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The Analysis of Integration of Ideological and Political Education and Mental Health Education for College Students

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Objective: After a period of theoretical investigation and practical implementation in the realm of political and ideological education, an optimal educational system has been established. The primary objective of political and ideological education in higher education institutions is to facilitate the cultivation of a constructive worldview and the reinforcement of students' spiritual underpinnings. However, there is a noticeable disparity in the attention given to mental health awareness (MHE), as fewer courses are dedicated to this aspect. Extensive research has been conducted; however, it has been conducted in a manner that neglects the interdependence of the variables under investigation and the significance of their collaborative functioning. **Proposed:** The integration paradigm of political and ideological education and mental health education is addressed by the introduction of a Bayesian optimisation with bidirectional long-term memory (BO-BLSTM). The BO-BLSTM model suggested in this study aims to specifically target the recognition and classification of a wide range of political sentiments. **Methods:** This study proposes the utilisation of a Bayesian optimisation with bidirectional long-term memory (BO-BLSTM) within the framework of integrating political and ideological education with mental health education. The objective of the BO-BLSTM model is to discern the diverse categories of political sentiments that are present. **Conclusion:** The application of the Bayesian Optimisation (BO) technique allows for the optimisation of hyperparameters in the Bidirectional Long Short-Term Memory (BLSTM) model. Through comprehensive experimentation, it has been established that the BO-BLSTM model exhibits superior performance compared to existing approaches.

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1. Introduction

Transmission equipment related to network communication is progressively becoming more prevalent in people's everyday lives as the new era of intelligent technology starts to take form. In the contemporary era, there is an escalating demand on potential workers due to advancements in science and technology, as highlighted by McGee and Stovall (2015). In China, college students hold significant value as valuable human resources, actively contributing to the nation's economic and societal progress. Presently, university students are grappling with extensive, veiled, and culturally ingrained mental health issues, stemming from the intensifying global and local competition. This process of advancement can be depicted through distinctive symbols denoting personal growth. The expansion of digital data has been accelerated by the implementation of broader coverage initiatives, programs aimed at alleviating network poverty, and regulations concerning the development of digital infrastructure in rural areas, as noted by Yang et al. (2015). As time progresses, conditions such as anxiety, depression, and other psychological well-being challenges are becoming increasingly prevalent. The recognition of the significance of mental well-being is on the rise. Recent years have witnessed significant media attention directed towards mental health challenges experienced by university students. Within the Chinese university student demographic, mental health disorders manifest with varying degrees of severity, impacting approximately one-third of the population with more substantial psychiatric difficulties. The primary avenues for imparting psychological health education involve lectures and mental health counselling. As we endeavour to pursue reforms and open ourselves to the global and domestic landscape, we will encounter numerous pivotal advancements. The academic pursuits, personal lives, emotional states, career aspirations, and other facets of college students' lives are all vulnerable to heightened social competition and stressors. A diverse spectrum of mental health concerns prevalent among college students can be attributed to these factors. Consequently, numerous institutions, if not the entirety of society, are dedicated to the physical and emotional well-being of university students. Conventional evaluation methodologies fall short in comprehensively and adequately addressing all pertinent factors. Nevertheless, in the contemporary era, traditional education methods have demonstrated themselves to be unproductive. This is primarily due to the excessive emphasis placed on pedagogical techniques and the linear dissemination of factual information from textbooks. As a consequence of this shift, political and ideological courses, which have historically been the primary platform for explicit instruction within universities and colleges, have redirected their focus towards classroom instructional strategies and theoretical concepts (Caldarella et al., 2013). Consequently, there is growing concern among students regarding the absence of shared experiences in specialized domains that are essential for enhancing the educational context of political and ideological courses. This absence stems from the lack of communication between educators responsible for teaching these courses and educators handling specific subjects. Additionally, there exists a deficiency in understanding the core features of majors studied by students, as highlighted by Ansari et al. (2020) and Barry, Huskamp, and Goldman (2010). These limitations have led to a reduction in the impact of political and ideological courses on students, preventing them from effectively fulfilling their intended role in administrative aspects of ideological education. Therefore, the investigation into the integration algorithm involving both implicit and explicit teaching methods became a significant focus, as addressed by Fazel et al. (2014). In response, we introduced a groundbreaking approach known as the BO-BLSTM Model, designed to seamlessly combine political and ideological education with Mental Health Education (MHE). The subsequent sections of this paper are structured as follows: Part II encompasses a review of related studies and outlines the problem statement. Part III details the methodology we have put forth. Part IV presents the results and subsequent discussion. Finally, Part V concludes the paper.

2. Related works

Political and ideological education within universities holds significant importance in nurturing skilled individuals. The physiological and behavioural patterns of college students undergo substantial changes, often leading to heightened emotional experiences and reduced self-regulation abilities. Consequently, dealing with issues related to information overload, online networking, companionship, and affection frequently gives rise to profound mental conflicts, contributing to emotional instability and personal development challenges. Through progressive educational reforms, the realm of political and ideological education is gradually transcending conventional limitations and intertwining with gratitude education and Mental Health Education (MHE). This convergence allows for the holistic development of students' intellect and ethical values, as discussed by Atkins et al. (2010) and Babury and Hayward (2013). MHE serves as an effective means to address students' negative emotional states, enhancing their alignment with society and life through heightened political awareness – a crucial element for advancing political and ideological education, as elucidated by Lubis (2011).

The prevalence of anxiety, depression, and various other mental health concerns has seen an upward trend. The recognition of the significance of mental well-being is gaining wider acceptance. Over the past few years, a considerable amount of attention has been directed towards the mental health of university students. A pivotal factor in underlining the importance of Mental Health Education (MHE) within political and ideological education lies in elucidating the correlation between these two forms of education and effectively incorporating them to enrich students' moral development. The sphere of education encompassing political and ideological theory and practice has yielded substantial outcomes over time, leading to the establishment of a comprehensive educational framework, as outlined by Grispini and Piccione (2017). While political and ideological education is focused on nurturing college scholars to develop a proper perspective on life and elevate their spiritual accomplishments, the insufficient emphasis on MHE, as noted by Koenig et al. (2014), becomes evident. However, numerous studies have disregarded the intrinsic connection between these two attributes and the substantial impact resulting from their convergence. The dissemination of psychological health education is primarily conducted through lectures and mental health counselling sessions. Consequently, owing to educational technologies, students are poised to develop a seamless and adept interaction with computers through various means such as language and text, facilitating software to simulate human behaviours like listening and engaging in conversation. Artificial intelligence holds potential in assessing children's capacity to manage stress, communicate proficiently with peers, and make well-informed decisions.

Budiharto and Meiliana (2018) and Zou et al. (2020) introduced a methodology and approach for model training, encompassing the identification of key words, utilization of significant datasets, and prediction of sentiment polarity. Employing the R programming language, the results vividly illustrate that Jokowi played a pivotal role in the year's election. In terms of accuracy, this predictive outcome is comparable to the findings of four Indonesian research institutions. Students not only symbolize the future and promise of the nation but also shoulder a considerable burden of responsibility for its future strength, prosperity, and affluence. Political and ideological education constitute pivotal elements within comprehensive educational program design, shaping ideological trends, fostering a sense of responsibility, and enhancing the holistic quality of college students. The trajectory of increasing reforms and openness will position us at the center of numerous consequential developments, both on the international and domestic fronts. College students are confronted with heightened social competitiveness and pressures that permeate all facets of their lives, encompassing their academic pursuits, emotional well-being, and career aspirations. Hence, the efforts of Qiu (2017) in bolstering political and ideological education hold significant importance for elevating the overall quality of the nation and fostering well-rounded individuals with diverse skills and capabilities.

Injadat et al. (2018) and Patsali et al. (2020) delved into the realm of psychological well-being among college students in Greece, particularly in light of the COVID-19 pandemic. The findings of their research underscored the heightened vulnerability of students to experiencing suicidal tendencies and depression as a consequence of the COVID-19 outbreak. Additionally, these studies identified specific risk factors and highlighted the prevalence of anxiety-inducing conspiracy theories. A diverse array of mental health challenges faced by college students can be attributed to these factors. Consequently, numerous institutions, if not society at large, are deeply invested in addressing the physical and emotional well-being of university students. Conventional assessment approaches fall short in comprehensively considering all pertinent variables in a comprehensive and satisfactory manner. An approach devised by Dorle and Pise (2018) involves the aggregation of public comments, which are then fed into a preprocessing model. This process includes tasks such as removing stop words, eliminating URLs, conducting stemming procedures, tokenization, and expanding abbreviations. The processed data is subsequently passed on to a neural network, leading to the achievement of the intended objective. Currently, it is being employed to predict the emotional response of the audience, discerning whether it leans towards positivity or negativity, through the utilization of a Recurrent Neural Network (RNN).

Hu and Li (2018) and Mody and Bhoosreddy (1995) employed surveys and integrated their findings by analysing feedback to address challenges within political and ideological education for university students on the Internet. This approach highlights the distinct attributes of political and ideological education in comparison to traditional teaching methods. The outcomes of their experiment underscore that the reduced effectiveness of political and ideological education among university students can be attributed to several factors, including inadequate data oversight, non-compliant student behaviour, insufficient consideration for public engagement, and an unfavourable online environment. In the work by Gadamsetty et al. (2022), the author suggests utilizing deep learning to detect ships in satellite imagery. The model integrates hashes to enhance stability. This model employs a controlled classification approach to categorize images, followed by the extraction of features using the Convolutional Neural Network technique, particularly utilizing the You Only Look Once version 3 (YOLOv3). In Krishnan et al. (2022), the proposed concept focuses on identifying the availability of resources, which can then be used to predict the levels of active student engagement as well as their behaviours. The data presented reveals insights into the completion of tasks and quizzes within designated timeframes. Meanwhile, in Iwendi and Wang (2022), the author introduces a technology that represents a next-generation electricity generation and storage device. One effective approach university can adopt to help students reach their full potential is by integrating mental health education into their offerings. In the twenty-first century, the rise of automation has captured the attention of major corporations, educational institutions, government bodies, and the general public alike. This proposed approach relies on methods and technologies that are increasingly vital in the creation of intelligent cities with distributed power sources.

This research introduces a novel approach called Bayesian Optimization with Bidirectional Long Short-Term Memory (BO-BLSTM) for integrating political and ideological education with Mental Health Education (MHE). The BO-BLSTM model is designed to identify various sentiment classes present in the realm of politics. To achieve this, the BO-BLSTM model initiates with data pre-processing and feature extraction procedures. Furthermore, the model employs Bidirectional Long Short-Term Memory (BLSTM) for data classification, which enables accurate identification of sentiments. The BO algorithm is utilized to fine-tune hyperparameters of the BLSTM model for optimal performance. The research culminates with a comprehensive experimental analysis, comparing the proposed BO-BLSTM model with recent methodologies to ensure its enhanced effectiveness.

The present study proposes a novel technique, known as the multi-directional long-short-term memory (MLSTM), for predicting the stability of smart grid networks. The findings obtained are compared to those generated by other prevalent deep learning techniques, including recurrent neural units (GRU), conventional long short-term memory (LSTM), and recurrent neural networks (RNN). According to Shahabaz and Afzal (2021), the empirical results indicate that the MLSTM technique exhibits superior performance compared to alternative machine learning methods (25).

Past studies have predominantly concentrated on the evaluation of height, weight, and body mass index (BMI) through the utilisation of automated techniques applied to comprehensive visual representations such as images and videos of humans. The significance of utilising facial photographs for estimating such characteristics has been understated. The data has been subjected to a cleaning process, which involves removing any inconsistencies or errors. Additionally, accompanying metadata has been included, containing relevant details such as the individual's height, body weight, age, and gender. This supplementary information serves to facilitate the subsequent analysis of the data (Li, 2021). The research conducted by Salihu and Iyya (2022) provides a comprehensive overview of the role of AI and deep learning in combating the COVID-19 pandemic. Additionally, there is a concerted attempt to establish a standardised framework for this research. Alazab et al. (2020) employed computational approaches in their study focused on the Indian stock market to assess the influence of COVID-19 on market dynamics.

Table 1

Summary of literature reviews

Reference Number	Title of the paper	Discussion
(Budiharto & Meiliana, 2018)	"Prediction and analysis of Indonesia Presidential election from Twitter using sentiment analysis"	R language efficiently forecasted the election results depending on counting tweets and sentiment analysis
(Qiu, 2017)	"Research on the ideological and political education of college students based on humanistic care and psychological counselling".	Humanistic care and psychological counselling improved student's overall performance. But it is not effective for all students due to the lack of knowledge on counselling importance
(Patsali et al., 2020)	"University students' changes in mental health status and determinants of behaviour during the COVID-19 lockdown in Greece".	The COVID-19 pandemic has been linked to an increased incidence of mental ill health in children, according to the authors.
(Dorle & Pise, 2018)	"Political sentiment analysis through social media".	The RNN model is used to anticipate the feelings of the audience, whether they be good or negative. But it is applicable only for single domain,
(Hu & Li, 2018)	"Innovative methods for ideological and political education of college students".	For ideological and political training in universities to be effective it must have self-discipline and an emphasis on social attitudes transmission, a stable involves managing, and an information supervision system in place that is lacking.
(Gadamsetty et al., 2022)	"Hash-Based Deep Learning Approach for Remote Sensing Satellite Imagery Detection"	Deep CNN approach and SHA256 is efficient in detecting the ships from satellite imagery.
(Krishnan et al., 2022)	"Smart Analysis of Learners Performance Using Learning Analytics for Improving Academic Progression: A Case Study Model"	Intelligent learning analytics are used to analyse the various learning activities of students in each course.

(Iwendi & Wang, 2022)	"Combined power generation and electricity storage device using deep learning and internet of things technologies"	Better computation and reduced complexity are made possible with the application of deep learning technologies and a fuzzy logic model.
(Ansari et al., 2020)	"Analysis of political sentiment orientations on twitter".	LSTM is used for political sentiment analysis It is sensitive to different random weight initializations.
(Zou et al., 2020)	"A water quality prediction method based on the multi-time scale bidirectional long short-term memory network".	For water quality prediction, a multi-time level lstm Model network is used
(Injadat et al., 2018)	"Bayesian optimization with machine learning algorithms towards anomaly detection"	Bayesian Optimization is used to fine-tune the parameters of SVM-RBF, Random Forest (RF), and k-Nearest Neighbour algorithms for a successful anomaly detection framework.
(Alazab et al., 2020)	"A multidirectional LSTM model for predicting the stability of a smart grid".	MLSTM efficiently predicts the smart grid stability
(Gadekallu et al., 2021)	"Identification of malnutrition and prediction of BMI from facial images using real-time image processing and machine learning".	Multi-task Cascaded Convolutional Neural Networks have been used for facial recognition. CNN, on the other hand, needs to improve its accuracy.
(Manoj & Shweta, 2021)	"A systematic review on artificial intelligence/deep learning applications and challenges to battle against covid-19 pandemic".	This research identified obstacles and concerns related with State-of-the-Art technologies to successfully regulate the COVID-19 scenario.
(Saravagi, Agrawal, & Saravagi, 2021)	"Indian stock market analysis and prediction using LSTM model during COVID-19".	It is possible to use the LSTM model to anticipate the stock values of companies listed by analysing the market's price levels and the returns of different sectors.

3. The Proposed Model

The integration of political and ideological education and mental health education (MHE) can be achieved through the utilisation of a distinctive Bidirectional Overlapping-Bidirectional Long Short-Term Memory (BO-BLSTM) model. The BO-BLSTM model provided in this study is designed to specifically target the classification of various sentiment classes within the realm of politics. This is achieved through the use of numerous subprocesses, which are outlined as follows.

3.1 Stage I: Data Pre-processing

To facilitate the development of a comprehensive dataset on student ideological and political education as well as mental health education, it is imperative to undertake the removal of inaccurate or erroneous data. Twitter employs a distinct protocol in contrast to other social networking sites due to the significant emphasis placed on pre-processing and cleansing raw Twitter data. The subsequent steps outline the preprocessing procedure: In order to maintain the distinctiveness of every tweet, the elimination of duplicate tweets and retweets is carried out, along with the removal of common stop words. Additionally, case folding is implemented to convert each token to lowercase. The dataset's average count of out-of-vocabulary (OOV) words has remained consistent over time, contrary to earlier findings.

The study examines four distinct types of feature vectors based on Term-Frequency; Term frequency (TF)–Inverse Document Frequency (IDF) for unigram, bigram, and trigram, as discussed by Gadamsetty et al. (2022) and Garg (2021). TF-IDF represents a significant statistical metric utilized to transform a collection of initial documents into a matrix through the interplay of IDF and TF. In simpler terms, it assigns weightage to a word based on its significance within a document. The TF-IDF equation is formulated as follows for the 'i' term in the 'j' document: [TF-IDF equation formula].

$$w_{i,j} = tf \times loglog\left(\frac{N}{df_i}\right) \quad (1)$$

While the variable "t_his" represents the frequency of the term "i" in document "j," the acronym DFI represents the number of documents that contain the term "i." Additionally, the symbol "N" is used to identify the total number of documents in the dataset.

3.2 Stage II: BiLSTM based Classification

A state of anxiety and stress has been found to be associated with the occurrence of memory impairment. There is a strong association between short-term memory loss and depression. The provision of mental health education has the potential to mitigate individuals' apprehensions and distress pertaining to mental health disorders. The reduction of fear surrounding mental illness can be achieved by increasing its prevalence in public awareness and fostering a culture of open discourse on the topic. Students are subjected to a range of stressors that may potentially exert a detrimental effect on their mental well-being. These stressors encompass financial concerns, significant life events, substance misuse, familial influence, clashing of cultures, and a dearth of pre-existing social networks. The utilisation of BO-BLSTM algorithm is employed for the purpose of categorising the mental health indicators pertaining to the student population. The BO-BLSTM model utilises a data classification approach that incorporates Bidirectional Long Short-Term Memory (BLSTM) to effectively discern attitudes. Long Short-Term Memory (LSTM) represents a distinct kind of Artificial Neural Network (ANN) that incorporates feedback connections. Long Short-Term Memory (LSTM) is frequently employed for the computation of video and image data, among other applications. For instance, this technique has extensive application in the fields of handwriting analysis, audio recognition, and human activity analysis. The typical architecture of LSTM networks comprises three key components, namely regulators, language processing units, and memory cells, which collectively facilitate the efficient management of data flow inside the LSTM. These components encompass the forget, input, and output gates. In addition, the LSTM unit was evaluated by Ahmed and Ali (2021) and Krishnan et al. (2022) using the GRU method. The mathematical formulations for the output, input, and forget gates of the Long Short-Term Memory (LSTM) model are as follows:

$$u_z = \sigma(W^u x_z + U^u h_{z-1}) \quad (2)$$
$$f_z = \sigma\left(W^f x_z + U^f h_{z-1}\right) \quad (3)$$
$$o_z = \sigma(W^o x_z + U^o h_{z-1}) \quad (4)$$
$$c'_t = tanh(W^c x_z + U^c h_{z-1}) \quad (5)$$
$$c_z = u_z \times c'_z + f_z \times c'_{z-1} \quad (6)$$
$$h_z = o_z \times tanh(c_z) \quad (7)$$

The above equation describes various components of a neural network model. The symbol represents an activation function, CZ designates the memory cell, represents the input vector at a specific time-step, indicates weight matrices, denotes an existing hidden state, and indicates a component-wise multiplication. Figure 1 illustrates the architectural structure of the Long Short-Term Memory (LSTM) model.

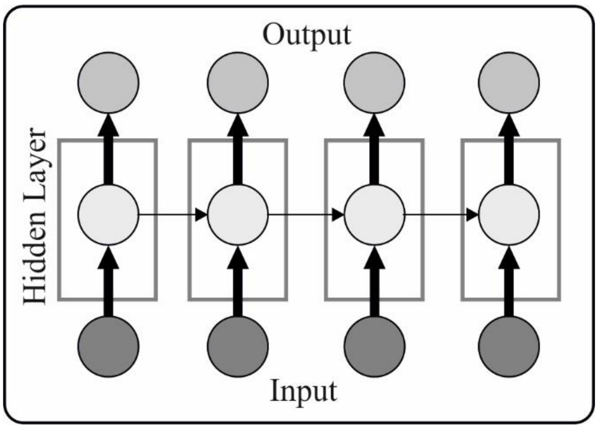

Figure 1. *Structure of LSTM*

Now, the memory cell keeps associations between the input feature and the memory cell itself. The input gate acquires the memory cell, whereas the forget gate manages the value it encompasses. The activation functions commonly used in Long Short-Term Memory (LSTM) networks are the sigmoid and tangent functions. Consequently, the output gate assumes the responsibility of determining the resultant state of a memory cell.

The Long Short-Term Memory (LSTM) model effectively incorporates the contextual information from the preceding elements in a sequence, but it may not be entirely adequate in certain scenarios. The implementation of a succession of operations is highly advantageous for retrieving forthcoming information. The Bi-LSTM model is composed of both forward and backward LSTM layers. Figure 2 depicts the architectural framework of the Bi-LSTM model. The temporal input signifies the embedding of the sample. Over time, the results of the backward hidden state align with the results of the forward hidden state. As a result, the characteristics of the hidden and backward units in the temporal dimension can be described by this alignment.

$$\vec{h}_t = L(w_t, \vec{h}_{t-1}, c_{t\_1}) \quad (8)$$
$$\overleftarrow{h}_t = L(w_t, \overleftarrow{h}_{t+1}, c_{t+1}) \quad (9)$$

Both the backward output and the forward output demonstrate the importance of integration in achieving the desired characteristic. It is necessary to simplify the notation, where H represents the number of cells present in the concealed state.

$$H_t = \vec{h}_t \parallel \overleftarrow{h} \quad (10)$$

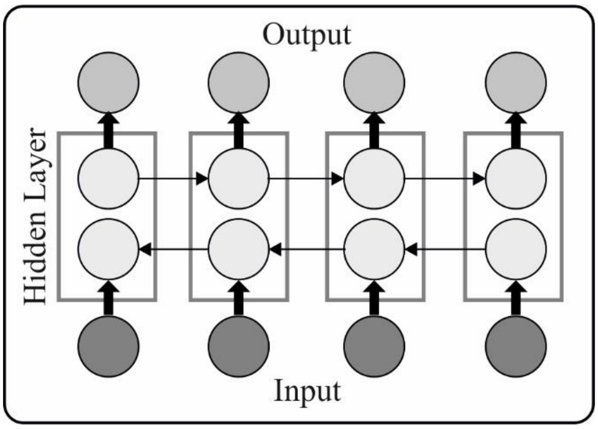

Figure 2. *Structure of BiLSTM model*

3.3 Stage III: Hyperparameter Optimization

In this study, the BO method is employed for the purpose of achieving optimal hyperparameter tuning of the BO-BLSTM model. The process of optimising hyperparameters requires expertise and extensive experimentation. Modifying hyper-parameters such as learning rate, batch size, momentum, and weight decay is not a straightforward or casual process. Deep learning models are characterised by a multitude of hyper-parameters, which pose challenges in determining the most suitable configuration for these parameters within a vast geographical area. The present study used the BO algorithm. During the training process, the Bayesian Optimisation (BO) component generates a function that incorporates relevant information from the acquired dataset. The primary objective in the Bayesian optimisation (BO) technique is to determine the optimal interconnected hyperparameter configuration that maximises the learning performance. In the arithmetical formula, they consider a global minimization/maximization problem of the black-box function f,

$$x^{\circ} = arg\max_{x \in X} f(x) \quad (11)$$

The following text depicts a designated area for exploration and investigation. Influenced by the Bayes formulation, Bayesian Optimisation (BO) evaluates the posterior probability of component D using the acquired dataset. The concept of posterior probability is closely linked to the probability of observation, denoted as P(O), and the multiplication of the prior probability P(D):

$$P(D|L) \propto P(L|D)P(D) \quad (12)$$

Equation (12) represents the primary performance metric of BO, as stated by reference [18]. In a succinct manner, the objective of Bayesian Optimisation (BO) is to identify the most optimal component from a set of alternatives. Currently, the cross-validation technique is a notable concept that comes to mind. Nevertheless, the task of determining the most optimal component from a multitude of samples poses a significant challenge. As a result, Bayesian optimisation (BO) expedites the process by reducing the computing expenses, without requiring the capability to make predictions about the output. This strategy integrates the previous distribution of function with the utilisation of prior knowledge in order to get the following outcome: The present posterior calculates the numerical values that characterise the expansion point of the system. The term used to refer to the criterion of the maximisation technique is commonly known as the acquisition function. The researchers provided a representation of BO in the form of pseudo-code. Now, $N_{1:i-1} = \{x_n, y_n\}_{n=1}^{i-1}$ reflects the trained data which contains observation $i-1$ of function *f*.

Algorithm 2: Bayesian optimization

For *i*= 1, 2, do
Search for x_i by improving the acquisition function v,

$$xi = \underset{x}{\operatorname{argmax}}\, v(x|N_{1:i-1})$$

Evaluate objective function: $y_i = f(x_i)$
Increase dataset $N_{1:i} = \{N_{1:i-1}, (x_i, y_i)\}$
Upgrading the model
End For

The BO algorithm generates a Fast Fourier transform (FF) as a crucial component in the process of parameter optimisation. By demonstrating the dominance of prospective resolutions, it produces a positive whole number. By utilising the equation, it becomes feasible to decrease the classification error rate (FF) (13). The solutions with higher costs exhibit lower levels of fitness compared to the options with lower costs.

$$fitness\ (\chi_i) = Classifier\ Error\ Rate(\chi_i) = \frac{number\ of\ misclassified\ samples}{an\ oral\ number\ of\ samples} * 100 \quad (13)$$

3. Results and Discussion

Students who experience anxiety may encounter difficulties in maintaining their focus on academic pursuits, resulting in adverse academic outcomes. This is attributed to their failure to sustain a good mental equilibrium. Consequently, the mental well-being of pupils possesses the capacity to exert a significant influence on the realm of education. This part focuses on the evaluation of the performance of the proposed system in relation to important metrics of mental health education, and provides a comparative analysis with existing systems. The evaluation of LSTM approaches' detection outcomes is conducted within the context of mental health education for college students. The experimental validation of the BO-BLSTM model was conducted using a dataset consisting of 750 tweets. These tweets were categorised into three groups: 250 positive tweets, 250 negative tweets, and 250 neutral tweets. The results of this validation are presented in Table 2. The BO-BLSTM model produces a sequence of confusion matrices as illustrated in Figure 3. The BO-BLSTM model achieved a classification accuracy of 80% on the training data, correctly identifying 182, 191, and 180 samples as positive, negative, or neutral, respectively. The Bo-BLSTM model has successfully classified 182, 191, and 180 samples as positive, negative, and neutral, respectively, using 70% of the overall test dataset.

Table 2

Sample test dataset

Class Names	No. of Samples
Positive	250
Negative	250
Neutral	250
Total	750

Figure 3. *Confusion matrices of BO-BLSTM technique (a) 80% of TR data, (b) 20% of TS data, (c) 70% of TR data, and (d) 30% of TS data*

Table 3 presents the comprehensive classification outcomes of the BO-BLSTM model, utilising 80% training (TR) data and 20% testing (TS) data. According to the findings presented in Figure 4, it is possible to employ an 80% training dataset to effectively categorise the BO-BLSTM model. The BO-BLSTM model has identified positive samples with $accu_{racy}$, $p_{ercent,recall,F-score}$, and MCC of 92.17%, 88.35%, 88.78%, 88.56%, and 82.61% respectively. In line with this, the BO-BLSTM method has identified negative samples with $accu_{racy}$, $p_{ercent,recall,F-score}$, and MCC of 96.50%, 94.55%, 95.02%, 94.79%, and 92.15% correspondingly. At the same time, the BO-BLSTM methodology has identified neutral samples with $accu_{racy}$, $p_{ercent,recall,F-score}$, and MCC of 95.67%, 93.75%, 92.78%, 93.26%, and 90.07% correspondingly.

A comparison of various BO-BLSTM method measures under 80% of TR and 20% of TS data is shown in **Table 3.**

Class Labels	Accuracy	Precision	Recall	F-Score	MCC
Training Phase (80%)					
Positive	92.17	88.35	88.78	88.56	82.61
Negative	96.50	94.55	95.02	94.79	92.15
Neutral	95.67	93.75	92.78	93.26	90.07
Average	**94.78**	**92.22**	**92.20**	**92.21**	**88.28**
Testing Phase (20%)					
Positive	95.33	95.24	88.89	91.95	88.78
Negative	98.00	94.23	100.00	97.03	95.62
Neutral	97.33	96.43	96.43	96.43	94.30
Average	**96.89**	**95.30**	**95.11**	**95.14**	**92.90**

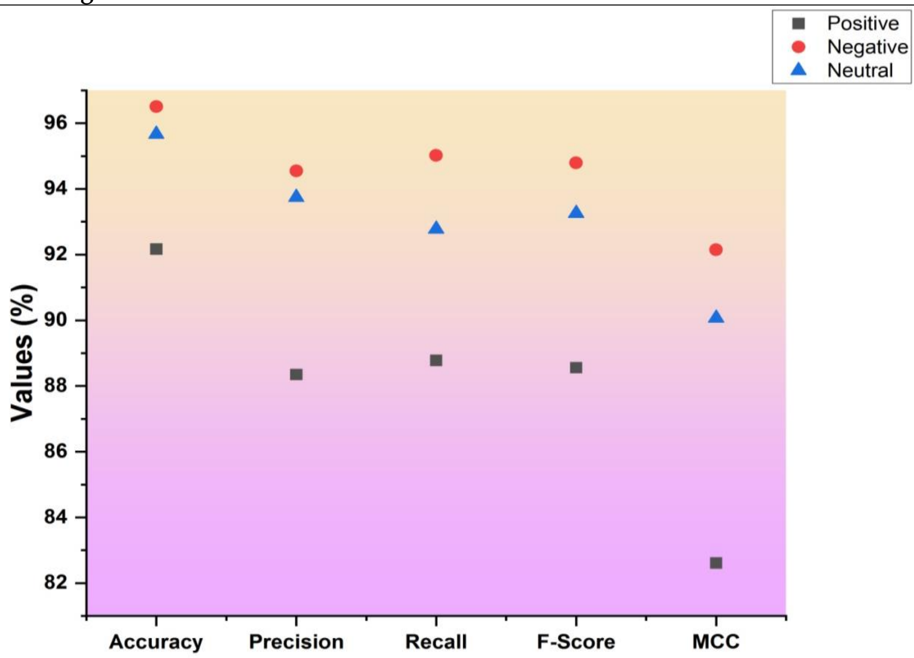

Figure 4. *Result analysis of BO-BLSTM technique under 80% of TR data*

Figure 5 highlights the classification performance of the BO-BLSTM approach using 20% of the time series (TS) data. The BO-BLSTM methodology has identified positive samples with $accu_{racy}$, $p_{ercent,recall,F-score}$, and MCC of 95.33%, 95.24%, 88.89%, 91.95%, and 88.78% correspondingly. with, the BO-BLSTM methodology has identified negative samples with $accu_{racy}$, $p_{ercent,recall,F-score}$ and MCC of 98%, 94.23%, 100%, 97.03%, and 95.62% correspondingly. Meanwhile, the BO-BLSTM techniques have identified neutral samples with $accu_{racy}$, $p_{ercent,recall,F-score}$, and MCC of 97.33%, 96.43%, 96.43%, 96.43%, and 94.30% correspondingly.

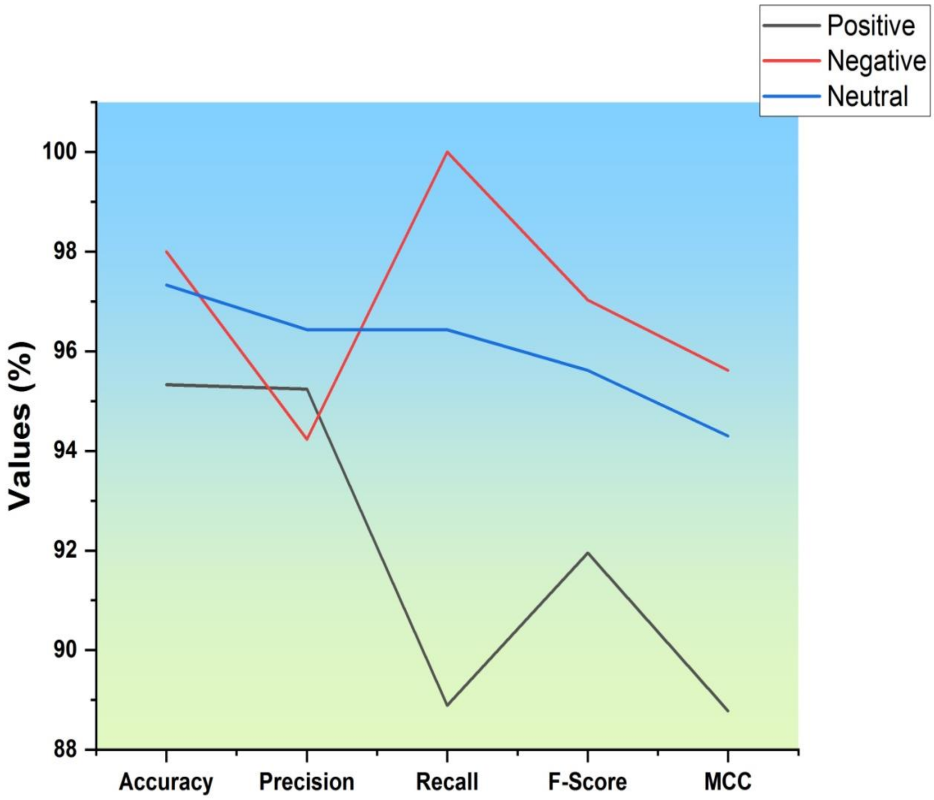

Figure 5. *Result analysis of BO-BLSTM technique under 20% of TS data*

As shown in Table 4, the BO-BLSTM approach achieved overall classification outcomes when trained on 70% of training (TR) data and tested on 30% of testing (TS) data. Figure 6 presents a concise overview of the classification performance achieved by the BO-BLSTM approaches using 70% of the training (TR) data. The BO-BLSTM model has identified positive samples with $accu_{racy}$, $p_{ercent,recall,F-score}$, and MCC of 96.19%, 95.83%, 92.53%, 94.15%, and 91.36% correspondingly. In line with this, the BO-BLSTM methodology has identified negative samples with $accu_{racy}$, $p_{ercent,recall,F-score}$, and MCC of 99.24%, 99.42%, 98.29%, 98.85%, and 98.28% correspondingly. Meanwhile, the BO-BLSTM model has identified neutral samples with $accu_{racy}$, $p_{ercent,recall,F-score}$, and MCC of 95.81%, 91.85%, 96.02%, 93.89%, and 90.75% correspondingly.

Table 4

Result analysis of BO-BLSTM technique with various measures under 70% of TR and 30% of TS data

Class Labels	Accuracy	Precision	Recall	F-Score	MCC
		Training Phase (70%)			
Positive	96.19	95.83	92.53	94.15	91.36
Negative	99.24	99.42	98.29	98.85	98.28
Neutral	95.81	91.85	96.02	93.89	90.75
Average	**97.08**	**95.70**	**95.61**	**95.63**	**93.47**
		Testing Phase (30%)			
Positive	97.78	94.94	98.68	96.77	95.12
Negative	98.67	98.65	97.33	97.99	96.99
Neutral	98.22	98.61	95.95	97.26	95.96
Average	**98.22**	**97.40**	**97.32**	**97.34**	**96.03**

Figure 7 highlights the classification results of the BO-BLSTM approach using 30% of the training set data. The BO-BLSTM model has identified positive samples with $accu_{racy}$, $p_{ercent,recall,F-score}$, and MCC of 97.78%, 94.94%, 98.68%, 96.77%, and 95.12% correspondingly. In line with this, the BO-BLSTM model has identified negative samples with $accu_{racy}$, $p_{ercent,recall,F-score}$, and MCC of 98.67%, 98.65%, 97.33%, 97.99%, and 96.99% correspondingly. Meanwhile, the BO-BLSTM model has identified neutral samples with $accu_{racy}$, $pp_{ercent,recall,F-score}$, $reca_{ll}$, F_{-score}, and MCC of 98.22%, 98.61%, 95.95%, 97.26%, and 95.96% correspondingly.

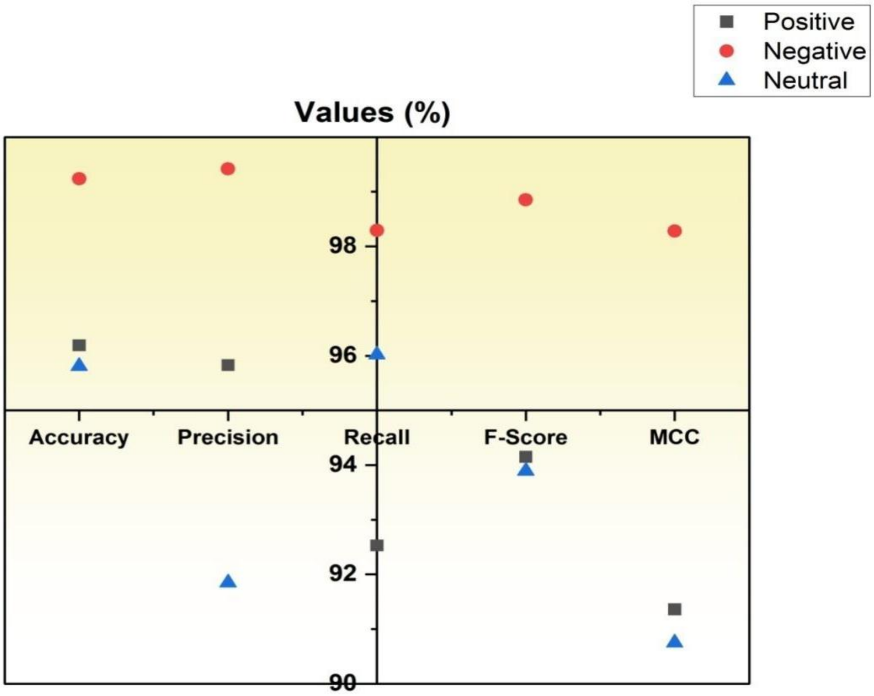

Figure 6. *Result analysis of BO-BLSTM technique under 70% of TR data*

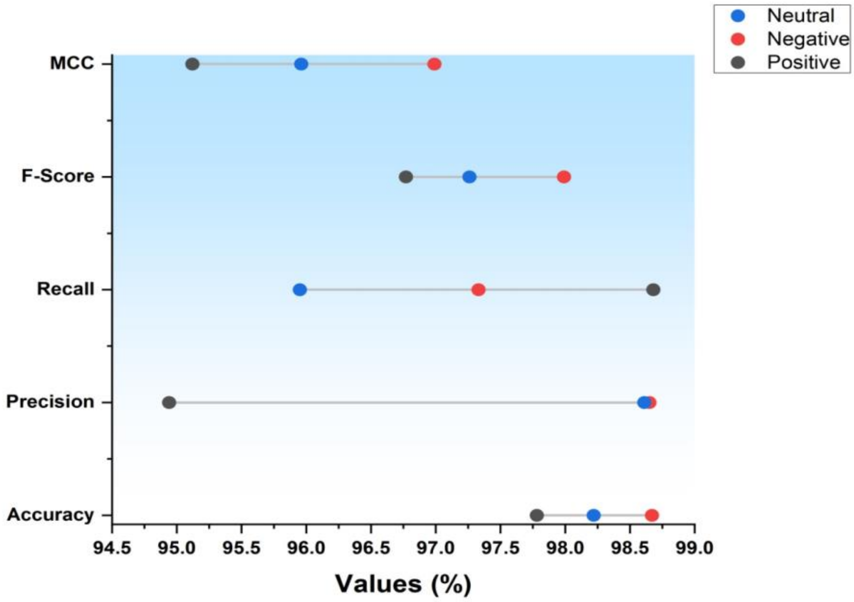

Figure 7. *Result analysis of BO-BLSTM technique under 30% of TS data*

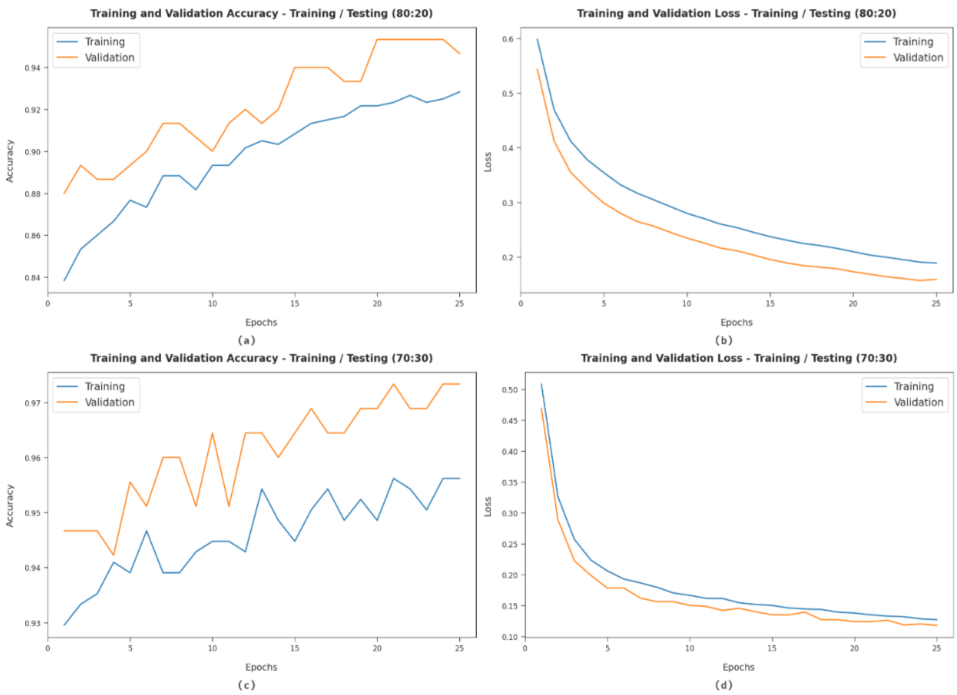

Figure 8. *Accuracy and loss analysis of BO-BLSTM technique (a) 80:20 of accuracy, (b) 80:20 of loss, (c) 70:30 of accuracy, and (d) 70:30 of loss*

Figure 8 displays the accuracy and loss graphs of the BO-BLSTM approach across many TR/TS datasets. The augmentation of epochs leads to enhanced precision and reduced loss. Moreover, a distinct collection of TR/TS datasets exhibits reduced training loss and enhance validation accuracy.

Figure 9 displays the classifier results of the ODCNN-RFIC approach on the test STARE dataset. The precision-recall analysis of this technique is depicted in Figures 9a and 9c, representing the TR/TS datasets with ratios of 80:20 and 70:30, respectively. The data indicates that the BO-BLSTM model has demonstrated superior precision-recall performance across all classes. The ROC analysis of the BO-BLSTM approach utilising TR/TS datasets with ratios of 80:20 and 70:30 is depicted in Figures 9b and 9d, respectively. Based on the data presented in the image, it can be observed that the DLBTDC-MRI model successfully differentiated between datasets categorised as positive, negative, and neutral.

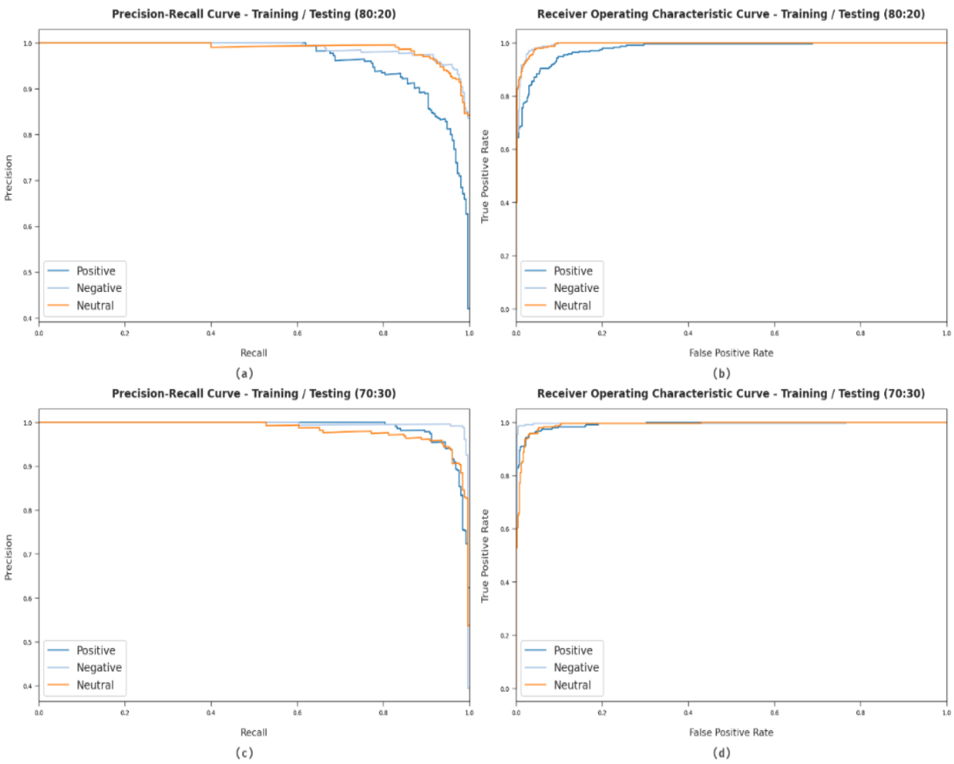

Figure 9. *Classifications analysis of BO-BLSTM technique (a) 80:20 of precision-recall, (b) 80:20 of ROC, (c) 70:30 of precision-recall, and (d) 70:30 of ROC*

Table 5 presents a comprehensive analysis of the data obtained from the BO-BLSTM model in comparison to other models. 1. Figure 1 presents a comparative analysis of the precision and recall evaluation metrics for the BO-BLSTM model in relation to other models. 10. the Logit-Boost, Bagging (SVM), RF (Tree), and Logistic Regression (SVM) models all had lower values of $p_{ercent,recall,F-score}$.

Table 5

Comparative analysis of BO-BLSTM technique with existing approaches

Methods	Precision	Recall	F-score	Accuracy
SVM Model	87.65	72.26	78.08	93.72
SLDA Model	90.66	68.83	75.91	92.00
Logit-Boost	84.79	72.54	77.33	94.67
Bagging	85.51	71.46	76.85	93.30
Random Forest	87.44	75.49	80.92	93.60
Tree Algorithm	87.42	60.51	68.29	93.03
BO-BLSTM	97.40	97.32	97.34	98.22

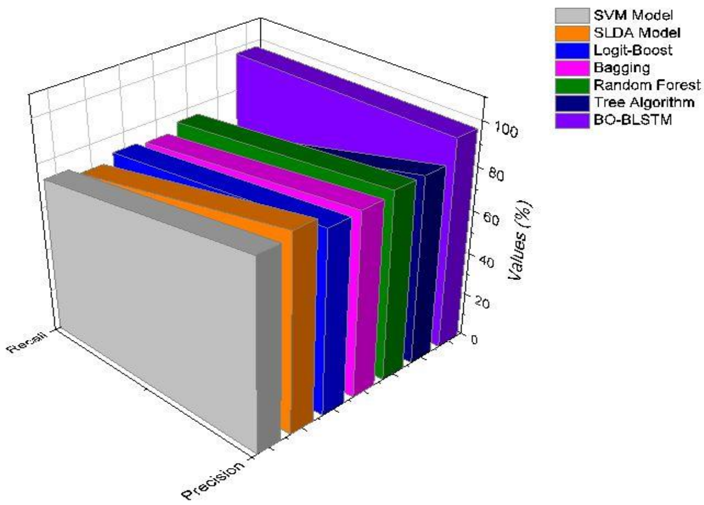

Figure 10. $Prec_n andreca_l$ *analysis of BO-BLSTM technique with existing approaches*

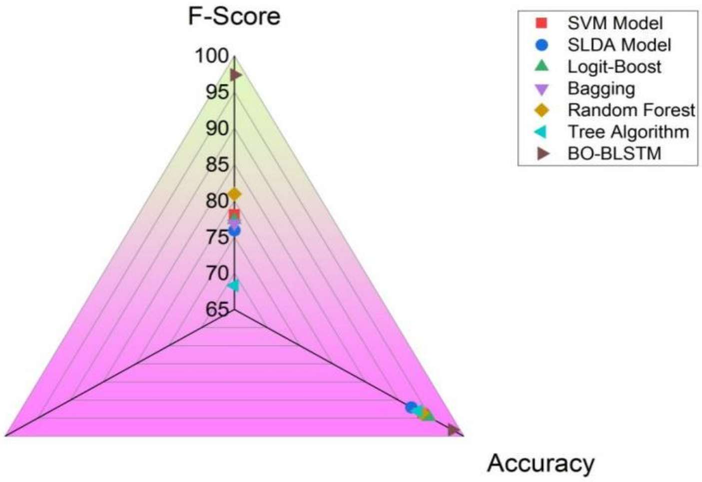

Figure 11. $F_{score} andaccu_y$ *analysis of BO-BLSTM technique with existing approaches*

At the same time, the SLDA model has tried to manage effectual outcomes with moderate $prec_{ision}$ and $reca_{ll}$ values of 90.66% and 68.83% respectively. However, the BO-BLSTM model has accomplished reasonable outcomes with $prec_{ision}$ and $reca_{ll}$ values of 97.40% and 97.32% respectively.

A quick F_{-score} and $accu_{racy}$ assessment of the BO-BLSTM techniques using current models is shown in Fig. 11. F score and accu racy were found to be lower in the Logit-Boost, Bagging, SVM, RF, and Tree methods. With $F_{score}$and $accu_{racy}$ values of 75.91% and 92%, the SLDA model has attempted to manage effective outcomes while maintaining a low F_{-score}. But, the BO-BLSTM method has accomplished reasonable outcomes with F_{-score} and $accu_{racy}$ values of 97.34% and 98.22% correspondingly. The BO-BLSTM model outperformed all other models, as shown in the graphs and tables above.

4. Conclusion

This work presents the development of a revolutionary BO-BLSTM Model for the integration of political and ideological education and mental health education (MHE). The BO-BLSTM model provided in this study is primarily concerned with the classification of various sentiment categories within the realm of politics. Enhancing the imaginative capacities and consciousness of college students, as well as promoting their psychological well-being, are crucial factors for the successful implementation of innovative Ideological and Political education inside higher education institutions. In the realm of college student innovation, Ideological and Political education, and mental health education, it is imperative to strategically cultivate and enhance the psychological well-being of college students. Further analysis of the psychological aspects has not been conducted, as there remain certain limitations in the existing research. Existing ways of analysing the causes of obsessive-compulsive feeling do not take into account the physiological changes experienced by students. Furthermore, it is worth noting that the current number of comparison models is inadequate, and the available application results are insufficient in providing comprehensive insights. Hence, it is imperative to enhance the level of depth in drawing judgements. In order to accomplish this, the BO-BLSTM model first employs data pre-processing and feature extraction procedures. Furthermore, the BO-BLSTM model incorporates a data categorization technique utilising Bidirectional Long Short-Term Memory (BLSTM) to effectively discern attitudes. The BO-BLSTM model utilises the BO method for effective hyperparameter tuning. The BO-BLSTM model was found to be superior to other current techniques with $prec_{ision}$, $reca_{ll}$, F_{-score}, and $accu_{racy}$ of 97.40%, 97.32%, 97.34%, and 98.22% accuracy in an exhaustive experimental investigation.

References

Ahmed, B., & Ali, A. (2021). Usage of traditional Chinese medicine, Western medicine and integrated Chinese-Western medicine for the treatment of allergic rhinitis *Science Progress and Research (SPR)*, *1*(1), 01-10. https://doi.org/10.52152/spr/2021.101

Alazab, M., Khan, S., Krishnan, S. S. R., Pham, Q. V., Reddy, M. P. K., & Gadekallu, T. R. (2020). A Multidirectional LSTM Model for Predicting the Stability of a Smart Grid. *IEEE Access, 8*, 85454-85463. https://doi.org/10.1109/ACCESS.2020.2991067

Ansari, M. Z., Aziz, M. B., Siddiqui, M. O., Mehra, H., & Singh, K. P. (2020). Analysis of Political Sentiment Orientations on Twitter. *Procedia Computer Science, 167*, 1821-1828. https://doi.org/10.1016/j.procs.2020.03.201

Atkins, M. S., Hoagwood, K. E., Kutash, K., & Seidman, E. (2010). Toward the Integration of Education and Mental Health in Schools. *Administration and Policy in Mental Health and Mental Health Services Research, 37*(1), 40-47. https://doi.org/10.1007/s10488-010-0299-7

Babury, M. O., & Hayward, F. M. (2013). A Lifetime of Trauma: Mental Health Challenges for Higher Education in a Conflict Environment in Afghanistan. *Education Policy Analysis Archives, 21*(68), n68. http://dx.doi.org/10.14507/epaa.v21n68.2013

Barry, C. L., Huskamp, H. A., & Goldman, H. H. (2010). A Political History of Federal Mental Health and Addiction Insurance Parity. *The Milbank Quarterly, 88*(3), 404-433. https://doi.org/10.1111/j.1468-0009.2010.00605.x

Budiharto, W., & Meiliana, M. (2018). Prediction and analysis of Indonesia Presidential election from Twitter using sentiment analysis. *Journal of Big Data, 5*(1), 51. https://doi.org/10.1186/s40537-018-0164-1

Caldarella, P., Chan, P., Christensen, L., Lin, X., & Liu, Y. (2013). School Mental Health Education in Beijing: A Survey of Practitioners. *New Horizons in Education, 61*(2), 77-92. http://www.hkta1934.org.hk/NewHorizon/abstract/2013May/5.pdf

Dorle, S., & Pise, D. N. N. (2018). Political Sentiment Analysis through Social Media. *2018 Second International Conference on Computing Methodologies and Communication (ICCMC)*, 869-873. https://doi.org/10.1109/ICCMC.2018.8487879

Fazel, M., Hoagwood, K., Stephan, S., & Ford, T. (2014). Mental health interventions in schools in high-income countries. *The Lancet Psychiatry, 1*(5), 377-387. https://doi.org/10.1016/S2215-0366(14)70312-8

Gadamsetty, S., Ch, R., Ch, A., Iwendi, C., & Gadekallu, T. R. (2022). Hash-Based Deep Learning Approach for Remote Sensing Satellite Imagery Detection. *Water, 14*(5), 707. https://doi.org/10.3390/w14050707

Gadekallu, T. R., Iwendi, C., Wei, C., & Xin, Q. (2021). Identification of malnutrition and prediction of BMI from facial images using real-time image processing and machine learning. *IET Image Processing, 16*(3), 647-658. https://doi.org/10.1049/ipr2.12222

Garg, H. (2021). Digital twin technology: Revolutionaryto improve personalized healthcare: *Science Progress and Research (SPR), 1*(1), 32-34. https://doi.org/10.52152/spr/2021.105

Grispini, A., & Piccione, R. (2017). Three Aspects of Mental Health Promotion in the Department of Mental Health Rome E. In *Promotion of Mental Health* (pp. 89-94). Routledge. https://doi.org/10.4324/9781315191010-10/

Hu, Z., & Li, J. (2018). Innovative methods for ideological and political education of college students. *Educational Sciences: Theory & Practice, 18*(5), 2069-2078. https://doi.org/10.12738/estp.2018.5.106

Injadat, M., Salo, F., Nassif, A. B., Essex, A., & Shami, A. (2018). Bayesian Optimization with Machine Learning Algorithms Towards Anomaly Detection. In *2018 Global Communications Conference (GLOBECOM)* (pp. 1-6). IEEE. https://doi.org/10.1109/GLOCOM.2018.8647714

Iwendi, C., & Wang, G.-G. (2022). Combined power generation and electricity storage device using deep learning and internet of things technologies. *Energy Reports, 8*, 5016-5025. https://doi.org/10.1016/j.egyr.2022.02.304

Koenig, H. G., Al Zaben, F., Sehlo, M. G., Khalifa, D. A., Al Ahwal, M. S., Qureshi, N. A., & Al-Habeeb, A. A. (2014). Mental health care in Saudi Arabia: Past, present and future. *Open Journal of Psychiatry*, 4(02), 113. https://doi.org/10.4236/ojpsych.2014.42016

Krishnan, R., Nair, S., Saamuel, B. S., Justin, S., Iwendi, C., Biamba, C., & Ibeke, E. (2022). Smart Analysis of Learners Performance Using Learning Analytics for Improving Academic Progression: A Case Study Model. *Sustainability, 14*(6), 3378. https://doi.org/10.3390/su14063378

Li, Z. (2021). Treatment and technology of domestic sewage for improvement of rural environment in China-Jiangsu: A research. *Science Progress and Research (SPR), 1*(4), 305-314. https://doi.org/10.52152/spr/2021.146

Lubis, S. A. (2011). Islamic Counseling: The Services of Mental Health and Education for People. *Religious Education, 106*(5), 494-503. https://doi.org/10.1080/00344087.2011.613347

Manoj, A., & Shweta, A. (2021). A systematic review on artificial intelligence/deep learning applications and challenges to battle against COVID-19 pandemic. *Disaster Advances, 14*(8), 90-99. http://dx.doi.org/10.25303/148da9021

McGee, E. O., & Stovall, D. (2015). Reimagining Critical Race Theory in Education: Mental Health, Healing, and the Pathway to Liberatory Praxis. *Educational Theory, 65*(5), 491-511. https://doi.org/10.1111/edth.12129

Mody, R. N., & Bhoosreddy, A. R. (1995). Multiple odontogenic keratocysts: a case report. *Annals of Dentistry, 54*(1-2), 41-43. https://pubmed.ncbi.nlm.nih.gov/8572545

Patsali, M. E., Mousa, D.-P. V., Papadopoulou, E. V. K., Papadopoulou, K. K. K., Kaparounaki, C. K., Diakogiannis, I., & Fountoulakis, K. N. (2020). University students' changes in mental health status and determinants of behavior during the COVID-19 lockdown in Greece. *Psychiatry Research, 292*, 113298. https://doi.org/10.1016/j.psychres.2020.113298

Qiu, H. (2017). Research on the ideological and political education of college students based on "humanistic care" and "psychological counseling". In *Proceedings of the 2017 2nd International Conference on Education, Sports, Arts and Management Engineering (ICESAME 2017)* (pp. 1487-1491). Atlantis Press. https://doi.org/10.2991/icesame-17.2017.320

Salihu, S., & Iyya, Z. (2022). Assessment of physicochemical parameters and organochlorine pesticide residues in selected vegetable farmlands soil in Zamfara state, Nigeria. *Science Progress and Research (SPR), 2*(2), 559-566. https://doi.org/10.52152/spr/2022.171

Saravagi, D., Agrawal, S., & Saravagi, M. (2021). Indian stock market analysis and prediction using LSTM model during COVID-19. *International Journal of Engineering Systems Modelling and Simulation, 12*(2-3), 139-147. https://doi.org/10.1504/ijesms.2021.115532

Shahabaz, A., & Afzal, M. (2021). Implementation of High Dose Rate Brachytherapy in Cancer Treatment. *Scientific Progress & Research (SPR), 1*(3), 77-106. https://doi.org/10.52152/spr/2021.121

Yang, W., Lin, L., Zhu, W., & Liang, S. (2015). An introduction to mental health services at universities in China. *Mental Health & Prevention, 3*(1), 11-16. https://doi.org/10.1016/j.mhp.2015.04.001

Zou, Q., Xiong, Q., Li, Q., Yi, H., Yu, Y., & Wu, C. (2020). A water quality prediction method based on the multi-time scale bidirectional long short-term memory network. *Environmental Science and Pollution Research, 27*(14), 16853-16864. https://doi.org/10.1007/s11356-020-08087-7