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A Machine Learning Framework for Classroom EEG Recording Classification: Unveiling Learning-Style Patterns

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Abstract: Classroom EEG recordings classification has the capacity to significantly enhance comprehension and learning by revealing complex neural patterns linked to various cognitive processes. Electroencephalography (EEG) in academic settings allows researchers to study brain activity while students are in class, revealing learning preferences. The purpose of this study was to develop a machine learning framework to automatically classify different learning-style EEG patterns in real classroom environments. Method: In this study, a set of EEG features was investigated, including statistical features, fractal dimension, higher-order spectra, entropy, and a combination of all sets. Three different machine learning classifiers, random forest (RF), K-nearest neighbor (KNN), and multilayer perceptron (MLP), were used to evaluate the performance. The proposed framework was evaluated on the real classroom EEG dataset, involving EEG recordings featuring different teaching blocks: reading, discussion, lecture, and video. *Results:* The findings revealed that statistical features are the most sensitive feature metric in distinguishing learning patterns from EEG. The statistical features and RF classifier method tested in this study achieved an overall best average accuracy of 78.45% when estimated by fivefold cross-validation. Conclusions: Our results suggest that EEG time domain statistics have a substantial role and are more reliable for internal state classification. This study might be used to highlight the importance of using EEG signals in the education context, opening the path for educational automation research and development.

Keywords: classroom EEG; academic; learning style; cross-validation; statistical measurements; automation; comprehensive; EEG recordings

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1. Introduction

Within the constantly developing domain of educational research and cognitive neuroscience, the incorporation of cutting-edge technologies has emerged as a critical factor in elucidating the complexities of the human brain's involvement in the learning process. Electroencephalography (EEG) stands out among these technologies as a potent and non-intrusive method for capturing neural activity in real-time [1]. It offers unique insights into the cognitive processes that occur in reaction to diverse stimuli. In the field of education, the integration of EEG recordings into the classroom environment signifies a fundamental change [2,3], providing an unprecedented opportunity to investigate the complex relationship between varied learning styles and neural patterns.

In recent years, several research works have been published on assessing learners' behavior in distance/online learning. Distance/online education has become more important during COVID-19, and plenty of courses in the latest technology have been offered online. Based on the EEG signals collected from 100 individuals, the authors proposed a decision support system to understand learners' attention behavior [4]. Nevertheless, they only studied binary classes (attentive/inattentive) and found that Support Vector Machines (SVMs) predicted attention better than other machine learning algorithms (91.68%). A recent study used 128 channel EEG signals to classify 34 university students' learning styles (learning and memory retrieval) using three types of deep learning models, including Long Short-Term Memory (LSTM), convolutional neural network (CNN), and Fully CNN (LSTM-FCNN). The authors reported a maximum mean accuracy of 94% for LSTM-CNN, which is more efficient than other DL models. In their earlier studies, the same researchers used frequency domain and time–frequency domain analyses and ML classifiers to classify visual and non-visual learners based on their alpha- and gamma-band EEGs [5]. Zhang et al. utilized EEG signals features extracted from 14 university students to classify their learning styles based on Felder–Silverman's processing dimension theory and achieved a maximum precision of 69.8% with an accuracy of 71.2% utilizing deep convolutional neural network [DCNN] [6]. In the study, [7] analyzed EEG signals to classify the learning styles of learners based on their IQ and stress levels. It was found that alpha-band EEG was more effective in distinguishing learning styles between IQ and stress tests.

Innovative methodologies have been made possible by developments in neuroscience research to examine the ways in which the brain facilitates dynamic social interactions in the real world. For instance, academics have initiated investigations into the neurological foundations of social interactions through the comparison of brain activity exhibited by numerous individuals across a range of semi-naturalistic tasks [3,8]. Brain synchrony and comprehension, as well as the predictability of an individual's communicative action, have been correlated in studies involving turn-taking in gestural communication. Significantly, additional research has demonstrated that intricate visual and auditory stimuli (such as natural films) provoke comparable neural activity and affective reactions in observers [9–12], and that these responses differ significantly according to the attentional engagement of the participants. In addition to demonstrating a correlation between synchrony at the neural and motoric levels, scanning neuroscience research has also demonstrated that the relationship between social factors and brain-to-brain synchrony is moderated by face-to-face interactions [13–15]. Joint action tasks reveal that increased sentiments of affiliation and social cohesion result from synchronous motor activity among interactive participants [16]; this is especially true in cooperative contexts as opposed to competitive ones, and this is reflected at the neural level.

Under semi-controlled conditions, the classroom is an ideal location for systematically investigating group interactions—such as those between students and their teacher while measuring cognitive and behavioral outcomes (e.g., student engagement and academic performance). It has been demonstrated that the dynamic interaction between a teacher and a group of students influences both student engagement and academic achievement, which are both fundamental to classroom learning [17,18]. Instruction and knowledge acquisition can be perceived as a collaborative effort involving both the instructor and the learners, in which aspects of the interactive companion and the activity are evaluated as stimuli in a two-way exchange. Exploring the neural activity that lies beneath student–teacher relationship exchanges in the classroom could help in comprehending and predicting educational outcomes from both the student's and the teacher's perspectives, according to research. In a recent study [19], researchers recorded nine students concurrently using portable EEG equipment in the classroom while they watched a natural movie. The results of these experiments were replicated from laboratory-based designs using commercial-grade equipment, showcasing the feasibility of applying such equipment to measure students' attentional engagement in real-world scenarios.

However, most of the existing research is limited by several drawbacks, as studies frequently neglect to examine social behavior in naturalistic settings, are routinely restricted to dyads, and fail to investigate social dynamics over time. To identify neural markers of group engagement during dynamic real-world group interactions, this research study [20] presents experiments that significantly transcend pairs and laboratory boundaries. They assessed the brain activity of 12 high school pupils throughout an entire semester (11 classes) during routine classroom activities using a portable electroencephalogram (EEG). Student class engagement and social dynamics can be predicted by the degree to which brain activity is synchronized across students [20], according to a novel analysis technique for evaluating group-based neural coherence.

Machine learning and deep learning have indeed gained significant popularity in signal processing domains such as PPG (photoplethysmography) [21,22], electrocardiogram [23], and EEG [24] analysis. Utilizing the multiple signal classification (MUSIC) model to extract features from multichannel EEG signals in an effective way, ref. [25] addresses the computational challenges associated with emotion recognition based on EEG. The research aims to enhance the efficiency of emotional state classification through the adjustment of MUSIC parameters to identify discriminative features.

Understanding a student's learning style is crucial for effective teaching, as it enables educators to tailor instructional methods to individual needs. Learning styles refer to the preferred ways in which students absorb, process, and retain information. By recognizing these preferences, teachers can design lesson plans that align with students' natural tendencies, thereby enhancing engagement, comprehension, and retention. This study aims to explore EEG data collected from real classrooms to assess the discriminative power of EEG in identifying different learning styles using machine learning. The key contributions of this work are as follows:

- First comprehensive ML framework: This study introduces the first comprehensive machine learning (ML) framework that utilizes EEG data from real classroom environments to examine the discriminative power of EEG in distinguishing different learning styles.
- Effective use of real-world data: The proposed ML framework demonstrates that EEG data from real-world classroom settings can be effectively used for the classification of different learning styles, highlighting the practical applicability of this approach.
- Advancement of Personalized Learning: By leveraging real classroom EEG data, the study advances the field of personalized learning, providing a potential pathway for creating more tailored educational experiences based on individual cognitive patterns.

The following sections are structured in the paper: Section 2 presents an extensive review of the relevant literature, with particular attention given to the substantial advancements that have occurred in this domain. A comprehensive dataset, methodology, and phased implementation summary are presented in Section 3. The comprehensive analysis and discussion of the study's results can be found in Section 4. Section 5 provides a summary of the primary study results.

2. Related Works

Frequently adapting to technological developments, higher education continues to provide students with educational instruction of the highest standard. The contribution of information technologies to modern education is significant, as a variety of technological resources can be utilized to deliver instruction using a variety of instructional methods [26].

The implementation of EEG signal analysis offers promising instruments for assessing and forecasting individualized cognitive characteristics in students, thereby providing a quantitative understanding of educational achievements. By analyzing EEG bands with high and low frequencies, it is possible to obtain information regarding the continuous cognitive processes of students while they are learning. The identification of alertness, active thought, attention, and multisensory processing states is facilitated by high-frequency bands [27]. Analyses of EEG signals to forecast intelligence and ability in children were reported in ref. [28]. The use of EEG spectral characteristics to identify mathematically gifted individuals was the subject of the study [28]. In the past, the mean score of the cohort was the standard for classifying students as gifted in this research. Mental load, attention, and relaxation were the three internal states for which the EEG apparatus designated epochs of the recording. The characteristics of these internal states that were classified as gifted according to the previously mentioned criteria were utilized as inputs for machine learning models: mean, median, standard deviation, minimum, and maximum values. The result shows that 76.00 of ability classifications were achieved for the optimal machine learning model. In another study, a simultaneous EEG recording of twelve students was conducted in the classroom over the course of eleven classes during the semester [20]. In addition to pleasure metrics, EEG synchronization metrics between the students and the instructor were computed. The study's findings revealed a correlation between the EEG metrics and both student performance and class enjoyment. The findings of these studies indicated that the classification and prediction of cognitive performance may be feasible through the analysis of EEG measurements. Sleep-deprived adolescents demonstrate diminished cognitive performance and increased levels of morning lethargy, according to research [29]. Adolescents, by an unfortunate coincidence, dedicate a considerable portion of their mornings to the task of retaining information. An active debate regarding secondary school commencement times has resulted from this. Indeed, it appears that even a 50 min delay in school start times has a substantial positive impact on student academic performance [30].

Comparing the EEG data collected during cognitive assessments in an actual classroom setting versus an identical virtual classroom was the focus of a prior investigation conducted by [31]. Between the actual and virtual environments, the results indicated that the frequency band-power of the EEG did not differ significantly. The initial findings suggested that immersive virtual reality (VR) technologies of the present day with high resolution may serve as a suitable surrogate for approximating neural responses to tangible, in-person architectural design elements [32]. A recent investigation [33] showcased the application of the attention monitoring and alarm method (AMAM), a neurofeedback instrument that analyzes the neural activity of students to perpetually monitor their attention throughout e-learning sessions. Students who utilized EEG devices were given attention-level feedback in an effort to assist them in refocusing during study sessions. The findings of the research demonstrated that the group utilizing the AMAM exhibited superior sustained attention and learning performance in comparison to the control group that did not utilize it. In another recent study [34], researchers recorded the attentional engagement of nine students concurrently while watching a natural movie using portable EEG equipment in the classroom. The results of these experiments were replicated using commercial-grade equipment and mirrored the findings from laboratory-based experimental designs, showcasing the feasibility of measuring students' attentional engagement in the real world. Brain-to-brain synchrony [35], also known as interbrain coherence or total interdependence [TI], among students during class activities was correlated with student engagement and classroom social dynamics, according to additional recent classroom-based research that served as the basis for the present study.

According to another study [20], students exhibited greater group affinity, focus, and empathy when their preferred teaching method (e.g., video) was utilized as opposed to the lecture method. Furthermore, the results pertaining to group social dynamics lend validity to the concept that the presence of other students modifies synchrony among students in the classroom. Students who participated in prelesson face-to-face baseline recordings exhibited the greatest pairwise synchrony during class with their mutual gaze partner, in contrast to other randomly selected students in the group [20]. Additionally, higher student ratings of their teacher were associated with a narrower disparity between video conditions (in which the teacher was not involved) and lecture conditions (in which the teacher was central). In conjunction with (i) stimulus properties, (ii) individual variances, and (iii) social dynamics, their findings indicate that brain-to-brain synchrony is dictated by all three. A self-study task-related EEG instrument that provides students with feedback regarding their level of attention was implemented in [36]. As student feedback, the utilized EEG apparatus generated an attention index; auditory feedback was delivered when the attention index dropped below a predetermined threshold. The experiments were conducted with two groups: one experimental and one control. The experimental group was provided with feedback, while the control group was not. The experimental group exhibited a greater duration of attentive periods as indicated by the results.

3. Materials and Methods

The following section outlines the EEG data used in this study and the methodological approach utilized to achieve the stated objectives of the study, which aims to establish a framework for classifying classroom EEG recording in relation to learning patterns. Figure 1 provides an illustration of the overall methods used to automatically classify different learning-style EEG patterns in real classroom environments.

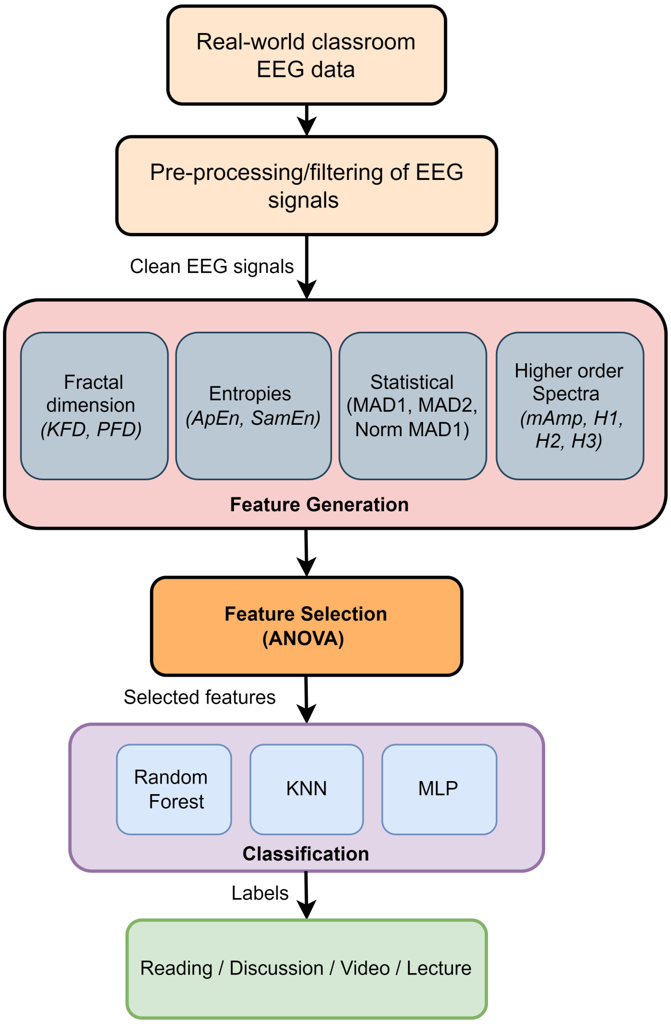


Figure 1. Flowchart of the proposed machine learning framework to classify classroom EEG recordings.

3.1. Dataset Description

The dataset employed in this research was constructed by Dikker et al. [20] in 2020 as described in their Social Cognitive and Affective Neuroscience article "Morning brain: real-world neural evidence that high school times matter" (pp. 1193–1202). According to the findings of Dikker et al. [20], learning may be most effective during the mid-morning window. To examine this, they deliberately opted for EEG recordings collected from 12 students during regular biology classes on weekday mornings (see Figure 2). The duration of these classes was seventeen days, and they were conducted at 10:30 a.m. Each original dataset contained four sessions of EEG recordings. Every session consisted of four discrete teaching blocks, with each block lasting between two and five minutes: “reading” sessions led by the instructor, “video” sessions involving educational video viewing, “lecture” sessions led by the instructor, and “discussion” sessions involving group discussions. The total number of recorded days in the original dataset varied significantly among the teaching blocks: 5 days were allocated for reading, 11 days were devoted to video, 5 days were devoted to lecture, and 11 days were dedicated to discussion. The EEG signals were recorded from 14 channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4) using the wireless Emotiv EPOC+ (Emotive Systems, Inc., San Francisco, CA, USA) neuro headset with sampling frequency of 128 Hz. The process of this data collection and the details about the available segments are presented in Figure 3 and Table 1, respectively.

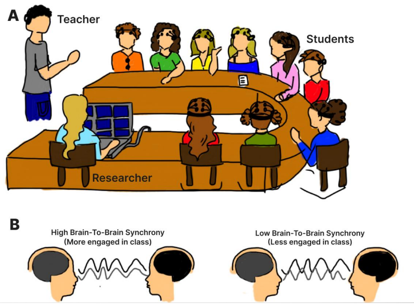


Figure 2. (**A**) Students’ brain waves can be measured using EEG in a high school classroom from Dikker et al. [20] and (**B**) the brain waves of students can exhibit rapid synchronization with those of their peers, a phenomenon observed in more engaged students (**left**). A lack of synchronicity with their peers (**right**) was observed among less engaged students.

Table 1. The table contains a summary of the dataset, details about the sessions conducted, and the available and used segments. To create a balanced class problem, we select a random subset of the available segments. The subset size is equal to the method with the fewest segments, reading (2284).

Method	Number of Sessions	Available Segments	Used Segments
Reading	2	2284	2284
Discussion	4	6842	2284
Lecture	2	2749	2284
Video	4	5777	2284
Total	-	19,855	9136

The subjects of this study were 12 healthy high school students in their senior year (9 females and 3 males, aged 17–18) with no known history of neurological disease. Regrettably, this study dataset lacked EEG recordings pertaining to students 7 and 12. The analysis was therefore performed on EEG recordings obtained from a sample of ten students. In addition, certain mid-morning session recordings were missing from the dataset, specifically, four sessions for discussion, two sessions for reading, and two sessions for video. Comprehending the complexities of dataset composition is crucial for grasping the context and constraints of this research, given that they influence the availability and comprehensiveness of the EEG data utilized in the training and evaluation of the proposed machine learning framework.

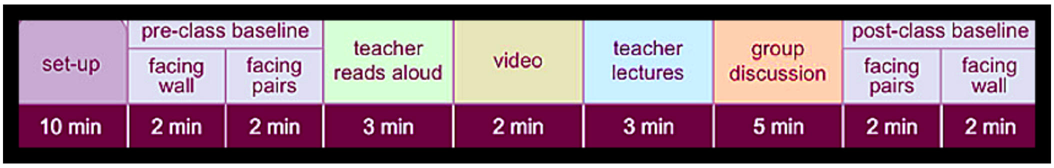


Figure 3. Figure from Dikker et al. [20], explaining the setup of the data collection process. Data for the four methods are taken for this study, which includes 'teacher reads aloud', 'video', teacher lectures', and 'group discussion'. The respective session time for each method is also mentioned in the figure.

3.2. Data Preprocessing

Data preprocessing encompassed several critical stages to safeguard the quality and integrity of the EEG recordings. The original dataset included epoched EEG signals that had already been segmented according to different learning conditions. In this study, the raw EEG signals were filtered using an infinite impulse response (IIR) Butterworth bandpass filter (4th order) with a cutoff frequency of 1–49 Hz. The cutoff frequency range of 1–49 Hz was chosen to effectively eliminate low-frequency noise, such as drift and movement artifacts, as well as high-frequency noise, including power line interference at 50/60 Hz. Following that, to improve the spatial resolution, a common average reference (CAR) was implemented. To facilitate analysis, the data were subsequently divided into 2 s epochs. To reduce the likelihood of encountering artifacts, an automated artifact rejection system was integrated. This system eliminated segments containing data that exceeded ±100 microvolts, with particular attention given to eye-blink artifacts. Following an extensive preprocessing stage, a grand total of 2284 artifact-free segments were preserved for further examination. This refined and immaculate dataset was utilized to extract features and classify classroom EEG recordings according to learning styles.

3.3. Feature Extraction

The objective of the feature extraction procedure was to comprehensively collect a wide array of properties from EEG signals to enable detailed analysis, thereby diving into their complicated character. By incorporating a wide range of feature categories, the proposed methodology sought to precisely represent the complex information that is inherent in the neural data. The selection of each category was conducted with great attention to offer a comprehensive comprehension of the implicit patterns present in the EEG recordings.

i Statistical features
Within the field of statistical characteristics, this study employed techniques that go beyond simply evaluating components of the EEG signal, delving into the complexities of signal dynamics [37]. The following approach permitted us to determine the statistical characteristics of the signal.

- The mean of absolute values of 1st difference (MAD): This feature provides two important functions: it measures the average of the absolute values of differences between consecutive data points and illuminates the dynamic character of the neural activity by indicating the signal variability:

$$\text{MAD1} = \frac{1}{N-1}\sum_{i=1}^{N-1}|x_{i+1} - x_i| \quad (1)$$

- The mean of absolute values of 2nd difference (MAD2): This is a metric that offers a nuanced perspective of the underlying neural processes by determining signal smoothness and trend information through the calculation of the average of absolute values of second-order differences:

$$\mathrm{MAD}_2 = \frac{1}{N-2}\sum_{i=1}^{N-2}|x_{i+2} - x_i| \tag{2}$$

- The utilization of the normalized 1st difference (NMAD): Normalizing the 1st difference enhances the interpretability of amplitude fluctuations in EEG signals by one dimension, thereby facilitating a more nuanced comprehension of amplitude changes throughout the recorded epochs:

$$\mathrm{NMAD} = \frac{\mathrm{MAD}_1}{\max(\mathrm{MAD}_1)} \tag{3}$$

where N represents the total number of EEG samples.

ii Fractal dimension features
The fractal dimension (FD) characteristics are of the utmost importance in our methodological endeavor to comprehend and describe the intricate dynamics that are intrinsic in EEG signals [38]. The phrase "fractal dimension" encompasses the intrinsic irregularities, complexities, and self-replicating qualities that are present in neural activity patterns that encompass multiple dimensions. In this study, we considered Katz and Petrosian FD algorithms, which are commonly used for EEG analysis [39].

- Katz Fractal Dimension (KFD): This is a critical metric utilized in our feature extraction procedure to decipher the complex characteristics of EEG signals. KFD plays a crucial role in the characterization of the EEG waveform's inherent irregularity and complexity [40]. Through the evaluation of the signal's self-similarity at various scales, KFD offers a more intricate understanding of the neural dynamics at play. The significance of this dimensionality measure increases significantly when it comes to capturing the various irregularities and patterns that could potentially signify differences in learning styles within EEG recordings from the classroom:

$$\mathrm{KFD} = \frac{log(N)}{log(\frac{d}{L}) + log(N)}, \text{where d is Euclidean distance} \tag{4}$$

- Petrosian Fractal Dimension (PFD): This provides an additional level of understanding regarding the intricacy of the EEG waveform, serving as a complementary component to the KFD. PFD, in its capacity as an indicator of signal irregularity, examines the intricate intricacies of the EEG signal, thereby capturing a broader range of details than conventional measures. By adding a significant dimension to our feature set, this metric becomes particularly relevant when distinguishing irregular patterns in neural activity. By incorporating PFD, our comprehension of complex neural mechanisms is enhanced, thereby bolstering the capability of our machine learning framework to accurately classify classroom EEG recordings according to individual learning styles:

$$\mathrm{PFD} = \frac{log(N)}{log(\frac{N}{N+0.4*N_{zero-crossings}})} \tag{5}$$

iii Higher-Order Spectral Features
Higher-order spectral (HOS) features are an essential component in the investigation of EEG signal characteristics, as they offer a more profound understanding of the complex dynamics of neural activity [41,42]. In contrast to conventional spectral analysis, higher-order spectra provide a more intricate viewpoint through the inclusion of phase couplings and non-linear interactions among distinct frequency components.

By revealing concealed intricacies in EEG signals, this class of characteristics proves indispensable for enhancing our comprehension of the neural mechanisms that underlay variations in learning styles within an educational environment.

- Bispectrum Magnitude (mAmp): The Bispectrum Magnitude (mAmp) is an essential metric in our feature extraction collection, providing valuable insights into the complex dynamics of EEG signals [43]. By displaying the magnitude of the bispectrum explicitly, this characteristic offers insight into the phase coupling that occurs among various frequency components. Through an examination of the interconnections among these elements, the mAmp function emerges as a pivotal factor in comprehending the non-linear dynamics intrinsic in the neural activity captured during instructional sessions.
- Summation of the Bispectrum Logarithmic Amplitudes Summation (H1): This enhances our set of features by encompassing the logarithmic amplitudes of the bispectrum. By acting as a perceptive lens, this characteristic reveals non-linearities that are concealed within the EEG signal. By employing logarithmic transformation, a more intricate viewpoint can be introduced, facilitating the recognition and analysis of intricate patterns that might serve as indicators of unique learning-style attributes.
- Summation of the Bispectrum Logarithmic Amplitudes of Diagonal Elements (H2): The bispectrum logarithmic amplitudes of diagonal elements summation (H2) enhances the comprehensiveness of our analysis by placing particular emphasis on the diagonal elements comprising the bispectrum. This functionality furnishes valuable insights into the precise interrelationships among frequency components, thereby facilitating a comprehensive comprehension of the distinctive spectral attributes inherent in the EEG recordings. By augmenting the interpretability of neural dynamics, the H2 feature fortifies the resilience of our machine learning framework.
- The 1st order moment of amplitudes of the spectral waves of diagonal elements of the bispectrum (H3): An analysis of the amplitude distribution within the bispectrum is conducted in the 1st Order Spectral Moment of Amplitudes of Diagonal Elements of the Bispectrum (H3) [44]. This functionality provides significant insights into the spectral composition of the EEG signal by presenting valuable information regarding its characteristics. H3 enhances our feature set by characterizing the distribution of amplitudes, thereby making a valuable contribution to the comprehensive comprehension of the neural processes documented in classroom EEG recordings.

iv Entropy features

Entropy features are highly influential metrics within the domain of EEG signal analysis, providing a distinctive viewpoint on the intricacy and consistency of neural activity. Entropy, an information theory-derived concept, offers a quantitative quantification of the disorder, uncertainty, and inconsistency present in a signal. In this study, the entropy feature set includes the approximate and sample entropy; these entropies are explained below.

- Approximate entropy (AE): The approximation entropy (AE) is an essential parameter for quantifying the unpredictability or irregularity of the electroencephalogram (EEG) signal [45]. The degree to which patterns within the signal repeat or remain consistent over time is quantified by AE. An elevated AE value indicates heightened intricacy, which corresponds to a more diverse and uncertain neural activity environment. Therefore, AE assumes a crucial role in identifying mild irregularities that could potentially serve as indicators of differences in learning styles:

$$AE(m,r) = -log(\frac{C_m(r)}{C_{m+1}(r)}) \quad (6)$$

- Sample entropy (SE): This serves as a complementary metric to AE, quantifying the degree of similarity that exists between subsequences contained within the EEG signal. SE offers valuable insights into the degree of regularity or repetition exhibited by patterns in neural activity. A reduced SE value indicates a higher degree of regularity, emphasizing occurrences in which particular patterns are more prone to recurrence. By quantifying the degree of regularity in the EEG signal, SE enhances our comprehension of the neural dynamics' stable and recurring components

$$SE(m, r) = -log(\frac{A_m(r)}{A_{m+1}(r)}) \tag{7}$$

3.4. Feature Selection Using ANOVA

The developed machine learning model's fine-tuning depends on feature options. Using ANOVA (analyses of variance), a rigorous statistical procedure, we refined this study feature set. ANOVA is successful in identifying and selecting EEG variables that significantly differentiate learning styles [46]. ANOVA [47] is used to examine the distribution of feature values across classes, discovering characteristics with significant differences that may be used to categorize learning styles. In this study, ANOVA was used to find discriminative traits that reveal important brain processes underpinning classroom learning styles. Since they comprise the most relevant data for distinguishing EEG signal-based learning approaches, the selected features improve the classification model. This feature selection approach boosts model performance and interpretability by selectively picking features. Thus, cognitive processes in the ever-changing classroom may be better characterized. ANOVA improves the statistical rigor of the feature selection procedure and ensures that the selected features are statistically significant and can detect learning-style differences in classroom EEG recordings. Statistical significance was defined as p-value < 0.05.

3.5. Learning-Style Classification

Three well-known classification techniques, random forest (RF), K-nearest neighbor (KNN), and multilayer perceptron (MLP), were applied and evaluated for EEG signal classification under various conditions, including reading, lecture, discussion, and video viewing using each EEG feature set described above, as well as a combination of all feature sets.

Random forest: The random forest (RF) classifier functions as a meta-estimator, in which several decision tree classifiers are fitted to different subsamples of the dataset [39]. By averaging the results, the RF classifier enhances predictive accuracy and mitigates the issue of overfitting. The machine learning algorithm is highly durable and is capable of effectively managing classification and regression tasks. The number of trees in the forest, the maximum depth of each tree, the minimum number of samples needed to divide an internal node, and additional factors may be among the optimized parameters for RF.

K-nearest neighbors: The K-nearest neighbors (KNN) algorithm is a refined and user-friendly machine learning technique utilized to address problems involving classification and regression [48]. KNN utilizes the principle of similarity to forecast the label or value of a novel data point by considering its K-nearest neighbors from the training dataset. The optimized KNN parameters may consist of, among other things, the distance metric employed and the quantity of neighbors to be considered.

Multilayer perceptron: The multilayer perceptron (MLP) classifier falls under the category of feedforward artificial neural networks [49]. The architecture comprises a minimum of three node layers and employs a non-linear activation function. MLP is an algorithm for supervised learning in which a function is learned through training on a dataset. The number of hidden neurons, the type of activation function, the solver for weight optimization, and additional factors may be among the optimized parameters for MLP.

3.6. Learning-Style Classification-Performance Evaluation

In this study, standard performance metrics, such as accuracy, precision, recall, F1-score, and area under the curve (AUC), were employed to assess the performance of the classifiers in differentiating EEG recordings from reading, lecture, discussion, and discussion. To obtain consistent recognition performance, fivefold cross-validation was employed in this study. For fivefold cross-validation, the features were randomly divided into five relatively equal subsets (folds). Four out of the five subsets were then used for model training, while the fifth subset was used for evaluation. This fivefold process was performed five times so that each fold was used as a test set, resulting in five classifier accuracy scores for each feature set classification method. To evaluate the overall classification performance, the average and the standard deviation (SD) of the final metrics were computed across the five folds. The cross-validation was conducted in a manner that preserved the independence of student trials across folds, ensuring that data from the same student did not appear in both the training and testing folds simultaneously. This strategy helped in obtaining reliable estimates of the model's performance and in selecting the optimal hyperparameters without compromising the model's ability to generalize to unseen data.

3.7. EEG Scalp Topography Related to Learning Style

In this study, the topographical distributions for each learning style were generated based on the feature set that achieved the best classification performance. To ensure comparability across features, each statistical feature was normalized using a z-score, which standardizes the data by subtracting the mean and dividing by the standard deviation. This normalization process allowed us to account for differences in scale and variability across features. The normalized features were then used to create topographical maps, which visually represent the spatial distribution of these features across the scalp. These maps provided insights into the distinct EEG patterns associated with different learning styles, highlighting the regions of the brain that are most active or significant for each style. In addition, two-tailed paired-sample *t*-tests were used to explore the pair-wise comparisons of different learning styles' significance.

4. Results and Discussion

The statistical significance and variability of various EEG features during distinct cognitive tasks (reading, discussion, lecture, and video) are comprehensively examined in Figure 4. A one-way ANOVA test was conducted to assess the effectiveness of features in differentiating between teaching methods. Features with p-values < 0.05 are highlighted, and their corresponding F-values indicate the strength of their discriminative power. There are statistically significant differences ($p < 0.001$) between MAD1, MAD2, and NMAD1, suggesting that the EEG signals exhibit differing levels of dispersion throughout the various activities. Significant differences are highlighted by the high F-values associated with these characteristics (836.89, 744.59, and 719.29, respectively). The KFD and PFD features demonstrate substantial differences ($p < 0.001$) in their respective F-values of 1577.9 and 1079.3, which emphasize the non-linear complexity of the underlying brain activity captured by FD. Significant variations in mAmp, H1, H2, and H3 are observed ($p < 0.0001$, F-value: 81.71, 1395.26, 1353.21, 1507.48, respectively), indicating that cognitive tasks possess unique spectral amplitude properties. Entropy measures, namely, AE, and SE, exhibit substantial F-values (671.66 and 544.83) that indicate significant differences ($p < 0.001$). These differences underscore the varied patterns of regularity and complexity observed in EEG signals throughout cognitive activities. In brief, the ANOVA results underscore the intricate character of neural reactions, illuminating the distinct EEG characteristics that distinguish cognitive initiatives, and furnishing significant data for comprehending cerebral intricacies through participation in reading, discussion, lecture, and video.

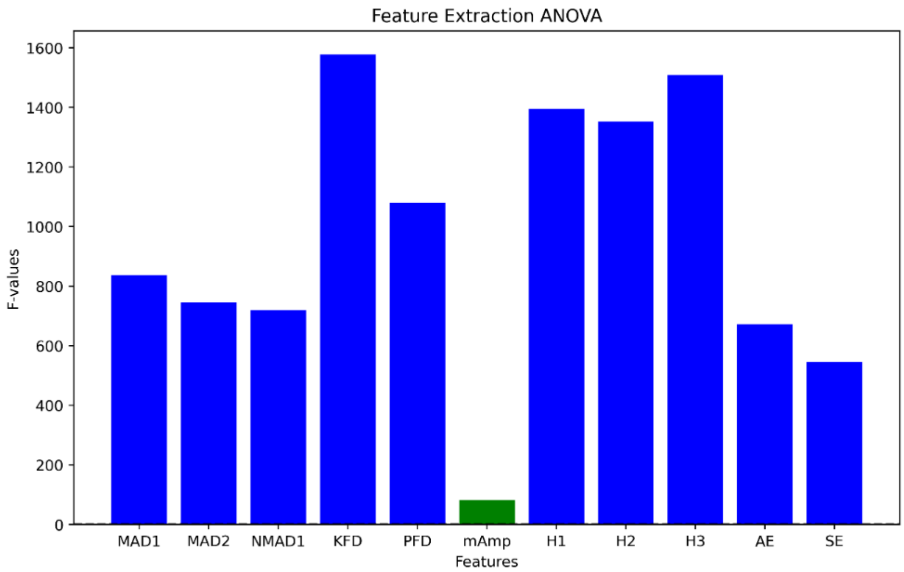


Figure 4. F-values bar plot for each significant feature from ANOVA. Green color bar denotes the lowest F-value.

Table 2 presents the average classification performance for reading, discussion, lecture, and video learning styles. Performance scores are shown for each feature classification technique, including the combination of all the feature sets. The highest scores across the feature sets are highlighted in bold. The mean class accuracies for the four teaching methods are reading (79.29%), video (82.79%), lecture (80.31%), and discussion (72.28%); the video class exhibits the highest performance, with a mean class accuracy of 82.79% across the three models. The majority of the feature sets perform reasonably well with average classification accuracy ($\geq$65.44%), precision ($\geq$65.52%), recall ($\geq$65.45%), F1-score ($\geq$65.37%), and AUC ($\geq$0.76). This is interesting, as it suggests a complex relationship between learning styles and many properties of EEG signals. As illustrated in Table 2, the performance of EEG statistical features is higher for classifying learning styles relative to other features when using RF, KNN, or MLP classifiers. One of the possible reasons that statistical features outperform could be that they utilize more time domain information. These results are also broadly consistent with previous research highlighting the significance of statistical features for recognizing the hidden internal discriminative information needed for learning-style identification [39]. Furthermore, the statistical feature set delivers classification results with the lowest SD of accuracy, precision, recall, F1-score, and AUC, showing that they perform more consistently than other features set in this study. This suggests greater stability or reliability of statistical feature sets for unveiling learning-style patterns.

Furthermore, we found that no prior research employed a machine learning approach specifically for classifying learning-style EEG data in real classroom settings. However, several studies have utilized EEG features to construct recognition models for learning-style classification based on the Felder–Silverman model, which divides learning styles into four dimensions: information processing, perception, input, and understanding. For example, Zhang et al. (2021) developed and validated an experimental method that effectively stimulates differences in the information-processing dimension, achieving an accuracy of 71.2% [6]. Additionally, other studies have recorded learners' behavior during interactions with learning objects in online courses and used mapping rules to infer learning styles according to the Felder–Silverman model, with reported classification accuracies ranging from 62.5% to 72.7% [50–53]. In comparison, our proposed framework demonstrates superior performance, achieving higher accuracy than previously reported studies for learning-style classification. This highlights the effectiveness of our approach and the potential of EEG features in educational research, warranting further exploration into effective learning-style recognition.

Table 2. Average classification performance of classroom EEG recordings based on statistical, FD, HOS, entropy, and combined features of EEG. All ACC, PRE, REC, and F1-S are given as % ± SD. The performance highlighted in pink color represents the highest performance scores across the feature sets.

Feature Set	Classifier	Accuracy	Precision	Recall	F1 Score	AUC
Statistical	RF	78.45 ± 0.85	78.9 ± 1.02	78.45 ± 0.85	78.49 ± 0.86	0.8563 ± 0.0056
	KNN	76.76 ± 1.46	76.78 ± 1.44	76.76 ± 1.46	76.67 ± 1.47	0.8451 ± 0.0097
	MLP	76.14 ± 1.22	76.37 ± 1.09	76.14 ± 1.22	76.06 ± 1.23	0.8409 ± 0.0081
FD	RF	76.78 ± 0.98	77.39 ± 0.9	76.78 ± 0.98	76.85 ± 0.98	0.8452 ± 0.0065
	KNN	76.70 ± 1.08	76.68 ± 1.08	76.70 ± 1.08	76.59 ± 1.06	0.8446 ± 0.0072
	MLP	75.41 ± 0.44	75.47 ± 0.41	75.40 ± 0.44	75.33 ± 0.45	0.836 ± 0.0029
HOS	RF	67.75 ± 1.64	68.47 ± 1.48	67.75 ± 1.64	67.82 ± 1.65	0.7850 ± 0.0109
	KNN	59.40 ± 0.5	59.43 ± 0.55	59.40 ± 0.51	59.17 ± 0.47	0.7294 ± 0.0034
	MLP	65.29 ± 1.29	65.53 ± 1.54	65.29 ±1.29	65.15 ± 1.29	0.7686 ± 0.0086
Entropy	RF	65.50 ± 0.91	66.46 ± 0.86	65.50 ± 0.91	65.62 ± 0.93	0.7700 ± 0.0061
	KNN	60.88 ± 1.75	61.25 ± 1.82	60.88 ± 1.75	60.59 ± 1.75	0.7392 ± 0.0116
	MLP	65.44 ± 0.84	65.52 ± 0.77	65.45 ± 0.84	65.37 ± 0.86	0.7696 ± 0.00560
Combined	RF	76.75 ± 1.11	77.41 ± 1.17	76.75 ± 1.11	76.82 ± 1.14	0.8450 ± 0.7402
	KNN	59.40 ± 0.5	59.43 ± 0.55	59.40 ± 0.51	59.17 ± 0.47	0.7294 ± 0.0034
	MLP	76.19 ± 0.5	76.30 ± 0.49	76.19 ± 0.50	76.15 ± 0.55	0.8413 ± 0.00342

Another finding of the present study is that the RF classifier performed better for discriminating learning-style patterns compared to KNN and MLP. As illustrated in Figure 5, the RF outperformed other classifiers irrespective of the feature choice made. In contrast, KNN and MLP exhibited results that are comparable in nature. Using a statistical feature set, we achieved the highest average performance accuracy of 78.45%, precision of 78.90%, recall of 78.45%, F1-score 78.49%, and AUC of 0.8563. This is in line with previous research supporting the utility of RF for EEG signal classification, showcasing its adaptability. Given that the statistical feature set was the most successful, the subsequent results primarily focused on outcomes for the statistical features and RF classifier model. Notably, entropy achieved the lowest accuracy in learning-style classification because it primarily measures the overall unpredictability or randomness of the signal, which can be highly influenced by the noise and artifacts inherent in EEG data [54]. This measure may lack the specificity needed to capture the distinct patterns or structures crucial for distinguishing between different cognitive states or tasks. Additionally, entropy does not account for the temporal dynamics of EEG signals, which are non-stationary and can change over time.

Topographical maps of statistical features (i.e., MAD1, MAD2, and NMAD1) associated with reading, video, lecture, and discussion learning-style patterns are plotted in Figure 7. The color coding (orange to red) indicates the degree of brain activity, with orange suggesting low activity and red indicating high activity.

From Figure 7, we observe that brain activity becomes more pronounced as certain activities, such as lectures or discussions, progress. During lectures, this increase in brain activity suggests that students are actively processing and integrating the information being presented over time. In contrast, reading sessions consistently show lower brain activity, which may indicate a more relaxed state or a different type of cognitive focus that requires less overall brain activation. Similarly, brain activity tends to rise during discussions, which likely reflects the active engagement and critical thinking required to analyze and respond to interactive content. When watching videos, the increase in brain activity over time indicates the ongoing processing of complex visual and auditory information. It is important to recognize that these general trends can vary widely among individuals and are influenced by the specific context and nature of the activity. Each person's unique cognitive and emotional response to different tasks may lead to variations in how brain activity evolves over time.

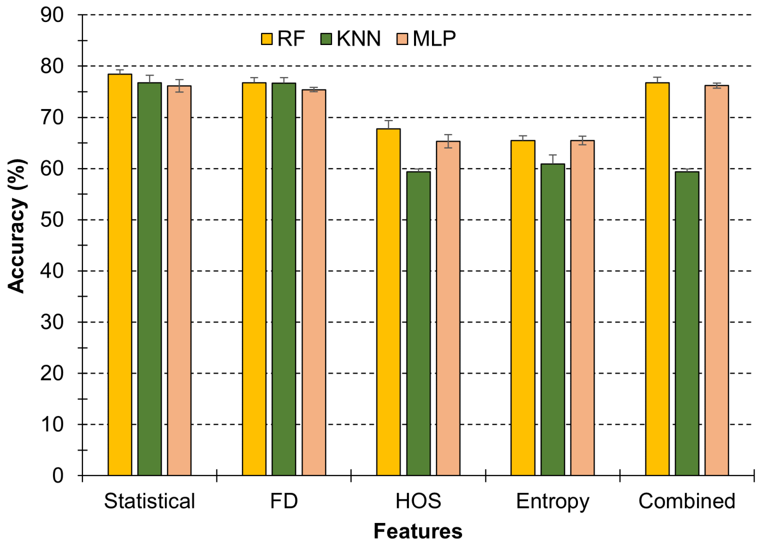
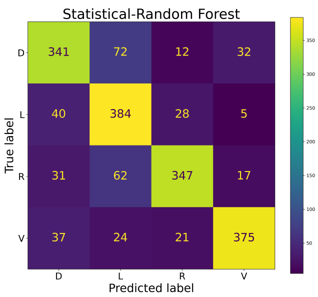
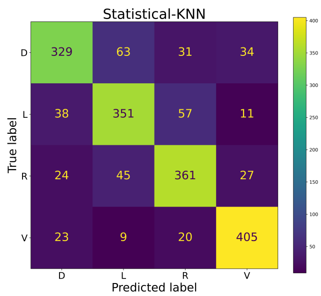


Figure 5. Comparison of classification performance with various features (in terms of accuracy).

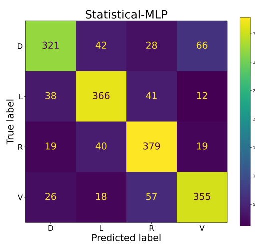
Figure 5 shows the classification performance, reflecting the performance of the statistical features using RF, KNN, and MLP classifiers, illustrating the time-domain statistical characteristics of EEG signals that can effectively discriminate reading, discussion, lecture, and video learning-style patterns. The confusion matrix, which is illustrated in Figure 6a, provided further insights into the performance results in accurately categorizing instances. Significantly, accurate classifications were made for 341 occurrences of discussion, 384 occurrences of lecture, 347 occurrences of reading, and 375 occurrences of video. Nevertheless, the model demonstrated its shortcomings through the misclassification of instances in diverse contexts. For example, 72 occurrences of discussion were incorrectly classified as lecture, which suggests areas that could be enhanced.



(**a**) RF



(**b**) KNN



(**c**) MLP

Figure 6. Confusion matrix of a fold using statistical features obtained from (**a**) RF, (**b**) KNN, and (**c**) MLP. The diagonal elements are the correctly recognized samples.

From the *p*-values displayed in Figure 8, it is evident that all pair-wise comparisons between the learning methods—reading, video, lecture, and discussion—show statistically significant differences. This uniform significance across all combinations can be attributed to several factors. Firstly, each learning method engages different cognitive and sensory processes, leading to distinct impacts on learning outcomes. For instance, reading involves textual processing, video incorporates both visual and auditory information, lectures provide verbal instruction, and discussions facilitate interactive engagement. These diverse modalities result in varied effectiveness in enhancing understanding and retention. Additionally, the statistical sensitivity of the paired *t*-tests ensures that even small but meaningful differences between the methods are detected. The significant differences observed suggest that each learning method offers unique advantages and challenges, which contributes to the varied effectiveness observed across all pairings.

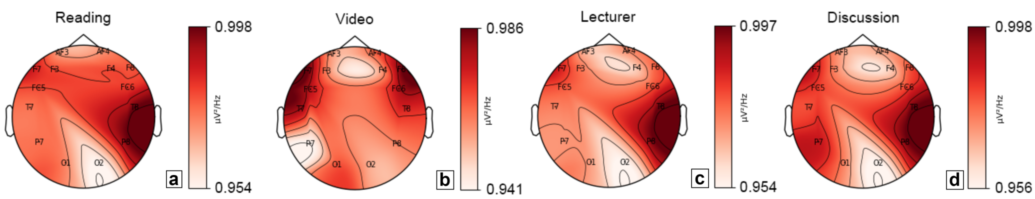


Figure 7. Topographical maps of different learning styles. (**a**) Reading, (**b**) video, (**c**) lecture, (**d**) discussion.

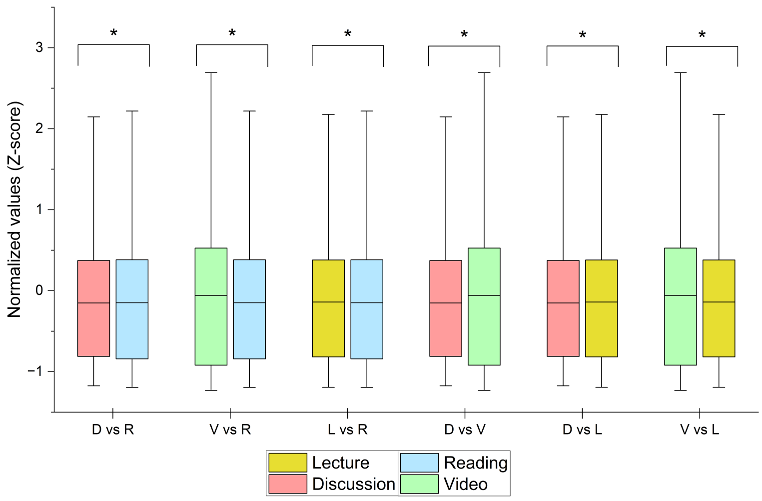


Figure 8. Statistical results of two-tailed paired *t*-test. * denotes $p < 0.0001$.

Limitations and Future Directions

This pilot study has several limitations to note. First, the sample size is relatively small, which may affect the generalizability of the results. A larger sample would help to confirm the findings and provide a more comprehensive understanding of the learning methods' effectiveness. Additionally, the sample exhibits a gender bias, which may influence the results and limit their applicability to all gender groups. Future research should aim to include a more balanced and larger sample to address these issues and ensure that findings are representative of diverse populations. Ensuring gender balance and a sufficient sample size will enhance the validity and generalizability of the study's conclusions. Second, further improvements in performance will be possible in the future by expanding and incorporating deep learning methods like convolutional neural networks that are inspired by neural network approaches. It is not feasible to explore this approach here due to a lack of data. Third, this study's data focus on high school students from one American school, limiting the generalizability of the findings. Additional research is needed to explore how neural patterns in different learning settings might unfold in other age groups or schools. Finally, Dikker et al.'s study [20] is the non-randomized nature of the data collection sequence. The fixed sequence of learning methods—reading, video, lecture, and discussion—is used throughout the study, which may introduce a learning effect that could influence the results. The participants are exposed to these methods in a specific order, potentially affecting their engagement and learning outcomes. To enhance the validity of future research, it is recommended that studies be designed with multiple groups, where the sequence of learning methods is varied. This approach will help to determine whether the sequence influences the results and contribute to a more robust understanding of the effectiveness of each learning method. Incorporating such variations in sequence will help establish the credibility of the findings by addressing the potential sequence-related biases.

5. Conclusions

This study aimed to develop a machine learning framework to automatically classify different learning styles of EEG patterns in real classroom environments. As the first complete machine learning framework to classify learning-style differences in classroom EEG data, this study advances the discipline. For this purpose, a set of features (statistical, FD, HOS, entropy, and combined) were extracted from the EEG signals, and a quantitative comparison was conducted of the feature extraction techniques with three different classifiers, RF, KNN, and MLP. The dataset constructed by Dikker et al. [20] was used to assess the performance of the study. It includes EEG recordings comprising various teaching blocks, such as reading, discussion, lecture, and video. The results showed that statistical features are the most sensitive feature metric for distinguishing learning patterns from EEG in terms of their ability to distinguish between them. This study achieved the highest average accuracy of 78.45% using statistical features and the RF classifier method. Based on the results of this study, it can be concluded that the EEG time domain statistical characteristics of EEG signals can be efficiently used to discriminate between different learning styles. This might result in the creation of an effective human interactive system, which may be useful in evaluating classroom teaching and learning. Furthermore, this innovative study has established a new standard in the area, emphasizing the revolutionary capacity of machine learning to comprehend and use the brain patterns linked to different cognitive processes in constantly evolving educational environments.

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Abbreviations

The following abbreviations are used in this manuscript:

AE	Approximate Entropy
AMAM	Attention Monitoring and Alarm Method
ANOVA	Analysis of Variance
AUC	Area Under the Curve
CNN	Convolutional Neural Network
EEG	Electroencephalogram
H1	Summation of the Bispectrum Logarithmic Amplitudes Summation

H2	Summation of the Bispectrum Logarithmic Amplitudes of Diagonal Elements
H3	1st Order Moment of Amplitudes of the Spectral Waves of Diagonal Elements of the Bispectrum
HOS	Higher Order Spectra
KFD	Katz's Fractal Dimension
KNN	K-Nearest Neighbor
LSTM	Long Short-Term Memory
MAD1	Mean of Absolute Values of 1st Difference
MAD2	Mean of Absolute Values of 2nd Difference
mAmp	Bispectrum Magnitude
MLP	Multilayer Perceptron
NMAD1	Normalized Mean of Absolute Values of 1st Difference
PFD	Petrosian fractal dimension
RF	Random Forest
SD	Standard Deviation
SE	Sample Entropy

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