Leveraging Cloud Computing And Big Data Analytics To Enhance Ideological Education Platforms In Universities

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Education is going through a remarkable transformation brought about by the convergence of cloud computing and big data, which have enabled educational institutions to develop very different and individualized learning experiences for each student depending on his/her needs. But, even with the technology in place, the tracking of engagement in ideological education has not been able to break its limitations, causing disengagement, which is consequently leading to slow overall learning. The authors of the paper propose to create a flexible and tolerant cloud-based educational platform using big data analytics powered by AI in the Higher Education sector. One of the main goals of the research is to establish a system that will employ AI for the real-time classification of student engagement based on EEG signals and behavioral data and will thus adapt the content and the learning paths accordingly. The investigation will utilize a combination of Multilayer Perceptron (MLP) and Long Short-Term Memory networks (LSTM) African Vultures Optimization Algori thm (AVOA) will be used for feature selection, and cloud-based data storage will be provided to make the system scalable. The performance results of the proposed system have shown a very significant improvement over traditional models, with the MLP-LSTM combination achieving an accuracy of 92.6%, precision of 92.1%, recall of 91.8%, and F1 score of 91.9%.

Keywords: EEG Analysis, Student Engagement, Feature Optimization, AVOA, Cognitive Monitoring, Intelligent Systems

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1. Introduction

The education industry has become increasingly technical in recent years, as previously predicted [1].The integration of cloud computing, big data, and Artificial Intelligence (AI) has significantly improved learning experiences through combined technological advancements. These technologies enable learning personalization, allowing educational systems to be tailored according to individual student preferences [2]. However, despite technological progress, the education sector still faces persistent challenges associated with traditional teaching methods [3]. The solution involves the development of a cloud computing platform that uses big data analysis and an artificial intelligence engagement classification technique using a hybrid MLP-LSTM model to classify student engagement based on their EEG signals and actions. Key Contributions are:

- Develop an EEG-based system to low, medium, and high student engagement.
- Preprocess EEG data and extract statistical and frequency-domain features.
- Apply AVOA for optimal feature selection and dimensionality reduction.
- Design a hybrid MLP-LSTM model for accurate EEG-based engagement prediction.

- Integrate big data and cloud support for scalable educational platform deployment.

Structure of the paper is as follows: literature review is done in Section 2, methodology is presented in Section 3, Section 4 covers experimental results and performance evaluation, and lastly Section 5 provides conclusions from the study.

2. Materials and methods

In , Ju and Xiang [4] discuss the digital data infrastructure for facilitating data-driven decisionmaking in the field of higher education, whereas Wu et al. [5] use artificial intelligence to show how personalized learning can be achieved. Both studies emphasize the need for cloud computing, big data, AI, blockchain, Industry 4.0, and the Metaverse in educationIn recent times, the significance of digital technology in higher education and management has been realized with an emphasis on data infrastructure, cloud computing, big data, artificial intelligence, blockchain, Industry 4.0, and the Metaverse. Tang & Yang [6] investigate the impact of cloud computing and big data technologies on the efficiency of the enterprise digital management process. The research employs a data envelopment analysis model to measure the performance of digital transformation, showcasing the benefits of cutting-edge data-driven methods through the improvement of operational efficiency, cost reduction, and service optimization. Zhai et al.[7] presents deal with the virtual teaching communities' strong side, and the Metaverse's support of educational equity through them. The virtual teaching communities' strong side, and the Metaverse's support of educational equity through them. The paper presents the historical development of Metaverse concepts and their classroom applications, mainly through virtual worlds, human-like interactions, and avatar-simulated character-to-character emotions.

2.1. Problem Statement

Cloud computing and big data have transformed university education by enabling personalized and data-driven learning [8]. This study proposes a cloud-based platform that uses big data and AI to classify student engagement from EEG signals and behavioral data [7]. The platform provides adaptive learning paths based on engagement levels, while cloud support ensures scalable and efficient data processing for improved educational quality [9, 10].

2.2. Methodology

The proposed EEG-based student engagement analysis framework combines big data analytics and cloud computing to develop intelligent ideological education. Preprocessing is done on the EEG signals to extract statistical and frequency domain features that are selected through the African Vulture Optimization Algorithm (AVOA) in Fig. 1.

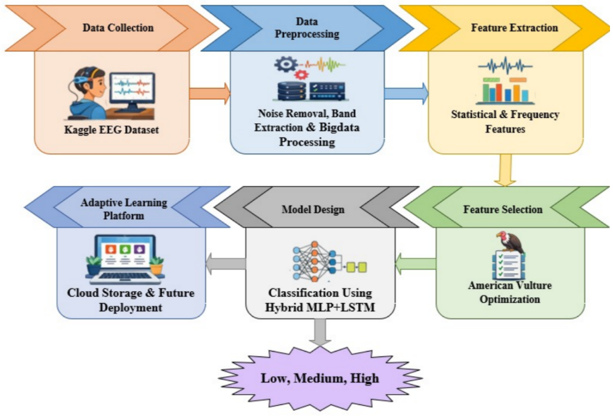

Fig. 1. The Overall Proposed Work

2.3. Data Collection

The data set employed in this study is the Kaggle EEG Student Engagement Data Set [11] which includes EEG signals recorded from multiple channels while students were engaged in educational activities. The raw EEG data are first stored locally for efficient processing and feature extraction and later stored in the cloud for scalability and reusability.

2.4. Data Preprocessing

EEG signals generally go through noise interference coming from blinks, muscle movements, as well as outside electrical interference. Assuming $x(t)$ indicates raw EEG signal; the filtered signal $x_f(t)$ is given in Eq. (1)

$$x_f(t) = x(t) * h(t) \tag{1}$$

Here, $h(t)$ represents the impulse response of the bandpass filter, and * denotes convolution. The EEG signals are then normalized using Z-score normalization to reduce variability across subjects and improve training stability, as given in Eq. (2).

$$x_n = \frac{x_f - \mu}{\sigma} \tag{2}$$

Here, x_f is the filtered EEG signal, μ is the mean, and σ is the standard deviation. The FFT helps in transforming the EEG data from the time domain to the frequency domain so as to extract Alpha, Beta, and Gamma features that are linked to attention and mental workload. The frequency domain representation is therefore more compact and informative. The power features for particular EEG bands like Alpha (8-13 Hz), Beta (13-30 Hz), and Gamma (30-50 Hz) are drawn from modified signal. The chosen frequency bands of the EEG contain distinct cognitive functions associated with learning. The Alpha frequency band (8-13 Hz) shows relaxation and attention, Beta frequency band (13-30 Hz) signifies active thinking and sustained attention, whereas Gamma frequency band ($30-50$ Hz) is associated with high-level cognitive activities like memory, reasoning, and information processing.

Big data techniques

Big EEG datasets are analyzed locally by means of NumPy and Pandas, while Dask facilitates parallel processing and GPU is used for computing heavy processes.

Cloud integration

The preprocessed EEG data may be transferred to the cloud storage to provide a secure storage and convenient sharing of the dataset. Artifact rejection is aimed at eliminating artifacts such as eye blinks, muscles movements and noise from the EEG data while preserving neurological information. Band pass filtering retains the necessary frequency bands, and equal time window segmentation ensures that the processing of all the EEG data is consistent.

2.5. Feature Extraction

Feature extraction from the preprocessed EEG signals is done by calculating the statistical and frequency domain features. The statistical features include the mean and variance while the frequency domain features include alpha, beta, and gamma bands.

Feature extraction, lstm sequencing, and cloud storage

The statistical feature extraction process involves obtaining the mean value, variance, and alpha, beta, and gamma power bands from the preprocessed EEG signal.

2.6. Feature Selection Using AVOA

AVOA selects the most discriminative EEG features for student engagement classification. Inspired by African vultures' search behavior, it balances exploration and exploitation to identify the optimal feature subset.

Initialization of population

At the start, an initial population size of N vultures is produced such that each vulture corresponds to a potential set of EEG features as stated in Eq. (3).

$$P(t) = [f, f_2, \ldots, f_n] \tag{3}$$

where $f_1, f_2, \ldots, f_n$ denote EEG statistical and frequency, and n is total number of extracted EEG features.

Fitness evaluation

The fitness for each vulture is then calculated during the initialization process considering the accuracy of the classification and the reduction in redundancy, where the formula for calculation is shown in Eq. (4)

$$\text{Fitness}(F) = \text{Accuracy}(F) - \lambda \cdot \text{Redundancy}(F) \tag{4}$$

Where $\text{Accuracy}(F)$ denotes the classification accuracy achieved with the chosen EEG features, Redundancy (F) indicates the correlation.

Hunger rate update

The function of hunger rate $F(t)$ regulates the change from exploring new areas to exploiting old ones. The hunger rate is determined as given in Eq. (5)

$$F_t(t) = (2 \times \text{rand} + 1) \times z \times \left(1 - \frac{t}{T}\right) + d_t \tag{5}$$

Where rand $\in [0,1]$ represents a random number, $z \in [-1,1]$ adds random variation, t is the present iteration, T is the limit of iterations, and d_k is a fixed value.

Exploration phase

In the exploration stage, vultures thoroughly scan the EEG feature space to spot various and probable informative feature subsets. The i^{th} vulture's position update is expressed as given in Eq. (6)

$$P_i(t+1) = R_i(t) - D_i(t) \times F_i(t) \tag{6}$$

where $R_1(t)$ represents the location of the leading vulture, $D_1(t)$ is the distance from the current vulture to the leader, and $F_i(t)$ indicates the hunger rate.

Exploitation phase

Where the hunger rate signals exploitation, vultures concentrate on narrowing down the most promising EEG feature subsets around the best solutions. The exploitation update rule can be formulated as given in Eq. (7)

$$P'_{(}(t+1) = R_1(t) - (S_1 - S_2) \tag{7}$$

Leader selection

During every iteration, the vultures with the highest fitness values are selected as possible leaders. The process of choosing a leader is represented as is given in Eq. (8)

$$R_1(t) = \text{BestVulture}_{\,1} \text{ or BestVulture}_{\,2} \tag{8}$$

This strategy ensures diversity while maintaining convergence efficiency.

Iteration-based optimization & final selection of features

These three steps of exploration, exploitation, and selection of leader continue until the number of iterations is exhausted.

The proposed AVOA is able to prevent early convergence using adaptive exploration and exploitation, based on its population update strategy that takes into account the hunger of its individuals. It starts by exploring globally to look for different combinations of EEG features.

Hunger rate in the AVOA algorithm becomes an adaptive control parameter that helps in maintaining an optimal balance between exploration and exploitation. A higher hunger rate leads to exploration of various combinations of EEG features, whereas a lower hunger rate leads to exploitation of good feature subsets is given in algorithm 1.

2.7. Classification Using Hybrid MLP + LSTM

The hybrid architecture that combines MLP and LSTM networks is really a powerful one for student engagement classification based on EEG signals. Combining both spatial and temporal learning for EEG-based engagement classification is the MLP-LSTM model, where the MLP learns complex spatial relationships and the LSTM learns temporal dependencies using the sequential EEG input. The extracted EEG feature vectors are sent to the MLP network for learning spatial information, the level of student engagement as either low, medium, or high engagement in Fig. 2. In EEG preprocessing, noise and interference can be removed through band-pass filtering and artifact rejection; this enhances the quality of extracted features. The features that will be used for cognitive state analysis include Alpha, Beta, and Gamma power spectral features, which are extracted using the FFT process. The input, forget, and output gates form the basis of the LSTM network. While the input gate helps to store information, the forget gate helps get rid of irrelevant information from the past while the output gate passes useful information to the next time step. The segmentation of EEG signals in time windows will allow the LSTM model to detect any change in student engagement over time since this preserves temporal information in the signal data. Prior to integration, the feature representations of MLP and LSTM are aligned to make sure that they correspond to the same input data. This is followed by the concatenation of their spatial and temporal features, allowing the learning of both simultaneously as given in Eq. (9)

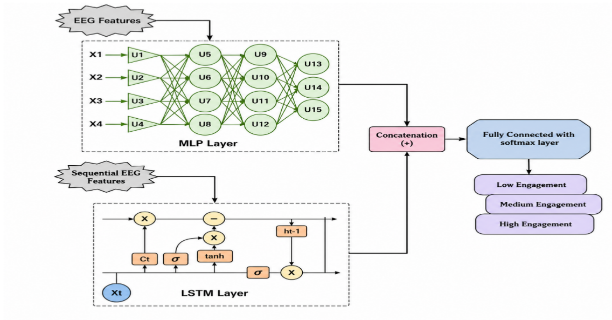

Fig. 2. Hybrid MLP-LSTM Architecture for EEG-Based Student Engagement Classification

$$P(y = k \mid F) = \frac{e^{z_k}}{\sum_{j=1}^{K} e^{z_j}} \tag{9}$$

Here, K stands for the total number of engagement classes (low, medium, high). SoftMax function converts the scores of the output layer into probability values in the range 0 to 1 , where the sum of all the probabilities is 1 . The class which has maximum probability is taken as the engagement level. The probability values make multi-class classification possible for engagement levels of students.

3. Results and discussion

The above-mentioned model had shown outstanding results with respect to accuracy, precision, recall and F1 scores. The steady increase in training and validation curves clearly reflects the learning capability of the model.

3.1. Computational resources

The experimental results were obtained using a 12th Gen Intel® Core™ i5-12400 (2.50 GHz) processor equipped with 8GB RAM, operating 64-bit Windows 11.

Fig. 3 demonstrates the results of the accuracy obtained after training and validating over 10 epochs.

The model was trained and validated for 10 epochs, as demonstrated in Fig. 4. In the process of training, the training loss dropped from 2.5 to 0.75, while the validation loss fell from 2.4 to 0.75 . The gradual decrease in training and validation losses clearly shows that optimization and minimization of the classification error is achieved. The

Algorithm 1. Pseudocode for African Vultures Optimization Algorithm

```
Initialize population of vultures with random feature subsets
for each vulture in N:
    vulture. Position = random features
    vulture. Fitness = evaluate (vulture. Position)
Repeat for max_iterations
for t = 1 to T:
    Update hunger rate
    for each vulture:
        update hunger rate
    Select leader vultures
        choose best vultures as leaders
    Update positions
    for each vulture:
        if exploring:
            explore new features
        else:
            exploit best features
        update fitness
Return best feature subset
Best_Feature_Set = vulture with highest fitness
return Best_Feature_Set
Function: evaluate (feature subset)
accuracy = classifier accuracy
redundancy = feature correlation
fitness = accuracy - penalty * redundancy
return fitness
```

close proximity of the two curves suggests convergence of the hybrid MLP-LSTM model, while no noticeable gap suggests proper generalization and appropriate learning rate and optimization algorithms.

3.2. Confusion Matrix

The confusion matrix exhibits some errors in misclassification at different levels of engagement that exist due to the overlapping Alpha, Beta, and Gamma waves during cognitive state changes. However, the new technique significantly reduces such errors. The model has efficiently classified 300 Low, 290 Medium, and 300 High in Fig. 5 below.

Here, Fig. 6 shows the precision-recall plots of the three engagement classes (Low, Medium, and High). The plots are clustered close to the top right corner of the plot, having average precision (AP) values of 0.999978, 0.996767, and 0.999989, respectively.

In Fig. 7, the ROC curves lie close to the top left point, implying that there is excellent classification of engagement levels (low, medium, and high). The ROC curve shows that the AUC is high, which means that the model is able to achieve high TPR with minimal FPR.

In Fig. 8, the model's accuracy, precision, recall, and F1-score performances. It gave an accuracy of 98.89%, 98.91% for precision, 98.89% for recall, and 98.88% for F1-score,

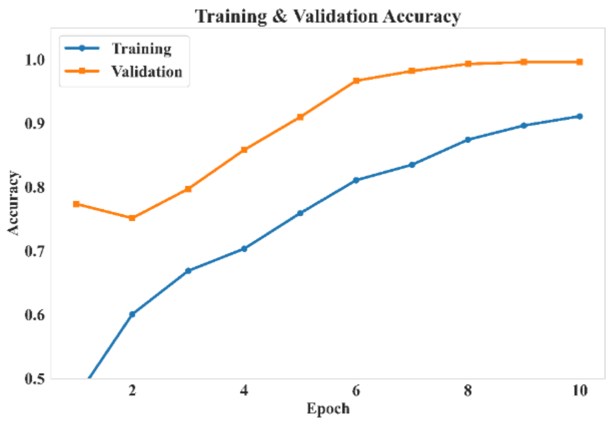

Fig. 3. Training & Validation Accuracy

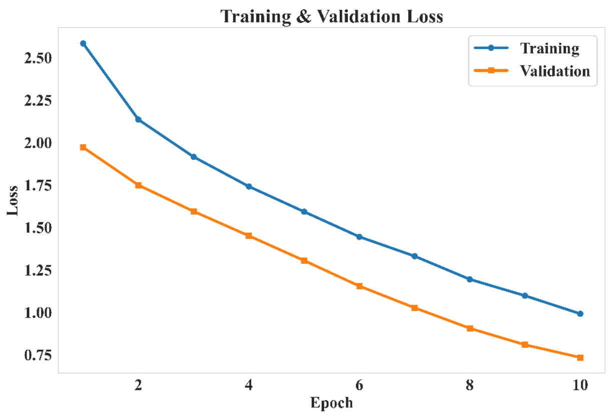

Fig. 4. Training & Validation Loss

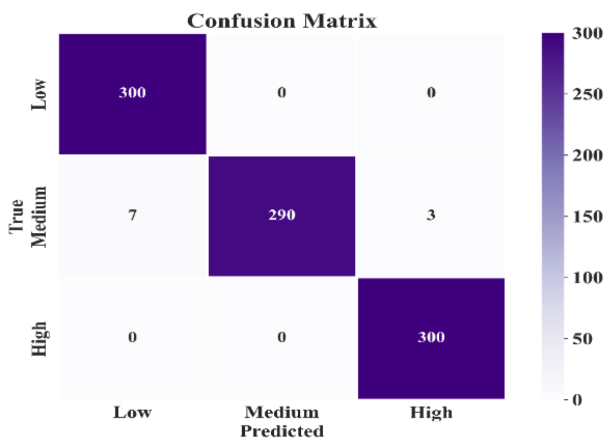

Fig. 5. Confusion Matrix

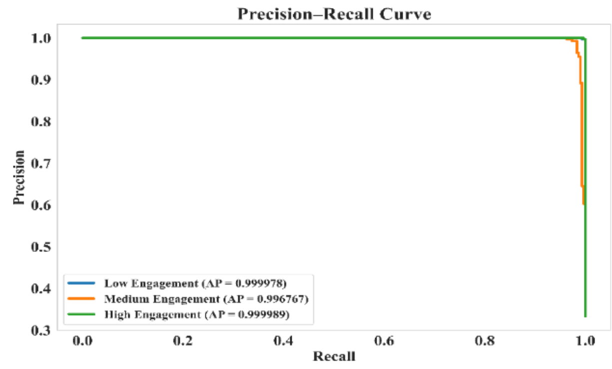

Fig. 6. Precision-Recall Curve

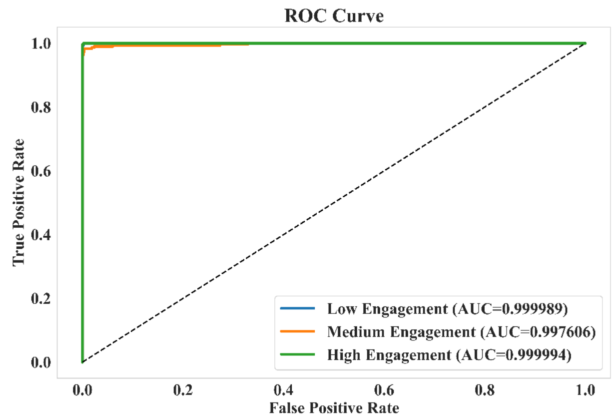

Fig. 7. ROC Curve

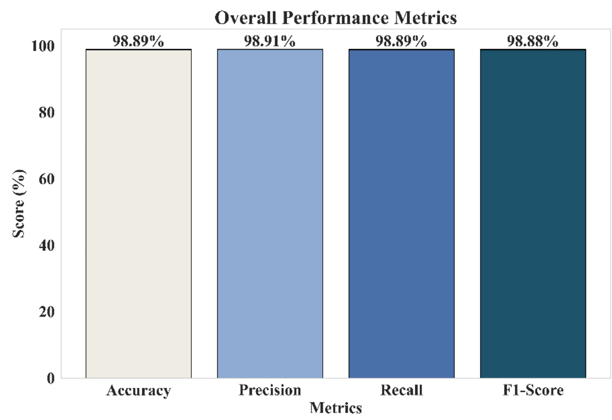

Fig. 8. ROC Curve

meaning that it has made reliable predictions.

The HDFS interface showing the directory /user/ADMIN/res_st_224/result (ST-224). This interface makes the storage and management of result files in HDFS easy. The temporal nature of EEG sequences is successfully captured using the LSTM layer in Fig. 9.

The proposed model combining MLP and LSTM yielded the highest performance in terms of 92.6% accuracy, 92.1% precision, 91.8% recall, and 91.9% F1-score, which is better than the SVM, CNN, LSTM, and MLP models, as presented in Table 1. The developed model is superior to SVM, CNN, and LSTM since it utilizes AVOA-based feature selection

Table 1. Comparison Table for the performance metrices

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Traditional ML (SVM) [12]	82.4	81.9	80.7	81.3
CNN-based Model[13]	86.1	85.4	84.9	85.1
LSTM-only Model [14]	88.3	87.9	87.2	87.5
MLP-only Model [15]	87.2	86.6	86.0	86.3
Proposed Model	92.6	92.1	91.8	91.9

Table 2. Ablation Study Performance Comparison

Model Variant	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Proposed (AVOA + MLP + LSTM)	98.89	98.91	98.89	98.88
Without AVOA	97.62	97.51	97.43	97.47
Without MLP	96.84	96.7	96.62	96.66
Without LSTM	97.28	97.12	97.05	97.08

Table 3. Robustness Evaluation Under EEG Conditions

EEG Condition	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Clean EEG	98.89	98.91	98.89	98.88
Noisy EEG	97.95	97.82	97.74	97.78
Incomplete EEG	96.73	96.61	96.55	96.58
Session Variability	98.12	98.03	97.96	97.99

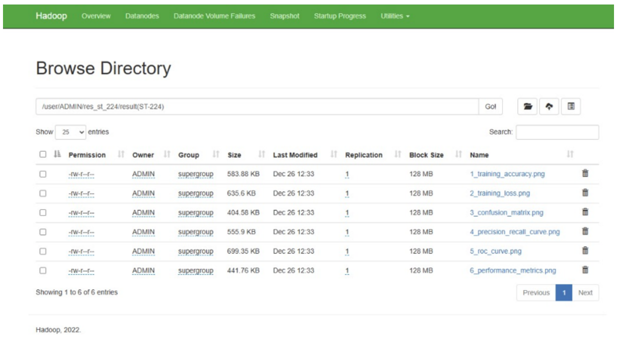

Fig. 9. ROC Curve

along with hybrid learning technique. In contrast to SVM, it utilizes AVOA to select best EEG features; on the other hand, unlike CNN and LSTM, it considers both spatial and temporal features.

3.3. Ablation Study

In an experiment, the role played by AVOA, MLP, and LSTM was investigated. MLP affected spatial learning while LSTM affected the temporal learning aspect. The full AVOA + MLP + LSTM performed best in Table 2.

3.4. Robustness Evaluation

The robustness of the proposed methodology was examined in the presence of noise, incompleteness, and session dependency of EEG data. It use of band-pass filtering and artifacts removal increased noise robustness and the AVOA decreased the effect of noisy feature in Table 3.

4. Conclusion and future work

This work suggests a novel EEG based student engagement detection system that is an amalgamation of big data analytics, cloud-based computing. Prediction of engagement facilitates adaptive learning through provision of relevant assistance depending on the levels of engagement. The suggested model performs better than other models such as the SVM, CNN, LSTM, and MLP models, scoring 92.6% accuracy, 92.1% precision, 91.8% recall, and 91.9% F1-score. In future studies, the integration of the EEG and facial expressions is intended. In the future, the framework will not only be for real-time cloud deployment on distributed platforms like Hadoop or Spark. EEG-based engagement classification requires secure data protection, user privacy, consent management, and scalable cloud deployment. Privacy and security in a cloud-based EEG system are important since the EEG data from students is sensitive. The data should be encrypted when transferring it, secured using authentication and access controls, and be anonymous. In ideological education, adaptive engagement monitoring through EEG analysis is used to measure the brain states of students. This method aims at recognizing attention and learning problems to ensure personalized learning.

Limitations

Model validation has been performed by using only one publicly available EEG engagement dataset. As a result, the generalization power of the model for other types of learners could be affected negatively. Another limitation of the model under consideration is that it is built based on the EEG measurement alone.

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Not Applicable

Declarations

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Conflict of interest

The authors declare that they have no conflicts of interest regarding this work.

Data availability

The data that support the findings of this study are not publicly available due to confidentiality agreements but are available from the corresponding author upon reasonable request.

Code availability

Not applicable.

Clinical trial number

Not applicable

Ethics

Not applicable

Consent to participate

Not applicable

Consent to publish

Not applicable

Author contributions

Weijian Shen: Conceptualization, Methodology, Formal analysis, Writing-original draft preparation.

Bingjun Yang: Data curation, Investigation, Visualization, Writing-review & editing.

Le Yang: Software, Validation, Resources.

Chaobiao Meng: Supervision, Project administration, Writing-review & editing.

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