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Article

Biosensor technology for adaptive intelligent education systems to enhance personalized English learning

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Abstract: The integration of biosensor technologies, like electroencephalography (EEG), has extended the limits of adaptive, intelligent education systems, offering real-time, personalized learning knowledge. This study explores the use of EEG to track and assess students' cognitive states, allowing for the improvement of an active, adaptive English learning system that tailors content according to every student's participation and improvement. Students' cognitive states serve as the foundation for personalized education responses that motivate and enhance their participation. EEG data are gathered during English language testing to assess the correlation between learners' cognitive states and their performance. Noise reduction is one of the preprocessing stages that ensures clear and pertinent data for analysis. Power spectral density (PSD) for feature extraction approaches is used to identify key cognitive patterns. Based on real-time EEG data, the personalized education feedback system constantly modified the course material, enhancing motivation and learning results. This research proposed a novel Dynamic Osprey Optimized Intelligent Gradient Boosting Machines (DOO-IGBM) to assess and improve the efficiency of an adaptive intelligent education system. The findings suggest that EEG-based adaptive systems make it possible to significantly progress English learning by offering personalized education paths based on brain activity to other conventional algorithms with 98.5% accuracy, 97.7% precision, 98% recall, and 98.6% F1-score. These outcomes provide precious insights and data to support the future development of adaptive, intelligent education systems for language learning.

Keywords: English learning; personalized education feedback; biosensor; adaptive intelligent education; Dynamic Osprey Optimized Intelligent Gradient Boosting Machines (DOO-IGBM)

1. Introduction

The goal of adaptive education systems is to modify the system through the information delivered based on every learner's exclusive desires. These systems are used in progress response to regulate lessons to every student's speed and favored process of education, ensuring a more efficient and personalized educational skill Mirata et al. [1]. Students' inclinations for how they process information and connect with the education environment are referred to as their knowledge styles. These preferences are mainly stable slanting in time and cognitive, emotive, or physiological. A student's preferred educational system helps them to become more self-aware, use their talents, and improve their weaknesses, especially in a variety of learning situations Bernard et al. [2]. Beyond the classic prospectus, teachers exploit this information to generate actions that improve outcomes of the different desires of their students. Student engagement, satisfaction, and education outcomes are improved by the adaptive educational systems that modify lessons to every student's exclusive education preferences. It has been demonstrated that these adjustments improve overall educational experiences, shorten education times, and boost education gains

Kanchon et al. [3]. The conventional academic on-the-stage approach to teaching English is giving way to the guide on the side, in which professors support students' education through investigation and problem-solving. Technology automates repetitive work, personalizes education, and offers data-driven insights to meet individual needs, particularly in online and hybrid education contexts Alam [4]. Teachers focus on motivating and engaging students since technology complements their jobs rather than replaces them. Adaptive education is one example of an innovation that aids in identifying education difficulties and offering focused remedies. Critical thinking, creativity, communication, and teamwork improved in English language education when instructor skills and technology are combined Burbules et al. [5]. The potential of biosensor technology in education, which offers real-time information on students' emotional and cognitive states, is being realized through adapted teaching Antoniou et al. [6]. When they perceive signs of stress or dissatisfaction, it enables teachers to adjust the complexity of the session or suggest assistance. Through individual desires adaptation, this process maximizes education and improves motivation, engagement, concentration, and generally educational attainment. **Figure 1** shows the personalized intelligence education system.

Figure 1. Adaptive intelligent English learning education system.

Disadvantages of conventional instructional strategies including their inability to accommodate learners' needs, they are impersonal, and do not offer timely feedback. Teaching by receiving information diminished participation, and issues with assessing mental and emotional states are the effects. In addition, some of these systems correctly incorporate contemporary technologies that facilitate effective and long-lasting adaptive education experiences Yu et al. [7]. The purpose of this research is to enhance individualized English instruction biosensor using integrate EEG into smart education systems. It generates a progressive cognitive condition to alter contents based on the reactions of students and their progress. To improve motivation, engagement, and acquired knowledge, the study proposes a DOO-IGBM model to assess the system's performance.

Contribution of the study

An adaptive intelligent education system aims to create personalized education experiences by dynamically adjusting content based on student progress and engagement. The key contributions of the study are given below.

1) The purpose of the study is to identify how EEG is used to track a student's cognition while learning English and how that data can be applied to improve an adaptive learning system.
2) The research collected EEG records from a student during the English language assessment to determine their cognitive states and association with their performance.
3) The pre-processing begins by highlighting noise reduction as their important feature and then using power spectral density techniques for extracting features and identifying significant cognitive patterns. The DOO-IGBM model tests the effectiveness of modifying content based on real-time EEG feedback for individualized education content in real-time.
4) The use of EEG in incorporating adaptive systems in learning offers benefits that are closely aligned with cognition in that students get feedback that is in concordance with what they are expected to learn. However, when it is done in real-time, content modifications have greater motivational and educational impact than traditional methods.
5) EEG-based adaptive education system that applies technique of real-time cognitive state monitoring to enhance education outcomes and learners' attentiveness enhance personal tutorship and, as a consequence, increase successful language educational experience.

The research demonstrates how biosensor technology accompanied by EEG helps to enhance adaptive education systems giving individual educational courses and future developments in the sphere of languages and other educational disciplines.

The remainder of the study is organized as follows: Section 2 provides the related articles. Section 3 provides the proposed methodology. Section 4 demonstrates the study outcomes. Section 5 gives the discussion and conclusion was summarized in Section 6.

2. Related work

This phase represents the evaluation of personalized education systems that have been applied to track cognitive states for improving education outcomes.

Wan and Yu [8] presented an adaptive education cognitive map technique to provide an e-education environment that dynamically modifies education activities and resources. The system's efficacy in individualized education environments was validated by a contrast experiment that demonstrated to increase in cognitive load while improving students' educational achievement, satisfaction, acceptance of technology, and interaction.

Chrysafiadi et al. [9] offered a brand-new adaptive e-assessment method that combined cognitive theories and fuzzy logic for customization. Students' knowledge levels were represented as fuzzy sets and education objectives were guided by the revised Bloom taxonomy. Based on student needs and test complexity, a fuzzy rule-based reasoned choice of test items. The evaluation demonstrated that the customized test creation was highly accurate.

Sargazi Moghadam et al. [10] presented an Artificial Intelligence (AI) based assessment framework for an online education platform that enhanced mood and education performance by using a Genetic Algorithm (GA) to suggest micro-break tricks depending on learners' moods. Findings from tests conducted on 40 English language learners demonstrated the framework's efficacy and usefulness for adaptive e-education systems, such as Moodle.

Liu and Ardakani [11] suggested an e-education platform that allows for material customization according to students' feelings. It used a K-nearest neighbors (KNN) algorithm to recognize emotional conditions in concurrent based on the EEG data collected from learners. The content was suggested by reinforcement education to sustain good emotions. In an evaluation involving 30 students, the accuracy of KNNs was 74.3%.

Boughida et al. [12] investigated the emotion-based adaption system for e-education that utilized a probability-based algorithm to simulate learner emotions based on facial expressions. The methodology suggested customized resources according to adaptive standards. Its efficacy was supported by five experiments that demonstrated test groups' increased motivation, engagement, and cognitive levels in comparison to control groups.

Kouahla et al. [13] suggested a technique for identifying education challenges through the analysis of emotional states through the identification of vocal and facial emotions. A recommendation generator offers educational or psychological remedies. Test and control group experiments validate the approach's efficacy by demonstrating that it improved learners' emotional states, motivation, and engagement.

Smart integrated learning was introduced by Ciolacu et al. [14] to improve student performance. It employed student activity models of real-time data and learning analytics to identify potential dropout causes. Using the non-invasive, inexpensive, adaptable, and distraction-free embedded biosensors found in wearable technology, real-time information might be utilized to promote students' academic performance, overall health, and well-being. According to the initial findings, there was a relationship among physiological responses and exam scores.

A portable, user-generic, low-profile EEG instrumentation equipment with a variety of in-ear and on-body biosensor capabilities was demonstrated by Paul et al. [15]. The electrodes were dependable and simple to construct for EEG, Electroocoulogram (EOG), and electromyogram (EMG) measurements in the forehead and the ears. Eye blinks, eye movements, and in-ear EEG waves during an alpha-modulated task were among the biosensors recorded by the wireless data collection system for electrophysiology (weDAQ) system at a high rate of sampling and data quality similar to clinical systems. Furthermore, facial electrodes recorded jaw muscle activity and eye movements. WeDAQ devices and electrode sensors were also shown to record multiple subjects while engaging in physical exercise.

Eltahir and Babiker [16] examined how pre-service student instructors at Ajman University perceived and performed academically when using AI-powered tailored education tools. AI tools improved performance, information retention, critical thinking, motivation, and engagement, according to a quasi-experimental design involving 110 students. This underscored AI's revolutionary potential in teacher education.

Wang et al. [17] offered a paradigm for multimodal evaluation of students' inspiration in online education settings to facilitate tailored interventions. According to the study, eye movements and brain activity were utilized to forecast motivational elements. Using Machine Learning (ML) classifiers to process EEG and eye gaze data, it achieved accuracy ranging from 68.1% to 92.8%.

Sajja et al. [18] presented a paradigm for individualized education in higher education that was powered by AI. AI is used by the system to lower cognitive burden, offer individualized support, and improve engagement with interactive features like flashcards and quizzes. The results demonstrated how AI-enhanced student performance and satisfaction in e-learning settings.

Wang et al. [19] compared the educational effects of customized adaptive education materials to both large- and small-group classroom instructions in China. Further research on adaptive education systems in Chinese education is based on the findings of two efficacy studies, which demonstrated that eighth-grade students utilizing Squirrel AI education fared better than those receiving traditional instruction.

Megahed and Mohammed [20] suggested an intelligent adaptive e-learning strategy that incorporated emotional states and student reactions. It combined a fuzzy approach to determine education progression with a convolutional neural network (CNN) to recognize facial expressions. The technique demonstrated adaptive education patterns and performance monitoring by combining facial expressions and using the corpora of 12 students.

Zammouri et al. [21] introduced a multi-agent-based architecture that used EEG to customize educational materials for each student. It calculated cognitive strain using the brain rhythms' PSD and Standardized Euclidean Distance (SED). PSD bands in the occipital lobe exactly indicate cognitive load, according to experimental data, which helps with educational assessment.

Liu et al. [22] suggested the inductive cognitive diagnosis model (ICDM) to rapidly determine the competence levels of new students in the Whale Optimization-Inspired Education System (WOIES). It presented a student-centered graph (SCG), which updated individual embeddings instead of aggregating the results of nearby students. ICDM performed faster and better than transductive approaches, was more efficient, and didn't require retraining.

Hussain et al. [23] suggested a novel method for annotating unlabeled student feedback by utilizing the Felder–Silverman Education Style Model (FSLSM) in combination with multi-layer subject modeling. Fuzzy logic, online usage mining, Deep Learning (DL), and sentiment analysis were combined to automatically identify education styles, improving the delivery of personalized content and surpassing current methods.

Chrysafiadi et al. [24] offered an assessment of an intelligent tutoring system (ITS) that educated computer programs using fuzzy logic. Undergraduate students participated in the assessment, which assessed context, accuracy, efficiency, effectiveness, usability, motivation, engagement, and satisfaction. According to results confirmed by t-tests, the fuzzy mechanism improved engagement, interaction effectiveness, learner satisfaction, and knowledge acquisition.

Ouyang et al. [25] gathered multimodal data and suggested a three-tiered architecture that combined education analytics and AI to examine group collaboration trends. It found three patterns of collaboration that were connected to performance levels. The study provided pedagogical and theoretical insights for Cyber-Physical Systems (CPS) research while highlighting the dynamic, multimodal character of collaboration.

Amin et al. [26] suggested a smart e-learning system based on Reinforcement Learning (RL) that used Markov Decision Process (MDP) to customize education paths. Through the use of Q-education for Sequential Path Recommendation (SPR), the framework modified suggestions in response to learner input. Results from experiments demonstrated notable enhancements and efficient operation under different parameter adjustments.

Kukkar et al. [27] suggested a new Student Academic Performance Predicting (SAPP) method that makes use of Gradient Boosting (GB), Random Forest (RF) and a 4-layer stacked Long Short Term Memory (LSTM) approach. With a 96% accuracy rate, the system outperformed current prediction models on both self-curated emotional datasets.

3. Methodology

The study gathers data from language tests and EEG to evaluate cognitive states and performance association. A bandpass filter is used to pre-process the EEG data and the PSD is used to extract features. Hyper-parameters are optimized for real-time adaptive education by DOO-IGBM. **Figure 2** shows the methodological flow.

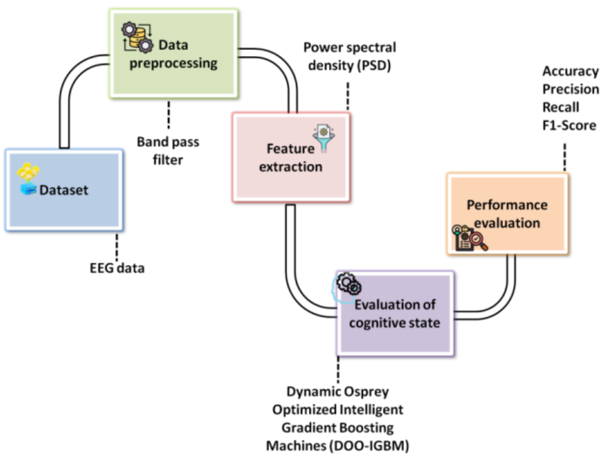

Figure 2. Overview of methodology flow.

3.1. Data collection

This dataset combines EEG data and language test scores to explore the relationship between learners' cognitive states and their performance in English language testing. The EEG data captures cognitive states such as attention, focus, and relaxation, using time-series data to display real-time cognitive arrangement during the test. Language test scores, including accuracy and completion time, are used to evaluate learner performance. To enhance the dataset, additional biosensor data, such as heart rate variability, galvanic skin response (GSR), and eye-tracking metrics, will be integrated. These biosensors provide valuable insights into emotional and physiological states, complementing the EEG data for a more comprehensive assessment of learner engagement. The combined data will enable the analysis of cognitive and physiological factors influencing language performance, offering a basis for developing adaptive educational systems that tailor content to the learner's cognitive state in real time, ultimately optimizing educational outcomes.

3.2. Data preprocessing

The gathered EEG signal data is preprocessed using a bandpass filter. It attenuates wavelengths beyond the specified range while permitting signals within that range to flow through. Its transfer function $G(e)$ is given by Equation (1)

$$G(e) = \frac{e_{high} - e_{low}}{e^2 + (e_{high} + e_{low})^2} \tag{1}$$

where $e_{high}\ and\ e_{low}$ represent the upper and lower cutoff frequencies, respectively, this filter passes frequencies between $e_{high}\ and\ e_{low}$ allowing relevant signals to pass while blocking unwanted noise. It isolates specific signals and removes irrelevant noise or disturbances, improving the quality of data used for further analysis.

3.3. Feature extraction

PSD is used to extract the noise-removed features from the data. It is used to describe how a signal's power is distributed across various frequencies. It aids in determining the prominent frequency components and offers insight into the distribution of a signal's power as a function of frequency. The average power P over some time S is defined as follows Equation (2) given a signal $y(s)$.

$$P = \begin{matrix} lim \\ S \to \infty \end{matrix} \frac{1}{S} \int_0^S |y(s)|^2\, cs \tag{2}$$

Equation (2) calculates the signal's mean power over an endless amount of time. To normalize the signal by the duration of the observation period, the integral divides the squared magnitude of the signal over time by S. The signal is subjected to Fourier processing to assess its frequency content. The frequency components of the signal are represented by the Fourier transform $\hat{y}(e)$ of the signal (s). Next, the predicted value of the squared magnitude of the Fourier-transformed signal is used to determine the PSD is given in Equation (3).

$$T_{yy}(e) = \lim_{S\to\infty} \mathbb{E}|\hat{y}(e)|^2 \tag{3}$$

Here, $\hat{y}(e)$ represents the signal $y(s)$ Fourier transformed, and the PSD. T_{yy}gives the power content at each frequency e. With the help of the expected value $\mathbb{E}$, which takes into consideration the averaging over time (as $S \to \infty$), the power distribution of a stationary signal is estimated. The PSD is frequently utilized in domains such as communications, EEG analysis, and signal processing since it is used to determine the dominant frequencies in a signal.

3.4. Evaluate student cognitive state using dynamic osprey optimized intelligent gradient boosting machines (DOO-IGBM)

DOO-IGBM optimizes hyper-parameters to improve predictive accuracy by combining the DOO algorithm and IGBM. It enhances biosensor adaptive education systems' ability to analyze EEG data, allowing for real-time content modification for more individualized feedback and improved education results.

3.4.1. Intelligent gradient boosting machines (IGBM)

Feature-extracted data is evaluated using IGBM. The conventional GBM architecture is enhanced by IGBM, which incorporates feature selection and sophisticated education techniques while dynamically optimizing parameters. With GB, a loss function $K(x,\hat{x})$ is minimized by iteratively creating models that fix the mistakes of the earlier ones. The model prediction at iteration s, represented as $\hat{x}$ is given in Equation (4).

$$\hat{x}_s = \hat{x}_{s-1} + \eta \times e_s(y) \tag{4}$$

where $\hat{x}_{s-1}$ is the previous iteration's prediction, η is the rate of education. $e_s(y)$is a weak learner fitted to the loss function's negative gradient. For sample$j$, the gradient of the loss function is given in Equation (5)

$$h_j = -\frac{\partial K(x_j, \hat{x}_{s-1})}{\partial \hat{x}_{s-1}} \tag{5}$$

First, use a constant model x_0, reducing the loss, at 0update position using Equation (6).

$$x_0 = \underset{d}{argmin} \sum_{j=1}^{m} K(x_j\,, d) \tag{6}$$

Iterative updates: For every iteration s, calculate the gradients h_j and the sample weights u_j. Develop a weak learner $e_s(y)$ to reduce weighted loss (y) using Equation (7).

$$e_s(y) = \underset{e}{\arg min} \sum_{j=1}^{m} u_j \times [h_j - e(y_j)]^2 \tag{7}$$

Adjusting the education rate dynamically using the education rate η in IGBM is dynamically modified according to performance parameters using Equation (8).

$$\eta_s = \frac{1}{\sqrt{s+\epsilon}} \tag{8}$$

This approach helps achieve a compromise between stability and convergence speed, where ϵ is a small constant that prevents division by zero. Feature significance scores, or T_i, are calculated to minimize overfitting and computational expense, frequently by using Equation (9).

$$T_i = \sum_{s=1}^{S} Gain(e_t, i) \tag{9}$$

$Gain(e_t, i)$is a boost in the loss unit brought about by splitting on feature i in tree e_t. Features that fall below a predetermined threshold, $T_i < \tau$, are eliminated. IGBM dynamically searches for the best hyper-parameters by using Equation (10).

$$\theta^* = \underset{\theta}{arg\,min} K(x, \hat{x}) \tag{10}$$

where θ stands for the set of hyper-parameters, IGBM gives samples weights $u_j$based on their significance or difficulty rather than treating all residuals equally as given in Equation (11).

$$h_j = -u_j \times \frac{\partial K(x_j, x_{s-1})}{\partial x_{s-1}}, \qquad u_j = \frac{1}{1 + \exp\left(-l.\left|q_j\right|\right.} \tag{11}$$

Update predictions using Equation (12).

$$\hat{x}_t(y) = \hat{x}_{s-1} + \eta_s \times e_s(y) \tag{12}$$

where $q_j = x_j - \hat{x}_{s-1}$ and l regulate the sensitivity of weighting. When to stop training use Equation (13).

$$\frac{1}{m} \sum_{j=1}^{m} K(x_j, \hat{x}_s) < Threshold \tag{13}$$

IGBM handles diverse data with excellent accuracy due to the addition of real-time optimization, feature selection, and adaptive weights. Because of these improvements, it is perfect for uses like personalized education systems, where adaptive feedback mechanisms are guided by EEG data, as demonstrated in the aforementioned study.

3.4.2. Dynamic osprey optimization (DOO)

Evaluated signals are optimized using DOO for increasing accuracy and reliability. It is an evolutionary algorithm created to solve dynamic optimization issues, drawing inspiration from Ospreys' hunting and movement patterns. Ospreys are a natural metaphor for maximizing functions in changing circumstances due to their extraordinary capacity to adjust to changes in their surroundings, such as shifting prey behaviors or environmental conditions. Adaptive techniques are incorporated into DOO to ensure effective solutions for space exploration and exploitation. There are 2 stages in the DOO algorithm: local development and global exploration. Similar to other meta-heuristic algorithms, the conventional osprey optimization technique initializes its population.

Osprey Population Initialization: The positions of each osprey are used as potential solutions to the crisis in the DOO and the initial osprey population is represented by the $M \times C$-dimensional matrix, which is made up of the placements of M osprey. Equation (14) is used to initialize each osprey's position at random.

$$W_{j,i} = Ja_i + q_{j,i} \times \left(va_j - Ja_i\right), j = 1,2, \ldots, M, i = 1,2, \ldots C \tag{14}$$

In the j^{th} problem variable, Ja_i and va_j represents the upper and lower bounds, respectively and $W_{j,i}$ gives the beginning position of the i^{th} object in the j^{th} dimension. The variables $q_{j,i} M, C$, and j represent the dimensions of the issue solution, the population number, and the j^{th} dimension, respectively. Osprey is considered a potential solution to the problem and its suitability is assessed based on the objective function E fitness value. Equation (15) is utilized in the computation of the fitness value.

$$E_j = E(W_j), j = 1,2, \dots, M \tag{15}$$

where W_i is the current position of the i^{th} osprey and E_j is its fitness value.

Positioning and Fishing (Phase 1): Submerging itself to hunt, the osprey locates the fish underwater and proceeds to attack it. As the global exploration step of the osprey optimization method, this procedure significantly alters the osprey's location in the exploration space**.** This process is represented in the DOO, where an underwater fish is any osprey that knows where previous ospreys with higher fitness values are located in the investigated space. In light of this, Equation (16) displays each osprey's position.

$$EO_j = \{W_l | l \in \{1,2, .. M\} \cap E_l < E_j\} \cup \{W_{best}\}, j = 1,2, .. M \tag{16}$$

where E_l represents the fitness values of the i^{th} and j^{th} osprey, correspondingly, M is the number of ospreys in the population, and EO_j is the position set of the i^{th} osprey. W_{best} is the best osprey's position. The osprey strikes at a fish randomly within the search area that it finds. The location update mechanism that occurs when the osprey approaches the fish is simulated using Equation (17):

$$W_{j,i}^{O1} = W_{j,i} + q_{j,i} \times (TE_{j,i} - J_{j,i}. W_{j,i}), j = 1,2, \dots, M; i = 1,2, \dots C \tag{17}$$

where W_i is the i^{th} osprey's initial position and $W_{j,i}$ is its j^{th} dimension; $W_{j,i}^{O1}$ is the i^{th} osprey's new position in stage1 and $W_{j,i}^{O1}$ is its j^{th} dimension. The fish selected by the first osprey are $TE_{j,}$ i, and $TE_{j,i}$ is its j-dimension. Whereas $J_{j,i}$ is randomly selected from the set $\{1,2\}$, $q_{j,i}$ is a random number that belongs to $[0, 1]$, and the boundary is handled by Equation (18) if the revised position is outside of it. The value of the inferior bound is assigned to the original place if it is smaller than the problem's lower bound. If the new position exceeds the higher bound, the upper bound value is assigned.

$$W_{j,i}^{O1} = \begin{cases} W_{j,i}^{O1}, Ja_i \le W_{j,i}^{O1} \le va_i \\ Ja_i, W_{j,i}^{O1} < Ja_i \\ va_j, W_{j,i}^{O1} > va_i \end{cases} \tag{18}$$

The prior position is replaced if the new location's fitness value, as determined by Equations (17) and (18), is greater. Equation (19) illustrates the operation and it is from this that the osprey's new position is determined.

$$w_j^1 = \begin{cases} W_j^{O1}, E_j^{O1} < E_j \\ W_j, E_j^{O1} \ge E_j \end{cases} \tag{19}$$

E_j^{O1} is the osprey's new location among the fitness values of phase 1. After phase 1, the osprey's position is indicated byw_j^1.

Bring the angle to the Right Position (Phase 2): The osprey determination transports the angle to a location where it believes it is secure to consume the following previous stage of fish hunting. This procedure improves the DOO local search capabilities while only slightly altering the osprey's location in the exploration space referred to as the local expansion phase. This stage's position update is completed by Equation (20). Equation (21) and other boundary processing procedures performed at this level in the same manner as the global exploration stage:

$$W_{j,i}^{O2} = W_{j,i}^{1} + \frac{Ja_i + q_{j,i} \times (va_j - Ja_i)}{s}, j = 1,2,..,M; i,..,C; s = 1,2,...,S \quad (20)$$

$$W_{j,i}^{O2} = \begin{cases} W_{j,i}^{O2}, Ja_i \leq W_{j,i}^{O2} \leq va_i \\ Ja_i, W_{j,i}^{O2} < Ja_i \\ va_j, W_{j,i}^{O2} > va_i \end{cases} \quad (21)$$

where s the current number of algorithm iterations is, S is the maximum number of iterations, q_j is a random number falling within $[0, 1]$ and $W_{j,i}^{O2}$is its j^{th} dimension. $W_{j,i}^{O2}$is the new location of thei^{th} predator in phase 2. The old site will be replaced if, as in the global exploration stage, the updated location's fitness value as determined by Equations (20) and (21) is higher. Equation (22), when applied, yields the new location of the osprey at this point:

$$w_j^2 = \begin{cases} W_j^{O2}, E_j^{O1} < E_j \\ w_j^1, E_j^{O2} \geq E_j^{O1} \end{cases} \quad (22)$$

where w_j^2 is the osprey's position following phase 2 and E_j^{O2} is the fitness value of locationE_j^{O2}. After completing the first two steps, until an ideal solution to the problem is found, or until the highest number of iterations is reached, the updates to the position of each osprey calculate the population iteratively. Through dynamic parameter adjustments, DOO improves model performance, ensuring quicker convergence and higher accuracy. Adaptive education systems can benefit greatly from their ability to overcome local minima, reduce computational complexity, and improve parameter tuning. With DOO, individualized and successful cognitive state-based education solutions are made possible by accuracy, resilience, and real-time flexibility.

The study introduces DOO-IGBM to improve adaptive education systems that combine DOO and IGBM. DOO improves predictive accuracy by optimizing IGBM parameters, such as education rate and tree depth, which are inspired by the hunting dynamics of ospreys. To extract features from EEG data and detect important cognitive patterns, DOO-IGBM applies power spectral density and noise reduction. This enables the educational materials to be instantly modified according to the cognitive states of the student, giving them tailored feedback and boosting their motivation. DOO-IGBM provides a strong foundation for data-driven, intelligent decision-making in individualized education systems due to its accuracy and scalability. Algorithm 1 shows the DOO-IGBM algorithm.

Algorithm 1 Dynamic Osprey Optimized Intelligent Gradient Boosting Machines (DOO-IGBM)

Start
***Step 1*:** Initialize parameters: Max-iterations, learning rate, feature threshold, max trees, max population, bounds, etc.
Step 2: IGBM model initialization (Learning rate, Loss function)
Initialize model with initial prediction x_0 for iteration $s = 1$ to max iteration:
Calculate the gradient of the loss function: $x_0 = \underset{d}{argmin} \sum_{j=1}^{m} K(x_j, d)$
Update model prediction: $x_s = x_{s=1}$
Calculate feature importance: T_i
Eliminate insignificant features based on $T_i < \tau$
Update learning rate:$\eta_s = \frac{1}{\sqrt{s+\epsilon}}$
Step 3: DOO for hyper-parameter optimization for each osprey j in the population:
Compute the fitness of osprey: E_j= Evaluation fitness (W_j)
Step 4: Positioning and fishing (Phases 1)
Identify the best position: EO_j
Update position: W_j^{O1}
Check boundaries and correct position
Calculate fitness of updated position: E_j^{O1}
If $E_j^{O1} < E_j$, update $W_j = W_j^{O1}$
Step 5: Bring the angle to the right position (Phase 2)
Update position: W_j^{O2}
Check boundaries and correct position
Calculate fitness of updated position E_j^{O2}
If $E_j^{O2} < E_j^{O1}$, update $W_j = W_j^{O2}$
Step 6: adaptive weighting and learning for each iteration
Update sample weights based on the fitness of ospreys
Fit weak learner $f_t(x)$ to minimize the weighted loss
Adjust learning rate dynamically based on updated weights
Update prediction: $\hat{x}_t(y) = \hat{x}_{s-1} + \eta_s \times e_s(y)$
Step 7: Training completion check
If the loss function is below the threshold stop training and output the final IGBM model
Step 8: Output final results
Return the final trained IGBM model with optimized parameters for a personalized education system.
END

4. Result

The study used Python 3.10 to create an intelligent, adaptive educational system that uses EEG data to customize biosensing educational materials for students. To evaluate the model's performance, the metrics used such as precision, recall, F1-score, and accuracy. Logistic Regression (LR) Gupta et al. [28], CNN Jamil and Belkacem [29] and Support Vector Machine (SVM) Gupta et al. [28] are the existing techniques that are compared.

Accuracy: It is the proportion of accurate forecasts made out of all the predictions. It is computed using Equation (23), in which FN stands for False Negative forecasts, TN for True Negative forecasts, FP for False Positive forecasts, and TP for the integer of True Positive forecasts. **Table 1** and **Figure 3** demonstrate the evaluation of accuracy rates.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{23}$$

Table 1. Estimation of accuracy value for adaptive intelligent education system.

Method	Accuracy (%)
SVM Gupta et al. [28]	91.68
LR Gupta et al. [28]	86.20
CNN Jamil and Belkacem [29]	94
DOO-IGBM [Proposed]	98.5

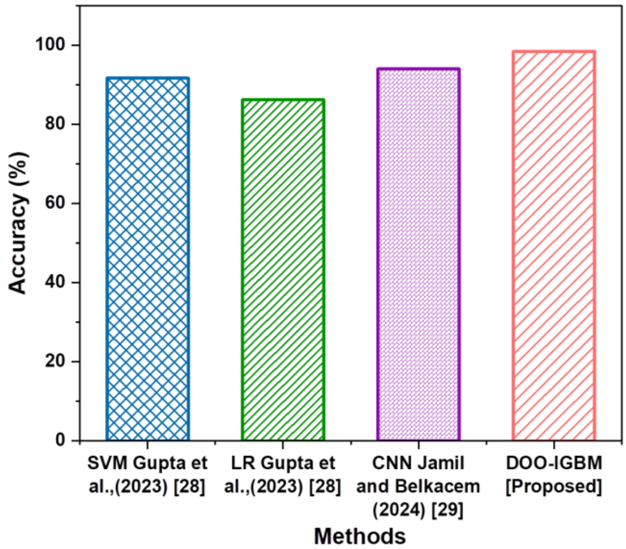

Figure 3. Result of accuracy for adaptive intelligent education system.

The accuracy of several models used to evaluate the effectiveness of English language education tools. While the accuracy of the LR is 86.20%, that of the SVM is 91.68%. With an accuracy of 98.5%, the suggested DOO-IGBM beat all other methods, while the CNN achieved 94%. This illustrates DOO-IGBM's exceptional performance in the English language educational adaptive education systems.

Precision: It is employed to demonstrate the model's ability to forecast a favorable emotional state. It is used to interpret how many instances of good emotions are categorized as negative. It is computed using the Equation (24). **Table 2** and **Figure 4** show the outcomes of the precision rate.

$$Precision = \frac{TP}{TP + FP} \tag{24}$$

Table 2. Estimation of precision value for adaptive intelligent education system.

Method	Precision (%)
SVM Gupta et al. [28]	91.23
LR Gupta et al. [28]	85.41
CNN Jamil and Belkacem [29]	94
DOO-IGBM [Proposed]	97.7

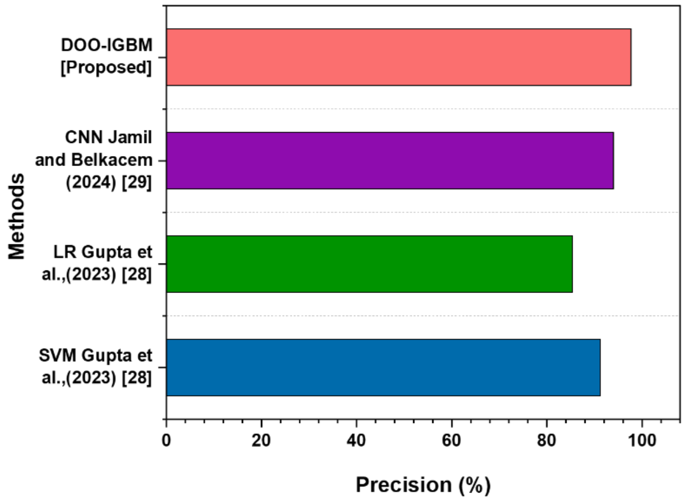

Figure 4. Evaluation of precision for adaptive intelligent education system.

The precision of the SVM is 91.23%, while the LR is 85.41%. The precision of CNN is 94%. With a precision of 97.7%, the DOO-IGBM approach beat these models, proving to be more efficient biosensing education system in the task.

Recall: It determines the proportion of TP emotions in the data to all positive projected cognitive states. As a result, a model that achieves a higher recall is more sensitive. The recall is computed as follows in Equation (25). **Table 3** and **Figure 5** denote the estimation of recall value.

$$Recall = \frac{TP}{TP + FN} \tag{25}$$

Table 3. Outcomes of recall value for adaptive intelligent education system.

Method	Recall (%)
SVM Gupta et al. [28]	92.11
LR Gupta et al. [28]	87.63
CNN Jamil and Belkacem [29]	95
DOO-IGBM [Proposed]	98

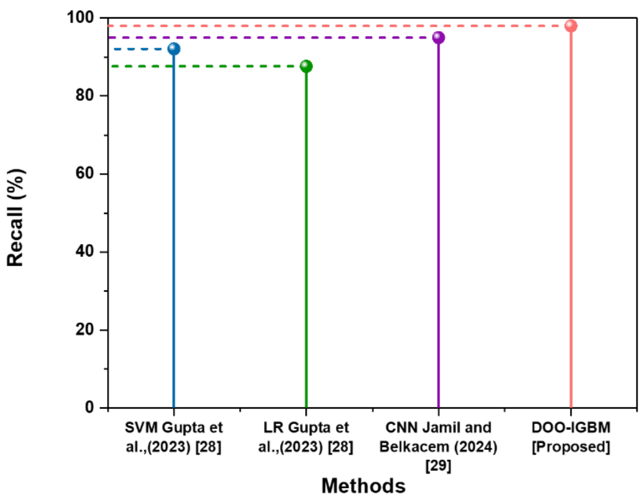

Figure 5. Evaluation of recall value for adaptive intelligent education system.

The recall is 92.11% for the SVM and 87.63% for the LR. The recall is 95% according to CNN. When it comes to accurately evaluating and improving the adaptive education system, the DOO-IGBM method performs better than any other method, with a 98% recall.

F1-score: Two structures comprise the F1 Score. Precision comes in second, while recall comes first. Using the F1 Score, the precision and recall metrics are merged to produce a single score. It's assessed using Equation (26). **Figure 6** and **Table 4** show the evaluation F1-score.

$$\mathrm{F1} - Score = 2 \times \frac{precision \times recall}{precision + recall} \tag{26}$$

Table 4. Outcomes of F1-score for adaptive intelligent education system.

Method	F1-score (%)
SVM Gupta et al. [28]	91.53
LR Gupta et al. [28]	86.76
CNN Jamil and Belkacem [29]	97
DOO-IGBM [Proposed]	98.6

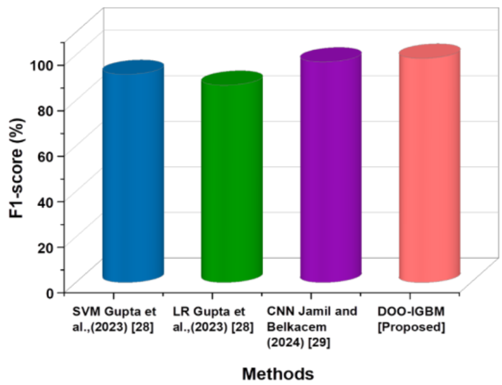

Figure 6. Estimation of F1-Score for the adaptive intelligent education system.

With an F1-score of 86.76%, the LR model outperformed the SVM model, which obtained an F1-score of 91.53%. Although the CNN model scored better at 97%, the DOO-IGBM surpassed all other models with an F1-score of 98.6%, indicating that it is more effective at the task at dispense.

Training accuracy: The DOO-IGBM training accuracy demonstrates how the model's accuracy increases during training. As the model learns from the training data, the accuracy initially starts lower. The accuracy progressively rises during training, showing that the model is a successful alternative to the patterns in the data. The model's capacity to generalize and the training accuracy shows that they performed effectively with the training dataset, which stabilizes at a high value by the later epochs. Its abrupt learning curve and eventual accuracy plateau show how well the DOO-IGBM adjusts. Its performance increases over time. **Figure 7** shows the training accuracy for the suggested method.

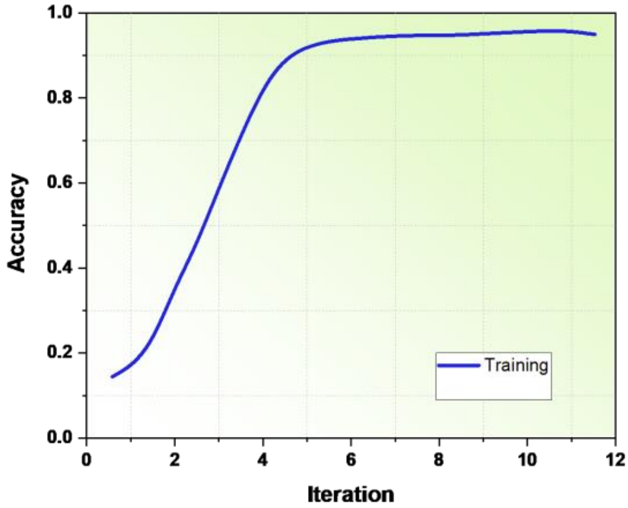

Figure 7. Training accuracy of the proposed DOO-IGBM model.

Training Loss: The training loss of the DOO-IGBM model is started with a loss of initiation larger than zero due to the random distribution of the parameters. This information become less with the increase in the training iteration, illustrating that the model is making better prediction towards the next elements of the sequence from the input EEG data. This implies that, for sufficient levels, the loss is stable, it is exhibits convergence implying that the model can predict accurate cognitive states. The declining loss rate depicted below highlights how effectively the model fits the adaptive education framework when it comes to offering learning opportunities to learners. **Figure 8** demonstrates the training loss of the proposed method.

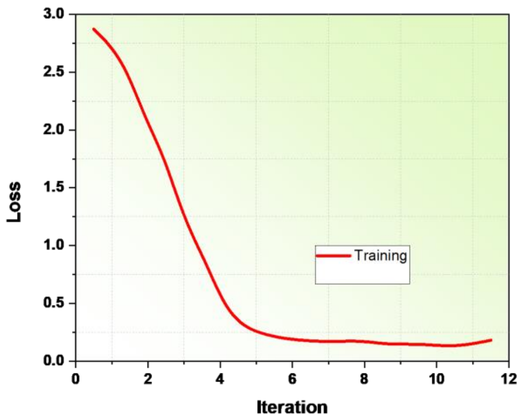

Figure 8. Training loss of proposed DOO-IGBM model.

5. Discussion

The valuation of students' cognitive states in personalized education feedback was crucial for improving education involvements since it enables systems to dynamically modify information according to every student's cognitive capacity and stage of engagement, which increases motivation and effects. Despite their usefulness, existing techniques like SVM [28], LR [28], and CNN [29] were limited in their ability to handle complicated EEG data due to their overfitting susceptibility. Real-time adaptation and more precise predictions from EEG data were made possible by the DOO-IGBM technique, which uses sophisticated IGBM optimized by DOO algorithms to tackle these problems. By doing this, the shortcomings of conventional models are overcome and improve student performance is ensured, resulting in a more efficient and customized education environment. By providing more individualized, effective education pathways, the results demonstrate how EEG-based adaptive systems have the potential to completely transform intelligent education systems.

6. Conclusion

The potential of an adaptable biosensor intelligent education system to provide individualized education experiences based on real-time cognitive states makes it significant to measure and improve its efficiency. The purpose of this study was to examine how EEG data are used to inform real-time adaption in education systems to acquire specific students' desires to deliver dynamic content related. The outcomes show that the use of the DOO-IGBM model is more efficient than original methods, achieving 98.5% accuracy, 97.7% precision, 98% recall, and 98.6% F1 score providing more accurate predictions and personalized feedback. However, there are some limitations such as the complete reliance on the EEG data, which have a lot of noise that require preprocessing before using them and the need for large datasets to further enhance the model. Future studies focus on improving on the scalability of the model to other educational settings, incorporation of more biometric data for analysis, and on real time adaption of the model. This strategy creates exciting chances for intelligent, flexible educational systems in the future.

Ethical approval: Not applicable.

Conflict of interest: The author declares no conflict of interest.

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