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Article

Research on the application of biosensor technology in teacher psychological monitoring and intervention

Ping Zhang

School of Education, Jiangsu University of Technology, Changzhou 213001, China; zhangping202411@163.com

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Abstract: Teachers' mental health and general well-being have been negatively impacted in recent years by the increasing stress they experienced as a result of several difficulties in both their personal and professional lives. Teachers' psychological stress is a crucial area for intervention since it results in burnout, decreased teaching effectiveness, and other health problems. However, there is still an abundance of research on the application of innovative technologies to track and manage teachers' mental health. This research suggests using deep learning (DL) techniques like the Intelligent Bottlenose Dolphin-Inspired Feed Forward Neural Networks based Teacher Psychological Monitoring and Intervention Model (IDBI-FFNN-TPMIM) combined with biosensor technologies. This model offers a novel method for determining mental stress levels, identifying early indicators of burnout, and classifying emotional states as neutral, negative, or positive using biosensors like EEG and biomechanical data. Using feature extraction approaches, the model properly depicts the physical and emotional states of teachers, allowing for automatic classification and feedback for prompt interventions. According to experimental data, Biosensor-based IDBI-FFNN-TPMIM results are $F1$-score at 91.1%, accuracy at 93.7%, recall at 91.5%, and precision at 92.3%. While performing well in psychological monitoring and emotion recognition while achieving high prediction accuracy. These findings demonstrate how biosensor technology is employ to improve overall well-being and strengthen programs for teachers' mental health care.

Keywords: Teacher Psychological Monitoring; Intervention; Biosensor; Mental Health and Well-Being; Deep Learning (DL)

1. Introduction

Teachers' mental or emotional states are referred to as their psychological well-being. It addresses topics including teachers' stress levels, resilience, emotional intelligence, burnout, and work satisfaction [1]. A teacher's ability to engage pupils, control classroom dynamics, and create a pleasant learning environment are all influenced by their psychological well-being. Teachers who are psychologically well are more likely to be driven, sympathetic, and encouraging in their instruction, all of which directly affect students' results. Burnout or psychological torture, on the other hand, impairs teaching quality overall, raises absenteeism, and lowers performance. For the sake of both the health of educators and the overall performance of the educational system, it is crucial to comprehend and promote their psychological well-being [2]. To identify specific biological chemicals or physiological states, biosensor technology mostly uses biological components with integrated sensors, like enzymes, antibodies, or amino acids. These sensors convert the biological response into an analytically measurable signal, which could be either electrical or optical [3]. Applications of biosensors extend into wearable, food security, monitoring of the environment, and health diagnosis. They can provide real-time monitoring solutions, which are quick, accurate, and inexpensive. Due to their contribution to disease diagnosis, biomarker level monitoring, and safety and quality control of a variety of products, they are indispensable tools in modern healthcare and biotechnology [4].

Applications of biosensor technology range from diverse fields, some of which include health care, monitoring the environment, food safety, and industrial processes. Such biosensors have applications in the prediction of diseases at an initial level, monitoring of blood glucose level, and biomarkers, which help in diseases like tumors and infections [5]. They promote environmental monitoring by aiding in the detection of diseases, toxin, and contaminants in the atmosphere, fluid, and soils. Apart from that, biosensors have their applications in the food industry, which is important for ensuring food safety through the identification of contamination and spoilage [6]. Biosensors are increasingly being integrated into wearable for the continuous monitoring of life signs such as body temperature, oxygen saturation, and heart rate. Given the real-time, accurate, and affordable solutions provided by this ever-increasingly complex biosensor technology, it bears the potential to reshape personalized medicine, sustainability efforts, and diagnostics in general [7]. Teacher psychological monitoring and intervention refers to the regular checking and supporting of teachers' mental health and well-being in the educational context [8]. It deals with the early detection of psychological stress, burnout, anxiety, or depression among teachers, which often results from work pressures, student demands, and organizational problems at work [9]. By maintaining a close watch on teachers' emotional and psychological states, the school implements prompt interventions through counseling, stress management courses, or professional development opportunities to enhance teachers' resilience, work satisfaction, and general mental health [10]. By creating a healthier and more productive teaching staff, this proactive strategy not only promotes the wellbeing of the teaching community but also enhances the learning environment and student results [11]. **Figure 1** and **Table 1** show the importance of biosensor technology in teacher psychological.

The research can apply biosensor technology to teacher psychological monitoring, including wearable sensors that can offer real-time data on stress and emotional well-being, thus enabling the early identification of psychological strain and allowing personalized interventions aimed at teaching stress-relieving techniques to reduce burnout and enhance teacher mental health. This will lead to an improvement in teacher well-being and the creation of healthier learning environments.

The main intention is to explore the use of biosensor technology for monitoring teachers' psychological well-being and providing targeted interventions to improve mental health and performance.

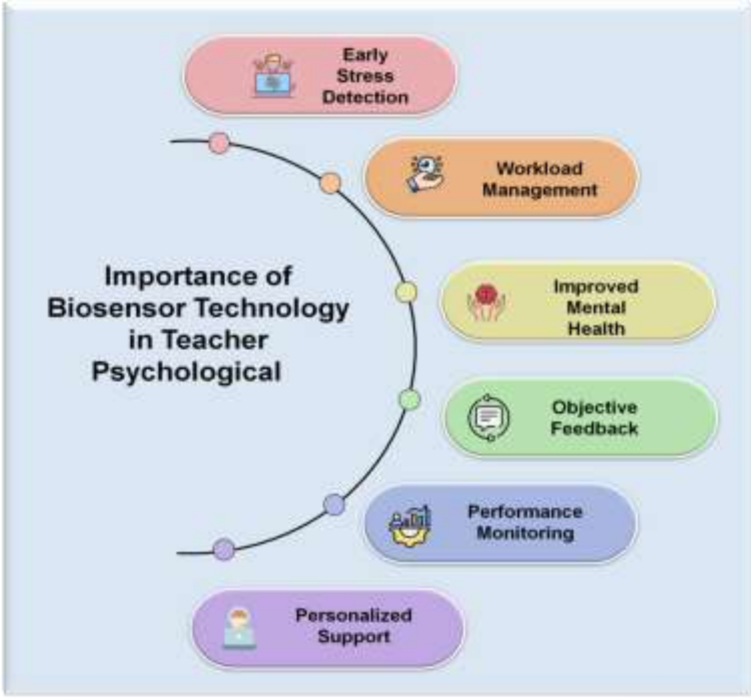

Figure 1. Importance of biosensor technology in teacher psychological.

Table 1 Description of importance of biosensor technology in teacher psychological.

Importance of Biosensor Technology in Teacher Psychological	Description
Early Stress Detection	To quickly identify stress and anxiety in educators, biosensors will analyze physiological indicators including heart rate, skin conductance, and brain activity.
Workload Management	Individualized treatments are made possible by ongoing monitoring, which assists in recognizing times of high cognitive load.
Improved Mental Health	Biosensor data provide guidelines on mental health interventions-for example, stress-relieving exercises or mindfulness practices-that might improve teacher well-being.
Objective Feedback	Biosensor technology provides objective information on teachers' emotional and mental states, reducing reliance on biased self-reporting.
Performance Monitoring	Biosensors analyze emotional and cognitive patterns to understand how stress affects teaching performance and target support accordingly.
Personalized Support	Data-driven approaches allow for tailored wellness programs based on individual physiological responses, fostering a healthier work environment.

Key contribution of this research

- The main objective is to explore the usage of biosensor technology for monitoring teachers' psychological well-being as well as providing targeted interventions to improve mental health and performance.
- 150 teachers will be selected based on the selection criteria. Data collection will be done through wearable biosensors.
- After that, preprocessing was done by Butterworth band-pass filter, low-pass filter, and *Z*-score normalization.
- Then, feature extraction was done by utilizing Power spectral density (PSD), Fast Fourier Transform (FFT), and time-domain analysis.

- Furthermore, the Intelligent Bottlenose Dolphin-Inspired Feed Forward Neural Networks based Teacher Psychological Monitoring and Intervention Model (IDBI-FFNN-TPMIM) is utilized for model development.

Research organization: The literature review has been provided in Section 2. The in-depth explanation of materials and methods is explained in Section 3. The performance analysis of this research is illustrated in Section 4. The discussion is presented in Section 5. The research's conclusion is demonstrated in Section 6.

2. Literature review

Biosensors are transforming research and healthcare by delivering inexpensive, efficient, and clarified medical equipment, examined by Bhatia et al. [12]. They enable illness identification and tracking, which allows for prompt intervention and therapy. Biosensors' sensitivity and specificity allow healthcare providers to spot modest indicators, improving overall health and well-being. The user-friendliness, scalability, and efficient production serve as significant equipment in healthcare. They investigated advances in biosensor technology, with a focus on cardiovascular illnesses and potential medical uses. The innovations result in innovative medical therapies, real-time evidence-based insights, tailored solutions, and educated advice.

Li [13] indicated a Biosensor-based and Deep Neural Network (DNN)-based College Student Mental Health Prediction Model (BDNN-CSMHPM) to identify mental stress in college students while on vacation. To identify emotional and biomechanical information, the algorithm relied on biosensor data such as electroencephalographic signals (EEG) and biomechanical measures. The model outperformed previous techniques in terms of mental health prediction, accuracy, emotion identification, and psychological monitoring.

Pilot research has in undertaken to evaluate Keep Calm, a mobile digital mental health software, for managing problematic behaviors in autistic children, investigated by Palermo et al. [14]. The software attempted to overcome obstacles such as difficulties articulating emotions, adopting individualized techniques, and tracking effective approaches. The experiment included 20 educational teams with problematic behaviors and focused on main outcomes such as usability, acceptability, feasibility, and appropriateness.

The creation and testing of a multi-modal-based wearable biosensor throughout the initial very-female unsupported ski traverse of the Antarctic land mass effectively relayed instantaneous physiological information back to the United Kingdom (UK) described in Smith et al. [15]. The bio-sensor devices have been meant to be worn constantly against the skin and collect physiological data such as rate of heart EEG, and body temperature, as well as sweat pH, salt, lactic acid, glucose, and bio impedance. An Android smartphone with a specially designed app was used to safely transmit the data to a research institution in the UK. Participants' post-expedition input helped to develop the ergonomics and technical specifications of the next generation of wearable gadgets.

Biosensors are an innovative type of detection and analysis instrument that was sensitive, accurate, and easy to utilize by He and Han [16]. The research have a large market in sports science, offering immediate monitoring of athletic performance and emerging as a significant approach in sports research and instruction. They investigated direction, sensor-related usage algorithm model, nanobiosensor variables, and competitive comparison of nanobiosensors in sports. The results indicated a 7.83% enhancement in algorithm efficacy.

The physiological functions to assess changes in students' arousal levels while lecturing was utilized in Francisti et al. [17]. The effort intended to gather and evaluate heart rate data during individual teaching activities during the COVID-19 epidemic. The suggested approach identifies changes in students' arousal, which improved teaching efficiency. The findings assist teachers in altering their teaching styles for certain contexts, hence improving student retention and understanding of instructional information. The suggested technique improved teaching process effectiveness and student knowledge of teaching contents.

Zai [18] investigated the utilization of bio-sensing technologies in teaching the Spanish language. Biosensors utilized physiological signals to uncover gaps in students' knowledge and understanding. The results demonstrated that teaching Spanish vocabulary using biosensing technology may significantly improve the educational results of pupils and engagement. The study offered new perspectives and approaches for integrating biosensing technologies into language learning, demonstrating how it might revolutionize conventional teaching strategies and improve student outcomes in Spanish instruction. An Arduino-based biosensor module that measured glucose concentration levels was created by Hsu et al. [19]. Physics, chemistry, biology, mathematics, electronics, and programming were all covered in the multidisciplinary module. Students are supposed to design a gadget that looks like a brand-name glucose meter. To impart concepts and techniques, teacher workshops were held. However, there were challenges in understanding and modifying the STEM curriculum, as well as in getting pupils ready for the advanced technological resources and abilities required by the program.

A combination of artificial intelligence (AI) and educational research, positive education attempts to enhance teacher well-being by utilizing self-diagnostic techniques, as discussed in Indrianti and Hermanus [20]. An assessment of a teacher's emotional and mental health that affects their level of happiness, contentment, tranquility, and life satisfaction is called well-being for teachers. Considering facial recognition-based applications, to calibrate a teacher's wellbeing tool using the Neuro research technique, which maximizes a teacher's work-life balance. There are three components to the instrument: behavior, emotion, and cognition. By optimizing the educator's professional life for appearance recognition-based applications, the intent is to promote contentment, enjoyment, and a sense of fulfillment in life.

The understanding and use of classroom management techniques for children with emotional and behavioral disorders (EBDs) in general education classrooms were examined in the pilot research McKenna et al. [21]. The participants were general educators who possessed a lack of expertise in working with special educators in the classroom. Higher levels of classroom management and differentiation method knowledge were indicated by those who had regular co-teaching chances. Furthermore, individuals who had more opportunities to co-teach also reported using classroom management techniques more frequently. Individuals with EBD in general education settings could not be given the proper educational chances if special education personnel did not provide them with enough assistance.

3. Materials and methods

The aim of the research is to explore the use of biosensor technology for monitoring teachers' psychological well-being and providing targeted interventions to improve mental health and performance. **Figure 2** displays the entire research flow.

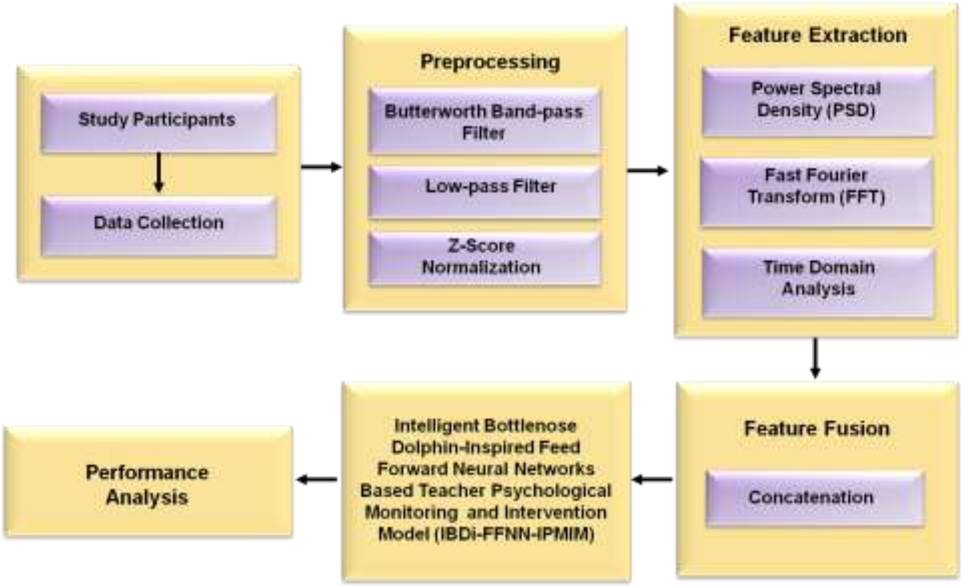

Figure 2. Basic concept of overall proposed research flow.

3.1. Research participants

It includes 150 participants of teachers from various educational levels (such as primary, secondary, and tertiary) and subject areas. The participants were recruited from schools and universities, which ensures the sample represents different age groups, genders, and teaching experiences. **Table 2** represents the participant's demographic data. 150 teachers were selected based on the selection criteria. The training data is 80% (120), and the testing data is 20% (30). The participants were over a 6–8 weeks period with multiple monitoring sessions for each participant, and teacher to capture various kinds of stress-inducing events as well as emotional states. Throughout this time, teachers have to wear non-invasive biosensors that can continuously measure their physiological and emotional conditions throughout their day. The selection criteria for the research are below.

Inclusion criteria: Full-time teachers with a minimum of one year of teaching experience. Teachers from different educational levels (primary, secondary, and tertiary) and Teachers from diverse subject areas (humanities, sciences, arts, etc.). Teachers are willing to wear biosensors and participate in the continuous monitoring of their psychological and emotional states. Teachers who provide informed consent for participation.

Exclusion criteria: Teachers with severe psychological or physical conditions that could interfere with data collection (e.g., neurological disorders, severe cardiovascular issues, etc.). Teachers who are on long-term medical leave or experiencing acute stress-related conditions that may require immediate professional intervention. Teachers who do not consent to participate.

Table 2. Demographic Breakdown Offers a Comprehensive View of the Study's Participant Data

Participants characteristics	**Category**	**Frequency (*n* = 150)**	**Percentage (%)**
Age	20–30 years	30	20
	31–40 years	50	33.30
	41–50 years	40	26.70
	51+ years	30	20
Gender	Male	70	46.70
	Female	80	53.30
Educational Level	Primary School	50	33.30
	Secondary School	60	40
	Tertiary Education	40	26.70
Subject Area	Humanities	40	26.70
	Sciences	50	33.30
	Arts	30	20
	Other (e.g., vocational)	30	20
Years of Teaching Experience	1–5 years	40	26.70
	6–10 years	50	33.30
	11–15 years	30	20
	16+ years	30	20

3.2. Data collection

EEG, biomechanical sensors skin conductance, and heart rate data in the context of a biosensor data collection system to capture physiological responses during teaching sessions. The data collection process of biosensor type's details is provided in **Table 3**.

Table 3. Biosensors used to monitor physiological and emotional response in teachers

Biosensors	**Details**
Electroencephalogram (EEG)	EEG sensors monitor the brainwave activity of teachers during their teaching sessions. The EEG data provide perceptions of the cognitive load, stress, and emotional responses by analyzing brainwave patterns, particularly in frequency bands such as alpha, beta, and theta waves. • Alpha waves: 8–12 Hz, associated with relaxation and calmness. • Beta waves: 13–30 Hz, associated with active thinking, problem-solving activity, or stress. • Theta waves: (4–8 Hz), are usually associated with drowsiness, deep relaxation, or light sleep.
Biomechanical Sensors	• Monitor physiological characteristics including tense muscles and posture. • These parameters serve to indicate emotional states, such as stress (tense posture, muscle stiffness) or relaxation (looser posture, muscle relaxation). • The physical reaction of the instructor to stress, tension, or relaxation during instruction can be determined through an examination of their posture and muscular activity. • Posture: upright or slouched. • Muscle Tension: Strain in the neck, shoulder blades, or back indicates tension.

Table 3. (*Continued*).

Biosensors	Details
Skin Conductance and Heart Rate Sensors	These sensors measure physiological responses associated with emotional arousal. Skin conductance responses (SCR) and heart rate variability (HRV) help assess autonomic nervous system activity, which is strongly linked to stress and emotional responses. • SCR: Increased at stressful times (e.g., when conveying a difficult idea). • HRV: Low HRV at high-stress motion (e.g., when managing a disruptive class).

The sensors have been integrated into wearable devices, such as headbands (for EEG), wristbands (for heart rate and skin conductance), and other comfortable, modest wearable that can be worn during regular teaching activities.

Intervention types

The goal of the intervention is to offer targeted strategies for stress management, burnout reduction, and mental health improvement among teachers. **Table 4** provides the intervention types.

Table 4. Intervention types provide a well-rounded approach to teacher mental health.

Intervention Type	Description
Stress Management Exercises	Techniques aimed at reducing stress, such as progressive muscle relaxation (PMR), guided imagery, and time management strategies.
Breathing Techniques	Exercises designed to reduce anxiety and stress, including deep breathing, diaphragmatic breathing, and box breathing.
Mindfulness and Relaxation	Activities such as meditation, mindfulness breathing exercises, and body scans promote relaxation and emotional regulation.
Counseling Referrals	For teachers flagged with sustained high levels of emotional distress or burnout, the system provided referral information for professional counseling.
Peer Support and Group Sessions	Encouraging social interactions and group discussions to promote collective well-being and reduce feelings of isolation.

3.3. Preprocessing

The purpose of preprocessing is to assure that biosensor data becomes clean, noise-free, and consistent, which improves signal quality for accurate evaluation and dependable psychological monitoring as well as intervention outcomes. The preprocessing includes a Butterworth band-pass filter for EEG, a low-pass filter for Biomechanical Sensors, Skin Conductance and Heart Rate Sensors, and *Z*-score normalization.

3.3.1. Butterworth band-pass filter

After the data collection, the Butterworth band-pass filter is used for the pre-processing. The purpose of the Butterworth band-pass filter eliminate noise as well as artifacts from EEG data signals while keeping critical frequency bands that are important for assessing mental conditions and stress. The Butterworth filter produces a reaction that is ripple-free as well as maximum flat in both the pass-band and the stop-band. This has strong averaged transient features and an extensive transition zone from the band-pass to the band-stop, which allows an effective compromise in amplitude reaction selectivity. In practical terms, the gathered raw EEG data signals consist of every frequency band like theta, alpha, and beta. For this research, the frequency band chosen is EEG Alpha Power (8–12 Hz), EEG Beta Power (13–30

Hz), and EEG Theta Power (4–8 Hz). The result is a clear EEG data signal with less noise. It concludes that the Butterworth band-pass filter improves signal quality, allowing for effective mental stress recognition as well as emotional condition classifications in teacher psychological monitoring.

3.3.2. Low-pass filter

The Butterworth band-pass filter data is fed into the low-pass filter. The purpose of a low-pass filter is to eliminate noise at higher frequencies from biomechanical sensor data, along with Skin Conductance and Heart Rate Sensors, while retaining essential movement as well as muscle tension patterns for reliable and accurate stress as well as emotional state assessment. It enables signals containing frequencies lower than a predetermined cutoff frequency value to transmit by attenuating the greater frequencies. This is employed to reduce higher frequency noises from data while maintaining the pertinent data. These filters fulfill the following transfer operation, Equation (1).

$$G(y) = \frac{(1 - y^{-\alpha})^2}{(1 - y^{-1})^2} = \frac{(1 - 2y^{-\alpha} + y^{-2\alpha})}{(1 - 2y^{-1} + y^{-2})} \quad (1)$$

The filter's amplitude response is determined in Equations (2) and (3).

$$z[m] = 2z[m-1] - z[m-2] + w[m] - 2w[m-\alpha] + w[m-2\alpha] \quad (2)$$

$$G(\omega) = \frac{1 - 2\cos\alpha\omega + \cos 2\alpha\omega + i(2\,sen\alpha\omega - sen\,2\alpha\omega)}{1 - 2\,cos\,\omega + co\,s\,2\omega + i(2\,sen\alpha\omega - sen\,2\alpha\omega)} = \frac{|cos\alpha\omega - 1|}{|cos\omega - 1|} = \frac{sen^2\left(\frac{\alpha}{2}\omega\right)}{sen^2\left(\frac{\omega}{2}\right)} \quad (3)$$

It concludes that the Low-pass filtering produces smoothened biomechanical data, and Skin Conductance and Heart Rate data with less noise, which allows for better detection of significant movement patterns. The consequence is enhanced signal quality, which improves further processes for stress and emotional analysis.

3.3.3. *Z*-score normalization

The low-pass filter data is entered into the *Z*-score normalization process. The purpose of *Z*-score normalization is to normalize the biosensor data through modifying variation among individuals, which enables consistency between participants as well as sessions for reliable psychological monitoring along with intervention assessment. The most frequently utilized normalization approach is *Z*-score standardization, which is additionally known as standard deviation (SD) normalization. The primary intent of the *Z*-score is to convert characteristics of various magnitudes into a similar magnitude and assess their characteristics using the derived *Z*-Score score to ensure their comparability. This approach indicates the mean and SD of the original data information to standardize it. The processed data obey the conventional standard distribution, which means the mean value is zero, the SD is one, and the transformation equation is given in Equation (4).

$$Y_{zscore} = \frac{Y_{inst} - V}{\delta} \quad (4)$$

Where, Y_{inst} denotes the initialized characteristic value, V represents the mean characteristic vector, and δ indicates the SD. The results are normalized data with a 0 mean as well as unit variance, and allow for accurate assessments, decreased biases, along enhanced performance of models in identifying psychological stress.

3.4. Feature extraction

The purpose of feature extraction is to convert the biosensor data into significant patterns, which allows reliable classifying of emotional conditions and elevated stress levels to provide efficient psychological intervention as well as monitoring. The feature extraction involves some approaches such as PSD for EEG, FFT for biomechanical sensors, and time-domain analysis for Skin Conductance and Heart Rate Sensors.

3.4.1. Power spectral density (PSD)

After preprocessing, PSD was employed as a feature extraction technique in this investigation. The purpose of PSD is to analyze EEG data signals by detecting brainwave activities in various frequency bands that reflect stress, emotional conditions, as well as cognitive burden in teachers. PSD is an effective technique for fixed signal processing as well as is beneficial for narrowband signals. This is a frequent signal processing method that distributes power from signals across frequencies along with indicating the energy strength as an operation of frequency. The present investigation used the Welch and Burg methods as part of the PSD.

- Welch method: A Welch method comprises a refined segmentation technique that is utilized to determine the averaged periodgram. In general, the Welch technique of the PSD could be described by the equations listed below, with the power of the spectra densities equation initially. After that, the Welch Power Spectrum expresses a mean average of the periodgram for every interval. Equation (5) & (6) expresses the power spectral density and average power spectral density.

$$P(f) = \frac{1}{MU} | \sum_{m=0}^{N-1} w_j\,(m) x(m) f^{-i2\pi e} |^2 \tag{5}$$

$$P_{welch}(f) = \frac{1}{K} \sum_{j=0}^{K-1} P(f) \tag{6}$$

where $P(f)$ denotes power spectral density at frequency f, $P_{welch}(f)$ indicates average power spectral density over k segments.

- Burg method: A Burg technique reduces forward as well as backward forecast errors, allowing it to fulfill the Levinson-Durbin Recursion. As the sequence of the Burg Method increases, reliability decreases and incorrect peaks appear in the spectra. That is, the Burg approach is highly ideal for smaller data sets since it can make accurate predictions and always results in a stable approach. The Burg technique for PSD is calculated using Equation (7):

$$P_{burg}(f) = \frac{\hat{F}_p}{|1 + \sum_{l=1}^{p} \hat{b}_p\,(l) f^{-2i\pi f}|^2} \tag{7}$$

where $P_{burg}(f)$ denotes power spectral density at frequency f, p is the burg model order. It concludes that the frequency domain information features power in the theta, alpha, and beta bands. These characteristics assist in the classification of elevated stress levels, emotional conditions, as well as cognitive load, which allows for early intervention.

3.4.2. Fast Fourier Transform (FFT)

After the process of PSD, FFT is used as another feature extraction technique. The purpose of the FFT is to assess biomechanical sensor signal information by extracting the frequency-domain aspects that indicate muscular tension as well as movement patterns associated with physical stress along with emotional states. The PSD data has been determined through Fourier converting the predicted autocorrelation series obtained using nonparametric approaches. The data series is then utilized for data filtering, producing enhanced periodograms. The data series, $w_j(m)$, is given in Equation (8).

$$w_j(m) = w(m + jC), m = 0,1,2, \dots, N - 1 \; while \; j = 0,1,2, \dots, K - 1 \tag{8}$$

Consider jC to indicate the starting point of the j^{th} series. Therefore K of length N indicates the data parts that are produced. In the filtering operation, V represents the power's regularization factor which has been selected and the following Equation (9) provides expression for V.

$$V = \frac{1}{N} \sum_{m=0}^{N-1} x^2(m) \tag{9}$$

where $x(m)$ represents the filtering operation. It concludes that the FFT separates frequency factors, which exposes muscular tension as well as movement frequency patterns. These characteristics help to recognize stress-related physical reactions, which contributes to precise psychological monitoring along with timely intervention for teachers' mental wellness.

3.4.3. Time-domain analysis

The FFT is fed into the Time-domain analysis. The purpose of Time-domain analysis is to extract features like HRV and skin conductance level to assess emotional arousal and stress, which reflects the teacher's psychological state for intervention. It is a technique for analyzing the biosensor data by tracking its modifications over an extended period. The time-domain analysis concentrates on extracting the significant characteristics from signals such as heart rate as well as skin conductance to determine both physiological and emotional conditions.

- Regarding heart rate, time-domain analysis entails measuring fluctuations in heart rate intervals across time that provide data on the autonomic nervous system's reaction to stress. HRV is an important outcome here, and a lower HRV suggests a greater level of stress and emotional strain.
- Skin conductance assessment concentrates on the changes in the electrical conductivity of the skin within the response to certain emotional stimuli. These features result in skin conductance level (SCL) and SCR which are indicators of

emotional arousal. A greater SCL indicates more emotional tension and anxiety, whereas SCR captures brief reactions to emotional experiences.

It concludes that the time domain analysis features provide insights into emotional states, which enable timely stress identification as well as intervention for teachers' mental well-being, and enabling monitoring and intervention for stress and burnout prevention.

3.5. Feature fusion

Then, feature concatenation is done after the process of feature extraction for feature fusion. Feature fusion is a process of merging several features obtained from various sensors or data sources into one that will better describe the system state. In the context of psychological monitoring using biosensors, concatenation simply involves joining the feature vectors from the different modalities such as EEG, biomechanical sensors, skin conductance, and heart rate into a single long vector. That vector then encapsulates the data from all the sensors and thus allows for a much deeper understanding of the psychological and physiological state.

Feature concatenation after the extraction of features from EEG data, skin conductance, and heart rate, together with biomechanical signals, means that all these extracted features are joined into one vector that can be used as input to the IDBI-FFNN-TPMIM model for classification or prediction. This approach ensures that the model is able to take advantage of multiple sources of data and improves its ability to accurately classify the emotional states along with detecting stress and burnout.

3.6. Model development

In this model development, IDBI-FFNN-TPMIM is utilized for monitoring and intervening in teachers' psychological stress, and emotional states, enhancing well-being and preventing early burnout indicators. The IDBI-FFNN-TPMIM is the integration of Intelligent Bottlenose Dolphin optimization (IBD), and Inspired Feed forward Neural Network (FFNN).

3.6.1. Inspired Feed forward Neural Network (FFNN)

After the feature fusion, FFNN is employed to classify teachers' emotional conditions as well as stress levels through examining biosensor data, which allows more precise psychological monitoring as well as prompt interventions for mental health treatments. FFNNs are artificial neural networks (ANN) that process data in a single direction through input, hidden, and output layers. They are used for classification, regression, and prediction. A fully-connected FFNN having two hidden layers (G) is described in Equation (10).

$$\hat{z} = e(G_2X_2 + a_3) with G_2 = e(G_1X_2 + a_2) and G_1 = e(wX_1 + a_1) \tag{10}$$

The output vector represents $\hat{z}$, the input vector w comprises sample characteristics, X represents the weight matrices, and a represents the bias vector for every separate layer. The hidden layers contain the tangent hyperbolic activation function (e) that is stated in the Equation (11).

$$tang(w) = \frac{f^{w} - f^{-w}}{f^{w} + f^{-w}} \tag{11}$$

This operation constitutes a rescaling of the logistic sigmoid operation, having an output interval ranging from $[-1, 1]$. The vector G includes the values from the hidden layers. The FFNN design could be modified as follows and specified that y defines the true operation in Equation (12).

$$\hat{z} = \hat{z}(w, X, a) \; and \; \{a', X'\} = Arg\left\{\min_{a,X}(\hat{z}, z)\right\} \tag{12}$$

The loss function $\mathcal{L}$ decreases to determine optimal weights X' and biases a' of a trained neural networking approach. **Figure 3** illustrates the architecture of FFNN. The fully connected FFNN architecture contains an input layer that has 3 features, two hidden layers have 8 neurons and the output layer has three outputs neutral, negative, and positive. The FFNN's outcome represents a classification of emotional states (such as neutral, negative, or positive), and stress levels, which allows for early intervention to improve teachers' mental health.

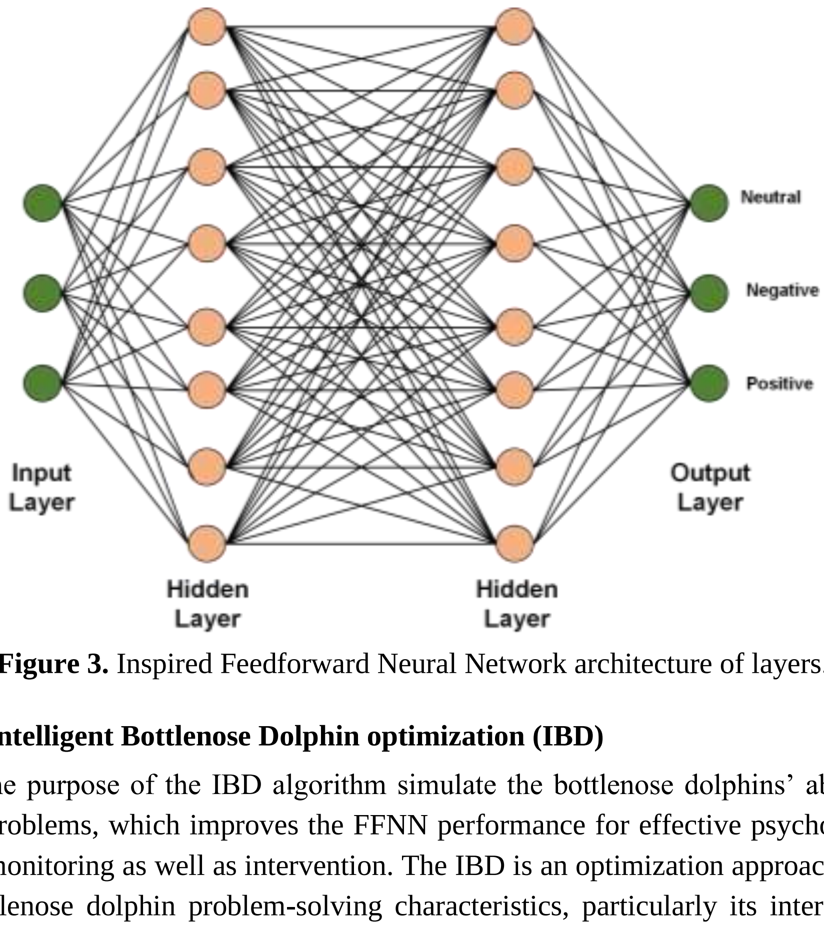

Figure 3. Inspired Feedforward Neural Network architecture of layers.

3.6.2. Intelligent Bottlenose Dolphin optimization (IBD)

The purpose of the IBD algorithm simulate the bottlenose dolphins' ability to solve problems, which improves the FFNN performance for effective psychological stress monitoring as well as intervention. The IBD is an optimization approach based on bottlenose dolphin problem-solving characteristics, particularly its interactions, social behaviors, as well as echolocation capabilities. Regarding psychological monitoring, IBD is implemented to improve the accuracy and effectiveness of models, which analyze the biosensors data. Through generating dolphin characteristics that include collaboration among groups and echolocation to facilitate data gathering, IBD efficiently chooses the significantly important characteristics from the processed data to improve the effectiveness of the model. This technique improves the identification of stress, emotional states, as well as early burnout symptoms in teachers, and allows for prompt interventions. The resultant of IBD is expressed in Equation (13).

$$Fitness(X) = \frac{1}{1 + \sum_{i=1}^{n} |TrueState_i - PredictedState_i|} \quad (13)$$

where X indicates the chosen characteristic set, $TrueState_i$ represents the true emotional or stress condition, $PredictedState_i$ denotes the model forecasted condition depending on the chosen characteristic, and the $Fitness$ function reduces the error among forecasted and true countries, improving the characteristic for improved classification efficiency performance. It concludes that the IBD improves the characteristics, enhancing the accuracy of emotional condition classification, detecting early stress, and offering appropriate early interventions, resulting in improved mental health management for teachers.

3.6.3. Intelligent Bottlenose Dolphin-Inspired Feed Forward Neural Networks based Teacher Psychological Monitoring and Intervention Model (IDBI-FFNN-TPMIM)

The IDBI-FFNN-TPMIM integrates an FFNN with the IBD optimization technique to monitor and intervene in teachers' psychological well-being. The FFNN is used to process and classify biosensor data to detect teachers' emotional and stress levels. It learns patterns in the sensor data to predict stress and burnout while classifying the emotional states into neutral, negative, or positive. The IBD optimization algorithm enhances this model by improving the characteristic selection and mimicking the problem-solving strategies of bottlenose dolphins to optimize network performance. It refines the FFNN by selecting the most relevant features from the sensor data, which ensures a more accurate classification of psychological states. The IDBI-FFNN-TPMIM model provides real-time feedback and interventions, which offer targeted support to teachers for early stress detection as well as mental health management.

4. Performance analysis

The aim is to generate a biosensor-based model with deep learning (DL) for monitoring and intervening in teachers' psychological stress, and emotional states, enhancing well-being and preventing early burnout indicators. The Python software with version 3.8 is utilized for this research. This section outcome includes feature importance, confusion matrix, performance metrics, error metrics, accuracy loss, intervention feedback response, impact of emotional states, and teacher satisfaction with the intervention system.

4.1. Feature importance

The objective of the feature importance is to recognize the important physiological markers that most efficiently forecast teacher emotional as well as psychological states, and this guide optimizing models for precise stress and emotion monitoring. **Table 5** shows the most relevant physiological markers that are significantly contributing to the prediction and monitoring of teachers' emotional and psychological states. It contains the important physiological features, which influence stress recognition in teachers, like EEG (alpha, beta, and theta), HRV, muscle tension, posture variability, and SCR. The output identifies EEG power, muscle tension, and HRV as significant for accurate psychological monitoring, and suggests these features guide effective stress intervention strategies.

Table 5. Insight into the relative significance of these features.

Feature	Importance Score
EEG Alpha Power (8–12 Hz)	0.25
EEG Beta Power (13–30 Hz)	0.20
EEG Theta Power (4–8 Hz)	0.05
Heart Rate Variability (HRV)	0.22
Posture Angle Variability	0.15
Muscle Tension	0.10
Skin Conductance Response (SCR)	0.13

4.2. Confusion matrix

To assess the efficiency of the emotional state classification approach by demonstrating how effectively it estimates teacher emotional states (Neutral, Negative, and Positive) and identifying the misclassifications. **Figure 4** illustrates the confusion matrix and shows how well the model classified emotional states of the utterances as a tool for performance evaluation. It concludes that the confusion matrix correctly forecasts the teacher's emotional states, and there are few misclassifications. Higher true positives suggest a superior classification of neutral, negative, and positive emotional states for purposes of intervention.

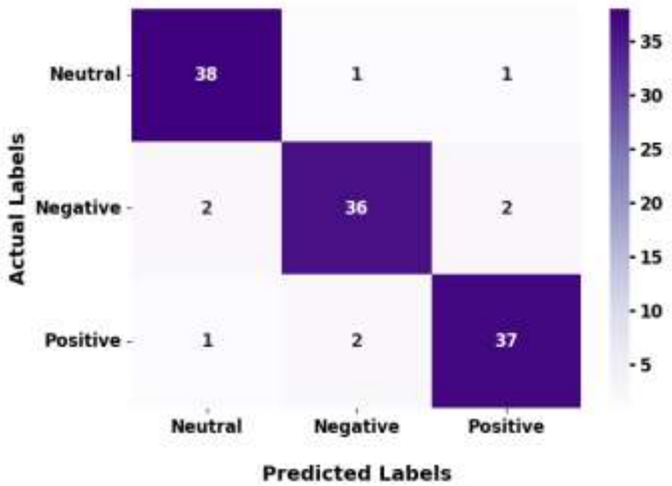

Figure 4. Confusion matrix performed for model classified emotional states.

4.3. Performance metrics

The included performance metrics are accuracy, precision, recall, and f1-score. The purpose of accuracy is to evaluate the approach's entire accuracy by determining the percentage of proper forecasts across every state of emotions in teacher psychological monitoring. The purpose of precision is to assess the capability of the approach to accurately detect positive emotional states while decreasing false positives and assuring that stated stress, as well as emotional condition, is indeed present. The purpose of recall is to evaluate the ability of the approach to detect every true occurrence of stress as well as emotional discomfort, reducing false negatives and ensuring immediate intervention. The purpose of the $f1$-score is to balance recall and precision, which gives a single result to assess the approach's entire capacity to identify as well as classify emotional states efficiently and maintain consistency. **Figure 5** and **Table 6** show the accuracy, precision, recall, and $F1$-score of the model. This shows the capability of the model in terms of emotional state classification. The outcomes of the performance metrics in IDBI-FFNN-TPMIM demonstrate robust performance in classifying emotional states. 93.7% high accuracy shows the overall effectiveness of the model in predicting emotional states. Precision (92.3%) measures the frequency of actual instances among the positive predictions, which underlines the model's capability of not creating false positives. Recall (91.5%) shows how well the model detects all actual instances of emotional states, emphasizing the importance of minimizing false negatives for timely interventions. F1-Score (91.1%) gives the balance between precision and recall, hence the model performs well consistently in both aspects. The IDBI-FFNN-TPMIM approach efficiently monitors teachers' emotional states, which offers dependable classifications for psychological intervention and assuring immediate as well as correct assistance for teacher well-being.

Table 6. Numerical outcomes of performance metrics.

Parameters	**Value (%)**
$F1$-Score	91.1
Accuracy	93.7
Recall	91.5
Precision	92.3

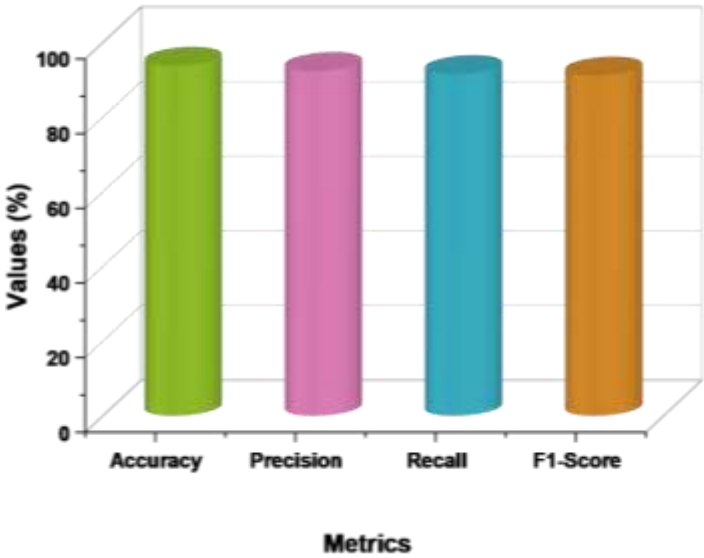

Figure 5. Graphical depiction of performance metrics outcomes.

4.4. Error metrics

The following error measures are considered in this research: root mean square error (RMSE), mean square error (MSE), and mean absolute error (MAE). The aim of the MAE is to assess the average absolute variance between forecasted and real values, which indicates the reliability of the model as well as the capability to forecast the stress levels of teachers. The purpose of the MSE, the average squared variance between anticipated and real outcomes is quantified, which emphasizes greater mistakes and makes it valuable for assessing the effectiveness of models in detecting stress. The RMSE is the square root of MSE provides an estimation of forecasting accuracy within the original measures, which demonstrates the amount of the approach error in predicting teacher emotional states. **Figure 6** displays error metrics such as MAE, MSE, and RMSE. These metrics assess the model's prediction accuracy and reliability. It concludes that the IDBI-FFNN-TPMIM method accurately forecasts teacher stress as well as emotional states while reducing error metrics and suggesting enhanced model efficiency performance across iterations.

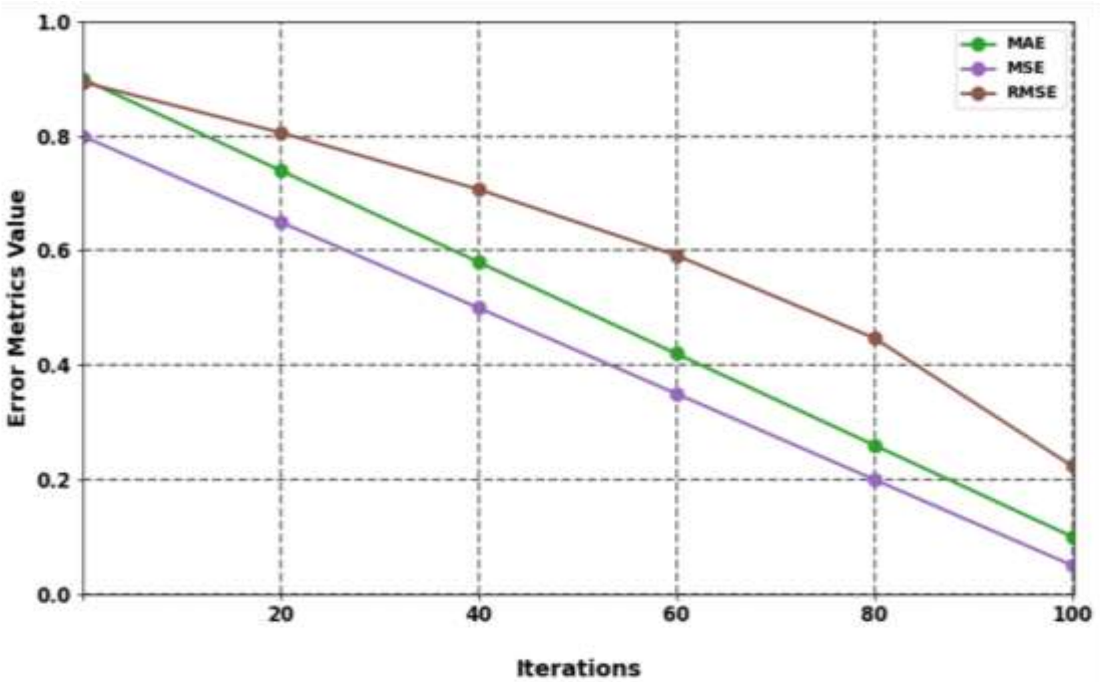

Figure 6. Graphical depiction of error metrics outcomes.

4.5. Accuracy loss

The purpose of the accuracy loss is to quantify the decrease in efficiency, which demonstrates improvements in the model. It facilitates monitoring the effectiveness of the intervention approach by observing how it decreases over iterations and results in more accurate predictions. **Figure 7** shows a constant decrease in accuracy loss, indicating that the model's predictive abilities are continuously increasing. It concludes that the accuracy loss reduces progressively, which indicates the IDBI-FFNN-TPMIM approach efficiently enhances their predictive capabilities. The consistent reduction in the accuracy loss indicates effective model training as well as psychological monitoring.

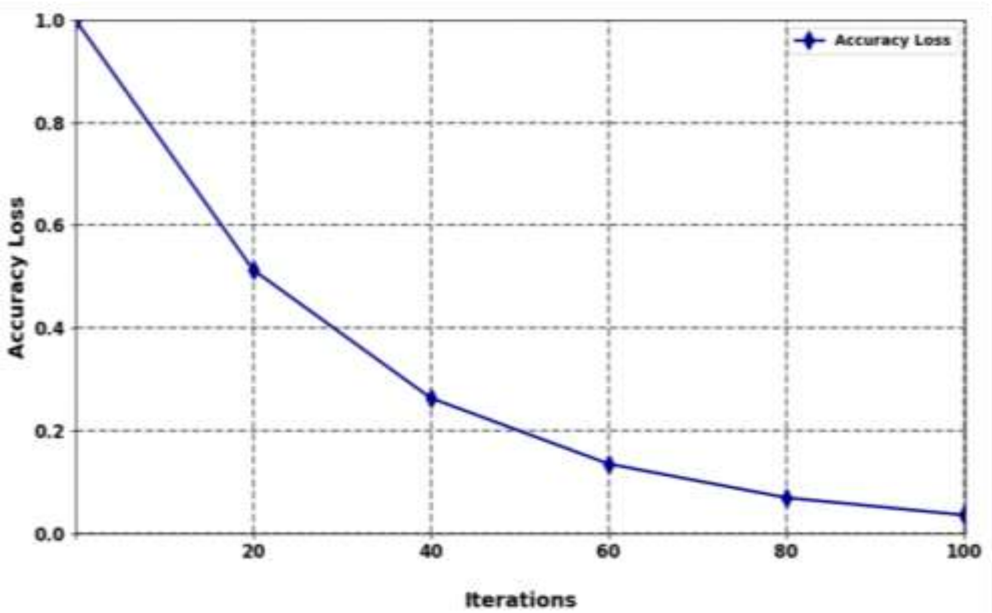

Figure 7. Graphical depiction of the outcome of accuracy loss.

4.6. Intervention feedback response

The purpose of intervention feedback response is to highlight teachers' involvement rates across different intervention types, which indicates the efficiency of every intervention type in managing psychological stress as well as emotional well-being. **Table 7** and **Figure 8** provide information on the effectiveness of various intervention methods based on the participation of teachers. It concludes that the higher involvement with stress management exercises as well as breathing methods shows their efficacy, but counseling referrals along with peer support sessions were having middling responses.

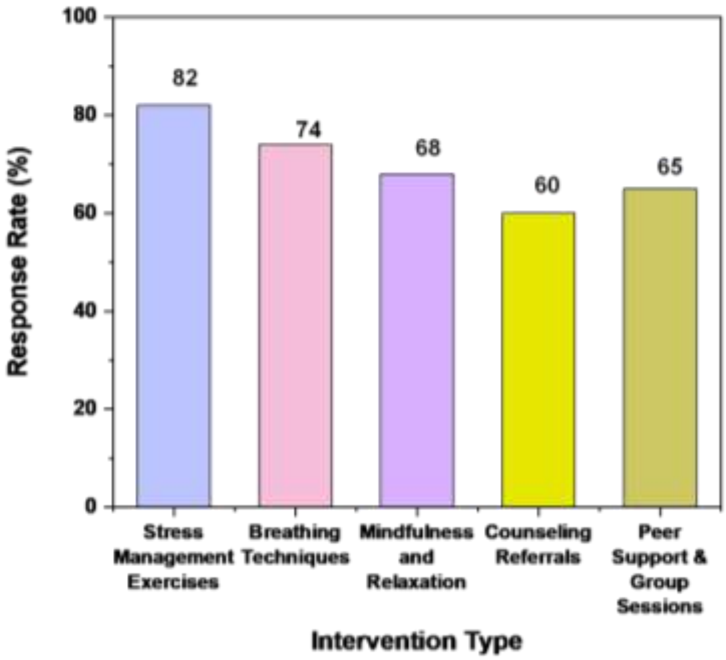

Figure 8. Intervention feedback response based on the participation of teachers.

Table 7. Intervention feedback response.

Intervention Type	Response Rate (%)
Stress Management Exercises	82
Breathing Techniques	74
Mindfulness and Relaxation	68
Counseling Referrals	60
Peer Support & Group Sessions	65

4.7. Impact of emotional states

The purpose of emotional states impact is to examine the efficacy of the interventions to enhance teachers' emotional states, lowering stress, along increasing entire psychological well-being using pre- and post-intervention evaluations. **Table 8** compares emotional states before and after the interventions. **Figure 9** represents the shift in emotional states from pre- to post-intervention. It concludes that the interventions substantially decreased negative emotional states while increasing neutral emotional states, which suggests their efficacy in enhancing teachers' psychological health and stress management.

Table 8. Emotional states among teachers.

Emotional State	Pre-Intervention (%)	Post-Intervention (%)
Neutral	70.1	80.4
Negative	20.3	13.5
Positive	9.6	6.1

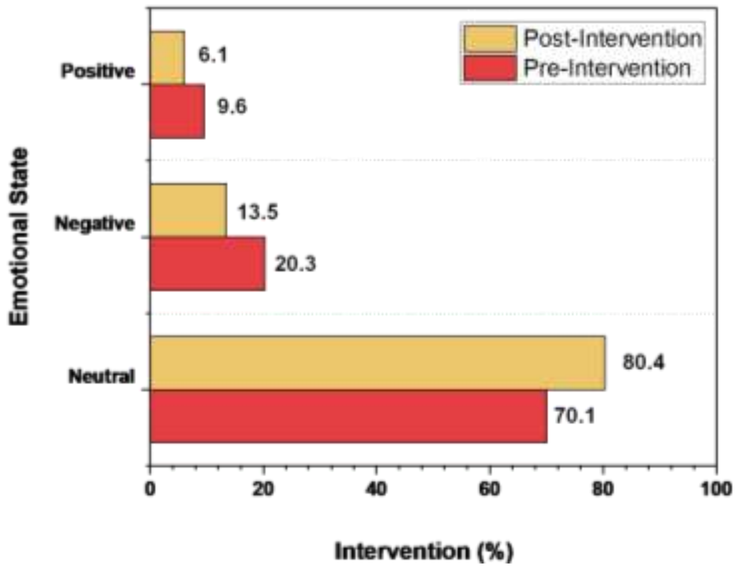

Figure 9. Emotional states among teachers based on pre- and post-intervention.

5. Discussion

This research explores the usage of biosensor technology for monitoring teachers' psychological health and providing targeted interventions to improve mental health and performance. Traditional biosensor technologies for teacher psychological monitoring have most often relied on heart rate, skin conductance, and brain activity for the measurement of stress, anxiety, and mental well-being. These have a number of disadvantages. For instance, they tend to be intrusive, with the teacher required to wear sensors that may be uncomfortable or distracting. In addition, there are possible shortcomings in that they may not be real-time insightful or easily adaptable to diversified environments. External factors, such as physical activity or environmental conditions, may affect the accuracy of such measures, and the complexity of psychological states cannot be fully captured by measures. Traditional methods may also not be integrated with other data sources, further limiting their effectiveness in providing comprehensive and personalized interventions. In **Table 7**, the outcomes of the response rate in intervention types are 82% in Stress Management Exercises, 74% in Breathing techniques, 68% in Mindfulness and Relaxation, 60% in Counseling referrals, and 65% in Peer Support & Group Sessions. In **Table 8**, the outcomes of Emotional states among teachers, the pre-intervention outcomes are 70.1% neutral, 20.3% in negative, 9.6% in positive, and post-intervention are 80.4% in neutral, 13.5% in negative, 6.1% in positive. This research indicates that integrating biosensor technology with DL models effectively monitors teachers' mental health provides timely interventions, as well as improves overall emotional well-being and stress management. IDBI-FFNN-TPMIM seems to be obvious better managing teachers' mental health through real-time, precise psychological monitoring and emotion recognition with biosensor data. Thus, it allows for early detection of stress and burnout, enabling timely interventions with personalized well-being support.

6. Conclusion

This research mainly focused on the usage of biosensor technology for monitoring the teachers' psychological health and providing targeted interventions to improve mental health and performance. The proposed IDBI-FFNN-TPMIM method achieved superior performance in performance metrics are accuracy (93.7%), precision (92.3%), recall (91.5%), and F1-score (91.1%), reduced error, accuracy loss reduced progressively, higher involvement with a stress management exercise and breathing methods show their efficacy, decreased negative emotional states, and increasing neutral emotional states. The present research effectively monitors teachers' mental health and provides timely interventions, as well as improved overall emotional health and stress management. Future research could focus on including more participants and improving accuracy.

Ethical approval: Not applicable.

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

References

1. Emeljanovas, A., Sabaliauskas, S., Mežienė, B. and Istomina, N., 2023. The relationships between teachers' emotional health and stress coping. Frontiers in psychology, 14, p.1276431. https://doi.org/10.3389/fpsyg.2023.1276431

2. Ghasemi, F., Gholami, J., Issazadegan, A. and Mohammadnia, Z., 2023. A pilot study of acceptance and commitment therapy to improve teachers' psychological well-being. Advances in Mental Health, 21(3), pp.228-246. https://doi.org/10.1080/18387357.2023.2200010
3. Dalal, S., 2023. Biosensors as recognition tool for bioelements. In Multifaceted Bio-sensing Technology (pp. 151-168). Academic Press. https://doi.org/10.1016/B978-0-323-90807-8.00004-X
4. Hemdan, M., Ali, M.A., Doghish, A.S., Mageed, S.S.A., Elazab, I.M., Khalil, M.M., Mabrouk, M., Das, D.B. and Amin, A.S., 2024. Innovations in Biosensor Technologies for Healthcare Diagnostics and Therapeutic Drug Monitoring: Applications, Recent Progress, and Future Research Challenges. Sensors (Basel, Switzerland), 24(16), p.5143. https://doi.org/10.3390/s24165143
5. Sharma, A., Badea, M., Tiwari, S. and Marty, J.L., 2021. Wearable biosensors: an alternative and practical approach in healthcare and disease monitoring. Molecules, 26(3), p.748. https://doi.org/10.3390/molecules26030748
6. Nokelainen, P., Pylväs, L. and Hartikainen, S., 2024. University teachers' self-reported emotions and electrodermal activity during teaching-related working events. Studies in Higher Education, pp.1-20. https://doi.org/10.1080/03075079.2024.2387750
7. Hayati, S. and Karim, A., 2024. The Development and Application of Biosensors in Medical Diagnostics in Indonesia. International Journal of Public Health, 1(3), pp.43-52. https://doi.org/10.62951/ijph.v1i3.68
8. Wasilewski, T., Kamysz, W. and Gębicki, J., 2024. AI-Assisted Detection of Biomarkers by Sensors and Biosensors for Early Diagnosis and Monitoring. Biosensors, 14(7), p.356. https://doi.org/10.3390/bios14070356
9. Shivakumar, N., 2024. Recent Advances in Biological Nanodevices and Biosensors: Insights into Applications and Technological Innovations. Malaysian NANO-An International Journal, 4(1), pp.86-101. https://doi.org/10.22452/mnij.vol4no1.6
10. Kern, L., Weist, M.D., Mathur, S.R. and Barber, B.R., 2022. Empowering school staff to implement effective school mental health services. Behavioral Disorders, 47(3), pp.207-219. https://doi.org/10.1177/01987429211030860
11. Maclean, L. and Law, J.M., 2022. Supporting primary school students' mental health needs: Teachers' perceptions of roles, barriers, and abilities. Psychology in the Schools, 59(11), pp.2359-2377. https://doi.org/10.1002/pits.22648
12. Bhatia, D., Paul, S., Acharjee, T. and Ramachairy, S.S., 2024. Biosensors and their widespread impact on human health. Sensors International, 5, p.100257. https://doi.org/10.1016/j.sintl.2023.100257
13. Li, K., 2024. Using biosensors and machine learning algorithms to analyse the influencing factors of study tours on students' mental health. Molecular & Cellular Biomechanics, 21(1), pp.328-328. https://doi.org/10.62617/mcb.v21i1.328
14. Palermo, E.H., Young, A.V., Deswert, S., Brown, A., Goldberg, M., Sultanik, E., Tan, J., Mazefsky, C.A., Brookman-Frazee, L., McPartland, J.C. and Goodwin, M.S., 2023. A Digital Mental Health App Incorporating Wearable Biosensing for Teachers of Children on the Autism Spectrum to Support Emotion Regulation: Protocol for a Pilot Randomized Controlled Trial. JMIR Research Protocols, 12(1), p.e45852. https://doi.org/10.2196/ 45852
15. Smith, M., Withnall, R., Anastasova, S., Gil-Rosa, B., Blackadder-Coward, J. and Taylor, N., 2023. Developing a multimodal biosensor for remote physiological monitoring. BMJ Mil Health, 169(2), pp.170-175. https://doi.org/10.1136/bmjmilitary-2020-001629
16. He, L. and Han, S., 2024. Application of wearable nano biosensor in sports. Molecular & Cellular Biomechanics, 21(1), pp.165-165. https://doi.org/10.62617/mcb.v21i1.165
17. Francisti, J., Balogh, Z., Reichel, J., Benko, Ľ., Fodor, K. and Turčáni, M., 2023. Identification of heart rate change during the teaching process. Scientific Reports, 13(1), p.16674. https://doi.org/10.1038/s41598-023-43763-x
18. Zai, X., 2024. Leveraging Bio-Sensing Technology and IoT for Optimizing Spanish Vocabulary Instruction Across Chinese and Western Cultures: A Biotechnological Approach. Journal of Commercial Biotechnology, 29(3), pp.305-314.https://doi.org/10.5912/jcb1822
19. Hsu, S., Sung, C.C. and Sheen, H.J., 2020. Developing an Interdisciplinary Bio-Sensor STEM Module for Secondary School Teachers: An Exploratory Study. Вопросы образования, (2 (eng)), pp.230-251. https://doi.org/10.17323/1814-9545-2020-2-230-251
20. Indrianti, Y. and Hermanus, D.R., 2023, September. Developing Instrument for Teacher Wellbeing Face Recognition Application. In 2023 10th International Conference on ICT for Smart Society (ICISS) (pp. 1-6). IEEE. https://doi.org/10.1109/ ICISS59 129. 202 3. 10291992

21. McKenna, J.W., Newton, X. and Brigham, F., 2023. Impact of co-teaching on general educator self-reported knowledge and use of inclusive practices for students with emotional and behavioral disabilities: A pilot investigation. Psychology in the Schools, 60(8), pp.2782-2794. https://doi.org/10.1002/pits.22890