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Molecular & Cellular Biomechanics 2025, 22(3), 1036.
https://doi.org/10.62617/mcb1036

Article

Dynamic identification model of psychological state in Ideological and Political Education based on biosensing

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CITATION

Wang L, Tang Z. Dynamic identification model of psychological state in Ideological and Political Education based on biosensing. Molecular & Cellular Biomechanics. 2025; 22(3): 1036. https://doi.org/10.62617/mcb1036

ARTICLE INFO

Received: 7 December 2024
Accepted: 23 December 2024
Available online: 14 February 2025

Abstract: Individuals' psychological states greatly influence how they participate and react to educational processes, especially when it comes to ideological and political education. Ideological and political education (IPE) is an essential component of educational systems that aims to develop a sense of national identity, social duty, and confidence in students. This research explores the application of biosensor technologies to analyze students' psychological states within the context of ideological and political education. Students' lifestyles and stress levels often lead to psychological issues, but conventional IPE techniques lack real-time, individualized data for effective mental health treatment. This research introduces a model, Efficient Osprey Optimized Dynamic Long Short-Term Memory (EOO-DLSTM), to identify the psychological state for Ideological and Political Education utilizing biosensing technologies to assess students' stress and emotional states in real-time. The model uses biosensors to collect real-time physiological data that reflects the psychological state of students. The data was preprocessed using a Gaussian filter to remove noise from biosensor data. Power spectral density (PSD) is used to extract the features from preprocessed data. EOO is used to optimize and select the feature from the biosensor, and DLSTM can be employed to identify the psychological state. Based on experimental findings, the model can accurately identify the psychological states of students, including information about their stress levels and emotional involvement. The proposed EOO-DLSTM outperforms the existing systems such as Accuracy (95.32%), Precision (93.97%), Recall (96.18%), and F1 score (97.62%). The EOO-DLSTM model surpasses traditional models through the utilization of advanced optimization techniques for enhanced accuracy in recognizing psychological states from biosensor data. It is effective in handling overlapping features and complex temporal dependencies, thus being very suitable for real-time monitoring of mental health. The approach emphasizes how biosensing technologies can be used in educational frameworks to support students' overall development.

Keywords: psychological state; Ideological and Political Education (IPE); biosensing; Efficient Osprey Optimized Dynamic Long Short Term Memory (EOO-DLSTM)

1. Introduction

The emergence of the internet has subtly altered people's lifestyles and occupations. The invention of the internet has transformed the previously relatively closed educational method of knowledge, importantly improved the quality of information, and caused the amount of extensive knowledge to continuously increase the ongoing development and expansion of IPE in universities and colleges [1]. Biosensors in political education would enhance the collection of real-time data on public feelings, health, and participation in political events. Such technology can be integrated into education in which physiological responses to the messages of politics can be followed for more effective, responsive education, ultimately deepening the understanding of politics and voter behavior [2]. Enhancing the quality of instruction in ideological and political theory courses is a crucial component in advancing the advancement of IPE. It also serves as a foundation for the creation of a scientific assessment index system in other research domains. The evaluation index system's research level could expand and deepen through the investigation of IPE courses in universities and colleges. This research can also serve as an orientation for the development of assessment key systems in other domains [3]. As a vital component of the development project of the contemporary period, university ideology and politics have great significance and are essential to the growth of moral instruction and the establishment of top-notch institutions of higher learning. Consequently, a fundamental prerequisite of socialist education is that the leadership of university associations should be constantly followed while fortifying their development [4]. Instructors should be aware of the importance of educational programs of IPE in directing medical students' conceptual instruction, formulating educational standards that support medical students' entry-level employment, and ensuring that their theoretical studies are grounded in the real world of society. In general, ideological conservatism perceives the environment as more hazardous than liberals perceive and are more cognizant of risks [5,6]. Teachers today focus more on imparting professional information in the classroom than they do on helping students learn political and ideological concepts. They also fail to naturally engage with it. Thus, in addition to the course's ideological and political demands, professional knowledge is learned and sensitive resources and sensors are used regularly to encourage students' values and feelings of social duty [7]. Teachers could gain unparalleled knowledge about students' intellectual and psychological states by utilizing biosensors to track and evaluate physiological reactions during learning. This allows them to adjust lessons in real-time to maximize learning results. Based on the idea of identifying and quantifying biological signals, biosensing technologies were first created for medical applications and investigation. Bio information gathering and analysis are becoming more and more important in the biological sciences [8,9]. In addition to the social context of the post-epidemic period, it examines whole-course, all-around, and full learning from the perspective of educational designs and methods and offers fresh suggestions for the implementation of precise IPE by evaluating the need [10]. The research aims to create an evolving identification model that uses biosensing technologies to evaluate mental states in IDE using a novel technique named EOO-DLSTM. During teaching sessions, the model attempts to monitor and evaluate people's emotional and cognitive reactions. This technique also enhances the knowledge of emotional dynamics in educational settings, which is its goal. Real-time psychological observation is intended to develop the effectiveness of IPE.

Key contributions

- Collection of data: The data collected for this research is taken from Kaggle, which contains various data on behavioral features, psychological state, education, and demographical background of students in IPE training.

- Data preprocessing: For preprocessing the collected data, a Gaussian filter is employed to reduce noise and vibration that affect the psychological state of students in an IPE environment.
- Feature extraction: Power spectral density (PSD) is utilized to evaluate the frequency of biosensors to predict signals of EEG. It also determines the prominent frequency band of psychological states like calmness, tension, etc.
- Proposed model: The novelty of the EOO-DLSTM model is implemented in this research to effectively identify the emotional state and stress level of students in real-time. The proposed model provides a biosensor to optimize the stress level in IPE education.
- Findings: While comparing the proposed model to the existing model, the proposed EOO-DLSTM model performs better and it shows that it would enhance the identification of the psychological state of the student in IPE.

This proposed research is categorized into five phases: Phase 1 contains an introduction, Phase 2 provides related work, Phase 3 describes the methodology of the research, Phase 4 includes the result and discussion, and finally Phase 5 derives a conclusion.

2. Related work

The ideology and negative stereotypes suggested in [11] could be linked through a variety of conscious and unconscious pathways, which do not always work together and people differ in their drive and capacity to control their reactions and engage in emotional reflection. As a result, it verified the favorable correlation between latent social conservatism (as determined by an IAT) and self-expressed conservative social views. The sports administration method established on the psychological well-being of students was examined in [12]. It also examined how frequently students engage in physical activity and how their mental health varies. It determined the influencing aspects of learners' well-being and assessed the psychological level of college instructors in physical education. As a result, the physical educational administration method in physical education instruction improved the therapeutic impact of physical training on students' mental health. The transparent, wellness, and practical evaluation method was presented in [13] based on cellular biosensor networks that were pertinent to the current level of political knowledge amongst Chinese university students. Issues with accuracy, multimodal integration, confidentiality, safety, convenience, and herbal translation of language were some potential future paths for speech recognition. The thorough evaluation method used in the present research demonstrated the value of cell networks in improving the political knowledge of college students. Biosensor design was proposed in [14], to emphasize the relevance of maintaining the health of future generations and providing substantial services to society; it urges a link between data science and decision science, emphasizes quality of service early in the design process, and warns against the impact of economics of scale on the success of biosensor systems. The college students' pro-environmental sentiments were affected by ideological and political instruction related to ecological civilization, as discussed in [15]. The findings demonstrate that college students' environment could be successfully fostered by environmental civilization's ideological and political instruction. This research provided an important reference, emphasizing the current consequences of environmental evolution training and the characteristics of the framework for academic instructors and representatives to stimulate the preservation of the natural ecosystem. The present educational paradigm was to incorporate political and ideological instruction into regular classes; this is known as "online and offline" combined teaching, which was employed in [16]. To provide guidance and assistance, this research examined the connection between mixed teaching and political and ideological instruction, analyzed mixed teaching techniques, and made recommendations for reforming the assessment system by the two sections. The interaction between artistic learning and IPE in higher education emphasizes the necessity of utilizing a strategy for improving art knowledge in ideological and political colleges to promote the process of concurrently developing IPE and art education in higher education proposed in [17]. A psychological education model with the IPE course content to optimize the teaching and implementation approach was evaluated in [18] to implement ideological and political instruction at colleges. According to the experiment, students were more eager to take part in the exploratory course and were more receptive to the instructional material. This relieved pupils' academic pressure, supported them in maintaining happy emotions and helped them develop sound moral principles. The effects of IPE in conjunction with emotional treatment on bipolar illness patients were evaluated in [19]. In addition to psychiatric care, the experimental group got political and intellectual instruction. According to the research's findings, participants in the treatment group have shown notable gains in emotional regulation and attitudes about their jobs and personal lives, as well as a 20% reduction in sadness and arrogance overall. The need for professional education, entrepreneurial and innovation education, along with political and ideological education was effectively integrated in [20]. It also offered an alternative research viewpoint for the advancement of both these fields of research. In terms of instructors, curriculum, teaching strategies, and teaching modalities, it offered the integration path of IPE, career development, and creativity and entrepreneurial training all at once. The humanistic treatment of college students' IPE, primarily by defining the term, assessing and analyzing the content, elucidating the requirements for humanistic care of college students' IPE, and investigating strategies to improve the collaborative education of college students' IPE was recommended in [21]. An integrated virtual reality technology with political theory and ideology courses at colleges and institutions was described in [22]. According to the experimental findings, the percentage of the two groups thinking about the theory of politics class increased by 8.2% and 8.14%, respectively, following VR classroom instruction. Teaching in virtual reality classrooms can increase students' motivation to research, foster information comprehension, and help them develop positive attitudes and values. Thorough analyses of college students' spending patterns were important for both the physical and mental well-being of students as well as the economy's superior growth [23]. It was discovered that there was a 100% chance of switching to diversified consumption after an incident of following consumption behavior. These findings have significant consequences for comprehending university students' buying patterns and the cause of both the economy and academics.

3. Methodology

The method involves numerous data gathered from the online source Kaggle, which provides heart rate, mood status, psychological state, etc. The collected data is preprocessed using a Gaussian filter that can remove the noise and fluctuation in the data. For feature extraction, PSD is utilized to extract the feature by the frequency band of the biosensor. The proposed EOO-DLSTM model is used to select the feature and detect the psychological state of the student in ideological and political training. **Figure 1** displays a schematic illustration of the systematic flow.

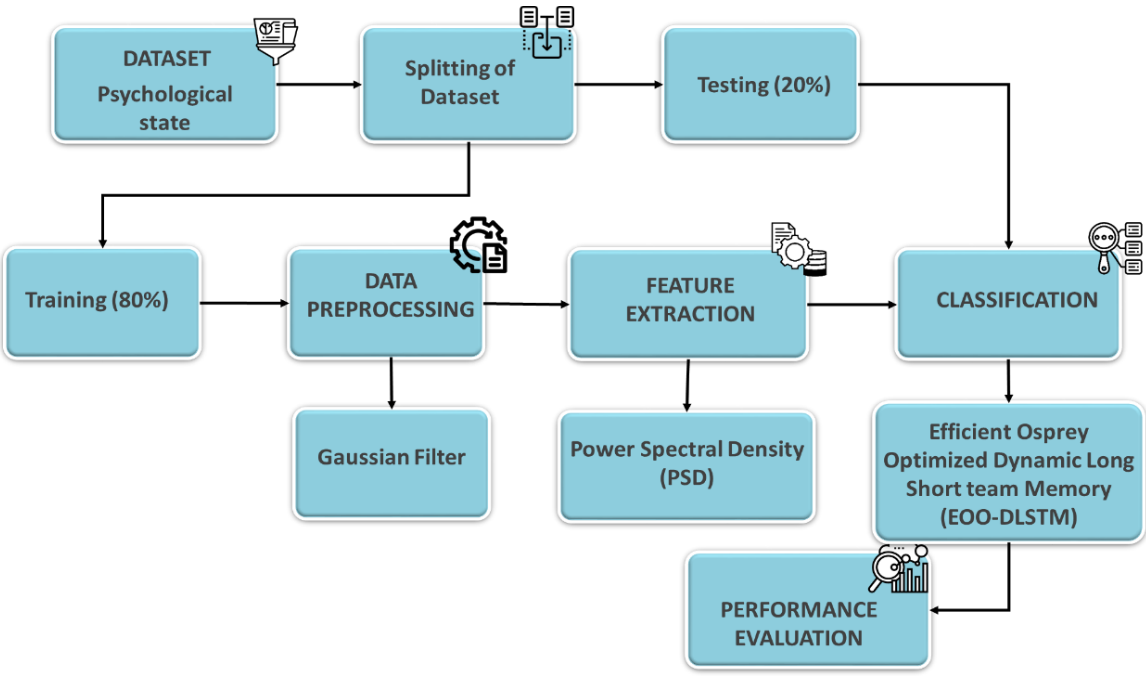

Figure 1. Methodology flowchart of research.

3.1. Data collection

The data was sourced from Kaggle (https://www.kaggle.com/datasets/ziya07/psychological-state-identification-dataset/data). There are data on 1000 students and support research on biosensors for the identification of the psychological state. Data collection was done in the Interprofessional Education (IPE) activities using biosensors to monitor physiological, behavioral, and environmental metrics like heart rate, skin conductance, noise, and lighting conditions. Participants were of diverse demographics and activities represented real-world collaborative scenarios so that psychological responses could be observed. The dataset is split into a training set (80%) and a testing set (20%). It split the development of the machine learning (ML) model. Psychological states are labeled as stress, relaxation, focus, and anxiety; the cognitive load has three categories: low, moderate, and high. Finally, students' emotional condition has been captured as happy, neutral, sad, and anxious. This all-encompassing dataset is meant to facilitate the development of sophisticated models such as EOO-DLSTM for the analysis of psychological states. The data further points out the possibility of biosensor technology in enriching mental health services through IPE by offering insights into cognitive and emotional states in real-time.

Data preprocessing using Gaussian Filter

Biosensor data are preprocessed and smoothed using the Gaussian filter to eliminate noise and oscillations that can affect the detection of psychological states of students. A linear technique that is often used as a form of low-pass filter to eliminate many types of noise is the Gaussian filter. The following Equation (1) is the 2D Gaussian filter:

$$H(w, z; \sigma) = \frac{1}{2\pi\sigma^2} f^{\frac{w^2+z^2}{2\sigma^2}} \tag{1}$$

where the form of the filter is determined by the variance, represented by σ^2.To evaluate the smoothing impact of σ^2, a 2D Gaussian filter is placed onto a pirated picture with varying σ^2 values. It is evident that as σ^2 rises, it also increases the degree of smoothing and the enhancement of visual features like edges of the data. By boosting the signal quality, this filtering procedure helps the flexible identification model, which is used to evaluate psychological, and emotional conditions in an environment of IPE perform better overall.

3.2. Feature extraction using Power spectral density (PSD)

The frequency of the biosensor data, especially the EEG, is examined using power spectral density (PSD) analysis. By offering a thorough understanding of the way, the signal energy is divided over multiple frequency ranges; PSD assists in determining the prominent frequency bands linked to distinct psychological states. Where the primary and secondary items on the right-hand side (RHS), respectively show the Gaussian and non-Gaussian components. "rr" and "S" are subscripts that denote that the non-Gaussian component originates from the trispectrum (S)and the Gaussian part is the combination of two power spectra(R), respectively. Using the discretized form of the power spectrum estimator, it can accurately compute the auto-covariance of the power spectrum with shot-noise adjustments. The power spectrum covariance can consequently be expressed as Equation (2):

$$Cov\left[\hat{R}(x), \hat{R}(x')\right] = \left(\frac{U}{M^2}\right)^2 \sum_{k\neq l} \sum_{j\neq i} g^{-jl.(wk-wl)} g^{-ki'.(wi-wj)} \left[< m_j m_l >_e + < m_j m_l >_e + < m_j m_i m_l m_k >_e\right] \tag{2}$$

The Gaussian portion is represented by the first two components on the RHS, which can be written as Equation (3):

$$Cov\left[\hat{R}(x), \hat{R}(x')\right]_{rr} = \left(\frac{U}{M^2}\right)^2 \left[\sum_{k,j} < m_j m_l > d^{f^{-kj'.w_l}}\right] \left[\sum_{k,l} < m_i m_k > d^{f^{-jl'.w_i}} f^{jl'} w_k\right] + (1\ Perm) \tag{3}$$

$$Cov\left[\hat{R}(x), \hat{R}(x')\right]_{rr} = \frac{(2\pi)^3 \delta_C(i + i') + (2\pi)^3 \delta_C(i + i')}{U} \left[Q^{(M)}(i)\right]^2 \tag{4}$$

Where the shot-noise concept is used to characterize the power spectrum as Equation (5):

$$R^{(M)}(x) \equiv R(x) + \frac{1}{\bar{m}} \tag{5}$$

It is generally known that the contribution from, for example, the $j = lori = k$terms causes the shot noise impact on the power spectrum covariance to persist despite the shot noise correction. The non-Gaussian component or tertiary variable on the RHS of Equation (2) is provided by:

$$
\begin{aligned}
Cov\left[\hat{R}(x), \hat{R}(x')\right]_S &= \left(\frac{U}{M^2}\right)^2 \sum_{(a \neq b),(i \neq j)} \langle m_j m_j m_l m_a \rangle_D g^{-jx.w_j} g^{jx.w_i} g^{-jx'.wb} g^{jx'.wa} \\
&= \left(\frac{U}{M^2}\right)^2 \sum_{a \neq b \neq i \neq j} \langle m_j m_j m_l m_a \rangle_D g^{-jx.w_j} g^{jx.w_i} g^{-jx'.wb} g^{jx'.wa} \\
&+ \left(\frac{U}{M^2}\right)^2 \left[\sum_{(a \neq b \neq j),(k=b)} \langle m^2{}_j m_i m_a \rangle_D g^{-j(x+b').wa} g^{jx.w_i} g^{jn'.wa} + (3\ perms) \right] \\
&+ \left(\frac{U}{M^2}\right)^2 \left[\sum_{(a \neq b),(j \neq i),(b=i)} \langle m^2{}_i m^2{}_j \rangle_D g^{-j(x+b').wa} g^{j(x+b')} g^{jn'.wa} + (1\ perm) \right]
\end{aligned} \tag{6}
$$

$$
Cov\left[\hat{R}(x), \hat{R}\left(x^{'}\right)\right]_S = \frac{1}{U} S^{(M)}\left(x, -x, x^{'}, -x \quad\right) \tag{7}
$$

Where the definition of the trispectrum term that includes shot-noise is given as Equation (8):

$$
\begin{aligned}
&S^{(M)}(x_1, x_2, x_1', x_2') \equiv (x_1, x_2, x, x_2') \\
&+ \tfrac{1}{m}[A(-x_1, -x_1', x_1, x_1') + A(-x_1, -x_2', x_1, x_2') + A(-x_2, -x_1', x_2, x_1') + A(-x_2, -x_2', x_2, x_2')] \\
&+ \frac{1}{\overline{m}^2}[R(x_1 + x_1') + R(x_1 + x_1')]
\end{aligned} \tag{8}
$$

Equations (5) and (9) provide the formula for the power spectrum of the covariance structure. After that, this data is included in the evolving identification model, improving its capacity to categorize and forecast student's psychological states.

3.3. Psychological state classification using Efficient Osprey Optimized Dynamic Long Short Term Memory (EOO-DLSTM)

Dynamic Long Short-Term Memory (EOO-DLSTM) is used in conjunction with Osprey Optimization to increase the precision and effectiveness of psychological state recognition. Python is essential for data processing, implementing models, and doing analyses. This implementation facilitates improved understanding and analysis of the dynamic shifts in psychological states that occur throughout IPE. The Osprey Optimizer guarantees optimal education and parameter selection, which improves model divergence and forecasting performance, while the adaptive character of DLSTM enables it to adjust to modifications in mental status over time.

3.3.1. Dynamic Long Short Term Memory (DLSTM)

The rapid fluctuations in psychological states are captured and predicted from biosensor signals over time using the Dynamic Long Short-Term Memory (DLSTM) framework. The two convolution layers work to further harvest the significant value included in the data. The DLSTM is then fed to biosensor output characteristics. Its memory units and special three gates allow it to further screen the characteristics. The input data configuration, convolutional kernel design, and activation function selection all affect the structural layout of the enhanced DLSTM. The detailed design of the suggested scheme is shown as a function of each of these three variables. A multiple-dimensional information matrix was selected as the data input in this technique. The most significant and relevant data are supplied into the prediction system when the data selection phase is finished. Certain data properties take a longer period to appear in the information, while others do the reverse since various data types have varying sensitivity to time scales. Three distinct time resolutions, such as high, medium, and low, are utilized in data collecting for various kinds of data information since it is inappropriate to employ the same time frame for data extraction. This ensures the precision and effectiveness of psychological state prediction. The ReLU function serves as the function of activation to guarantee the biosensor's capacity for nonlinear approximation and elimination of misleading signals, which are presented in **Figure 2**. The following Equation (10) is the expression for the e function:

$$e(w) = max(0, w) \tag{9}$$

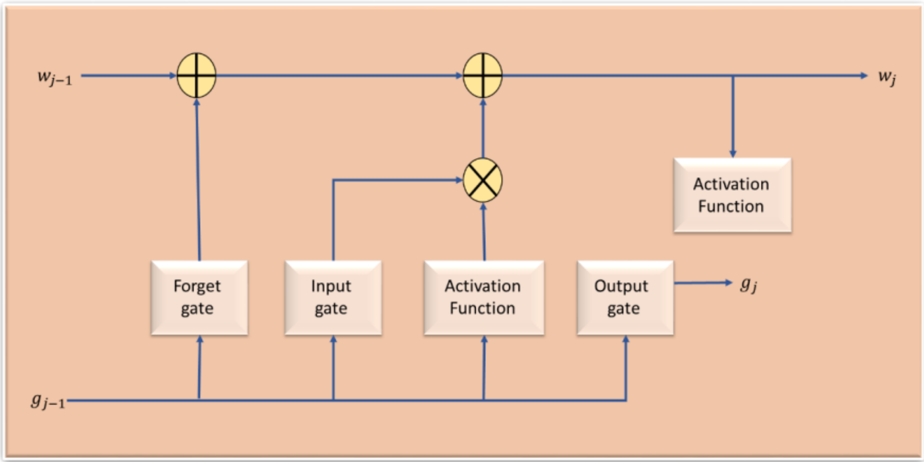

Figure 2. DLSTM Unit's structural diagram.

3.3.2. Efficient Osprey Optimization (EOO)

This optimization algorithm is inspired by nature, characterized by mimicking the hunting and foraging behavior of an osprey. As an optimization algorithm, it is capable of solving several complex optimization problems through a balance between exploration and exploitation. Applications of EOO include a variety of fields obtained with improvements in efficiency and accuracy over conventional methods. The traditional OOA statistical model simulates two of the ospreys' real behaviors: capturing the aquatic creature in the region that was selected and moving the prey to a suitable spot. Even though OOA has demonstrated better performance in certain optimization tasks, it yet has the potential to find it in local optimal, has limited exploitative capabilities, and is unable to identify the optimal solutions for high-dimensional, more complex situations. OOA should be improved even further. This research augmented the basic OOA with three enhancements, namely the Brownian movement strategy, Lévy flight strategy, and roulette fitness distance balance (RFDB) selection technique to improve global search and accelerate convergence. The specifics are displayed below.

Brownian motion approach: Instage 1 of OOA, an additional option for fish hunting is to enhance individual selection using the Brownian motion strategy. This tactic, which allows individuals to investigate psychological states, is derived from the Brownian movement of students, a probabilistic exploration technique. The ospreys could search the entire area more effectively as a result. The following is how the updated Equations (10) and (11) are displayed:

$$W_{j,i}^{O1} = W_{j,i} + O \times CF \times randn \times \left(randn \times SF_{j,i} - J_{j,i} \times w_{j,i}\right) \tag{10}$$

$$CF = \left(1 - \frac{s}{S}\right)^{\left(2 \times \frac{s}{S}\right)} \tag{11}$$

Where a random number that fits the conventional normal distribution is called $rand\ n$ and S is a constant that has been fixed to 0.5.

RFDB selection approach: According to the RFDB selection approach, stage 2 OOA has the potential to enhance exploitation. This technique considers the distance covered and the fitness level of individuals. Thus, the selection of students will be influenced by both distance and fitness values. In this case, the RFDB selection process might be considered inverted. The global optimal solution can be found by using the roulette wheel approach to identify the high-potential solution student. The following equations explain the specifics of the RFDB selection process. Determine the separation between the most effective osprey and the i-th osprey.

$$C_{Oj} = \sqrt{\left(Q_{[j,1]} - Q_{[best,1]}\right)^2 + \left(Q_{[j,2]} - Q_{[best,2]}\right)^2 + \cdots + \left(Q_{[j,C]} - Q_{[best,C]}\right)^2} \tag{12}$$

Construct the distance vector:

$$C_O \equiv \begin{bmatrix} c_1 \\ \vdots \\ c_n \end{bmatrix} \tag{13}$$

Determine each person’s score based on their distance and fitness metrics:

$$T_{Oj} = E \times normf_j + (1 - E) \times normC_{Oj} \tag{14}$$

The weight coefficient (E) is set at 0.5. The standardized fitness and distance values for the j-th person are denoted by $normf_j$ and $normC_{Oj}$.

Construct the vector of RFDB scores:

$$T_O \equiv \begin{bmatrix} T_1 \\ \vdots \\ S_M \end{bmatrix} \tag{15}$$

Using the roulette wheel screening approach, a potential student is chosen at random based on the score vector findings. This student is used to create a new position by applying Equation (16).

$$W_{j,i}^{O2} = W_{j,i} + \frac{W_{RFDB}}{s} \quad (16)$$

The student chosen from the psychological state selected using the RFDB selection technique is denoted by XRFDB.

Lévy flight strategy: The option Γ in the OOA broad search procedure restricts the ospreys' search region, which must be changed. Techniques for optimization can effectively avoid local minima by using the Lévy flight strategy (LFS). The following Equations (17) and (18) are used to get the Lévy flight value:

$$Levy(1) = \frac{v}{|u|^{\frac{1}{\beta}}} \quad (17)$$

$$\sigma_v = \left(\frac{\Gamma(1+\beta) \times sin\left(\frac{\pi\beta}{2}\right)}{\Gamma(\frac{1+\beta}{2}) \times 2\left(\frac{\beta-1}{2}\right)} \right) \frac{1}{\beta} \quad (18)$$

where $v \sim (0, \sigma_v^2),\ v \sim (0, \sigma_v^2), \sigma_u = 1, \beta$= 1.5, and conventional gamma function denotes Γ, and v and u fulfill the Gaussian distribution. The MOOA substitutes the random number Γ with the Lévy flight strategy. Equation (19), the new equation for searching psychological state, is updated.

$$W_{j,i}^{O1} = W_{j,i} + Levy(1) \times \left(SF_{j,i} - J_{j,i} \times w_{j,i}\right) \quad (19)$$

Examination of the EOOA's time complexity: For the optimization algorithm, temporal complexity is a crucial metric. The population size M, optimization issue dimension C, setup, and maximum iteration count S are the associated influencing factors. The initialization complexity of time in the original OOA is $P(M \times C)$. Phase one's temporal complexity is $P(M \times C \times S)$. Phase two's temporal complexity is $P(M \times C \times S)$. Consequently, OOA's overall time complexity is $P(M \times C \times (2S + 1))$ .By using the fitness-distance-based selection method such as the Brownian motion strategy, and Lévy flying tactics to enhance the basic OOA to EOOA. The temporal complexity remains $P(M \times C \times S)$ in both the new phases one and two. As a result, the EOOA's overall temporal complexity is $P(M \times C \times (2S + 1))$, which is identical to that of EOOA.

The work builds a better and more effective model for recognizing psychological states from bio-sensing data by combining the advantages of Dynamic Long Short-Term Memory (DLSTM) with the EOOA. By effectively locating the ideal configuration, the Osprey Optimizer draws inspiration from the osprey birds' natural hunting behavior optimizes the DLSTM model's parameters, and enhances its capacity to recognize periods in the biosensor data. Because DLSTM is dynamic, it could adjust to changing psychological states across the duration and pick up on minute variations in emotional reactions. Additionally, Python makes it easier to handle and visualize data in real time, which makes it possible to integrate biosensor data, forecasting of models, and performance analysis with ease. The EOO-DLSTM algorithm combines these two methods in a Python framework to improve learning and prediction accuracy. This allows for efficient tracking and categorization of psychological states through

IPE, even when complicated or noisy biosensor data is present. The pseudocode for the EOO-DLSTM model is shown in Algorithm 1.

Algorithm 1: Pseudocode of EOO-DLSTM model

```
import pandas as cf
importtensorflow as ed
fromsklearn.model_selection import train_test_split
fromsklearn.preprocessing import StandardScaler
# Load and preprocess data
psych_data = cf.read_csv("student_psychological_data.csv")
features = StandardScaler().fit_transform(psych_data.drop('outcome', axis =
1)).reshape(−1, 1, psych_data.shape[1] − 1)
target = psych_data['outcome']
# Split data
Z_train_set, Z_test_set, w_train_set, w_test_set = train_test_split(features, target, test_size = 0.2)
# Build and compile model
model = ed.keras.Sequential([
ed.keras.layers.LSTM(50, input_shape = Z_train_set.shape[1: ], return_sequences = False),
ed.keras.layers.Dropout(0.3),
ed.keras.layers.Dense(1, activation = 'sigmoid')
])
model.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy'])
# Train and evaluate
model.fit(Z_train_set, w_train_set, epochs = 15, batch_size = 64, validation_data = (Z_test_set, w_test_set))
# Output test accuracy
print("Test Accuracy: ", model.evaluate(Z_test_set, w_test_set)[1])
```

4. Result

The suggested EOO-DLSTM method is employed to identify the psychological state of the student in ideological and political training using biosensors. The system configuration includes Python 3.10, which is suitable with Tensor Flow 2.8 and Keras for the model, and Python 3.10 was employed to apply the suggested technique. The investigation was carried out using Python 3.9 on a Windows 10 machine, which is appropriate for incorporating biosensing data and identifying adaptive psychological states. The proposed method, EOO-DLSTM, is compared with existing methods, such as support vector machine (SVM) [24], improved extreme learning machine (IELM) [25], and decision tree (DL) [26], for identifying the performance of biosensing data.

Visualization of key features and performance analysis

The matrices comparing the actual and the predicted labels of the four dependent variables, namely "Stressed", "Relaxed", "Focused", and "Anxious", are displayed in **Figure 3a**. For each category, this creates binary labels, taking the current category as positive and all others as negative to compute and visualize the confusion matrix. For visualizing the results, the heat map from Seaborn has been used along with the confusion matrix function from sklearn, which has represented the performance of the model in terms of classifications made for each state with these confusion matrices arranged to form a 2 × 2 grid, creating a clear view. Much potential confusion can be made from this approach while evaluating the model concerning the states classified against the predictions based on the actual data. **Figure 3b** signifies that the frequency of the beta wave among the EEG wave parameters has great predictive power in learning states, with alpha wave trailing next followed by delta, theta, and gamma waves according to their predictive capabilities. The best predictor is the beta wave followed by the alpha wave.

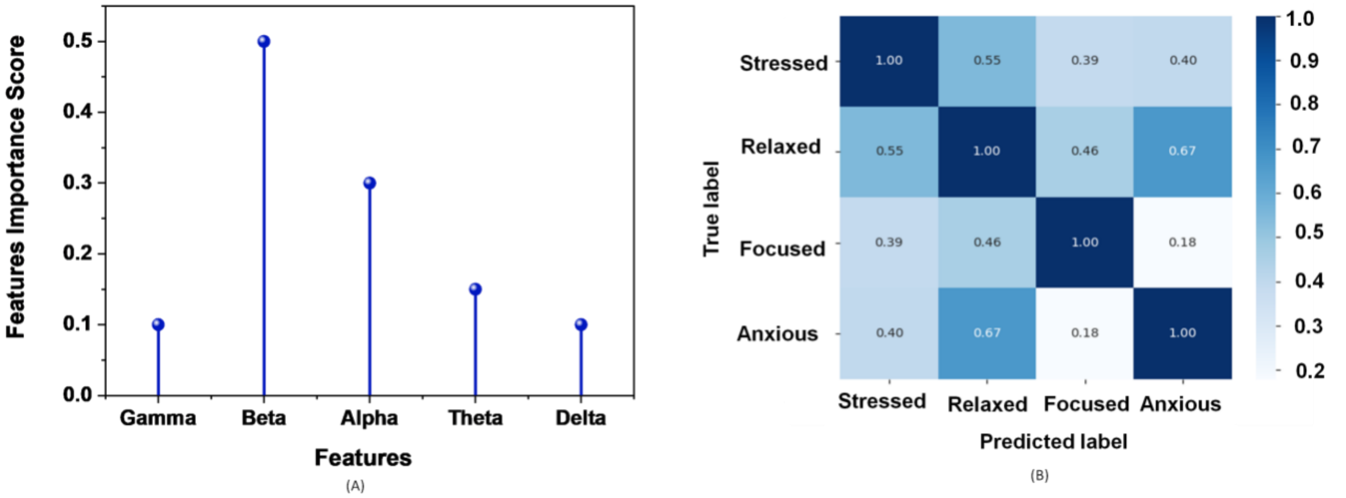

Figure 3. (**A**) Frequency of EEG wave parameter; (**B**) Confusion matrix of obtained dataset.

Table 1 gives the classification accuracy and error rate for the EOO-DLSTM model for various emotional states. It gives a high level of accuracy in predicting stress levels, with the most accurate classification at 96% for relaxation. Error rates are low; thus, the focused state has an error rate of 0.4%. The overall average classification accuracy of 95.32% constitutes evidence for the model's ability to recognize emotional states in a highly successful manner.

Table 1. EOO-DLSTM Model Evaluation: Classification Accuracy vs. Error Rate.

EOO-DLSTM [Proposed]		
Students Psychological State Classification	**Accuracy (%)**	**Error rate**
Stressed	94.50	0.1
Relaxed	96.00	0.3
Focused	95.50	0.4
Anxious	95.28	0.2
Average	**95.32**	**0.25**

The proposed EOO-DLSTM model is contrasted with the current approach in **Table 2** to assess the innovative model's efficacy. The suggested method is compared to the existing acquisition models, SVM [24], IELM [25], and DT [26]. In contrast, it shows that the proposed model exceeds the previous method with higher variation, which concludes that the EOO-DLSTM model performs well in identifying the psychological state of students.

Table 2. Contrasting performance metrics with the previous and proposed method.

Performance metrics	**SVM [24]**	**IELM [25]**	**DT [26]**	**EOO-DLSTM [Proposed]**
Accuracy (%)	91.68	87.28	-	95.32
Precision (%)	91.23	-	68	93.97
Recall (%)	92.11	89.13	58	96.18
F1 score (%)	91.53	-	69	97.62

Accuracy: In this given Equation (20), those cases that get correctly predicted as positive are known as True Positives while the correctly predicted cases as negative are termed True Negatives. False Negatives are cases that are misclassified as negative while False Positives are those that are misclassified as positive.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{20}$$

Figure 4 compares different models among performance metrics in terms of their accuracy. The SVM model according to [24] has an accuracy of 91.68%. Moreover, the IELM model in [25] has a classification accuracy of 87.28%. The decision tree model does not provide the accuracy statement in [26]. In contrast, the proposed EOO-DDLSTM model improved significantly with an accuracy of 95.32%, thus emphasizing its superiority over the other models.

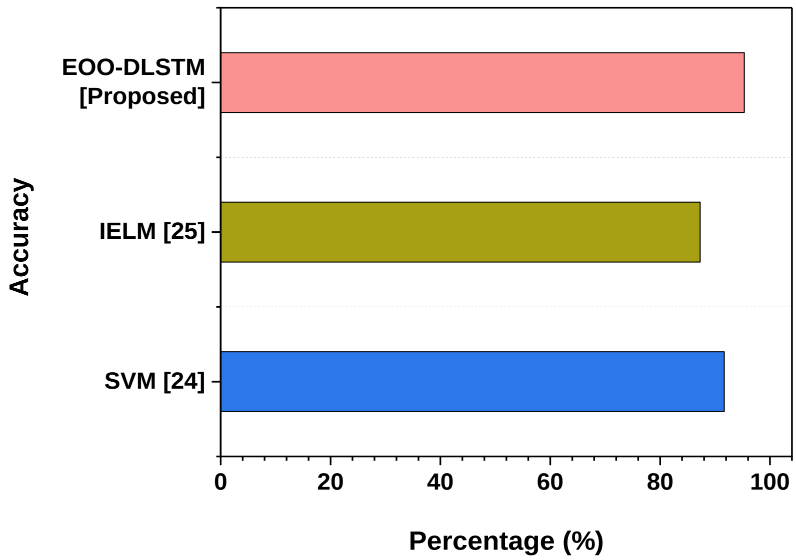

Figure 4. Accuracy performances for political education.

Precision: The proposed EOO-DLSTM model adapts from biosignal variations over time to reduce false positives, or inaccurately detecting a psychological state. A high precision means that the system can accurately identify the right psychological states, which improves the efficacy of instructional activities as shown in Equation (21):

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{21}$$

The result of various models based on performance metric, precision, is reflected in **Figure 5**. The SVM model has an efficiency of 91.23% precision, according to [24]. The IELM model as per [25] does not mention any precision value. On the contrary, according to [26], the decision tree model only achieved 68% precision. However, in contrast to the rest of the models, the newly proposed EOO-DLSTM model outperforms all other models with an achieved precision of 93.97%, thus proving efficiency in the classification of positive instances as compared to other models.

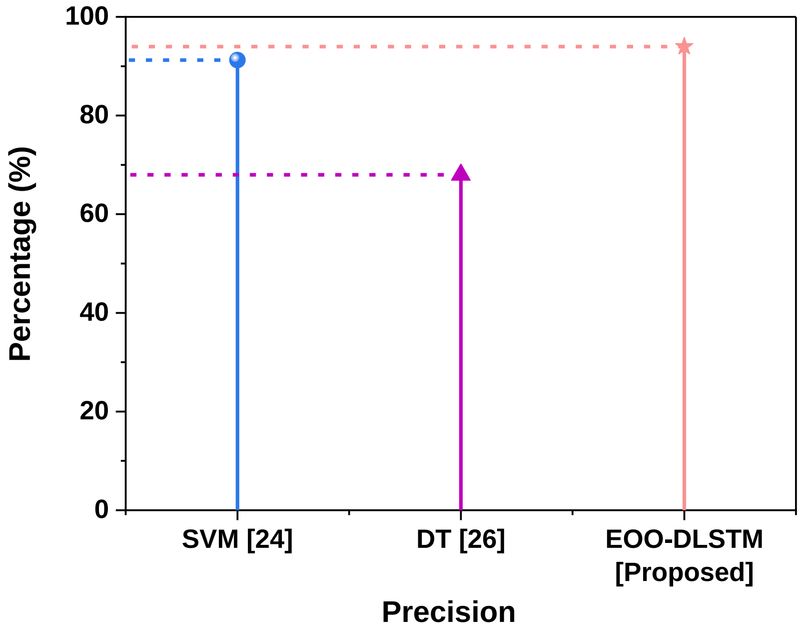

Figure 5. Visualization of precision outcomes in political education using biosensing technology.

Recall: The model's recall gauges its capacity to accurately detect all pertinent occurrences, especially true positives, and suggests the EOO-DLSTM model captures all true positive psychological states. The model's ability to detect a wider variety of psychological disorders and reduce missing cases is demonstrated by a higher recall. This is especially important in learning environments where proper psychological state assessment has a big impact on intervention and support plans for students can be written as Equation (22):

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{22}$$

Figure 6 compares the overall performance of models in all aspects with an emphasis on recall. The SVM model, as cited in [24], achieved a recall value of 92.11%. This value corresponds well with an ideal model for positive instances. The IELM model attained a recall value of 89.13%, as described in [25]. The DT in [26] was observed to cover only a recall of 58%. This shows a relatively low capability in spotting positive cases. Comparably, the proposed model EOO-DLSTM performed much better, with a recall of 96.18%, establishing superior performance regarding capturing positive instances across the dataset.

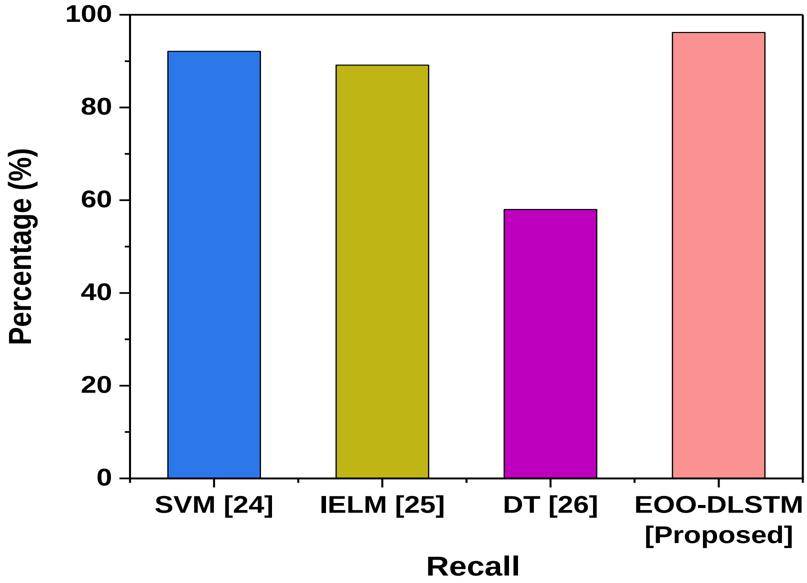

Figure 6. Comparison of recall outcomes across different political education.

F1-score: The F1 score provides a thorough assessment of the model's capacity for recognizing mental states from biosensing information by achieving a balance between precision and recall. The EOO-DLSTM model strives for excellent F1 performance by maximizing the identification of true positives and reducing false positives and negatives as described in Equation (23):

$$F1\ \text{Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} - \text{Recall}} \tag{23}$$

Figure 7 summarizes the performance metrics of different models with F1 scores. According to [24], the SVM model achieves an F1 score of 91.53% and indicates optimum values of precision and recall. In [25], the IELM model does not provide an F1 score. The DT model in [26] has achieved a score of 69%, which denotes a lower trade-off between precision and recall. However, the proposed EOO-DLSTM model surpasses the rest with a score of 97.62%, which indicates its effective overall performance in precision and recall.

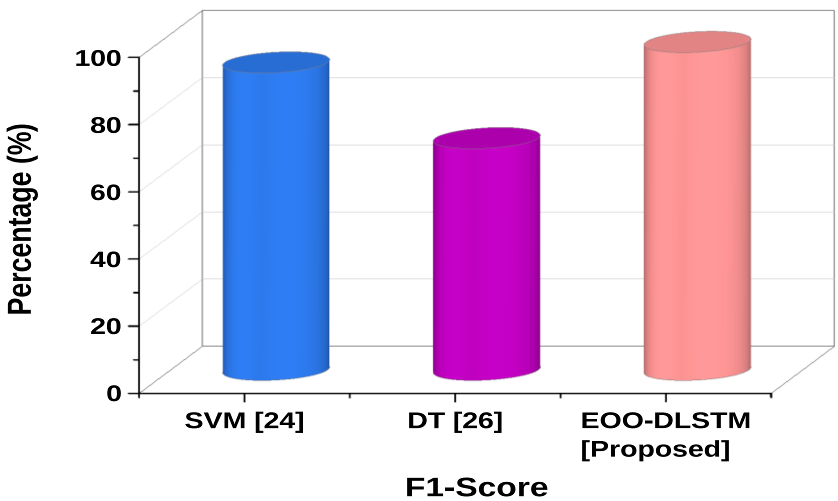

Figure 7. Evaluation of F1-Scores for various political education.

5. Discussion

In **Table 1**, the performance metrics of data comparison depict the proposed EOO-DLSTM model outperforming existing models such as SVM [24], IELM [25], and DT [26] when evaluating students' psychological conditions during ideological and political training using biosensing data. The EOO-DLSTM uses EEG wave parameters to extract features accurately. This is important to help identify psychological characteristics accurately. The evaluation used a confusion matrix implemented in Python to provide detailed performance under metrics like accuracy, precision, recall, and F1 score. Such high performance in recall and precision ensures that the proposed model could accurately classify positive cases correctly, ensuring reliable categorization of psychological states, like stress, relaxation, focus, and anxiety. It also ensures that overlapping or complex feature dependencies in psychological states can be managed effectively to identify the states dynamically, and more efficiently compared with traditional methods. Further, the adaptability of EOO-DLSTM to biosensor data makes it more scalable and applicable in real-world training scenarios. This advancement brings out critical insights into how machine learning techniques can be refined for biosensor-based psychological analysis, thus bringing more personalized and accurate mental health interventions. The results indicate that the methodology could pave the way for improved practices in mental health monitoring and training.

6. Conclusion

This research provided the novelty of the EOO-DLSTM model to identify the psychological state of students in IPE to evaluate their emotional status. For this, the data gathered information from 1000 students with psychological behaviors of stress, anxiety, focus, and relaxation. To preprocess this data, a Gaussian filter was employed to remove the noise and vibration of the data from the biosensor. PSD was utilized to extract the feature of the frequency component in biosensors, particularly EEG. By integrating biosensor data, the proposed EOO-DLSTM method can effectively identify the psychological state of the student. This research's limitation is that, when handling a large dataset, the proposed method is computationally complex and takes a longer time to process. To tackle this drawback, using simultaneous computing and distributing processes helps to accelerate the training of large datasets. The EOO-DLSTM method's prospective applications involve real-time biosensing devices to provide ongoing psychological state monitoring, which would allow for preventative measures in educational and therapeutic contexts.

Author contributions: Conceptualization, LW and ZT; writing—original draft preparation, LW and ZT; writing—review and editing, LW and ZT. All authors have read and agreed to the published version of the manuscript.

Ethical approval: Not applicable.

Conflict of interest: The authors declare no conflict of interest.

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