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Article

Using biosensors and machine learning algorithms to analyse the influencing factors of study tours on students' mental health

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Abstract: College students nowadays will inevitably deal with stress. Personal emotional and behavioural responses may be extremely strong when faced with stress. One of the most prevalent sources of stress for college students throughout the globe is mental health issues connected to stress. However, there is a lack of research focusing on the impact of specific activities, such as study tours, on students' mental health and how these activities can be monitored using advanced technologies. As a result of its ability to analyze, classify, and alert college students' psychological data with high quality, deep learning and machine learning have recently found widespread application in college students' mental health education and management. Moreover, the integration of biomechanics and biosensor data offers new insights into understanding the physical and psychological impacts of study tours on mental health. This can potentially promote the development of colleges' mental health education programs. Hence, this study proposes the Biosensor-based and Deep Neural Network-based College Student Mental Health Prediction Model (BDNN-CSMHPM) for detecting the mental stress of college students during study tours. Using biosensor data, including EEG and biomechanical metrics, this model employs the most effective BDNN to categorize the mental health condition as normal, negative, or positive. Consequently, BDNN is utilized to categorize the gathered emotional and biomechanical information, and based on the classification outcomes, the emotional condition of college students is determined. Considering that different features might stand in for different elements in the original data, it is necessary to extract several biosensors features to represent the information in the original EEG data accurately. Second, fusing various features is essential in the auto-learn model integration method. Third, the BDNN is fed the combined features, resulting in emotion classification. The numerical outcomes demonstrate that the BDNN-CSMHPM model enhances the student's mental health prediction ratio of 98.9%, accuracy ratio of 96.4%, emotion recognition ratio of 95.3%, Pearson correlation coefficient rate of 97.2% and psychological monitoring ratio of 94.3% compared to other popular methods.

Keywords: student's mental health; biosensors, biomechanics; deep neural network; influencing factors; study tours; emotional state

1. Introduction

Students' mental health is a prime concern because of the occurrence of depression, anxiety, poor mood, and academic struggles [1]. College students must familiarize themselves with the inclusive online teaching state and complete different learning responsibilities the institutions arrange. Negative emotional states, including isolation, anxiety, sadness, and fear, will develop in college students who endure uncomfortable emotions for a long time in such environments [2]. Colleges and universities and students should pay special attention to students' emotional and mental health in the wake of the pandemic and their studies [3]. College student management professionals often rely on oral presentations given by class informants, surveys, and interviews better to understand students' emotional states [4]. The primary issues with these approaches are as follows: first, some students may be unwilling to share information truthfully for fear of negative consequences or other reasons, leading to the collection of erroneous information [5]. Second, since some students are either disgusted or unwilling to spend time reading the questions, they fill them in at random, which could lead to erroneous results [6]. Third, it's impossible to get correct information by observing teachers and fellow students since certain students hide their feelings. Consequently, objective physiological data is the perfect basis for building effective and accurate emotional data [7]. As time passes, more biosensor-based physiological signal-based emotion identification systems arise due to the increased objectivity of these results [8]. These physiological signals are easy to collect from the person, do not cause any harm, and show how emotions impact the autonomic nervous system. Emotion identification often makes use of electrocardiograms (ECGs), electromyograms (EMGs), electro-skin resonance (GSRs), respiration rates (RRs), and electroencephalograms (EEGs), along with biomechanical data that can provide insights into physical responses during emotional states [9]. Emotion identification typically makes use of physiological markers, namely EEG signals. Research on swallowing, mental state analysis, and neuropsychiatric disease diagnosis have all extensively used EEG signals in conjunction with biomechanical data [10].

The mental health concerns of college students, particularly during activities like study tours, can be evaluated using a system that combines biosensor data, including EEG signals and biomechanical metrics, with machine learning techniques. [11]. To quickly recognize students' psychological requirements and assist them in actively responding, use state-of-the-art sensing technologies, biomechanical analysis, image and language recognition, big data analysis, etc. [12]. The field known as "machine learning" focuses on improving upon previously established knowledge structures, simulating or realizing human learning behaviours on computers [13]. A multi-layered neural network is called a deep neural network (DNN). The features learned by one layer are sent into the feature-learning process by the following layer [14]. This is achieved by learning a better feature representation for the input via layer-by-layer mapping features, which involves mapping the features of the current spatial samples to another feature space [15]. One major benefit of DNN over first-generation neural networks (such as perceptrons) is that it can handle more complicated data classification issues, including non-linearly separable [16]. A growing number of educational institutions are beginning to use neural networks to assess the efficacy of their curriculum [17]. These networks have recently achieved remarkable advances, displaying formidable skills across multiple fields. As a result, educators can make better decisions based on assessments that use deep neural networks to measure the efficacy of mental health education, consequently encouraging higher-quality and more efficient mental health education at universities especially during experiential learning activities like study tours [18]. The system can be structured as follows: an acquisition unit that gathers students' biosensor data, including EEG and biomechanical metrics, medical and family history data as well as their real-time mental health symptoms [19]; a prediction unit that uses this data to forecast students' mental health during study tours [20]; and finally, a transmission unit that provides a predicted psychotic mental state.

The major contribution of the article is:

- Designing the Biosensor-based and Deep Neural Network-based College Student Mental Health Prediction Model (BDNN-CSMHPM) for detecting the mental pressure of college students during study tours.
- Collecting the biosensor data, including EEG data and the mathematical model of the BDNN model for classifying the emotions of college students.
- Implementing numerical outcomes that demonstrate the suggested BDNN-CSMHPM model increases the accuracy, mental health prediction, Pearson correlation coefficient, emotion recognition, and psychological monitoring ratio.

The remainder of the paper is planned: section 2 deliberates the related study, section 3 proposes the BDNN-CSMHPM model, section 4 reflects the experimental outcomes, and section 5 concludes the research paper.

2. Related study

Ding et al. [21] suggested the Biosensor-based and Deep Integrated Support Vector Algorithm (BDISVA) for the Depression Detection Technique for University Students. To identify college students suffering from depression, this research used text-level mining of data collected from Sina Weibo. To begin, the author gathers text information from Sina Weibo users who are college pupils and transforms it into machine learning input data. The feature extraction process uses BDNN. BDISVM enhances the steadiness of the recognition models and, to a smaller degree, the precision of depression diagnosis. By analyzing Sina Weibo data, the suggested depression identification system can identify college students who may be suffering from depression, according to simulation tests. Fei et al. [22] proposed the Deep Convolution Network Based Emotion Analysis (DCN-EA) for Mental Health Care. The suggested system has a novel approach to processing facial pictures and understanding the changing dynamics of emotions. It uses typical Linear Discriminant Analysis Classifiers to derive the last classification outcome and extract profound features from AlexNet's Fully Connected Layer 6. Datasets include FER2013 and AffectNet and benchmarking databases JAFFE and KDEF, which are used to evaluate it. The overall accuracy of facial expression detection is greater than other approaches. Adler et al. [23] recommended the Machine Learning Models (MLM) for mental health symptom forecasting using generalizations across longitudinal mobile sensing research. Using publicly accessible data, this research shows that models trained on pooled longitudinal study information can forecast mental health symptoms. Data from the Student Life study (using college students) and the Cross Check study (with people with schizophrenia) were integrated by the author. The author oversampled less-represented severe symptoms and personalized models to align mobile sensing data; the author tested generalizability to see if it enhanced model performance. This paper details the findings of a leave-one-subject-out cross-validation (LOSO-CV) analysis. These outcomes recommend that MLM trained on data from many longitudinal studies may be able to apply its findings to other datasets.

Ogunseye et al. [24] discussed the AdaBoost Algorithm (ABA) for the predictive analysis of mental health states. After experimenting with many supervised algorithms for patient classification, the author settled on AdaBoost as the best tool for this task. The databases have been prepared and predicted utilizing the AdaBoost ML models, which attained an accuracy of 81.75%, adequate for decision-making. Additional ML models were employed for the data, including bagging, K-Nearest Neighbor (KNN) and Random Forest (RF); the stated accuracy ranged from 81.22% to 75.93%, which is very suitable for decision-making. AdaBoost is the most accurate model for foretelling the results of mental health therapy. Jawad et al. [25] deliberated the novel particle swarm-cuckoo search (PS-CS) optimization model for the prediction of depression. To optimize the network parameters more efficiently and effectively, the PS-CS method syndicates the capabilities of the cuckoo search with particle swarm optimization. To measure the efficacy of the suggested techniques, the author compared them to several popular models in classification and deep learning. These models included decision trees, KNN, and support vector regression (SVR). The results demonstrate that PS-CS, the proposed strategy, attained a maximum accuracy of 99.5% when combined with the CNN models, surpassing all other techniques. The accuracies of other models, including logistic regression, KNN, and decision trees, were lower, falling between 69% and 97%. Deng [26] presented the fuzzy qualitative simulation (FQS) to analyze college students' mental health conditions. This corresponds with the real world, where the incidence of mental subhealth is 1.605% of college pupils accepted to perfect colleges. From a conditional guarantee standpoint, the author a species assesses the college mental health education program's hardware facilities, management system, and professional team. The author examines the program's teaching, educational activities, psychological counselling, and crisis intervention efforts from a content perspective. Finally, from an effect perspective, the author measures the program's outcome regarding students' degree of objective attainment, satisfaction, and social adaptation and the program's overall impact. Part four delves further into the assessment indexes for college students' mental health education, the optimization route and substance of the exam, and the creation of the weights of the guiding indexes. According to the study's findings, college students' mental health is affected by both external and internal factors, with the latter having a more significant impact.

Han [27] introduced the Fuzzy clustering algorithm (FCA) for performance and psychological fitness detection of university pupils. This research uses the proposed HFCA to examine the mental aspects impacting students' academic achievement. This research used the Fuzzy Cognitive Map (FCM) to predict students' performance. The most important components of student achievement, including student engagement and happiness, were identified in this research using fuzzy clustering algorithms. To guarantee that students who are at risk for mental health problems may receive the care they need, the author needs a deeper knowledge of the elements that put them at risk and those that put them at protection. Only then can the author design policies and interventions specific to their needs. Compared to other techniques, the experimental analysis reveals that the suggested HFCA approach achieves excellent student performance ratios of 96.7%, 97.2% cognitive development, 97.5% engagement, and 95.1% prediction. Tian [28] investigated the K-means Clustering Algorithm for Predicting College Students' Mental Health. Data mining is used to repurpose the students' psychological data based on the fundamental operations of the old system. Optimizing the iterative procedure of the K-means algorithm allows for extracting useful components from the psychological data of many more students. Managers are led in the scientific management of students' mental health processes by a built data model. During analysis, the system sets up the data mining model, which retrieves psychological data from a database, examines the features of college students' mental health states, and then provides a solution. Based on 1000 students' mental health records, the test found that the system used the k-means algorithm to classify them into three groups: 20, 31, and 47. 1 percent. This is 1.6 percentage points off from the ideal state data test results. Ramzan et al. [29] offered the Fuzzy Expert System (FES) to predict Anxiety Levels accurately. Anxiety levels may be predicted by expert systems that use fuzzy inference systems (FIS) introduced in this study. The system tackles the concern's intricate and unpredictable nature using various input variables and fuzzy logic approaches. Anxiety disorders are medically well-understood, and this assessment may help professionals diagnose and treat these conditions. Using real-world datasets, the algorithm proved to be quite accurate in predicting the severity of anxiety. There are currently no effective treatments for anxiety disorders; nevertheless, the FIS-based expert systems provide a strong method to deal with ambiguity and vagueness. Notably, the system attained an accuracy ratio of 87%. Robinson et al. [30] suggested Adaptive Neuro-Fuzzy Inference Systems (ANFIS) for Early Depression Forecast among University Students. Users choose ANFIS because of its transparency, its capacity to categorize and detect hidden depressive symptoms, and its propensity for reducing memory errors. Connected to the ANFIS architecture, the database stores user data, symptoms, and medicines, allowing for the early-phase depression diagnosis. Information was gathered from UUTH and the University of Uyo Primary Health Care Centre. While JAVA was used to create the application that forms the input interface, MATLAB was used to develop the ANFIS model. With an average testing error of 4.6648 and a training error of 6.0138e-0.5, the model achieved 95% classification accurateness in detecting early depression in college pupils. This was achieved after passing the training dataset through ANFIS for 10 epochs.

Based on the investigation, there are numerous problems with existing techniques in attaining high accuracy, mental health prediction, Pearson correlation coefficient, emotion recognition, and psychological monitoring ratio. Hence, this study proposes the Deep Neural Network-based College Student Mental Health Prediction Model (DNN-CSMHPM) for detecting the mental stress of college students.

3. Biosensor-based and deep neural network-based college student mental health prediction model (BDNN-CSMHPM)

College students nowadays are under a lot of pressure from all sides: academics, employment opportunities, and life in general. Those not good at handling stress are more likely to let their negative emotions get the best of them, which can lead to a downward spiral of self-criticism. Student mental health issues might worsen with time if they do not learn healthy ways to express their feelings. Colleges and universities prioritize students' academic performance to the detriment of their emotional health. Many educational institutions place a greater emphasis on students' academic performance than on their mental health, and when it comes to college students' struggles with mental illness, many institutions provide inadequate support. Thus, two crucial aspects influencing college students' development are their education degree and psychological well-being. Problems with one part will inevitably spread to the other and hinder college students' growth as individuals. Students may have a specific baseline for their fundamental skills and mental toughness at the university level. Consequently, it is critical to address college students' mental health issues from a professional point of view since there is always a connection between college and mental wellness. Examining their relationship is crucial for college students to develop moral principles and accurate ideological consideration.

Compared to other models, the BDNN-CSMHPM model demonstrates superior performance due to its effective combination of biosensor data and deep neural networks, allowing for a more comprehensive analysis of both emotional and biomechanical information. The model excels in accurately representing EEG data by extracting multiple biosensor features and employing a feature fusion approach that enhances the learning capabilities of the model. Additionally, BDNN's auto-learn model integration method optimizes classification accuracy, ensuring a higher mental health prediction ratio and more precise emotion recognition. The numerical results further validate that the BDNN-CSMHPM model outperforms other models, particularly in accuracy, emotion classification, and monitoring capabilities, achieving a higher Pearson correlation coefficient and prediction reliability.

Given the increase in experiential learning activities such as study tours, there is a growing need to assess the impact of these activities on students' mental health using advanced technologies like biosensors and biomechanics. Research into the potential applications of ML and Biosensor data in mental health has been prompted by the growing number of cases and the pressing need for efficient medical treatment. Biosensors provide a non-invasive way to capture physiological data, while biomechanics offers insight into physical responses that may correlate with emotional states. ML is an approach that uses improved statistical and probabilistic methods to build models that can learn and improve over time. In terms of mental health prediction, it is a very helpful tool. It facilitates the development of automated intelligent systems, tailored experiences, and several researchers' acquisition of crucial data. To that end, health preventive programs may better use machine learning classifiers to fill this knowledge gap and conduct more accurate mental health evaluations at earlier stages. New research indicates that DNN, CNN, and

SVM are the best machine learning algorithms for predicting college students' mental health issues, like anxiety, stress and depression. Hence, this study proposes the Biosensor-based and Deep Neural Network-based College Student Mental Health Prediction Model (BDNN-CSMHPM) for detecting the mental stress of college students.

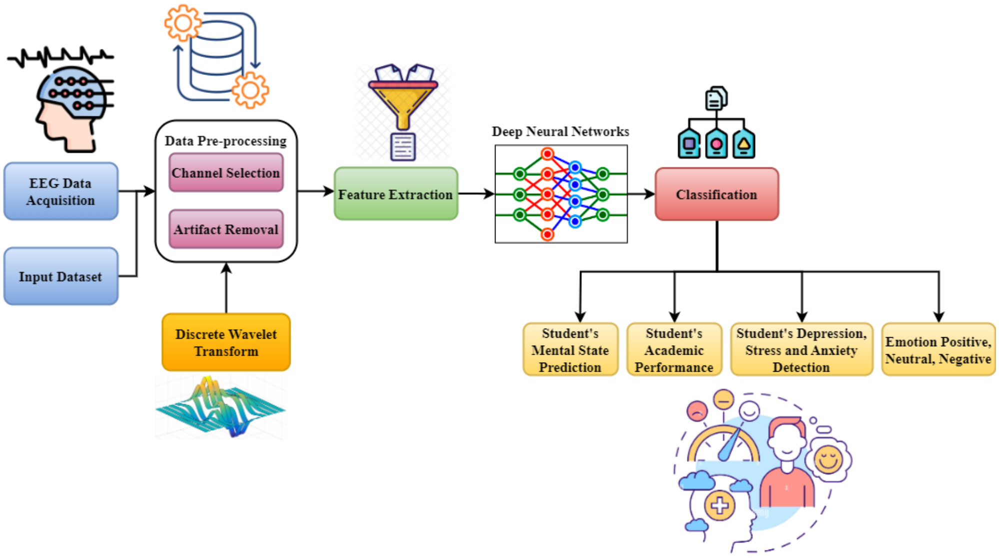

Figure 1. Proposed BDNN-CSMHPM model.

Figure 1 shows the proposed Biosensor-based and DNN-CSMHPM model. The data are from the depression and students' academic performance Kaggle dataset [31]. Using biosensors and electroencephalographic signals (EEG), this research investigates the potential for monitoring students' mental engagement index and physical responses through biomechanics while they participate in study tours. With a sample rate of 128 Hz, the EEG data was captured. Decomposition of the normal and depressed EEG signals into eight levels is achieved using the discrete wavelet transform (DWT) to distinguish between five unique EEG rhythms. In the pre-processing module, a typical deep neural network-based channel selection technique handles the complex estimation caused by channel idleness in perceiving mental fatigue conditions using multi-channel EEG information. When collecting data associated with brain activity, EEG artefacts are a major problem. Immediate and effective artefact removal forms the basis of the following emotional state analysis. This investigation used the popular EEG artefact removal strategy. Following that, either an explicit or implicit development process for the feature extraction step might be initiated. The first chooses features in the frequency or time domain using hand-crafted functions that may be chosen using machine learning methods. Through several hidden layers, DNNs can exhibit strong nonlinear expression capabilities; the objective of these networks is to enable them to acquire features for use in classification or regression tasks automatically. This study employs the DNN model as its training framework, effectively protecting the behaviour correlation and feature extraction model to forecast students' performance based on every type of behaviour data. This verifies the importance of multi-source behaviour for achievement prediction. Pupils' academic success is often measured by GPAs, which are continuous numerical numbers. This study presents a classification task definition of academic performance prediction: determining whether a student will have good, excellent, or poor performance. To classify the students' emotions as positive, neutral, or negative, this study used the biosensor and EEG data and a DNN model to determine their emotional features during the assessment of study tours.

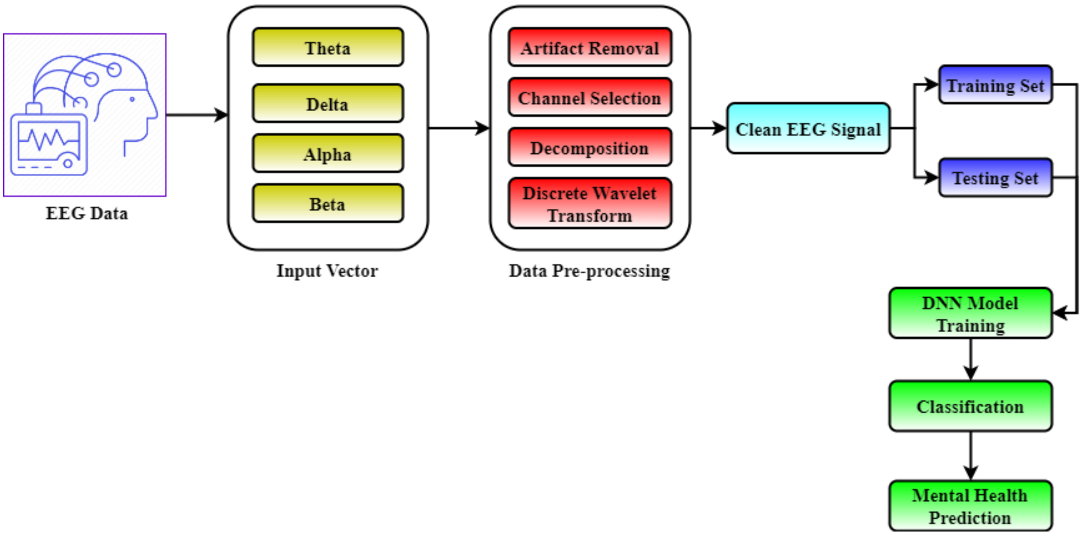

Figure 2. Flowchart of processing biosensor and EEG Signals.

Figure 2 shows the flowchart of processing biosensor and EEG signals. For every epoch, the following boundaries have been employed to derive power estimates for the EEG bands: theta (3.5–7.5 Hz), delta (1–3.5 Hz), beta (12.5–30 Hz) and alpha (7.5–2.5 Hz). Power band threshold, frequency filtering, and elimination of anomalous epochs are employed to eliminate the most apparent artefact contaminations. Segments of biosensor and EEG were converted to frequency spectra after manual cleaning. An RF classifier was used to classify the three sample types using spectral information from various frequency bands. This allowed us to ascertain the classification performance of each band. A one-dimensional vector representing the multi-channel spectrum for each frequency band was restructured and fed into the radio frequency (RF) classifier after the whole spectrum was segmented into five sections corresponding to the five bands of frequencies (gamma, delta, theta, alpha, beta, and beta). After decomposing the channel into sub-bands, this approach decreases the estimated wavelet coherence value for a particular channel pair throughout non-overlapping 5s and frequency band. Wavelet coherence is confined correlation coefficients in time-frequency spaces. The features are combined to form patterns. The DWT may be managed by finding a discrete estimate of the variables. Discovering the relationship between the electroencephalogram (EEG) signal and the mother wavelet (MWT) function enables its execution applied a Discrete Wavelet Transform (DWT) to the electroencephalogram (EEG) data, and then used the decomposed DWT coefficients to extract relative wavelet energy and different entropy properties. The DNN classifier was then trained using these features to accurately distinguish between normal and depressed EEG data, allowing students to identify depression with a high degree of accuracy. The 10-fold cross-validation (10-FCV) method splits the EEG dataset. Every fold uses 60 samples from the testing dataset and 540 samples from training datasets; the dataset is then separated into 10 equal fragments. This is repeated 10 times with various training and testing dataset combinations. Lastly, the performance of each fold is averaged.

Since the deep neural network (BDNN) method effectively solves image recognition problems across many domains, it is apparent from the research that BDNN-based studies transform one-dimensional physiological signals into images while affecting some of the signal's characteristic information, specifically to emphasize it more. Given this context, imaging in the time or frequency domain can only capture the signal's fundamental properties. In contrast, non-stationary signals like EEG may exhibit the distribution of frequency components with unique properties throughout time via time-frequency conversion. Fine-grained time-frequency visualization may show areas with many signal components and distinguishing features. Consequently, the spectrogram approach, a time-frequency display methodology, was deemed appropriate for this investigation to transform the possible aura and normal EEG-labeled EEG epochs into an image format. The spectrogram plots the signal's spectrum density against time. If the signal is not steady, like an electroencephalogram (EEG), the short-time Fourier transform (STFT) method may show it in a spectrogram form. A time-frequency representation of an electroencephalogram (EEG) signal is provided by the STFT technique. Studies have shown that the frequency components of electroencephalogram (EEG) data provide crucial details about brain processes. Since this is the case, it will be helpful to transform the EEG epochs into a time-frequency image format. It may find the mathematical formulation of the STFT technique in Equation (1).

$$Y(m,s) = \sum_{m=-\infty}^{\infty} y(n).s(m-n)e^{-ism} \tag{1}$$

here, $(n).s(m-n)$ signifies the short time of the Y signals at time m. Besides, discrete STFT can be articulated as in Equation (2).

$$Y(m,l) = Y(m,s)|_s = \frac{2\pi l}{M} \tag{2}$$

In Equation (2), M signifies the number of discrete frequency. The statistical expression of the spectrograms is provided in Equation (3).

$$W(m,l) = |Y(m,l)|^2 \tag{3}$$

Consequently, the time-frequency domain provides a two-dimensional representation of EEG signals labelled potential aura. Coefficients based on STFT have their normalized square size defined by the spectrogram. The EEG epochs used in this investigation, which were 1 second long and included 500 samples, were converted into a spectrogram picture with dimensions 536 × 678 pixels using the STFT technique with a window size of 128. The spectrogram images have been reduced to 32 × 32 pixels in grayscale to create suitable input and decrease the processing burden of the BDNN method. As shown in **Figure 2**, the spectrogram approach was used to turn EEG epochs marked as a possible aura for a patient sample into an image.

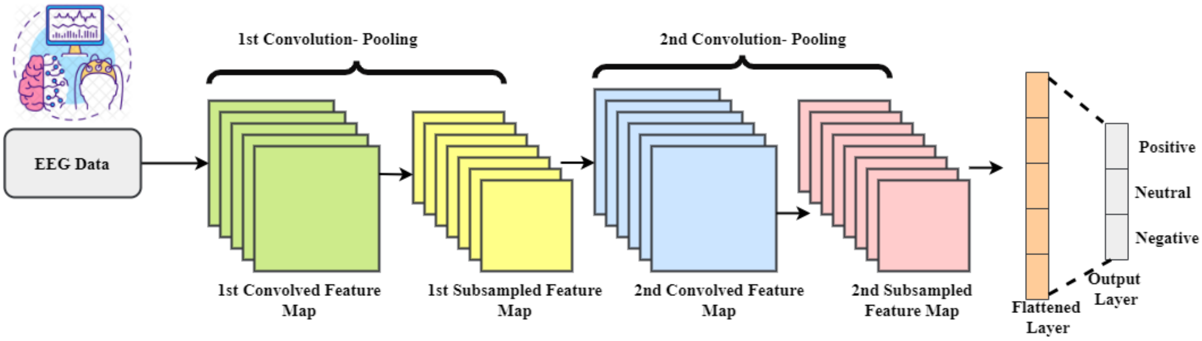

Figure 3. BDNN model.

Figure 3 shows the BDNN model. To enhance the accuracy of college students' psychological pressure predictions, a deep neural network is first trained on a data set reflecting an accurate representation of college students' mental health. The convolutional layer constructs a convolved feature map by filtering several image pixels. As part of the process of upsampling the EEG data segmentation information in each processing layer, for each position in the obtained feature map that is indicated by the inputted EEG data segmentation information, there are indications for feature map positions included in the same area of the reconstructed signal that are used as upsampled segmentation information. This provides positions in a subsampled feature map, the accompanying biosensor and EEG segmentation flags, and a spatial link between the reconstructed signal (or reconstructed feature map). In a CNN, a subset of DNNs, an activation function and a pooling layer come before each convolutional layer. The number of spatial dimensions is reduced to one by flattening a layer, which allows for faster computing. In most cases, the output layer will be the dense layer, the simplest predictive layer that takes data from the layers below it. A 2D input is multiplied element by element by the 2D convolution.

The particular operation stages are as follows. Supposing that the psychological pressure and psychological stressors response of college students are Y_j and Y_i, correspondingly, in the two periods of $j$and i, the association between Y_j and Y_i is computed as $W_{\{Y_j,Y_i\}}$, and the set of college students' psychological pressure behaviour is c''_W ; the physical network data model is articulated as follows:

$$S'_W = \frac{c''_W + W_{\{Y_j,Y_i\}}}{\{Y_j,Y_i\}} + \frac{\{j,i\}}{i'_{ilk}} \quad (4)$$

In Equation (4), where i'_{ilk} denotes the weight of the efficient psychological pressure behaviour of college students. The primary goal of using DNN is to train the algorithm by extracting appropriate features from input EEG data. Biosensor-based and Deep neural networks (DNNs) primarily use convolutional processes in combination with neural networks. The feature map is obtained by running the designated kernels over the input data during convolution. The following equation is used to obtain the convolved output:

$$x(t) = (y * t) = y(\omega)l(t-\omega)d\omega \quad (5)$$

As discussed in Equation (5), where $x, y,$ and ω indicate the output feature maps, input filter and data, correspondingly. Given that there are 64 channel, window sizes of 20, and batch sizes of 40, various architectures were explored for the convolution layer by adjusting the kernel size. At last, a kernel of 64 × 5 was selected, successfully capturing information from EEG signals at 4 Hz and above.

Two common types of pooling layers are maximal pooling and average pooling. The average pooling and maximum pooling layers contribute to the receiving area's average value, which is then passed on to the following layer and sent to the next layer, where the values are sent. Here is the pooling operation formula, supposing that an is a pooling layer:

$$G_j = subsamplings\left(G_j - 1\right) \tag{6}$$

Significant features are extracted by convolving these filters with the input data matrix of the EEG signal. The activation functions, rectified Linear Units (ReLU), enhances the algorithm's stability after the convolution layer. ReLU receipts y values for the positive input and make 0 for the negative input, as demonstrated in the Equation (7):

$$f(y) = \max(0, y) \tag{7}$$

Then, after ReLU, the features that have been extracted are produced. The loss function measured in the DNN networks is binary cross-entropy losses, $I(\Theta)$, for the binary classifier, which is calculated utilizing the subsequent equation:

$$I(\Theta) = -\frac{1}{M}\sum_{j=1}^{M} x_j \log\left(\widehat{x_j}\right) + \left(1 - x_j\right)\log\left(1 - \widehat{x_j}\right) \tag{8}$$

As inferred from Equation (8), where $\widehat{x_j}$ and x_j correspondingly, the forecasted and actual class labels of the ith sample and M is the overall number of samples. The model is trained over manifold iterations to reduce the values of the $I(\Theta)$. Using electroencephalogram (EEG) data and machine learning, this research demonstrates models for predicting mental health in educational environments. Stress, depression, and anxiety are the three main concerns that this research predicts would affect college students, and it begins by explaining the nature of these disorders and the elements that contribute to them. The two most prevalent features in this research were the absence of a conducive learning environment and social support. The suggested BDNN-CSMHPM model increases the accuracy ratio, mental health prediction ratio, Pearson correlation coefficient ratio, emotion recognition ratio, and psychological monitoring ratio compared to existing models.

4. Results and discussion

This study presents the Deep Neural Network-based College Student Mental Health Prediction Model (DNN-CSMHPM) for detecting the mental stress of college students. The data are from the depression and students' academic performance Kaggle dataset [31]. The data was collected by surveying students in the US studying at various education levels such as high school, college, bachelor's, and master's. As a result, the data was collected from students from varying age groups. A total of 352 students were included in the research. Data were gathered from the students using a questionnaire method with informed consent. This is data from mental health surveys all across the world. In a recent college competition, this dataset had a chance to explore an interesting story and draw insights from it. Likewise, four machine learning models predict if one will be diagnosed with a mental health illness. The performance of the suggested BDNN-CSMHPM model has been analyzed based on metrics like accuracy ratio, mental health prediction ratio, Pearson correlation coefficient ratio, emotion recognition ratio, and psychological monitoring ratio.

4.1. Students' mental health prediction ratio

Mental wellness issues have been largely reported in college and university students. The present research has identified the main risk aspects for mental health issues, including anxiety disorders and depression, among students. Several machine learning models have been used for clinical mental health state prediction. A study suggests that psychological issues among students are most often caused by worry and sadness. Included in this research are two essential factors: relationships and academic success. Since it is sometimes rather difficult to categorize data related to mental health, the features used by machine learning algorithms substantially impact how well the algorithms do categorization. The extent to which a BDNN classifier does its task depends on context. This research investigates the present state of student well-being and utilizes ML techniques like the BDNN network to make predictions using data on academic competence among university students. **Figure 4** shows the student's mental health prediction ratio.

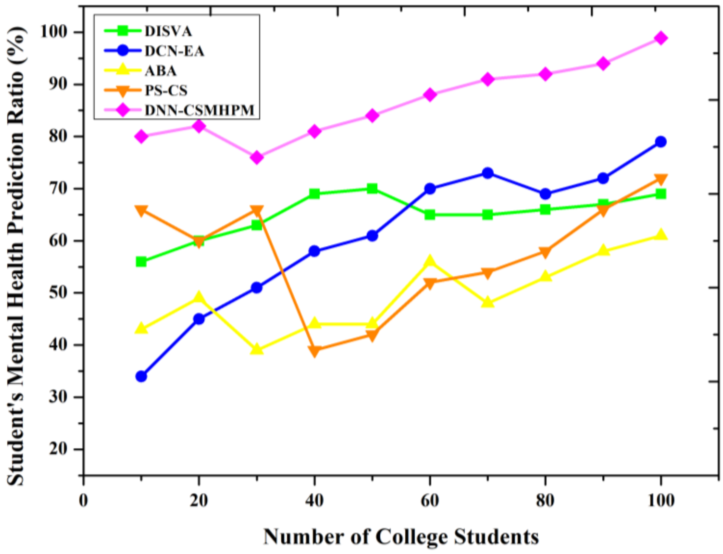

Figure 4. Student's mental health prediction ratio.

4.2. Accuracy ratio

Equation (9) shows that accuracy is the metric that indicates the proposed model's performance in classifying EEG spectrogram data as normal or abnormal. Building reliable Brain-Computer Interface (BCI) systems relies heavily on emotion estimation from Electroencephalogram (EEG) data. This research investigated EEG-based emotion identification using a deep neural network (BDNN). This has been prompted by the recent efficiency and accuracy gains in pattern recognition and classification applications using deep learning methods. **Figure 5** shows the accuracy ratio.

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{True Positive} + \text{True Negative} + \text{False Positive} + \text{False Negative}} \tag{9}$$

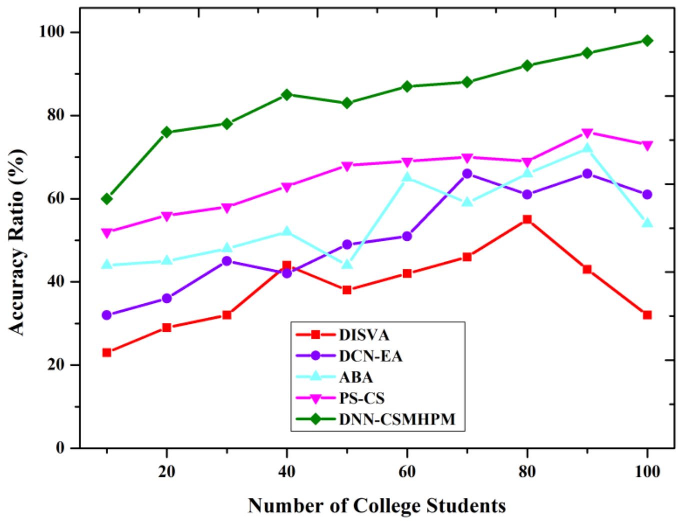

Figure 5. Accuracy ratio.

4.3. Emotion recognition ratio

Furthermore, physiological signal characteristics in frequency, time, and non-linearity are extracted by an emotion detection application that relies on traditional ML methods. This study employs a BDNN to automatically extract features from physiological inputs and then predicts the user's emotional state using layers of fully connected networks. Rather than focusing on diagnosing psychopathology, the view mentioned above of mental health highlights the positive features of psychological functioning. Mental health is defined from this perspective as the extent to which an individual's psychological, emotional, and social health are in harmony with one another. A low neuroticism level is linked to a more positive emotional state, less concern or anxiety, a positive mental attitude toward stressful circumstances, and a less negative perception of the effects of stress. People who are easily overwhelmed by their emotions often tend to see their methods of coping as inadequate and view stresses as more risky. **Figure 6** shows the emotion recognition ratio.

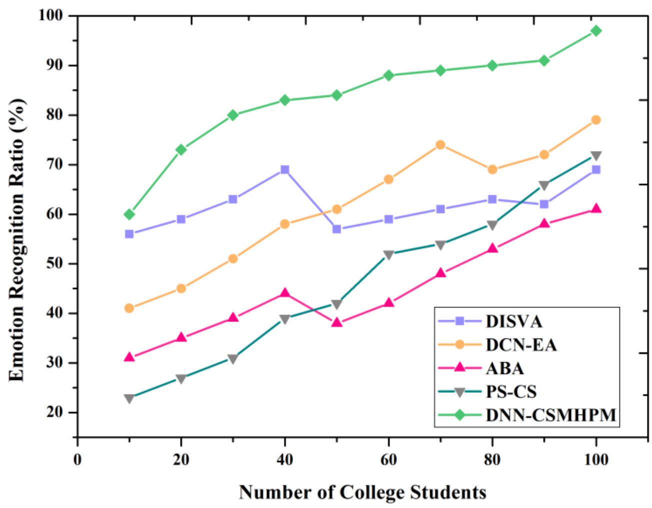

Figure 6. Emotion recognition ratio.

4.4. Pearson correlation coefficient ratio

To find the degree of linear association between any two variables, one may use Pearson's correlation coefficient. The following formula shows how to calculate the proportion of covariances and standard deviations of two parameters.

$$\sigma_{Y,X} = \frac{cov(Y,X)}{\rho_{Y,X}} \tag{10}$$

As shown in Equation (10), where Y and X signify two random variables, $cov\,(Y,X)$ denotes the covariance between Y and X, symbolizes the standard deviation between X and Y.

The assortment of Pearson's correlation coefficients are −1 to 1. When the value is positive, it specifies a strong positive correlation between the two parameters; when it's negative, it indicates a strong negative correlation; and when it's zero, it indicates no linear association. When looking at the feature's relevance to the target issue, a bigger absolute value of the correlation coefficients indicates a robust relationship between the two. A combination of correlation and regression analysis was utilized to examine the interrelationships of the variables. This study began by describing the variable's interrelationships through the Pearson correlation coefficients. The next step was to forecast the general state of mental health using a linear regression. The statistical importance of the correlations was evaluated at a level of 0.01 due to the small sample size. **Figure 7** signifies the Pearson correlation coefficient ratio.

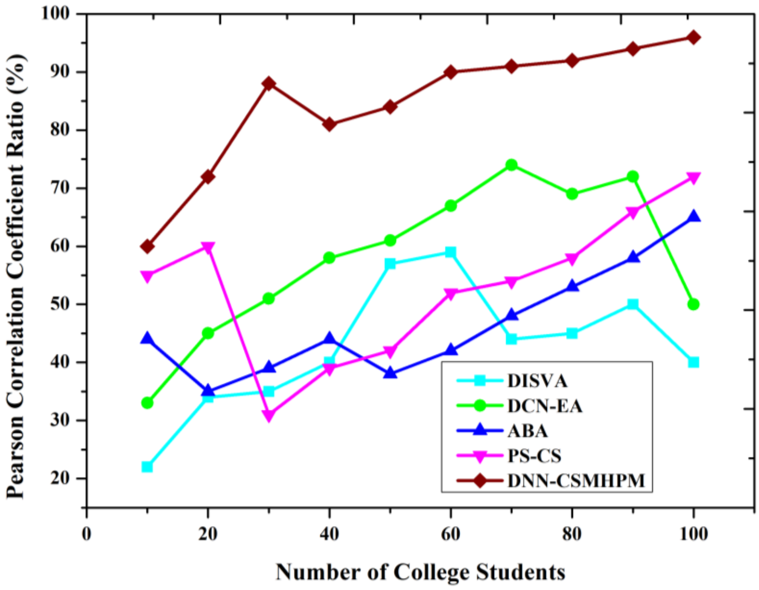

Figure 7. Pearson correlation coefficient ratio.

4.5. Psychological monitoring ratio

Lack of psychological fitness among students is inevitable and negatively affects adolescents' growth, social relationships, self-esteem, and peer pressure. College students' mental health may be most affected by academic stress. Research into better ways to monitor students' mental health is very important. Developing systems to monitor individuals' mental and behavioural health is a major step forward in the evolution of technology in therapy. According to the study, academic performance is influenced by students' mental health. The greatest way for students to take care of their mental health is to learn to control their emotions and develop self-awareness. Determining if a person has a constructive or expressive personality type is the primary goal of this research. Heart rate variability (HRV), electroencephalogram (EEG), skin temperature (ST), galvanic skin response (GSR), sleep, blood pressure (BP), blood oxygen saturation (SpO2) and salivary cortisol are now the most often used signals in mental health detection. Finally, a combination of electrocardiogram (ECG) signals, core body temperature, and other data may precisely recognize a person's level of mental fatigue, lending credibility to the extensive utilization and targeted usage of mental health evaluations. **Figure 8** shows the psychological monitoring ratio.

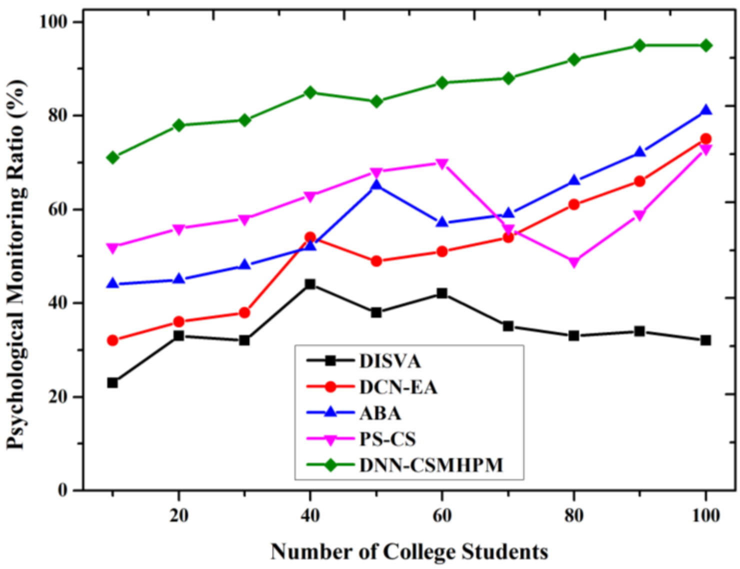

Figure 8. Psychological monitoring ratio.

5. Conclusion

This study presents the Biosensor-based and Deep Neural Network-based College Student Mental Health Prediction Model (BDNN-CSMHPM) for detecting the mental stress of college students. To differentiate between stressful and non-stressful states, this research uses frontal EEG channels to identify features. A deep neural network, a time domain, a frequency domain, and a combination of the three were researched as EEG features. The researchers used ML algorithms as their field of study and EEG data as the research object to thoroughly analyze the features of EEG signals and suggest a high-performance method for detecting mental states. The benefits of deep neural network models are completely reflected in the DNN-based approach to forecasting the psychological pressures experienced by college students that are suggested in this research. The numerical findings demonstrate that the BDNN-CSMHPM model raises the student's mental health prediction ratio of 98.9%, accuracy ratio of 96.4%, emotion recognition ratio of 95.3%, Pearson correlation coefficient rate of 97.2% and psychological monitoring rate of 94.3% compared to other popular techniques. Despite its high performance, the BDNN-

CSMHPM model has certain limitations. One major limitation is the dependency on high-quality biosensor data, which might not always be available or feasible for continuous monitoring in real-world study tour settings. The model's reliance on EEG and biomechanical metrics can also be resource-intensive, requiring specialized equipment and consistent data acquisition, which could hinder large-scale deployment.

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References

1. Sheldon E, Simmonds-Buckley M, Bone C, et al. Prevalence and risk factors for mental health problems in university undergraduate students: A systematic review with meta-analysis. Journal of affective disorders. 2021; 287: 282-292.
2. Wu Y, Sang ZQ, Zhang XC, et al. The relationship between resilience and mental health in Chinese college students: a longitudinal cross-lagged analysis. Frontiers in psychology. 2020; 11: 450850.
3. Li W, Zhao Z, Chen D, et al. Prevalence and associated factors of depression and anxiety symptoms among college students: a systematic review and meta-analysis. Journal of Child Psychology and Psychiatry. 2022; 63(11): 1222-1230. doi: 10.1111/jcpp.13606
4. Huang C. A meta-analysis of the problematic social media use and mental health. International Journal of Social Psychiatry. 2020; 68(1): 12-33. doi: 10.1177/0020764020978434
5. Gál É, Ștefan S, Cristea IA. The efficacy of mindfulness meditation apps in enhancing users' well-being and mental health related outcomes: a meta-analysis of randomized controlled trials. Journal of Affective Disorders. 2021; 279: 131-142. doi: 10.1016/j.jad.2020.09.134
6. Patsali ME, Mousa DPV, Papadopoulou EVK, et al. University students' changes in mental health status and determinants of behavior during the COVID-19 lockdown in Greece. Psychiatry Research. 2020; 292: 113298. doi: 10.1016/j.psychres.2020.113298
7. Marciano L, Ostroumova M, Schulz PJ, et al. Digital Media Use and Adolescents' Mental Health During the Covid-19 Pandemic: A Systematic Review and Meta-Analysis. Frontiers in Public Health. 2022; 9. doi: 10.3389/fpubh.2021.793868
8. Visser M, Law-van Wyk E. University students' mental health and emotional wellbeing during the COVID-19 pandemic and ensuing lockdown. South African Journal of Psychology. 2021; 51(2): 229-243. doi: 10.1177/00812463211012219
9. Zhao S, Ng SC, Khoo S, et al. Temporal and Spatial Dynamics of EEG Features in Female College Students with Subclinical Depression. International Journal of Environmental Research and Public Health. 2022; 19(3): 1778. doi: 10.3390/ijerph19031778
10. Komarov O, Ko LW, Jung TP. Associations Among Emotional State, Sleep Quality, and Resting-State EEG Spectra: A Longitudinal Study in Graduate Students. IEEE Transactions on Neural Systems and Rehabilitation Engineering. 2020; 28(4): 795-804. doi: 10.1109/tnsre.2020.2972812
11. Oyebode O, Alqahtani F, Orji R. Using Machine Learning and Thematic Analysis Methods to Evaluate Mental Health Apps Based on User Reviews. IEEE Access. 2020; 8: 111141-111158. doi: 10.1109/access.2020.3002176
12. Opoku Asare K, Terhorst Y, Vega J, et al. Predicting Depression from Smartphone Behavioral Markers Using Machine Learning Methods, Hyperparameter Optimization, and Feature Importance Analysis: Exploratory Study. JMIR mHealth and uHealth. 2021; 9(7): e26540. doi: 10.2196/26540
13. Su C, Xu Z, Pathak J, et al. Deep learning in mental health outcome research: a scoping review. Translational Psychiatry. 2020; 10(1). doi: 10.1038/s41398-020-0780-3
14. Nijhawan T, Attigeri G, Ananthakrishna T. Stress detection using natural language processing and machine learning over social interactions. Journal of Big Data. 2022; 9(1). doi: 10.1186/s40537-022-00575-6
15. Souri A, Ghafour MY, Ahmed AM, et al. A new machine learning-based healthcare monitoring model for student's condition diagnosis in Internet of Things environment. Soft Computing. 2020; 24(22): 17111-17121. doi: 10.1007/s00500-

020-05003-6

16. Raj S, Masood S. Analysis and Detection of Autism Spectrum Disorder Using Machine Learning Techniques. Procedia Computer Science. 2020; 167: 994-1004. doi: 10.1016/j.procs.2020.03.399
17. Nemesure MD, Heinz MV, Huang R, et al. Predictive modeling of depression and anxiety using electronic health records and a novel machine learning approach with artificial intelligence. Scientific Reports. 2021; 11(1). doi: 10.1038/s41598-021-81368-4
18. Campbell F, Blank L, Cantrell A, et al. Factors that influence mental health of university and college students in the UK: a systematic review. BMC Public Health. 2022; 22(1). doi: 10.1186/s12889-022-13943-x
19. Coutts LV, Plans D, Brown AW, et al. Deep learning with wearable based heart rate variability for prediction of mental and general health. Journal of Biomedical Informatics. 2020; 112: 103610. doi: 10.1016/j.jbi.2020.103610
20. Liang, Y. Research on the Prediction and Intervention Model of Mental Health for Normal College Students Based on Machine Learning. International Journal of Intelligent Systems and Applications in Engineering. 2024; 12(6): 369-385.
21. Ding Y, Chen X, Fu Q, et al. A Depression Recognition Method for College Students Using Deep Integrated Support Vector Algorithm. IEEE Access. 2020; 8: 75616-75629. doi: 10.1109/access.2020.2987523
22. Fei Z, Yang E, Li DDU, et al. Deep convolution network based emotion analysis towards mental health care. Neurocomputing. 2020; 388: 212-227. doi: 10.1016/j.neucom.2020.01.034
23. Adler DA, Wang F, Mohr DC, et al. Machine learning for passive mental health symptom prediction: Generalization across different longitudinal mobile sensing studies. Chen CH, ed. PLOS ONE. 2022; 17(4): e0266516. doi: 10.1371/journal.pone.0266516
24. Ogunseye EO, Adenusi CA, Nwanakwaugwu AC, et al. Predictive Analysis of Mental Health Conditions Using AdaBoost Algorithm. ParadigmPlus. 2022; 3(2): 11-26. doi: 10.55969/paradigmplus.v3n2a2
25. Jawad K, Mahto R, Das A, et al. Novel Cuckoo Search-Based Metaheuristic Approach for Deep Learning Prediction of Depression. Applied Sciences. 2023; 13(9): 5322. doi: 10.3390/app13095322
26. Deng X. A Fuzzy Qualitative Simulation Study of College Student's Mental Health Status. Sun G, ed. Discrete Dynamics in Nature and Society. 2022; 2022(1). doi: 10.1155/2022/5177969
27. Han H. Fuzzy clustering algorithm for university students' psychological fitness and performance detection. Heliyon. 2023; 9(8): e18550. doi: 10.1016/j.heliyon.2023.e18550
28. Tian Z, Yi D. Application of artificial intelligence based on sensor networks in student mental health support system and crisis prediction. Measurement: Sensors. 2024; 32: 101056. doi: 10.1016/j.measen.2024.101056
29. Ramzan M, Hamid M, Alhussan AA, et al. Accurate Prediction of Anxiety Levels in Asian Countries Using a Fuzzy Expert System. Healthcare. 2023; 11(11): 1594. doi: 10.3390/healthcare11111594.
30. Robinson SA, Udoh AE, Dan EA, et al. Early Depression Prediction among Nigerian University Students Using Adaptive Neuro-Fuzzy Inference System (ANFIS). Journal of Advances in Mathematics and Computer Science. 2024; 39(2): 1-10. doi: 10.9734/jamcs/2024/v39i21864
31. Available online: https://www.kaggle.com/datasets/kanerudolph/depression-and-academic-performance-of-students (accessed on 2 June 2023).