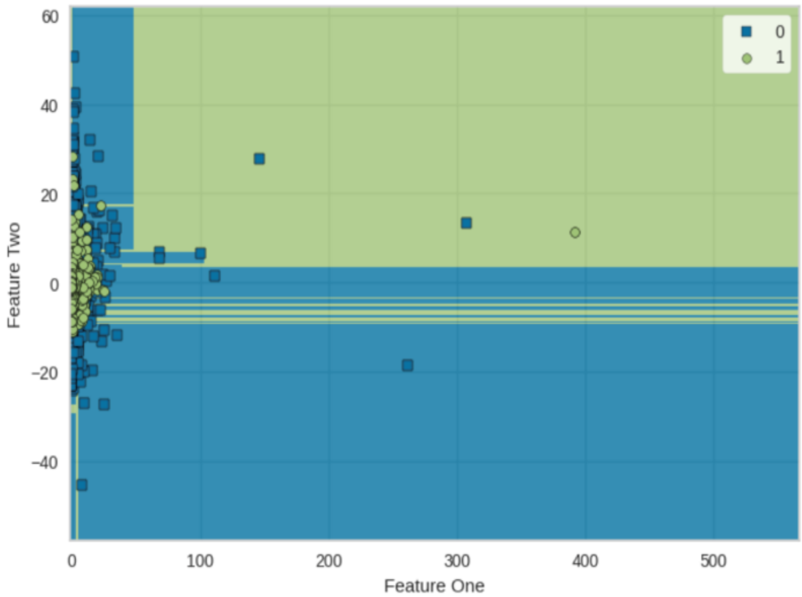

Figure 2. Decision boundary

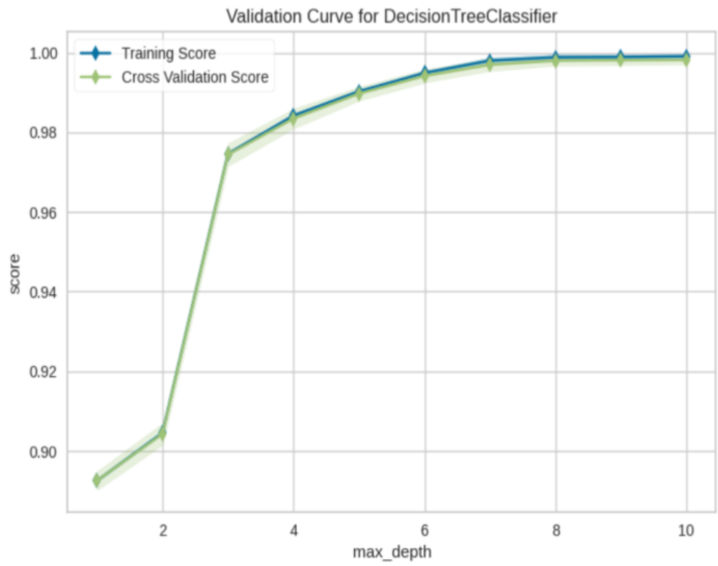

Figure 3. Validation curve

3.4. Comparative analysis

Contemporary predictive models designed based on EEG data are studied and compared with the proposed model. In contrast to many existing systems predominantly relying on SVM, the proposed method employing the DT classifier demonstrates superior performance. A detailed comparative analysis is presented in Table 2. Notably, decision trees exhibit a significant advantage in the preprocessing phase, requiring less data preparation effort than SVM. For extensive datasets, SVM's performance diminishes, especially when dealing with noisy data and overlapping target labels. Unlike SVM, which depends on kernels to address non-linear problems, the DT approach navigates these challenges by constructing hyper-rectangles within the input space. Consequently, when juxtaposed with SVM, the DT algorithm emerges as a proficient choice, excelling in handling categorical values and addressing collinearity concerns.

Table 2. Comparative analysis of the proposed model with state-of-art models

Reference	Algorithm employed	Accuracy as metric
Liu *et al.* (2013) [23]	SVM	76.8%
Ke *et al.* (2014) [24]	SVM	85.2%
Peng *et al.* (2020) [25]	SVM	84.8%
Zhang *et al.* (2021) [27]	SVM and BP	71.2%
Apicella *et al.* (2022) [28]	Filter bank, common spatial pattern, and SVM	77.0%
Proposed method	DT	99.9%

4. CONCLUSION

This paper undertakes a systematic approach that commences with EEG data analysis and extends to the meticulous fine-tuning of hyperparameters for the chosen optimal model. Identifying missing values within the dataset prompts the utilization of suitable imputation techniques, resulting in discernible enhancements in the model's performance. The pursuit of an adept classifier involves the implementation of fifteen distinct ML algorithms. A comprehensive evaluation ensues across seven distinct metrics, thoroughly examining their performance. Notably, boosting algorithms demonstrate promising outcomes, including ADA, gradient, and extreme gradient. However, these algorithms exhibit extended training times. In contrast, the DT algorithm exhibits extraordinary results, nearly reaching perfection across all metrics. Impressively, it accomplishes this feat within an astonishingly brief training duration of merely 1.7 seconds. This remarkable performance observed in a large EEG dataset comprising dimensions (68831, 87) positions the DT as a compelling contender for an efficient model within the online learning evaluation system. Considering the trajectory ahead, using ML algorithms on EEG data recordings bears substantial potential for unraveling diverse facets of human behavior in various contexts. This hints at the broader applicability and significance of the approach in understanding human cognitive processes and behavior in the future.

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