EEG-based Engagement Prediction in e-Learning Environments Using Machine Learning Techniques

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Abstract. Accurately assessing learner engagement in e-learning environments is crucial for enhancing educational outcomes and optimizing personalized learning experiences. This study presents a machine learning (ML) framework for electroencephalogram (EEG)–based engagement prediction, leveraging multi-channel EEG recordings to capture cognitive responses during learning sessions. A well-defined methodology was implemented, including EEG signals preprocessing, feature extraction based on Power Spectral Density (PSD), and three techniques for feature ranking and selection to identify the most relevant neural features for engagement classification. By evaluating several ML models, including Logistic Regression (LR), Support Vector Machines (SVM), Random Forest (RF), Gradient Boosting Machines (GBM), Neural Networks (NNs), Convolutional NNs (CNNs), and Hybrid Ensemble approach, we demonstrate that feature selection significantly enhances classification performance. The Hybrid Ensemble model achieved the highest accuracy (92.7%) and the area under the ROC curve (AUC) (95.1%) when trained on a highly refined set of 14 features, improving interpretability while reducing computational complexity. The selected features, primarily from temporal, occipital, and parietal EEG channels, align with established neural mechanisms underlying memory processing, sensory integration, and attentional regulation. The results reinforce the potential of EEG-based analytics for real-time engagement monitoring, supporting adaptive e-learning systems that personalize content based on cognitive states.

Keywords: E-learning · EEG · Machine Learning · Classification

1 INTRODUCTION

The advent of e-learning has significantly transformed the educational landscape, offering unprecedented opportunities for flexible and accessible learning experiences. However, this paradigm shift has brought about new challenges, especially in maintaining learner concentration on a task. Engagement is a critical factor in educational success, influencing both the retention of information and the overall learning experience. Traditional methods of assessing engagement, such as questionnaires, self-reports and behavioural observations, are often subjective and prone to biases. They constitute a simple method to collect initial information about a subject, but the acquired model about the learner's profile isn't dynamically updated/adapted using feedback from the objects in the interaction environment. Consequently, there is a growing interest in leveraging objective physiological measures to gain deeper insights into learner engagement [15, 21].

In Human-Computer Interaction (HCI), there has been a rising tendency to design systems able to detect internal physiological changes, process the acquired raw data, and recognize and respond to users' cognitive states. The term "cognitive state" indicates the human cognitive processes and resources such as perception, attention, cognitive effort, engagement, working memory, arousal, stress and fatigue. A major goal in interaction design is to decrease the cognitive load for users [13]. In recent years, the scientific community has been increasing their efforts for the joint application of advanced signal processing, machine/deep learning (DL) and cognitive computing techniques to develop reliable systems predicting human cognition status [16].

In this context, EEG, a neuroimaging technique that records human brain activity, has emerged as a promising tool. EEG can provide real-time knowledge of cognitive and emotional states by capturing brainwave patterns across different frequency bands. These patterns can indicate various cognitive and mental states [32, 20], including attention, relaxation, and cognitive load, which are all relevant to engagement in learning activities. By analyzing EEG data, researchers can obtain a more accurate and dynamic understanding of how learners interact with online materials [6, 36].

Recent advancements in EEG technology combined with ML have significantly improved the interpretation of cognitive and physiological states. EEG signals have been effectively utilized in diverse areas, such as eye-state classification for clinical diagnostics, neuroscience research, and brain-computer interfaces (BCIs). Additionally, ML techniques like ensemble algorithms, often coupled with class imbalance handling methods such as Synthetic Minority Oversampling Technique (SMOTE), have consistently improved the accuracy and robustness of EEG-based models [33, 34].

In educational contexts, EEG-based ML methods offer promising approaches to accurately detect and enhance learner engagement, leveraging adaptive learning and immersive technologies, including Augmented Reality and Virtual Reality. However, practical implementation poses challenges such as addressing the digital divide, ensuring data privacy, and creating scalable, equitable solutions. Consequently, robust methodological frameworks are required to maximize the educational benefits of EEG analytics in adaptive e-learning environments [9, 35].

Engagement is a fundamental factor in e-learning, directly impacting learning retention, comprehension, and overall academic performance. EEG-based engagement prediction offers a more objective and responsive approach by capturing neural activity associated with cognitive states during learning. However, effectively leveraging EEG data requires advanced preprocessing, feature selection, and ML techniques to enhance accuracy while minimizing computational complexity.

At this point, it should be noted that the current study represents an extended version of [10] detailing and further enhancing the methodology and findings presented in the original study. More specifically, the key contributions of this work are four-fold:

- A structured methodology consisting of EEG signals collection, preprocessing, feature extraction and selection, and ML models training and testing for engagement classification.
- Feature extraction was performed through power spectrum analysis, focusing on specific frequency bands, including alpha, low and high beta, theta, and gamma.
- Estimated Pearson Correlation Coefficients (CCs), Information Gain (IG), and Gain Ratio (GR) to identify the most relevant EEG features, improving classification accuracy and interpretability.
- Evaluated multiple ML models (LR, SVM, RF, GBM, NN, CNN, and Hybrid Ensemble), demonstrating that feature selection enhances predictive performance.

The rest of this paper is organized as follows. Section 2 presents related works for the subject under consideration. In Section 3, the methodological framework for EEG-based engagement prediction is outlined, while Section 4 provides data analysis. Next, Section 5 offers a performance evaluation of the engagement models. Finally, Section 6, summarizes the findings of this study.

2 Related Works

Capturing attention in educational settings has seen significant advancements with the application of EEG-based BCI systems [31]. Numerous studies have explored various computational methods and classification approaches to effectively monitor and enhance student engagement in both traditional and e-learning environments.

Firstly, in [23], a novel approach was presented for real-time emotion classification leveraging EEG data streams. The proposed system called the "Real-time Emotion Classification System" (RECS), employed LR and trained online with the Stochastic Gradient Descent (SGD) algorithm. The research used the DEAP dataset for validation, demonstrating that RECS could classify emotional states more effectively in real-time compared to existing offline and online classifiers, including Hoeffding Tree (HT), Adaptive RF (ARF), and others. The system was designed for practical applications, particularly in e-learning environments, where real-time emotional feedback can enhance learning. The authors in [32] introduced an ML methodology by comparing various classifiers trained and tested on EEG data, specifically focusing on band power, attention, and mediation features collected by the MindSet device. The goal was to effectively differentiate between "Confused" and "Not-Confused" individuals. Notably, the J48 model emerged as the most effective, achieving optimal performance with accuracy, precision, and recall rates of 99.9%, and an AUC of 1.

Moreover, [4] proposed a BCI system to enhance the quality of distance education by using EEG signals to detect students' attention during online classes. The study extracted PSD features from a public dataset and calculated various attention indexes using the fast Fourier transform (FFT). K-nearest neighbours (KNN), SVM, and RF models were employed to assess their performance in recognizing students' attentive states. The results showed that the RF classifier achieved the highest accuracy of 96%, indicating its effectiveness in distinguishing attention states in online learning environments.

In [27], a novel solution that employed real-time EEG data collected from individuals wearing EEG headsets during online courses was presented. This method focuses on a CNN model, which efficiently classifies these EEG signals with an accuracy rate of 70%. The performance highlighted the speed of processing and accuracy of the developed models, offering a promising solution to current e-learning validation challenges. Research work [26] introduced DL model to address the limitations of existing ones in ML, which rely on manual feature extraction and training with limited data. Real-time e-learning data was gathered from students wearing EEG headsets during online classes. This approach overcame the challenges associated with traditional ML models and historical data. The proposed CNN model classified students into different grade levels, aiding in the creation of an automated system to monitor student learning progress and provide recommendations to enhance e-learning course materials.

Also, [8] presented a novel approach utilizing Probability-Based Features (PBF) derived from RF and GBM models to enhance the performance of ML classifiers for detecting confusion in students during online learning sessions. The study evaluated various classifiers, including RF, GBM, LR, SVC, and Extra Trees Classifier (ETC), achieving an accuracy, precision, recall, and f1-score of 100%, with the proposed PBF approach. Additionally, the approach was validated using a separate EEG dataset, demonstrating superior performance compared to existing methodologies. The best-performing model numerically was the proposed PBF using RF and GBM features, achieving consistent top scores across all evaluation metrics. Moreover, [29] proposes an e-learning system that enhances learning by adapting content based on users' emotional states detected through EEG signals. Using the Neurosky Brainwave detector and the RF classification method, the study demonstrates how brainwave analysis can predict learners' attention levels and trigger personalized content adjustments. The system provides alerts for low concentration and recommends suitable videos, ultimately aiming to improve knowledge retention and engagement.

Finally, [2] evaluated learners' attention levels in MOOC (Massive Open Online Courses) environments and compared them with traditional classroom settings using brain signals. The proposed approach involved capturing EEG frequency bands from various subjects during short lectures in both e-learning and classroom environments. An SVM model was employed to classify students' mental states as either attentive or non-attentive. Additionally, [18] develops a classification system based on EEG signals to detect mental effort in MOOCs. Using different normalization techniques and supervised learning algorithms, the study shows that EEG data can be processed effectively to classify cognitive load levels with high accuracy, precision, and recall. This approach facilitates self-awareness of mental effort among learners and enables automated feedback mechanisms to enhance learning experiences in online education.

Unlike previous studies summarized in Table 1 that primarily relied on either raw EEG signals or spectral features, the present work integrates both spatial (electrode-based) and spectral (PSD) features, ensuring a comprehensive representation of engagement-related neural activity. In contrast to approaches that employ large, unfiltered feature sets, our study applies a rigorous feature selection process using Pearson CCs, IG, and GR, refining the feature space to retain only the most relevant 14 features. This targeted selection not only enhances interpretability but also improves classification accuracy and computational efficiency. Additionally, while prior research has often focused on individual ML models, this work conducts an extensive comparative evaluation of various classifiers, including LR, SVM, RF, GBM, Neural NNs, CNN, and a Hybrid Ensemble model, demonstrating that feature selection improves predictive performance across all models. Furthermore, our findings align with established neuroscientific evidence by emphasizing engagement-related cortical regions, particularly in the temporal, occipital, and frontal lobes, reinforcing the validity of EEG-based engagement monitoring. By systematically optimizing feature selection and evaluating model performance, this study advances the field by providing a structured, scalable, and interpretable framework for EEG-based engagement prediction in e-learning environments.

3 Methodological Framework for EEG-based Engagement Prediction

The EEG-based learner engagement prediction framework follows a structured, multi-stage approach designed to capture, process, and analyze neural responses during e-learning sessions. EEG data are initially collected using wearable EEG devices in controlled learning environments, allowing for real-time monitoring of cognitive activity while learners engage with digital educational content.

To ensure signal integrity, the raw EEG recordings undergo rigorous preprocessing, including noise reduction, artifact removal, and normalization, thereby mitigating inter-individual variability. Subsequently, a comprehensive feature extraction process is applied to derive meaningful characteristics that serve as additional indicators of learner engagement. The methodological framework consists of five key stages

- **Data Acquisition and Preprocessing** – Capturing EEG signals and ensuring data quality through filtering, artifact removal, and normalization.
- **Feature Extraction** – Computing spectral features (besides raw data) to quantify engagement levels.

Table 1. Summary of EEG-Based Learning Related Works.

Ref.	Objective	Method	Best Performance
[23]	Real-time emotion classification using EEG	LR, DEAP dataset validation	Accuracy = 99.9%, AUC=1
[32]	Distinguish 'Confused' vs. 'Not-Confused' using EEG features	J48 Decision Tree model, EEG band power features	Accuracy = 99.9%, AUC=1
[4]	Detect attention in distance learning using EEG	KNN, SVM, RF applied to EEG spectral features	RF achieved highest accuracy of 96%
[27]	Use CNN for EEG classification in e-learning	CNN for EEG signals	CNN classification accuracy = 70%
[26]	DL model to classify student engagement	DL-based classification of engagement levels	CNN model effectively classified student levels
[8]	Enhance ML classifiers for confusion detection in students	RF, GBM, LR, SVC, ETC	Accuracy = 100% using PBF with RF and GBM
[29]	Adapt learning content using EEG-based emotion detection	Neurosky Brainwave detector with RF	Personalized attention tracking using EEG
[2]	Analyze learner attention in MOOCs vs. classrooms	SVM for EEG frequency bands	SVM effectively classified attentive vs. non-attentive states
[18]	Detect cognitive load and mental effort in MOOCs	Supervised learning algorithms with normalization techniques	High accuracy in detecting cognitive load levels

- **Feature Selection and Dimensionality Reduction** – Identifying the most relevant features while reducing complexity and improving computational efficiency.
- **Classification** – Applying advanced ML models, including DL architectures, to predict engagement state.
- **Evaluation** – Assessing model performance using stratified cross-validation and statistical metrics to ensure robustness and reliability.

Figure 1 illustrates the EEG-based data acquisition framework using the EMOTIV Epoc-X headset, detailing the entire processing pipeline, from raw EEG signal collection to engagement classification. The figure highlights the placement of the 14 EEG electrodes strategically positioned to capture cognitive, sensory, and motor-related brain activity. It also outlines the sequential data processing steps, including noise filtering, artifact removal, and normalization, followed by feature extraction and selection to refine the most informative EEG characteristics. The extracted features serve as inputs for ML models, enabling the classification of learner engagement [37]. The structured approach depicted in Figure 1 ensures a robust methodology for interpreting cognitive states in e-learning environments while maintaining data reliability and model accuracy.

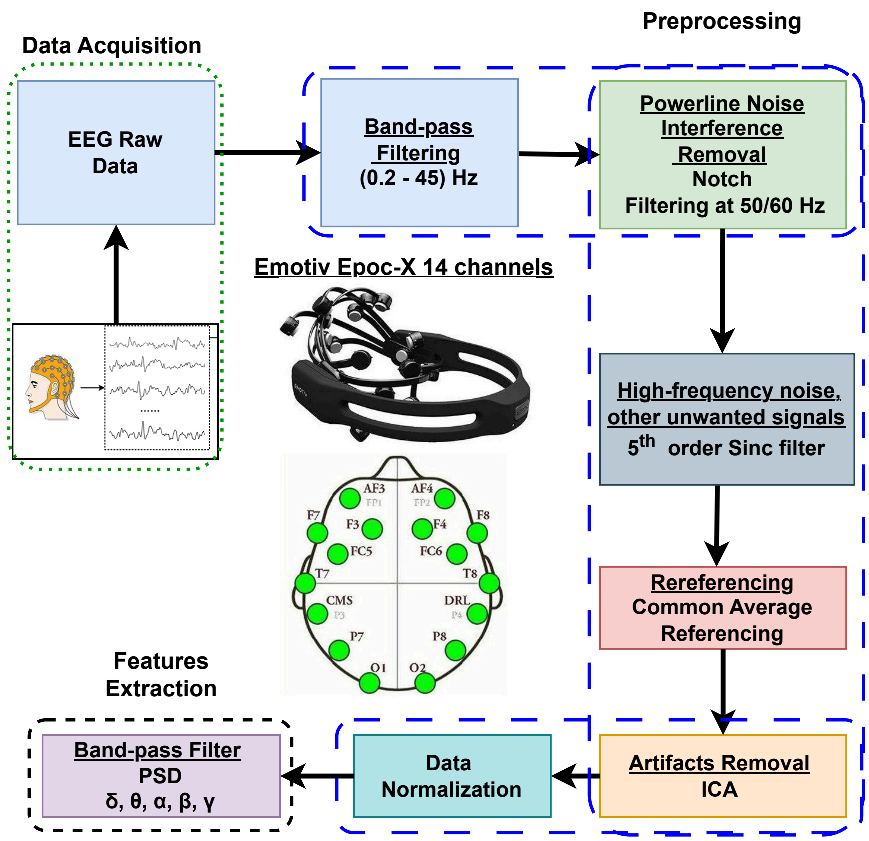

Fig. 1. EEG-based processing pipeline in multi-channel Emotiv Epoc-X device [10]

3.1 Data Acquisition

The EEG data acquisition process employs the EMOTIV Epoc-X [7], a high-resolution, wireless 14-channel EEG headset designed for real-time cognitive monitoring in controlled e-learning environments. This non-invasive device captures neural activity, providing valuable insights into learner engagement, cognitive workload, and attentional focus.

Following the 10-20 international electrode placement system, the Emotiv Epoc-X ensures comprehensive brain region coverage. The frontal electrodes (AF3, AF4, F3, F4, F7, F8) monitor cognitive processing and attention regulation, while T7 and T8, positioned over the temporal lobes, capture activity related to memory formation and language comprehension. Electrodes in the parietal region (P7, P8) track spatial processing and sensory integration, whereas O1 and O2, located in the occipital lobe, record visual perception and processing. Additionally, FC5 and FC6, near the prefrontal cortex, play a key role in executive functions, motor planning, and decision-making. The letters in the electrode names indicate the lobe locations: F (frontal), P (parietal), T (temporal), O (occipital), and C (central). Odd numbers correspond to the right hemisphere, and even numbers correspond to the left hemisphere.

Table 2 outlines the functional significance of each EEG channel, detailing the specific brain activity recorded and its corresponding brain region. The precise placement of these electrodes facilitates a comprehensive assessment of learner engagement, allowing for targeted analysis of cognitive states, attentional fluctuations, and neural responses during e-learning sessions [30].

Table 2. Description of EEG Channels in Emotiv Epoc-X.

Channel	Activity Captured	Brain Lobe/Region
AF3	Attention, executive functions, working memory	Frontal Cortex (Left)
AF4	Attention, executive functions, working memory	Frontal Cortex (Right)
F3	Logical processing, decision making, cognitive workload	Frontal Lobe (Left)
F4	Logical processing, decision making, cognitive workload	Frontal Lobe (Right)
F7	Verbal expression, language processing, analytical tasks	Frontal/Temporal Lobe (Left)
F8	Emotional expression, social interaction, creative tasks	Frontal/Temporal Lobe (Right)
FC5	Verbal fluency, speech production, cognitive control	Frontal/Central Region (Left)
FC6	Emotional regulation, attentional control	Frontal/Central Region (Right)
T7	Auditory processing, language comprehension, memory retrieval	Temporal Lobe (Left)
T8	Auditory processing, emotional memory, sensory integration	Temporal Lobe (Right)
P7	Visual-spatial processing, object recognition	Parietal/Occipital Lobe (Left)
P8	Visual-spatial processing, facial and emotional recognition	Parietal/Occipital Lobe (Right)
O1	Primary visual processing, visual perception	Occipital Lobe (Left)
O2	Primary visual processing, visual perception	Occipital Lobe (Right)

The EEG signals are recorded at a sampling rate of 128 Hz with a 16-bit resolution, ensuring high temporal precision suitable for cognitive state analysis. Bluetooth low-energy connectivity facilitates seamless data transmission, enabling real-time monitoring without restricting participant mobility. The hydrophilic polymer sensors use a saline-based gel, ensuring optimal impedance levels for high-quality signal acquisition while maintaining participant comfort. A built-in signal quality indicator continuously monitors electrode connectivity, ensuring data reliability throughout the recording session.

During e-learning sessions, EEG signals are continuously recorded while participants engage with digital learning materials. The data collection process is synchronized with instructional content, capturing fluctuations in cognitive engagement levels as learners interact with the educational material. After data recording, engagement levels are annotated using self-reported questionnaires and behavioral markers, enabling the creation of labeled datasets for training predictive models.

In the following paragraphs, we will focus on the collected signals preprocessing (noise removal), feature extraction, and selection to enhance interpretability before being used for ML-based engagement prediction.

3.2 Preprocessing

Effective preprocessing of EEG data is crucial for ensuring accurate and reliable analysis. Raw EEG signals often contain noise and artifacts that obscure the underlying neural activity associated with engagement. To address these challenges, a multi-step preprocessing pipeline is employed to enhance signal quality and optimize the data for ML analysis.

The Emotiv Epoc-X incorporates dedicated digital filtering mechanisms to preprocess raw EEG signals. Band-pass filtering is first applied to retain frequencies between 0.2 and 45 Hz, which encompass the key spectral components relevant to cognitive and emotional state analysis. This step effectively removes low-frequency drifts and high-frequency noise, preserving only the frequencies that contribute to engagement detection. Additionally, the device integrates built-in digital notch filters at 50 Hz and 60 Hz, eliminating power line interference that could otherwise distort the signal and impact the accuracy of PSD calculations. In EEG-based ML models, unwanted power line noise could introduce false correlations in feature selection. Hence, notch filtering ensures that only meaningful neural activity is used for engagement prediction. A 5th-order Sinc filter is also utilized, providing a sharp cutoff to suppress high-frequency noise and aliasing artifacts, further refining the EEG data for analysis.

Independent Component Analysis (ICA) is applied to remove physiological artifacts, isolating and eliminating noise sources such as eye blinks, muscle movements (EMG), and cardiac activity (ECG), thereby preserving the integrity of engagement-related neural signals. Following artifact removal, Z-score normalization is performed on each EEG channel to reduce inter-subject variability and prevent features with larger magnitudes from dominating the learning process. This transformation standardizes the data to have a zero mean and unit variance, ensuring that extracted features remain comparable across participants and improving the robustness of ML models. The Z-score normalization is computed as

$$X' = \frac{X - \mu}{\sigma}, \tag{1}$$

where X represents the original feature value, μ is the mean of the feature, and σ is its standard deviation. This transformation enhances model stability and improves the effectiveness of ML algorithms in engagement classification.

By implementing this structured preprocessing approach, the EEG data are effectively denoised, standardized, and optimized for subsequent feature extraction and classification, ensuring a reliable foundation for engagement prediction [11].

3.3 Feature Extraction

Following normalization, band-pass filtering was applied to isolate relevant frequency components of the EEG signals, ensuring accurate estimation of PSD. The PSD serves as the primary feature extraction method, quantifying the distribution of signal power across different frequency bands. These bands are closely linked to cognitive processes, including attention, relaxation, and cognitive load, making them essential for engagement assessment.

The PSD was computed using the Fast Fourier Transformation (FFT), which decomposes the EEG signal into its constituent frequencies. The PSD at frequency f is estimated as

$$PSD(f) = \frac{1}{N} \sum_{n=1}^{N} |X(n, f)|^2, \tag{2}$$

where $X(n, f)$ represents the Discrete Fourier Transform (DFT) of the EEG signal at frequency f, and N is the total number of frequency components. This method provides a spectral representation of neural activity, enabling the identification of engagement-related patterns in different frequency bands.

By analyzing the PSD across established EEG frequency bands, including θ (4-8Hz), α (8-12Hz), low β (13 - 20Hz), high β (20-30 Hz), γ (30 - 45 Hz), meaningful neural signatures associated with cognitive engagement are extracted. These spectral features serve as inputs for subsequent classification, forming the basis of EEG-based engagement prediction [3].

3.4 Feature Ranking and Selection

To enhance model interpretability and reduce computational complexity, feature selection is applied using three key ranking methods: Pearson CCs, IG, and GR. These techniques identify the most relevant EEG features for engagement prediction by assessing their relationship with the target variable.

Pearson CCs measures the linear relationship between feature X and target variable Y. It is computed as

$$r_{X,Y} = \frac{\sum_{i=1}^{N} (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{N} (X_i - \bar{X})^2} \sqrt{\sum_{i=1}^{N} (Y_i - \bar{Y})^2}}, \tag{3}$$

where $\bar{X}$ and $\bar{Y}$ are the mean values of feature X and Y, respectively, and N is the number of samples. X_i, Y_i are the values of two specific features for the i-th sample in the dataset. A higher absolute correlation value ($|r_{X,Y}|$) indicates a stronger linear dependency between the feature and engagement level [38].

IG evaluates the reduction in uncertainty about the target variable Y when knowing a feature X. It is defined as

$$IG(X) = H(Y) - H(Y|X), \tag{4}$$

where $H(Y)$ is the entropy of Y, given by $H(Y) = -\sum_{i=1}^{2} P(Y_i) \log_2 P(Y_i)$ and $H(Y|X) = -\sum_{j=1}^{m} P(X_j) \sum_{i=1}^{2} P(Y_i|X_j) \log_2 P(Y_i|X_j)$ is the conditional entropy with $P(Y_i)$ being the probability of class Y_i, and $P(Y_i|X_j)$ is the conditional probability of Y_i given feature value X_j. A higher IG value indicates a more informative feature [24].

GR is an extension of IG that normalizes the feature importance by considering its intrinsic entropy, thereby mitigating bias toward attributes with many unique values. It is given by

$$GR(X) = \frac{IG(X)}{H(X)}, \tag{5}$$

where $H(X) = -\sum_{j=1}^{m} P(X_j) \log_2 P(X_j)$ is the intrinsic entropy of feature X. A higher GR indicates a feature that provides high discriminative power while maintaining generalization.

After ranking the EEG features using the three aforementioned methods, the most informative subset is selected based on their scores. Features exhibiting strong correlation, high IG, or a high GR are retained for classification. This ensures that the feature set maximally contributes to engagement prediction while reducing redundancy and improving model efficiency [17].

3.5 Machine Learning Models

We assume a training set consisting of M EEG data instances and a test set comprising N instances, each labelled with a categorical variable Y, representing learner engagement. Under the defined problem, this class variable is binary taking two possible values: Y = "Engaged" (denoted as "1") or Y = "Not Engaged" (denoted as "0"). Each EEG instance i is represented by a feature vector $f_i = (f_{i1}, f_{i2}, \ldots, f_{iF})$ of size F, containing multiple extracted features capturing distinct EEG signal characteristics relevant to cognitive states.

Subsequently, the selected EEG features serve as inputs for training classical and advanced supervised ML models. The selection of appropriate ML models is critical to successfully predicting e-learning engagement using EEG data. This study investigated several ML models with distinct strengths and capabilities, to determine the most effective approach for this task. The models evaluated include LR, SVM, RF, GBM, NNs, CNN, and a hybrid ensemble model.

The primary goal is to achieve high predictive accuracy and reliability, specifically emphasizing recall or sensitivity (correct identification of engaged learners) and the AUC, to ensure accurate (real-time) identification of learner engagement. All models are rigorously validated using stratified k-fold cross-validation, which preserves class proportions in training and testing datasets, ensuring representative evaluation, robust predictive generalization, and minimized selection bias. The following analysis provides a detailed description of each model and the rationale behind their selection.

LR [19] model is based on the logistic function (a special case of sigmoid function), which maps any real-valued number to a value between 0 and 1. This function is particularly useful for binary classification tasks. The LR equation can be expressed as follows: $P(y = 1 \mid X) = \sigma(z) = \frac{1}{1+e^{-z}}$, where $P(y = 1 \mid X)$ is the probability that the output y is 1 (engaged) given the input features X. Also, z is defined as $z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n$, where $\sigma(z)$ is the logistic function, $(\beta_0, \beta_1, \beta_2, \ldots, \beta_n)$ are the coefficients of the model and $(X_1, X_2, \ldots, X_n)$ are the input features. Putting it all together, the LR model can be written as $P(y=1 \mid X) = \frac{1}{1+e^{-(\beta_0+\beta_1 X_1+\beta_2 X_2+\ldots+\beta_n X_n)}}$. This equation calculates the probability that the input X belongs to class 1 "engaged". The predicted class label can be determined by applying a threshold (typically 0.5) to this probability.

SVM [28] with a radial basis function (RBF) kernel, mainly aims to find the optimal hyperplane that separates the classes with the maximum margin. The mathematical formulation involves solving a quadratic optimization problem. The decision function for SVM is given by: $f(X) = \operatorname{sign}\left(\sum_{i=1}^{n} \alpha_i y_i K(X_i, X) + b\right)$, where α_i are the Lagrange multipliers, y_i are the class labels, $K(X_i, X)$ is the kernel function and b is the bias term.

Our focus here is on the RBF kernel whose function K is defined as: $K(X_i, X) = \exp\left(-\gamma \|X_i - X\|^2\right)$, where γ is a parameter that determines the spread of the kernel. Summarizing these together, the decision function with the RBF kernel is $f(X) = \operatorname{sign}\left(\sum_{i=1}^{n} \alpha_i y_i \exp\left(-\gamma \|X_i - X\|^2\right) + b\right)$.

RF [12] is an ensemble learning method that combines multiple decision trees to improve the robustness and generalizability of the model. The overall prediction of the RF model is obtained by aggregating the predictions of individual trees, often by taking the mode (majority vote) in classification tasks. Here's the mathematical formulation for RFs:

1. **Individual Decision Tree Prediction**-Let $h_m(X)$ be the prediction of the m-th decision tree in the forest for input X.
2. **RF Prediction**-The final prediction $H(X)$ of the RF is obtained by taking the majority vote of all M trees' predictions:

$$H(X) = \operatorname{mode}\{h_1(X), h_2(X), \ldots, h_M(X)\}$$

GBM [5] is an ensemble learning technique that builds models sequentially, with each new model correcting errors made by the previous ones. The goal is to optimize the overall prediction by minimizing the loss function. Here's the mathematical formulation for GBMs:

1. **Model Initialization** $F_0(X) = \arg\min_\gamma \sum_{i=1}^{n} L(y_i, \gamma)$, where L is the loss function, and y_i are the actual target values.
2. **Additive Model**-The model is built in a stage-wise manner. At each stage m, a new model $h_m(X)$ is added to minimize the loss: $F_m(X) = F_{m-1}(X) + \eta h_m(X)$, where η is the learning rate, and $h_m(X)$ is the new model fitted to the residuals of the previous model.
3. **Residual Calculation** - For each stage m, compute the residuals $r_{im} = -\left.\frac{\partial L(y_i, F(X_i))}{\partial F(X_i)}\right|_{F(X_i)=F_{m-1}(X_i)}$
4. **Fit New Model** $h_m(X)$ to the residuals:

$$h_m(X) = \arg\min_h \sum_{i=1}^{n} \left(r_{im} - h(X_i)\right)^2$$

5. **Update the Model** with the new fitted model $F_m(X) = F_{m-1}(X) + \eta h_m(X)$.

NNs [14] are DL models that use multiple layers of neurons to capture intricate patterns in data. In a feedforward neural network, the data flows from the input layer through multiple hidden layers to the output layer. Each neuron computes a weighted sum of its inputs, applies an activation function, and passes the result to the next layer. The training process involves backpropagation to adjust the weights. The mathematical formulation for a feedforward neural network is as follows:

1. **Weighted Sum and Activation for a Single Neuron**-For each neuron in layer l, the output $a_i^{(l)}$ is computed as: $z_i^{(l)} = \sum_{j=1}^{n^{(l-1)}} w_{ij}^{(l)} a_j^{(l-1)} + b_i^{(l)}, a_i^{(l)} = \sigma(z_i^{(l)})$, where $z_i^{(l)}$ is the weighted sum of inputs to the i-th neuron in layer l, $w_{ij}^{(l)}$ are the weights from neuron j in layer $l-1$ to neuron i in layer l, $b_i^{(l)}$ is the bias term for the i-th neuron in layer l, σ is the activation function (e.g., ReLU, sigmoid, tanh), and $a_j^{(l-1)}$ is the activation of the j-th neuron in the previous layer.
2. **Output Layer**, the process is similar: $z_k^{(L)} = \sum_{j=1}^{n^{(L-1)}} w_{jk}^{(L)} a_j^{(L-1)} + b_k^{(L)}, \hat{y}_k = \sigma(z_k^{(L)})$, where L is the final layer, and $\hat{y}_k$ is the predicted output.
3. **Loss Function** L measures the difference between the predicted outputs $\hat{y}$ and the true targets y. For example, using Mean Squared Error (MSE) $L = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2$, where N is the number of training examples.
4. **Backpropagation:** During this step, gradients of the loss with respect to the weights and biases are computed and used to update the parameters. For weights $w_{ij}^{(l)}$: $w_{ij}^{(l)} \leftarrow w_{ij}^{(l)} - \eta \frac{\partial L}{\partial w_{ij}^{(l)}}$, where η is the learning rate.

CNNs [25] are DL architectures particularly effective at modeling data that exhibit spatial-temporal relationships. EEG signals inherently contain both spatial information (due to electrode positions) and temporal dynamics (signal variations over time), making CNNs highly suitable for EEG-based predictive tasks. In this study, EEG data were reshaped into spatial-temporal feature maps, enabling convolutional filters to learn discriminative patterns related to learner engagement. Each convolutional layer applied multiple filters (kernels) across EEG signals, capturing localized spatial-temporal features indicative of engagement. Convolution operations are mathematically represented as

$$X_{conv}^{(l)} = \sigma\left(\text{conv}(X^{(l-1)}, W^{(l)}) + b^{(l)}\right),$$

where $X^{(l-1)}$ denotes the input from the previous layer, $W^{(l)}$ represents convolutional kernel weights, $b^{(l)}$ is the bias vector, and σ is the Rectified Linear Unit (ReLU) activation function. Following convolutional layers, pooling layers reduced feature-map dimensionality and computational complexity by summarizing feature representations. Extracted features were then flattened and passed to dense layers, culminating in a sigmoid activation function for binary classification

$$\hat{y} = \sigma\left(\sum_{i=1}^{m} w_i a_i + b\right).$$

The CNN was trained using the Adam optimizer to minimize binary cross-entropy loss, ensuring efficient convergence and robust predictive accuracy.

Hybrid Ensemble Model combines multiple individual classifiers to enhance predictive accuracy by leveraging the strengths of diverse modeling approaches. In this research, the hybrid ensemble integrates three powerful algorithms: GBM, RF, and NNs, combined through stacking. In this stacking approach, each base model independently predicts probabilities of learner engagement. These predictions serve as inputs—meta-features—for a LR meta-classifier, which makes the final prediction. Mathematically, the base-model predictions $P_{GBM}(X)$, $P_{RF}(X)$, and $P_{NN}(X)$ are combined into a final prediction given by the LR meta-model:

$$\hat{y}_{ensemble} = \sigma\left(\beta_0 + \beta_1 P_{GBM}(X) + \beta_2 P_{RF}(X) + \beta_3 P_{NN}(X)\right).$$

The GBM model contributes iterative error minimization, the RF model adds robustness through ensemble-based decision-making, and the NN captures complex nonlinear EEG data patterns.

3.6 Evaluation Metrics

Several metrics were used to evaluate the performance of the ML models, accuracy, precision, recall, F1-score, and AUC [22]. These metrics provide insights into models' performance, ensuring a robust assessment of their predictive capabilities. It should be noted that the ultimate value in each metric was derived by averaging the outcomes of both classes from all folds. The definition of these metrics is based on the confusion matrix consisting of the elements true-positive (Tp), true-negative (Tn), false-positive (Fp) and false-negative (Fn). Below is a brief description of each metric:

- **Accuracy** is the proportion of correctly predicted instances out of the total instances. It is a straightforward metric indicating the overall correctness of the model. Accuracy $= \frac{\text{Tp}+\text{Tn}}{\text{Total Instances}}$.
- **Precision** is the ratio of correctly predicted positive observations to the total predicted positives. It reflects the accuracy of the positive predictions made by the model. Precision $= \frac{\text{Tp}}{\text{Tp}+\text{Fp}}$.
- **Recall** is the ratio of correctly predicted positive observations to all the observations in the actual class. It measures the model's ability to capture all relevant instances. Recall $= \frac{\text{Tp}}{\text{Tp}+\text{Fn}}$.
- **F1-score** is the harmonic mean of Precision and Recall. It provides a single metric that balances the trade-off between Precision and Recall, especially useful when the class distribution is imbalanced: F1-Score $= 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}}$.
- **AUC** measures the ability of the model to distinguish between classes. It represents the degree of separability achieved by the model. An AUC of 1 indicates a perfect model, while an AUC of 0.5 suggests no discriminative power.

These metrics provided a comprehensive view of the model performance, enabling the identification of the most effective model for predicting e-learning engagement based on EEG data.

4 Data Analysis

The dataset used in this study comprised EEG recordings collected from participants engaged in an e-learning activity. More specifically, 8 students, with varying levels of education (High school, Middle school, Undergraduate) were invited to watch 11 online video lectures (e.g., Quantum Physics, Statistics, String Theory, Photosynthesis, Linear Algebra, Biology, Numbers and Operations, Computational Geometry, Mythology). During these lectures, the students' EEG brain waves were recorded using the Emotiv Epoc X 14-channel headset, a multi-channel EEG system.

The dataset contained preprocessed data from the channels AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4, as shown in Figure 1. The target class captures whether a student understood the lecture or not. In total, the dataset consists of 85 features, 54370 samples in class "Engaged" and 14461 samples in class "Not-Engaged".

4.1 Statistical Measures

An exploratory data analysis was conducted to gain a deeper understanding of the dataset. Figure 2 summarizes, across all participants, the statistical measures of PSD, namely, mean, minimum, maximum and standard deviation values across different frequency bands per engagement class, allowing for easy comparison.

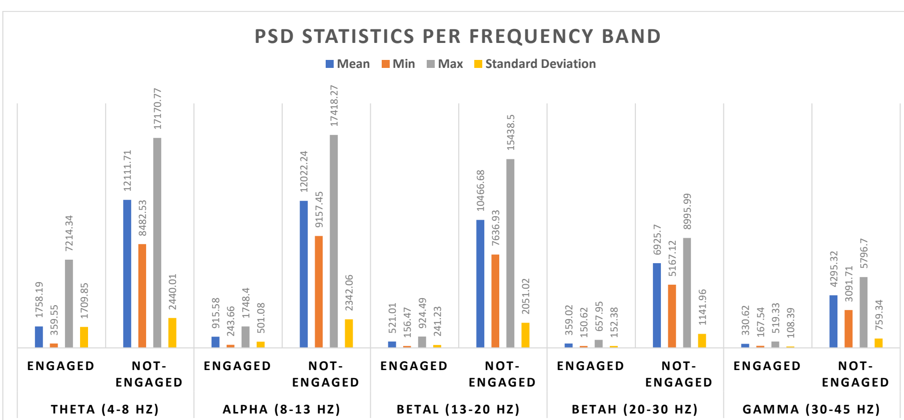

Fig. 2. Statistics of PSD per frequency band and engagement state [10]

In the following, such an analysis is presented.

1. **Theta band**: In the engaged group, theta activity remains relatively low, indicating efficient cognitive processing with minimal unnecessary effort. Conversely, the non-engaged group exhibits elevated theta activity, which may suggest increased cognitive effort without effective comprehension, potentially reflecting mind-wandering or cognitive overload.
2. **Alpha band**: Engaged learners demonstrate lower alpha activity, which aligns with focused attention and active information processing. In contrast, the non-engaged group shows higher alpha power, often associated with inattentiveness or relaxation, suggesting that these individuals may be disengaged from the learning process.
3. **Low Beta band**: Engaged learners display moderate beta activity, which corresponds to active cognitive engagement and problem-solving. However, the non-engaged group shows excessively high beta activity, indicating cognitive effort without effective learning, possibly reflecting stress or inefficient cognitive strategies.
4. **High Beta band**: The engaged group maintains consistent high beta activity, which is typically linked to sustained focus and cognitive effort. In contrast, the non-engaged group exhibits greater fluctuations, suggesting unstable concentration and inefficient mental resource allocation.
5. **Gamma band**: Gamma activity is associated with information processing and integration. In the engaged group, gamma levels are regulated, reflecting effective learning and comprehension. However, in the non-engaged group, gamma activity is elevated but inconsistent, suggesting that while some information is being processed, it may not be meaningfully integrated into learning.

The engaged group exhibits stable, well-regulated EEG activity, corresponding to focused attention, efficient cognitive processing, and active learning. Meanwhile, the non-engaged group demonstrates excessive but unstable neural activity, indicating cognitive effort without effective comprehension, potentially due to mind-wandering, stress, or disengagement. These findings highlight the importance of monitoring EEG patterns to understand better and enhance learner engagement in educational settings.

4.2 Feature Ranking and Selection

Figure 3 presents the Pearson correlation heatmap for EEG-based learner engagement features. The heatmap visually represents the CCs between different EEG channels recorded during e-learning sessions, illustrating the degree of linear relationship between each pair of features. Darker red colors indicate a stronger positive correlation, whereas cooler colors (closer to light blue) signify weaker or negative correlations. Key observations highlight that AF3 exhibits the strongest overall associations with other channels, reinforcing its role in attention regulation and cognitive workload processing in the prefrontal cortex.

Additionally, the correlation between the “Class” variable (learner engagement) and EEG features reveals that T8, O1, P8, T7 and O2 have the highest correlations, indicating their importance in engagement classification. In contrast, AF4 and FC6 show weak or slightly negative correlations, suggesting they may contribute less significantly to engagement prediction. These findings underscore the importance of selecting relevant EEG features for improving model accuracy while minimizing redundant or weakly related signals.

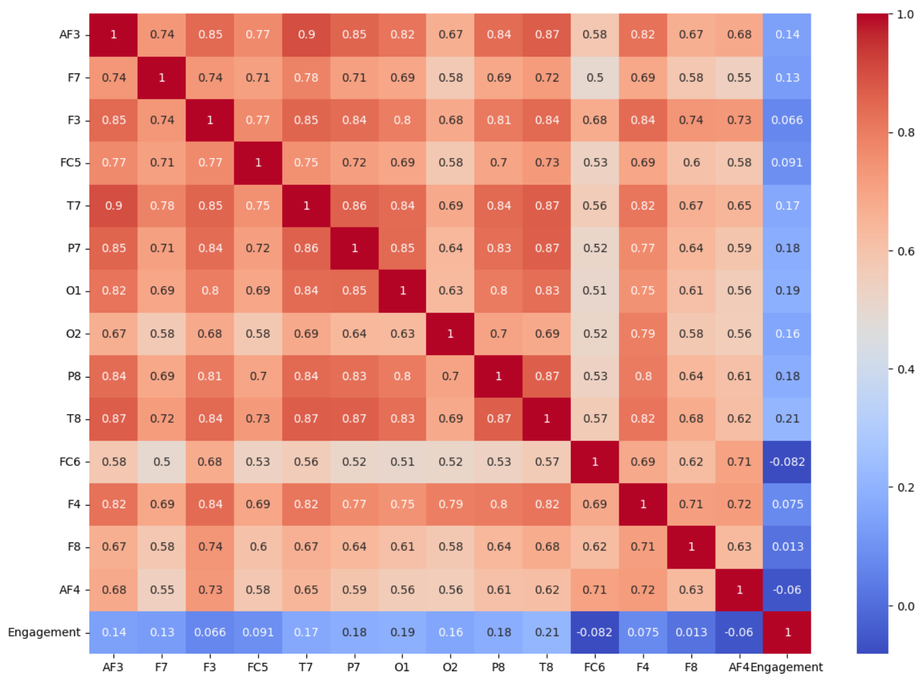

Fig. 3. Pearson Correlation Matrix among the 14 EEG Channels.

Additionally, Figure 4 depicts the correlation between PSD-based features including engagement class (engaged, non-engaged) using a heatmap. This visualization helps identify which frequency bands are most closely associated with the engagement class.

It was observed that power-based features are highly linearly dependent on one another, but according to the Pearson CCs in the blue area of the heatmap, their importance in improving the predictive performance of the ML models is low. Hence, further and extensive analysis should be conducted to understand the features' importance and apply proper selection techniques to indicate the most important ones that raise the model's performance while reducing complexity.

Table 3 presents the ranking of EEG-based features selected for engagement prediction using three distinct methods: Pearson CC, IG, and GR. These tech-

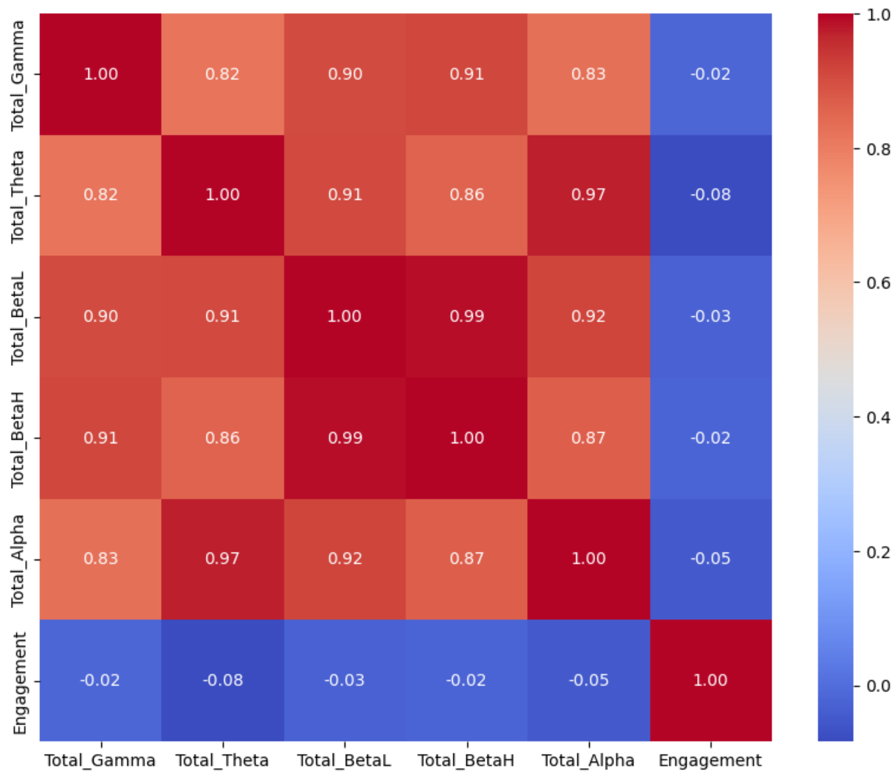

Fig. 4. Correlation between PSD features and engagement class [10].

niques evaluate feature importance from different perspectives, providing complementary insights into the most relevant EEG features for classification.

The Pearson CC, as defined in equation (3), assesses the linear relationship between each EEG feature and the engagement class label. Features with higher absolute correlation values indicate stronger associations with engagement levels. Notably, EEG.T8, EEG.O1, and EEG.P8 exhibit the highest correlation values, suggesting that neural activity in the temporal and occipital regions plays a significant role in engagement prediction.

In contrast, IG, computed using equation (4), quantifies the reduction in uncertainty about the engagement state when a given feature is known. Features with higher IG scores provide more discriminative information for classification. The rankings in Table 3 highlight EEG.T7, EEG.O1, and EEG.T8 as the most informative raw EEG channels, while power spectral features such as POW.F7.Theta and POW.FC5.Theta also achieve high scores, indicating that spectral characteristics contribute meaningfully to engagement differentiation.

The GR, derived from equation (5), refines IG by normalizing it with the intrinsic entropy of each feature, reducing bias toward attributes with a high number of unique values. The rankings in Table 3 demonstrate that spectral features such as POW.F7.Theta, POW.F7.Alpha, and POW.FC5.Theta outperform some raw EEG signals, reinforcing the relevance of frequency-based features in engagement classification.

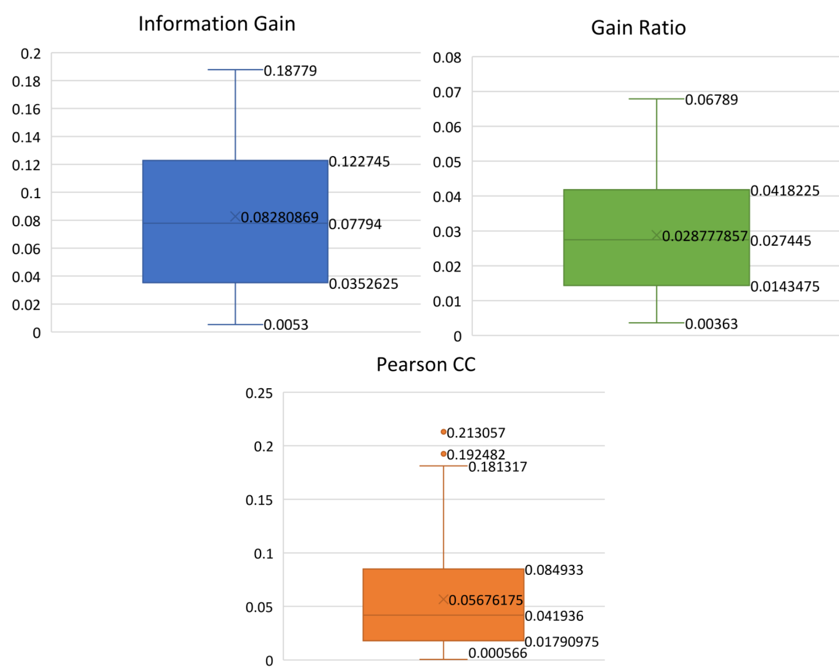

Fig. 5. Statistics for 3 feature selection techniques assuming the whole (84) feature set.

The statistics of the ranking scores are captured in Figure 5, providing an overview of the distribution of feature importance across the three feature selection techniques: Pearson CC, IG, and GR. This visualization offers insight into the variability in feature relevance depending on the selection criteria. While Table 3 presents a subset of the most relevant features, Figure 5 ensures a comprehensive representation of the entire feature set, allowing for a comparative evaluation of ranking consistency and the influence of specific EEG channels and spectral power components. This combined approach justifies the selection of the final reduced feature set by demonstrating the statistical patterns in feature importance, ensuring that only the most discriminative and informative features are retained for engagement classification.

Feature selection was performed to enhance model interpretability and improve classification performance by reducing redundancy while retaining the most informative EEG features for engagement prediction. The selection process integrated Pearson CC, IG, and GR as ranking criteria. Features were cho-

Table 3. Feature Importance based on the score estimated by Pearson CCs, IG and GR.

Feature	CC	Feature	IG	Feature	GR
EEG.T8	0.2131	EEG.T7	0.1878	POW.F7.Theta	0.0679
EEG.O1	0.1925	EEG.O1	0.1808	POW.F7.Alpha	0.0615
EEG.P8	0.1813	EEG.T8	0.1794	POW.FC5.Theta	0.0614
EEG.P7	0.1799	POW.F7.Theta	0.1761	POW.T8.Theta	0.0578
EEG.T7	0.1670	POW.FC5.Theta	0.1733	EEG.T8	0.0554
EEG.O2	0.1575	POW.T8.Theta	0.1733	POW.T7.Theta	0.0542
EEG.AF3	0.1395	POW.T8.Alpha	0.1728	EEG.F3	0.0536
POW.F7.Theta	0.1293	POW.T7.Theta	0.1645	EEG.FC5	0.0527
EEG.F7	0.1278	EEG.F3	0.1634	POW.T8.Alpha	0.0516
POW.F8.Theta	0.1230	EEG.P8	0.1634	EEG.P8	0.0503
POW.T7.Theta	0.1136	EEG.O2	0.1550	EEG.T7	0.0484
POW.P8.Theta	0.1095	EEG.P7	0.1512	POW.P7.Theta	0.0479
POW.F3.Theta	0.1087	POW.F8.Alpha	0.1497	POW.F3.Theta	0.0479
POW.F8.Alpha	0.1083	EEG.AF3	0.1491	EEG.O1	0.0478
POW.FC5.Theta	0.0958	POW.P7.Theta	0.1481	EEG.AF4	0.0471
POW.P7.Theta	0.0911	EEG.FC5	0.1451	EEG.AF3	0.0467
EEG.FC5	0.0910	POW.T8.BetaL	0.1430	EEG.O2	0.0458
POW.F4.Theta	0.0906	EEG.F4	0.1411	POW.T8.BetaL	0.0436
POW.O2.Theta	0.0882	EEG.F7	0.1353	POW.F8.Alpha	0.0433
POW.AF3.Theta	0.0869	POW.F3.Theta	0.1312	EEG.FC6	0.0431
POW.T8.Theta	0.0858	POW.F8.BetaH	0.1232	EEG.F4	0.0419
EEG.FC6	0.0822	POW.F8.BetaL	0.1213	EEG.P7	0.0417
POW.F3.Alpha	0.0794	POW.O2.Theta	0.1162	POW.F4.Theta	0.0413

sen based on their consistently high rankings across these methods, ensuring a balance between raw EEG electrode signals and spectral PSD features.

The final selection of 14 features was made by prioritizing attributes that contributed unique and non-redundant information while discarding those with overlapping or low-importance scores. This approach ensures that the retained features effectively capture engagement-related brain activity without excessive dimensionality, which could introduce noise and reduce model efficiency. The selected features include EEG.O1, EEG.T8, EEG.T7, EEG.AF3, EEG.FC5, EEG.F7, EEG.F4, POW.FC5.Theta, POW.P8.Theta, POW.F3.Alpha, POW.F4 .Theta, POW.O2.Theta, POW.AF3.Theta, and POW.T8.Theta. These features provide a comprehensive representation of frontal, temporal, and occipital lobe activity, as well as frequency-specific engagement markers, ensuring an optimal trade-off between performance and interpretability.

5 Performance Evaluation of Engagement Models

The ML models' evaluation was carried out using WEKA [1], a free software suite offering a range of tools for data preprocessing, classification, regression, clustering, and visualization. The experiments were executed on an Apple MacBook Pro with a 13.3" Retina Display, equipped with an M2 chip, 16GB of RAM, and a 256GB SSD.

Each model was trained on the preprocessed EEG dataset using a stratified 10-fold cross-validation to ensure robust performance evaluation. Hyperparameter tuning was performed using grid search to identify the optimal parameter settings for each model as shown in Table 4.

Table 4. Optimal Hyperparameter Tuning for ML Models.

Traditional ML Models		
Model	**Hyperparameter**	**Optimal Value**
LR	Regularization (C)	1.0
SVM	Kernel Type	RBF
	Kernel Coefficient (γ)	0.01
	Regularization (C)	10
RF	Number of Trees	100
	Maximum Depth	None (unlimited)
	Minimum Samples Split	2
GBM	Number of Estimators	200
	Learning Rate	0.1
	Maximum Depth	3
NN	Number of Layers	3
	Neurons per Layer	[64, 128, 64]
	Activation Function	ReLU
	Learning Rate	0.001
	Batch Size	32
	Epochs	150

DL and Hybrid Models		
Model	**Hyperparameter**	**Optimal Value**
CNN	Convolutional Layers	3
	Kernels per Layer	[32, 64, 128]
	Pooling Method	MaxPooling
	Fully Connected Layers	[128, 64]
	Activation Function	ReLU
	Optimizer	Adam
	Learning Rate	0.001
	Batch Size	32
	Epochs	150
Hybrid Ensemble	Base Learners	GBM, RF, NN
	GBM Estimators	200
	RF Estimators	100
	NN Layers	[64, 128, 64]
	Meta-classifier	LR (C = 1.0)

The performance results, presented in Table 5, highlight the impact of feature selection on EEG-based engagement prediction. Our methodology follows two distinct approaches: i) leveraging the full feature set and ii) incorporating feature selection (as analyzed in Section 4.2). Feature selection plays a crucial role in EEG-based engagement prediction by reducing feature space dimensionality, and enhancing model interpretability and classification performance. The selected features in this study include EEG.T8, EEG.O1, EEG.P8, EEG.T7, EEG.AF3, EEG.FC5, EEG.F7, EEG.F4, POW.FC5.Theta, POW.P8.Theta, POW.F3 .Alpha, POW.F4.Theta, POW.O2.Theta, and POW.AF3.Theta, and align with neuroscientific findings and prior research in EEG-based engagement prediction for e-learning. It has been consistently shown that engagement-related cognitive activity is reflected in distinct cortical regions and frequency bands, particularly those associated with attention, memory, sensory integration, and cognitive load regulation.

The temporal and occipital electrodes (e.g., EEG.T8, EEG.O1, EEG.P8) correspond to memory retrieval and visual processing functions, which are fundamental to learning engagement. Also, right temporal lobe activation (EEG.T8) has been linked to active listening and information retention, indicating its strong association with engagement intensity in auditory learning tasks. Similarly, occipital electrodes (EEG.O1, O2) play a critical role in visual attention and cognitive load regulation, particularly in multimedia-based learning environments, where visual engagement determines comprehension and retention.

Additionally, the parietal electrode P8, selected as a key feature, is supported by studies highlighting its role in sensorimotor integration and attentional control. Sustained engagement in e-learning has been shown to correlate with increased parietal cortex activation, reflecting cognitive processing, attentional shifts, and sensory integration. The inclusion of POW.F7.Theta and POW.FC5.Theta reinforces the neuroscientific basis of engagement prediction, as theta power in frontal and fronto-central regions has been associated with working memory load, sustained attention, and cognitive focus.

The impact of feature selection on model performance is evident in the results. By retaining only the most relevant features, classification models exhibited higher accuracy, precision, recall, and AUC scores compared to models trained on all features. The Hybrid Ensemble model, integrating GBMs, RF, and NN, achieved the highest performance, with an accuracy of 92.7% and an AUC of 95.1% when trained on the selected 14 features. This finding suggests that eliminating less informative features not only reduces computational complexity but also enhances model generalization. Similarly, the CNN model, leveraging spatial and temporal dependencies in EEG signals, demonstrated superior classification performance with feature selection, indicating that a refined feature set improves DL models' ability to capture engagement-related patterns.

These findings are consistent with prior EEG-based engagement prediction studies, which emphasize that targeted feature selection eliminates redundant data while preserving only the most discriminative neural signatures of engagement. Research in EEG-driven learning analytics has demonstrated that optimized feature sets, particularly those based on PSD and spatial cortical activations, contribute to higher classification accuracy and model efficiency. The feature selection methodology applied in this study ensures that models are not overwhelmed by noise or irrelevant variability, thereby improving the robustness, interpretability, and reliability of engagement prediction.

The results also reinforce the scientific validity of EEG-based engagement classification in e-learning. By aligning feature selection outcomes with established neurophysiological evidence, this study underscores the importance of strategic feature selection in optimizing engagement prediction models for real-world applications.

6 Conclusions

This study explored EEG-based engagement prediction in e-learning environments using ML models. By leveraging EEG signals recorded from learners during online educational sessions, we developed a robust framework for feature extraction, selection, and classification to assess engagement levels. The results demonstrated that integrating feature selection techniques significantly enhances

Table 5. Performance Comparison of Models with All Features vs. Selected Features

	All Features (84)					Selected Features (14)				
Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**AUC**	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**AUC**
LR	78.0%	75.0%	76.0%	75.5%	80.0%	79.1%	76.5%	77.3%	76.9%	81.5%
SVM	82.0%	80.0%	81.0%	80.5%	84.0%	83.2%	81.5%	82.3%	81.9%	85.7%
RF	85.0%	83.0%	84.0%	83.5%	87.0%	86.1%	84.5%	85.2%	84.8%	88.6%
GBM	87.0%	85.0%	86.0%	85.5%	89.0%	88.0%	86.4%	87.1%	86.8%	90.5%
NN	90.0%	88.0%	89.0%	88.5%	92.0%	91.2%	89.8%	90.5%	90.1%	93.0%
CNN	89.0%	87.5%	88.2%	87.8%	91.5%	90.3%	89.0%	89.7%	89.3%	92.8%
Hybrid Ensemble	91.5%	90.2%	91.0%	90.5%	93.7%	92.7%	91.5%	92.0%	91.8%	95.1%

model interpretability and performance by reducing redundancy and preserving the most informative neural features.

The evaluation of multiple ML-based engagement models, including traditional classifiers (LR, SVM, RF, GBM, Hybrid Ensemble) and DL architectures (NNs and CNNs), revealed that feature selection leads to improved classification performance. The Hybrid Ensemble model achieved the highest accuracy (92.7%) and AUC (95.1%) when trained on the selected 14 features, demonstrating the effectiveness of a refined feature set in optimizing engagement prediction. Furthermore, the CNN model, designed to capture spatial and temporal dependencies in EEG signals, also exhibited strong performance, reinforcing the importance of DL approaches in EEG-based learning analytics.

The selected features related to EEG channels T7, T8, O1, P8, AF3, FC5, F4, F7, the PSD of F4, AF3, FC5, P8, and O2 at θ band, and the PSD of F3 at α band, align with neuroscientific evidence linking engagement-related cognitive processes to specific cortical regions and frequency bands. The temporal, occipital, and parietal electrodes capture critical aspects of memory retrieval, sensory integration, and attentional focus, while spectral power features provide insights into cognitive load and sustained attention.

By systematically refining the EEG feature space, this study highlights the advantages of targeted feature selection in improving computational efficiency while maintaining high classification accuracy. Our findings support the broader adoption of EEG-based engagement monitoring systems in adaptive e-learning environments, enabling real-time adjustments to instructional content based on learners' cognitive states.

Future research should explore the integration of real-time EEG-based adaptive learning systems that dynamically adjust content delivery based on engagement levels. Additionally, expanding the study with a larger and more diverse participant pool would further validate the generalizability of the proposed approach. The intersection of EEG analytics and ML holds immense potential for revolutionizing personalized e-learning by providing objective, data-driven insights into learner engagement, ultimately enhancing educational outcomes.

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