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Article

# Emotion monitoring and feedback system for ideological and political education using biosensor technology

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**Abstract:** The use of technology to enhance educational experiences has gained significant attention, particularly in the field of emotional engagement monitoring. Active student participation can promote a greater knowledge of values, ethics, and social duties, which is particularly crucial in university ideological and political education. The research objective is to establish a biosensor-based emotional monitoring and feedback system for university ideological and political education. This research proposed a novel Battle Royale fine-tuned Deep Bidirectional Long Short-Term Memory (BR-DBiLSTM) to detect both cognitive and emotional engagement in students. The system uses a combination of biosensors to monitor physiological and behavioral indicators and collect emotional data. The feedback system uses an instructor dashboard to display emotional states and engagement levels and alerts to trigger responses if students show disengagement or stress. The data was preprocessed using Z-score normalization to reduce noise from the obtained data. Feature extraction was implemented using the Fast Fourier Transform (FFT), BR is to optimize and select the features and DBiLSTM model to improve its classification accuracy. The experimental findings show that the suggested model has a high degree of reliability in identifying cognitive and emotional involvement, with a Micro-F1 of 90.62%, Micro-P of 89.95%, and Micro-R of 88.34%. This system demonstrates the potential for enhancing engagement in ideological and political education through adaptive feedback mechanisms based on biosensor data.

**Keywords:** emotional monitoring; feedback system; ideological and political education; battle royale fine-tuned deep bidirectional long short-term memory (BR-DBiLSTM)

## 1. Introduction

Technology has advanced so quickly in recent years that it has had a significant impact on many academic disciplines, including education, where more creative approaches are being used to develop teaching and learning processes. University student attitudes, Ideological and political education have an important attitude and behavior. Which provides a basis for fostering civic involvement and establishing fundamental socialist principles [1]. Ideological and political education (IPE) is essential for student's academic and personal growth; it might be difficult to engage students and adequately gauge their attitudes, emotions, and reactions during education sessions. Using biosensor technology to track students' physiological reactions and provide immediate feedback response [2]. The physiological indicators were frequently connected to emotional states for ensuring the instantaneous assessment of student's participation and their emotional experiences during IPE activities. Instructors could make dynamic adjustments to teaching tactics with the use of real-time emotions [3]. During ideological teaching sessions, the system will use biosensor technology to monitor students' emotional reactions, such as tension and enthusiasm. The logical feedback mechanism allows teachers to modify their teaching strategies in real-time based on students' emotional involvement. The adaptation of teaching strategies was essential in IPE, where ideological information might be disconnected from students [4]. Teachers could determine whether students engaged with the subject by employing emotional monitoring. Furthermore, student's critical thinking and self-awareness could improve the use of emotional feedback [5]. Real-time reflection of students' emotional reactions allows understanding of their own emotional biases and engagement levels. For instance, if the students exhibit symptoms of stress or disinterest, the system could encourage the intricacy of the subject matter to influence the blame of emotional reactions. The ideological education was critical thinking, which might be improved in students through introspective exercises. The rising trend of individualized learning experiences in higher education constitutes the use of biosensor technology. Students becoming more experienced in customizing their unique requirements, tastes, and learning preferences in the digital era [6].

Active learning promotes a higher degree of reflection and growth by enabling students to interact with their emotional states. Teachers might address each student's emotional profile and learning results by using personalized feedback [7]. To enhance student's mental health, the individualized approach maximizes their educational experience and promotes a learning environment. Biosensor technology can revolutionize the conventional teacher-student interaction. The emotional monitoring and feedback system will include different parts of the design. During ideological education classes, students are allowed to wear wearable biosensors [8]. The physiological data will be interpreted and transformed into emotional feedback indications that show the stress levels and emotional involvement of the students. Through an intuitive interface, the teacher's real-time feedback encompasses the patterns and trends of emotional reactions in students. Ethical and privacy concerns might be carefully taken into account while designing the system. Since the information being gathered was sensitive, it was essential for student emotional data to be handled and kept securely by data protection laws [9]. Emotional involvement constitutes the system that might provide teachers feedback like teaching strategies and material delivery. Students' emotional needs were satisfied with an individualized approach without interfering with the lesson flow and academic progress [10]. Individual differences in physiological reactions might cause misunderstandings and compromise the validity of therapies and feedback. Continuous monitoring may be difficult due to variations in sensor data caused by changes in the surrounding environment, user activity, and emotional intensity [11].

The research aims to create a new Battle Royale fine-tuned Deep Bidirectional Long Short-Term Memory [12] that can identify students' emotional and cognitive engagement. The goal is to create a biosensor-based system that can measure emotions and give feedback for higher education political and ideological instruction.

Contribution of the research:

- The research aim is to develop a novel BR-DBiLSTM to detect both cognitive and emotional engagement in students;

- The system uses a combination of biosensors to monitor physiological and behavioral indicators and collect emotional data. The data was preprocessed using Z-Score normalization to reduce noise from the obtained data and feature extraction using FFT;
- BR is used to optimize and select the features of the DBiLSTM model to improve its classification accuracy;
- In the context of University political and ideological education, the research develops a biosensor-based emotional monitoring and feedback system.

The research is organized into several sections: Part 2 covers the related works, Parts 3 and 4 methodology and findings, and Parts 5 provide the conclusion.

## 2. Related works

Students' lifestyles have been changed by the Internet era, and employment and efficacy have increased in tandem with societal development [13]. The development of the proper ideals and outlook on life, as well as a positive learning attitude for ideological character, might be facilitated by political and ideological education. The results of the experiment showed that internet habits were good.

The network society had expanded; college students' lives had become more interviews and used a multitude of channels to engage with many kinds of information [14]. New barriers to ideological practices were made by learners. To use a proactive and positive strategy to enhance students' political education and ideological network. The results of the trial showed how well the system worked and performed.

The research [15] evaluated educational ideology as the cultures, customs, and beliefs that influence education in the areas of politics, economics, religion, knowledge and truth, and morals. Changes in governmental policy, protection from political risks, various forms of spending, and business partnerships were all key components of ideological and political education. Organizations used economic linkages and ideological teaching to resolve domestic problems. The results of the experiment showed that the instruction was effective.

The creation of theoretical systems that integrate everything in the universe and multi-dimensional space-time through Internet governance principles expedited the development of political and ideological instruction at universities and colleges. The experiment's outcomes demonstrated the students' expectations and areas in need of improvement [16].

The content of ideological ideas, such as the reasons for people's belief in omniscient gods or a fascist worldview, had been the focus of psychological research on ideology. Because of the theoretical focus, political, religious, moral, and biased attitudes were addressed by distinct sub-disciplines. The research addressed the fact that ideological thinking was a significant psychological phenomenon and listed subcomponents. The outcome demonstrated how social ties were conceptualized hierarchically [17].

The institutions and methods of political and ideological teaching in Chinese universities were thoroughly described. The research demonstrated the institutionalization and nationalization of education in Chinese colleges. It demonstrated how the education methods institutionalize patriotism and conformity as suitable ideological viewpoints for learners. The outcome demonstrated the formal instruction [18].

Critical effective literacy was argued for in civic education classes. By incorporating ideas and theories from affective citizenship, critical emotion studies, and agonistic political theory, critical affective civic literacy questions the rationalistic slant of civics education and provides teaching methods for fostering students' political beliefs. The result showed how the flow of emotion was used to create affective barriers in social studies classes [19].

Political and ideological activism had a bigger impact on university school administration. One of the practical issues and challenges facing university political organization activities was the development of ideologies and politics. The universities should increase their overall strength, actively support the development of the country's talent, and raise the standard and caliber of education. The outcome demonstrates new opportunities for political and ideological work [20].

The research [21] examined how respondents' traits, perceptions of socioeconomic conditions, and perceived traits of politicians, political parties, and institutions all predicted their level of political confidence in particular politicians and political parties. The outcome demonstrated the intricate nature of political trust.

Poor network information might readily skew college students' ideology and value orientation, a thorough evaluation of network community opinion's posture. The outcome demonstrated how the network environment and political education operate together [21].

The new intelligent wearable system would be the emotion recognition that was proposed and integrated with several sensors for accurate categorization and detection. Real-time information engagement was made possible through the establishment of a 3D display platform that used the three-branch spatial-temporal feature extraction network (TBSFENet) [22]. The system's ability to achieve virtual reality information exchange between a digital human and a live individual was demonstrated by experimental results, which had implications in virtual reality and intelligent healthcare.

A software program called the Semantic Decision Support System (SDSS) [23] was created to enhance decision-making skills in potentially life-threatening situations. It employed a recommender engine for team management and cognitive analytics on wearable bio-signal sensors to offer input on risk categorization. The system allowed for continual real-time tracking and display of crucial data by integrating multisensory data streams with evaluation modules, risk stratification, and recommender engines. Careful monitoring and quick reaction to new threats in a variety of operational settings were made possible by the consolidated dashboard.

The importance of online engineering education for lifelong learning and career advancement was growing. To identify students' emotions and evaluate their mental states, an intelligent framework integrates deep learning techniques. Convolutional neural network-random forest (CNN-RF) [24] and a visualization dashboard were the elements that make up the framework. Assessment questionnaires validate the model's efficacy as an adaptive learning approach.

Psychology, neurology, and interaction between humans and computers were among the domains where emotion recognition had attracted a lot of interest. Unimodal approaches were limited in their ability to capture human emotional expression. Multimodal Emotion Recognition (MER) [25] provides a thorough comprehension of a person's emotional condition. The research looks into contactless methods of gathering MER data, pointing up gaps in the field and suggesting a comparative schema for assigned MER criteria to particular combinations of modalities.

A machine learning method for identifying mood, age-gender, drowsiness, and social distance was presented. For a variety of tasks, the model employs K-Nearest neighbors, independent component analysis, principle component analysis, linear discriminant analysis, and support vector machine. The method had promise for jobs that were more precise and effective with an accuracy of 96.3% [26].

## 3. Methodology

The emotional monitoring dataset is used to contain physiological and emotional data from subjects with audiovisual stimuli, offering heart rate, Electroencephalography (EEG), and emotional ratings. Biosensor data is preprocessed through Z-score normalization, ensuring consistency, which boosts the accuracy of the classification model as noise is reduced and the Fast Fourier Transform is used for feature extraction. The method used is the Battle Royale fine-tuned Deep Bidirectional Long Short-Term Memory that captures both forward and backward temporal dependencies in the physiological data and optimizes the feature selection through Battle Royale optimization in improving the model. The overall flow of this research is depicted in **Figure 1**. This system enables real-time emotional and cognitive engagement detection with adaptive feedback for instructors.

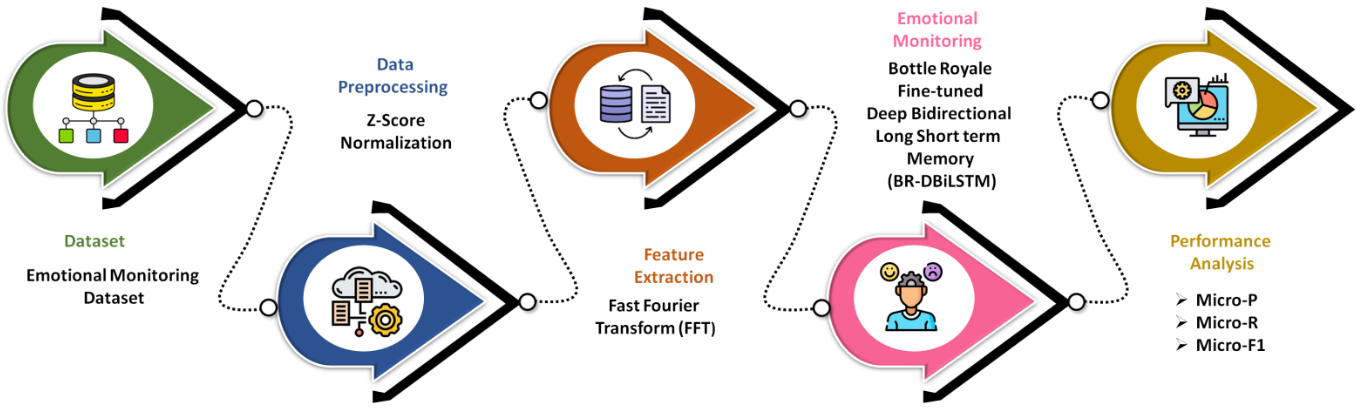


**Figure 1.** Overall proposed method flow.

### 3.1. Dataset

The dataset was created especially for university ideological and political education and it is intended for use in emotional monitoring and feedback systems. Heart rate, skin conductance, EEG, temperature, pupil diameter, smile intensity, frown intensity, cortisol level, activity level, ambient noise level, and lighting level are among the features of this dataset that are intended to capture physiological and behavioral responses that are likely indicative of students' emotional and cognitive states. It was gathered from a Kaggle source [27]. It classifies students into three categories highly engaged, moderately engaged, and disengaged, by the integration of these features. This dataset is designed to mimic real educational settings, where it makes checking up-to-date actions of students through biosensors straightforward and provides actionable insights into how teaching strategies and learning outcomes could improve. It was designed especially for university ideological and political education and offers an alternative way of understanding students' emotional and cognitive states by looking at physiological and behavioral responses. More, however, would be added about the data collection process to increase its utility and credibility. This information would facilitate the replication of the research or its adaptation to any particular researcher's context, thereby optimizing its impact.

### 3.2. Preprocessing using Z-score normalization

Z-score normalization to standardize biosensor data, so that all features lie around zero with unit variance. General preprocessing usually helps the model absorb scale variations of physiological signals and, consequently enhances the BR-DBiLSTM model's ability to attain stable accuracy in classification. A technique for normalizing data based on its mean and standard deviation is called Z-score normalization. If the data's true lowest and highest values are unidentified this approach is quite helpful. The following formula is applied in the Equation (1).

$$W_{new} = \frac{W - \mu}{\sigma} = \frac{W - Mean(W)}{StdDev(W)} \tag{1}$$

The normalized findings' new value is denoted by $W_{new}$. $W$ is the old value. $\mu$ is the population mean and $\sigma$ is the standard deviation value.

### 3.3. Fast fourier transform (FFT) using feature extraction

Extracting frequency-domain information from physiological inputs, the FFT is used in this work to better identify patterns in emotional and cognitive involvement. It increases the BR-DBiLSTM model's accuracy and feature selection. The spectral properties of alpha waves (8 Hz–13 Hz) are extracted using the power frequency units. Power Spectral Density (PSD) calculates the spectral intensity for each unit of frequency. An estimate of the frequency of the signal's content can be made using the PSD. Equation (2) provides the expected power at a chosen frequency.

$$PSD = \frac{1}{2\pi}\int_{\omega_1}^{\omega_2} T_w(\omega)d\omega \tag{2}$$

$$T_w(\omega) = \lim_{S\to\infty}\left[\frac{F[E_w(\omega)^2]}{2S}\right] \tag{3}$$

where $\omega_1$ and $\omega_2$ are the smallest and highest frequencies of the spectrum results, and $E(\omega)$is the value of the input signal's Fourier spectrum result. The dominating spectral energy from the power spectrum is determined using the Spectral Centroid (SC). It is typically employed in speech and audio recognition systems to identify the dominant frequency in speech or audio signals. Equation (4) provides the formula for calculating the centroid.

$$SC = \frac{\sum_{l=1}^{M} kF(L)}{\sum_{l=1}^{M} E(L)} \tag{4}$$

where $E[l]$is the DFT spectrum amplitude that corresponds to bin$l$, and the energy of the frequency (alpha wave) was also used in this work in addition to the SC and PSD. Equation (5) provides the spectral energy circulation of a certain signal.

$$SE = \sum_{l=1}^{M-1} W(l)^2 \tag{5}$$

The FFT spectrum result of the input signal is represented by$W(L)$, where $L$ is the total number of bins in the FFT.

### 3.4. Battle royale fine-tuned-deep bidirectional long short-term memory (BR-DBiLSTM)

The BR-DBiLSTM hybrid method extracts from the Deep Bidirectional LSTM and Battle Royale optimization with the aim of university education emotional monitoring and feedback systems. In the approach, DBiLSTM processes the sequential physiological signals coming from biosensors, like heart rate and skin conductivity, and therefore captures both forward and backward temporal dependencies, which are important to the full emotional context that students place in their activities. Optimization of Battle Royale optimizes the model to select the most relevant features from the sensor data; it reduces noise and improves classification accuracy. The hybrid model is more accurate and responsive in real time to stress, engagement, and relaxation levels. In response, adaptive feedback is provided to the instructors using a dashboard showing the levels of emotional and cognitive engagement, disengagement, or stress alerts, hence fostering a responsive and supportive learning environment. The BR-DBiLSTM approach is represented by Algorithm 1, which is provided below.

**Algorithm 1** The Process of BR-DBiLSTM

```
import tensorflow as tf
from tensorflow.Keras.Models import Sequential
from tensorflow.Keras.Layers import Dense, LSTM, Bidirectional, Dropout
def DBiLSTM(input_shape):
  model = Sequential([
    Bidirectional(LSTM(units), input_shape = input_shape, return_sequences = True),
    Dropout(dropout_rate),
    Bidirectional(LSTM(units)),
    Dense(output_classes, activation = 'softmax')
  ])
  return model
def BR(input_shape):
  model = Sequential([
    Dense(units, input_shape = input_shape, activation = 'relu'),
    Dropout(dropout_rate),
    Dense(output_classes, activation = 'softmax')
```

**Algorithm 1** (*Continued*)

```
    ])
    return model
def BR_DBiLSTM(input_shape):
    model = Sequential([
        Bidirectional(LSTM(units), input_shape = input_shape, return_sequences = True),
        Dropout(dropout_rate),
        Bidirectional(LSTM(units)),
        Dropout(dropout_rate),
        Dense(output_classes, activation = 'softmax')
    ])
    return model
def compile_mdl(mdl):
    mdl.compile(optimizer = 'opt', loss = 'cat_cross', metrics = ['acc'])
def train_eval(mdl, train_data, train_lbls, test_data, test_lbls):
    mdl.fit(train_data, train_lbls, epochs = epochs, batch_size = batch_size, validation_data =
(test_data, test_lbls))
    return mdl.evaluate(test_data, test_lbls)
def main():
    data, lbls = load_data()
    train_data, test_data, train_lbls, test_lbls = preprocess_data(data, lbls)
    input_shape = (seq_len, num_features)
    for model_func in [DBiLSTM, BR, BR_DBiLSTM]:
        mdl = model_func(input_shape)
        compile_mdl(mdl)
        loss, acc = train_eval(mdl, train_data, train_lbls, test_data, test_lbls)
        print(f"{model_func.__name__} − Loss: {loss}, Accuracy: {acc}")
if __name__ == "__main__":
    main()
```

### 3.4.1. Deep bidirectional long short term memory (DBiLSTM)

The DBiLSTM method employed by the research effectively captures forward and backward temporal dependencies of students' physiological data to accurately detect emotional and cognitive engagement for real-time feedback in educational settings. The model, which is based on LSTM, uses three gates: the input gate, the forget gate, and the output gate. The following Equation (6) is a precise description of an LSTM unit.

$$j_s = \sigma\left(Z_j \times w_s + X_j \times g_{s-1} + a_j\right) \tag{6}$$

When the input gate at time $j_s$ is represented by, the bias term by $Z$ and $X$, the matrix multiplication process by the sigmoid function of $\sigma$, the input data at time $s$ by $w_s$, and the output of the previous LSTM unit by $g_{s-1}$ are all demonstrated to determine whether particular data from the previous unit has to be changed, the input gate is essential.

$$e_1 = \sigma(Z_e \times w_s + X_e \times g_{s-1} + a_d) \tag{7}$$

where $e_s$ stands for the forget gate, which is in charge of determining the information's importance and erasing previous knowledge is determined in Equation (7).

$$\tilde{d}_s = \tanh\,(Z_d \times w_s + X_d \times g_{s-1} + a_d) \tag{8}$$

$$d_s = e_s \odot d_{s-1} + j_s \odot \tilde{d}_s \tag{9}$$

where the applicant's $d_s$ state is ascertained by applying the tangent activating function, as shown in Equation (7). The current condition of the cell is then assessed and given in Equations (8) and (9), which $\odot$ stands for point-to-point multiplication.

$$h_s = \sigma(Z_h w_s + X_h g_{s-1} + a_h) \tag{10}$$

$$g_s = h_s \odot \tanh(d_s) \tag{11}$$

In Equation (10), the output gate $g_s$ is computed, and in Equation (11), $h_s$stands for the LSTM unit's output. The baseline LSTM model uses just historical data to forecast current human activities. Evaluating the data in a one-way fashion may result in the loss of some information. The two LSTM layers that make up the Deep BiLSTM function both forward and backward, as shown in **Figure 2**. The Deep BiLSTM's output layer is constructed as follows in Equation (12).

$$u_s = [\overrightarrow{g_s}\overleftarrow{g_s}] \tag{12}$$

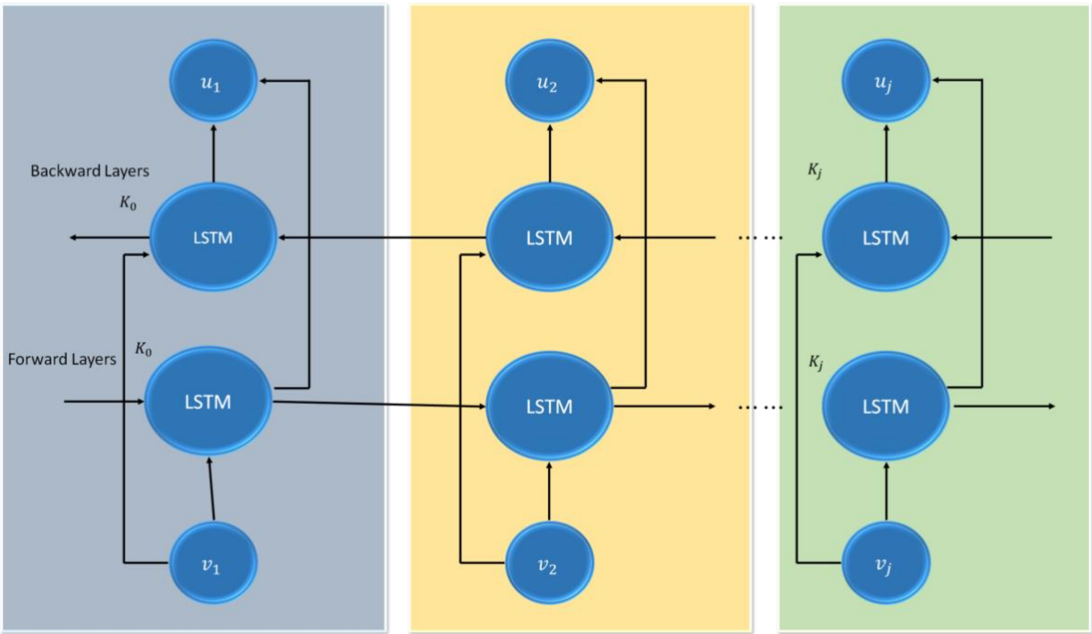


**Figure 2.** Deep BiLSTM (Bidirectional long short-term memory) framework.

The symbols $\overleftarrow{g_s}$ and $\overrightarrow{g_s}$ stand for the forward and backward results of the LSTM units, respectively. The output is created by combining these two LSTM units. The core idea behind the Recurrent Neural Network (RNN) is that we introduce the data gradually, one at a time; sequentially, thereby including the temporal variable as well, as opposed to sending the entire set of input data to the neural network in a single instance. It can feed the beginning value into the network and get a corresponding output if it has an array of input values. The next output is then produced by feeding the next input with the previous output.

#### 3.4.2. Battle royale optimization (BRO)

The Battle Royale optimization method for optimizing feature selection and input data quality is applied in the research. It helps eliminate noises, improve extraction of relevant features, and increase classification accuracy in finding engagement by the

DBiLSTM model. The last survival tactic in a difficult setting served as the inspiration for the Battle Royale Optimization (BRO) algorithm, a game-based optimization technique. Players (soldiers) engage in competitive combat with one another in various kinds of fighting games. Each player's objective is to kill as many other players as possible after initially surviving. A player will respond in a random area of the game field if injuries continue during gameplay for a predetermined period. The BRO method randomly distributes the first potential solutions over the issue space in Battle Royale games. Each response would be contrasted with its closest neighbor. The winner would be the answer with the highest fitness value, and the loser would be the other option.

Every potential solution has a parameter that keeps track of each solution's degree of damage or loss. Following each damage parameter would increase. A solution will be shifted around by Equation (13) and it absorbs damage repeatedly for a specified amount of time, the damage level will be reset to zero. If the damage is less than the threshold, reallocation will be accomplished using Equation (14).

$$w_{dam,c} = q(va_c - ka_c) + ka_c \tag{13}$$

$$w_{dam,c} = w_{dam,c} + q\left(w_{best,c} - w_{dam,c}\right) \tag{14}$$

In this equation, the positions of the destroyed and most recognized solution in dimension $c$ are denoted by $w_{dam,c}$ and $w_{best,c}$, respectively, where $q$ is a number that is evenly distributed in the region [0,1]. $va_c$ and $ka_c$ stand for higher and lower constraints on the dimension of the problem space $c$ respectively.

The algorithm's key characteristic is that, if iteration$\leq \Delta$, the search space narrows and approaches the optimal answer by $\Delta = \Delta + \left\lceil \frac{\Delta}{2} \right\rceil$ with every $\Delta$ iteration. The safety zone will get smaller if the iteration is raised to a value of $\Delta$. $\frac{\text{Max}Cicle}{round\left(\log_{10}(\text{Max}Cicle)\right)}$, where $MaxCicle$ the greatest number of iterations is the default value for $\Delta$. The space boundary is intended to push all potential solutions in the direction of the most promising one. To defend elitism, remember that each round's best solution is saved. The problem space can be made smaller by applying Equation (15), where $SD(\overline{w_c})$ is the population standard deviation in dimensions.

$$\begin{aligned} ka_c &= w_{best,c} - SD(\overline{w_c}) \\ va_c &= w_{best,c} - SD(\overline{w_c}) \end{aligned} \tag{15}$$

## 4. Result and discussion

### 4.1. Result

In the experiment, a Personal Computer (PC) with 500 Gigabytes (GB) of storage and 16 GB of Random Access Memory (RAM) serves as the computational platform that facilitates the efficient execution of machine learning algorithms and data analysis tasks. Libraries like TensorFlow and Scikit-learn are used for developing and deploying real-time emotion tracking and feedback generation systems that will ensure robust model performance. The biosensors are integrated using dedicated equipment that collects and transmits physiological data to be processed. The Python is used for advanced data analysis by utilizing its extensive libraries and flexibility.

Emotion detection indicates the spread of the emotional state observed in the students during the sessions of political education measured by the detection of emotional states with a biosensor-based emotional monitoring and feedback system. Neutral emotion is prominent and represents 71% of all instances where emotions have been found. This suggests that most students exhibit a balanced emotional state, likely because the content being discussed did not elicit extreme reactions. Anger, at 14%, would tell that a sizeable proportion of the students had a sense of frustration or disagreement, suggesting areas of potential conflict or dissatisfaction with the content or delivery of the course. Sadness, at only 8%, represents an important proportion of students who were probably disillusioned or disconnected from the material warranting further examination to determine the cause. The percent of happiness is 2.5%, the percent of fear is 2%, the percent of disgust is about 1.5%, and the percent of surprise is 1%. All these percentages were relatively low, suggesting that while there were emotional spikes, to occurred infrequently. Such events can better elucidate some of the reactions toward parts of the school curriculum and present opportunities for changing the delivery of content, teaching techniques, or mechanisms for effective support. Overall, this emotional information is beneficial in optimizing the learning environment by adjusting appropriate educational content and methods to conform with how students respond emotionally, thereby creating a more involved and receptive space for ideological and political education. The value of the above statement is represented in **Figure 3**.

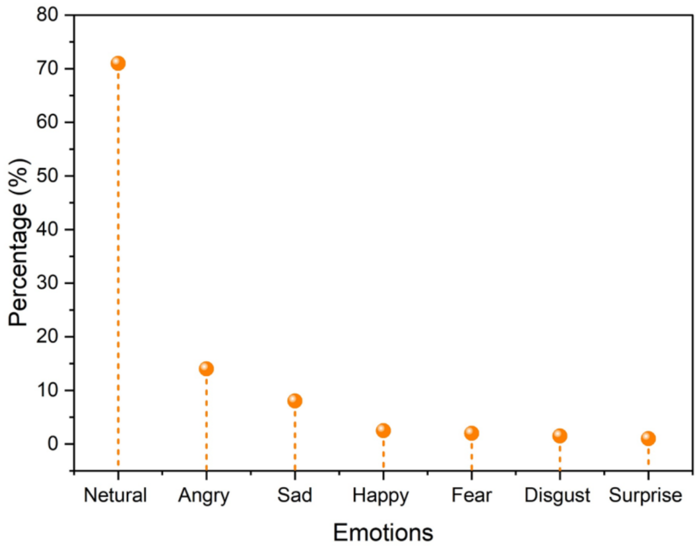


**Figure 3.** Performance values in emotions.

The cognitive engagement detection introduces four types of student engagement levels and it will define these factors to indicate the capabilities of a system to measure different attention and participation levels in ideological and political education. The cognitive engagement level is illustrated in **Figure 4**. With 35% displaying high instances of engagement, the results show that there is a fully immersed, number of students who are intensely engaged, actively participating, and responsive to education.

Moderate engagement which stands at 24% is students who seem attentive but would not be wholly focused like the rest in the high engagement category. Low engagement, which comprises 26%, simply implies a student being present with very little cognitive investment, possibly being distracted or less concerned. The non-engaging of 15% indicates students who have the lowest cognitive or affective response. Because this is a real-time feedback system via biosensor technology that measures the level of real-time cognitive and emotional engagement, its results are useful for teachers to adapt instruction to maximize engagement in students at all levels.

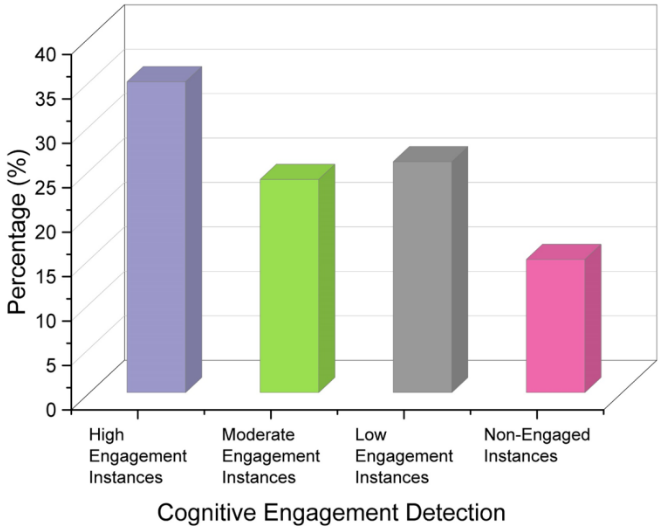


**Figure 4.** Cognitive engagement detection using biometric sensors.

The proposed Battle Royale fine-tuned Deep Bidirectional Long Short-Term Memory (BR-DBiLSTM) method was outperformed by several existing methods, including the Bidirectional Encoder Representations from Transformers and Multi-Head Attention (BERT-MHA), BERT-Bidirectional Gate Recurrent Unit (BiGRU), and BERT-BiGRU-MHA [27]. The characteristics of Micro-P, Micro-R, and Micro-F are examined in this section.

Micro-Precision: This refers to how well each model can identify emotions and provide insightful feedback. **Figure 5** and **Table 1** illustrate the micro precision value, the best was the BERT-MHA, with an accuracy of 63.99%, and a multi-head attention mechanism helped fit the model into complex emotional patterns. The BERT-BiGRU model, which follows the structure of bidirectional GRU architecture, scored 62.28%, even outperforming the base BERT in terms of its contextual understanding. The BERT-BiGRU-MHA model, with the inclusion of both attention and bidirectional mechanism, reached an accuracy of 64.49%, which not only shows that the role of attention in a recurrent structure contributes towards the better perception of emotions but is also remarkable since it understands the fact that the BR-DBiLSTM model, based on the fine-tuned bidirectional LSTM structure for monitoring emotion, achieved an extraordinary precision score of 89.65%. This implies that BR-DBiLSTM is dramatically effective for the monitoring of cognitive engagement, making it suitable for feedback systems in education settings requiring accurate emotional detection.

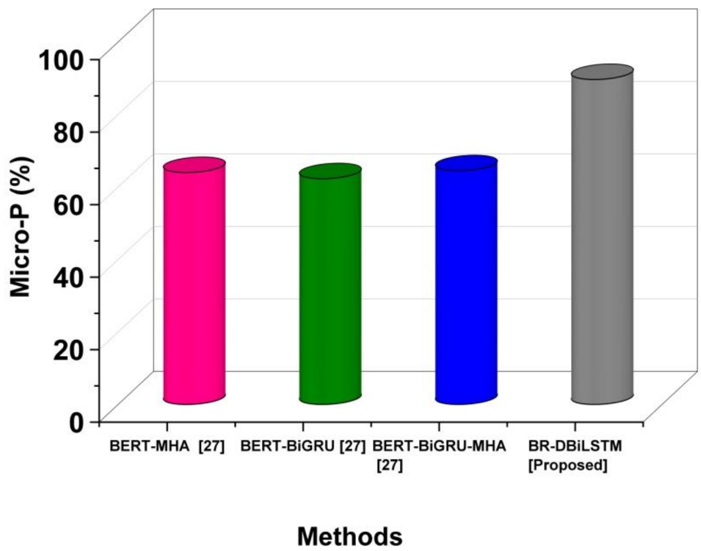


**Figure 5.** Micro-P results across different experimental conditions.

**Table 1.** Summary of Micro-P analysis results.

| Methods | Micro-P (%) |
|---|---|
| BERT-MHA [28] | 63.99 |
| BERT-BiGRU [28] | 62.28 |
| BERT-BiGRU-MHA [28] | 64.49 |
| BR-DBiLSTM [Proposed] | 89.65 |

Micro-Recall: The ability of each model to recognize emotional and cognitive engagement in this particular environment is indicated by micro-recall ratings. **Figure 6** and **Table 2** illustrate the micro recall value. A recall score of 59.23% was attained by the BERT-MHA model, which uses multi-head attention to capture subtle emotional elements. By contrast, the BERT-BiGRU model demonstrated better recall at 61.90%. This model makes use of a bidirectional GRU layer for greater sequence understanding. The importance of integrating attention and bidirectional architectures for emotional detection was further supported by the similar recall level of 61.61% attained by the BERT-BiGRU with multi-head attention combination (BERT-BiGRU-MHA). With a remarkable 88.34% recall, the BR-DBiLSTM model much surpassed the rest. Because of its high recall, the model can better identify and remember emotional cues, which makes it ideal for use in educational feedback systems that need to track emotional engagement accurately and consistently.

**Table 2.** Micro-R analysis outcomes: Evidence and interpretation.

| Methods | Micro-R (%) |
|---|---|
| BERT-MHA [28] | 59.23 |
| BERT-BiGRU [28] | 61.9 |
| BERT-BiGRU-MHA [28] | 61.61 |
| BR-DBiLSTM [Proposed] | 88.34 |

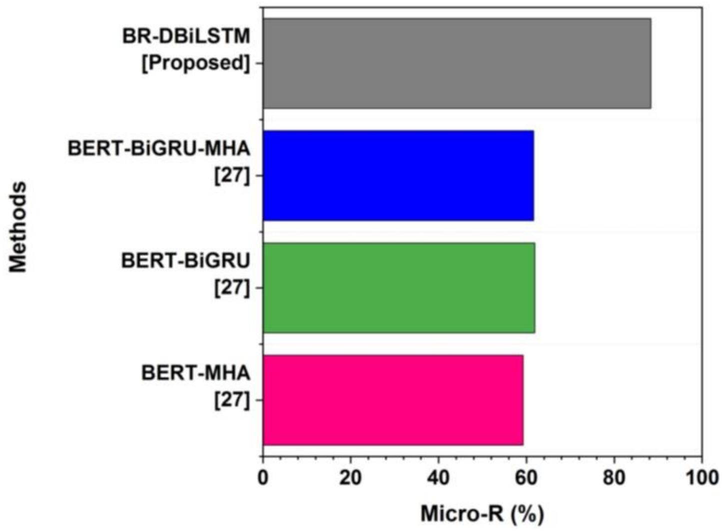


**Figure 6.** Outcomes of Micro-R: A comprehensive overview.

Micro-F1-score: The micro-F1-score is a crucial metric that illustrates the model's performance. Better overall at selecting appropriate, pertinent emotional states and generating reliable feedback, when their F1 scores are greater. **Figure 7** and **Table 3** illustrate the micro F1-score value, BERT-MHA with multi-head attention was able to draw a moderate F1-score: 61.51%, showing its fair ability to capture cues. The BERT-BiGRU will utilize the bidirectional GRU mechanism to attain the F1-score of 62.08%, taking advantage of the enhanced sequential processing mechanism. The BERT-BiGRU-MHA, which incorporates both mechanisms, attained a higher F1-score of 63.01%, as demonstrated to be more accurate in balancing while detecting emotions. However, this model did not manage to climb to the performance zenith of the BR-DBiLSTM with its colossal F1-score of 90.62%. It reflects how well BR-DBiLSTM seizes complex emotional and cognitive engagement cues, making it a good fit for nuanced educational feedback systems where fine-grained monitoring of emotions is critical to effective learning support.

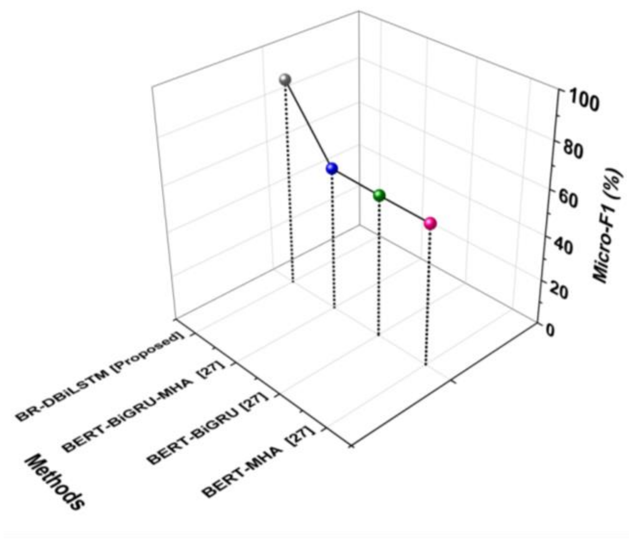


**Figure 7.** Micro-F1 performance results.

**Table 3.** Performance metrics based on Micro-F1 score.

| **Methods** | **Micro-F1 (%)** |
|---|---|
| BERT-MHA [28] | 61.51 |
| BERT-BiGRU [28] | 62.08 |
| BERT-BiGRU-MHA [28] | 63.01 |
| BR-DBiLSTM [Proposed] | 90.62 |

### 4.2. Discussion

BR-DBiLSTM technique offers a significant advantage in emotional monitoring, particularly for ideological and political education, by attaining higher classification accuracy in emotions. Every existing method, including BERT-MHA, BERT-BiGRU, and BERT-BiGRU-MHA, has shortcomings. Although BERT-BiGRU-MHA combines multi-head attention with recurrent structures, its practical application is limited, due to its limited scalability and computational inefficiencies; BERT-BiGRU struggles to process long-term contextual relationships, which results in lower recall rates, and BERT-MHA struggles to capture sequential dependencies in complex emotional data, which affects its precision. By using a strong bidirectional LSTM structure that efficiently collects both forward and backward contextual information and fine-tuning to improve responsiveness to small emotional cues, the BR-DBiLSTM technique gets around these drawbacks. This strategy improves performance across a range of educational emotional and cognitive engagement to increase model sensitivity and decrease misclassification rates. It is suited for real-time educational applications because of its optimized architecture, which guarantees both outstanding accuracy and efficiency. The proposed model, "BR-DBiLSTM," has several merits over other models. First, it combines the BiLSTM architecture with a BRO retrieval mechanism, which allows the model to capture forward and backward dependencies within sequential data, thus helping in improving context understanding. This design enhances the model's capabilities to process time-series or sequential inputs, such as emotional data, more effectively. Moreover, the BRO component enhances the retrieval accuracy of the model by dynamically adjusting its focus on relevant features to ensure better generalization. Compared with traditional models, the BR-DBiLSTM model improves predictive performance and offers greater adaptability to various input variations, providing a more comprehensive and reliable analysis for emotion monitoring in complex educational settings.

## 5. Conclusions

The developed research concluded with a new biosensor-based emotional monitoring and feedback system to improve the ideological and political education of students through better engagement. The BR-DBiLSTM model, implemented on Battle Royale, was able to recognize the levels of cognitive and emotional engagement. The results proved that the model is robust and precise, obtaining a Micro-P of 89.95%, Micro-R of 88.34%, and Micro-F1 of 90.62%. The values illustrate its accuracy in classification and reliability. The adaptive feedback on the system, based on real-time data from biosensors, offers tremendous benefits for educators to detect student disengagement and stress responses and take corrective measures in time. This can create a great potential for the stimulation of active involvement and further deepening students' knowledge about values, ethics, and social norms in university ideological and political education circumstances.

### Limitations and future scope

Biosensor data might not adequately or properly capture the complexity of emotional experiences. Individual differences in physiological reactions might cause misunderstandings and compromise the validity of therapies and feedback. Continuous monitoring might be difficult for variations in sensor data caused by changes in the surrounding environment, user activity, and emotional intensity. Future scope might offer personalized feedback, for modifying instructional materials and intervention strategies to fit the emotional needs of each learner. Ideological and political education might become more successful and interesting with the help of adaptable features.

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

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