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Artificial Intelligence Technology-Driven Teacher Mental State Assessment and Improvement Method

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ABSTRACT

With the development of technology, people expect real-time communication with computers. Wearable devices, such as those for monitoring physiological signals, have rapidly developed and are now being applied in college and university evaluation. Due to the non-standard and unscientific practices in teaching, teachers may experience psychological obstacles when evaluating students. To ensure successful evaluation, we must motivate teachers to correctly understand and actively participate in the evaluation process, thus facilitating communication between people and computers. Emotion recognition based on multi-physiological signals, such as ECG, pulse, electromyography, electrodermal, and respiratory signals, is an effective method for achieving this. This dissertation conducts in-depth research on the methods for emotion recognition based on multi-physiological signals. It explores feature extraction methods, feature selection, and fusion to provide objective assessments of physiological and psychological activity states, which are used as a basis for accurate emotional judgments.

KEYWORDS

Artificial Intelligence, Higher Education Evaluation, Mental State, Teachers

China is currently in a period of social transformation and facing major economic changes. This period is characterized by rapid changes in social structure, people's lifestyles and behavioral patterns, and changes in national culture and social values (Mallik & Gangopadhyay, 2023). As the pace of life accelerates, interpersonal relationships become more complex and social competition becomes increasingly intense (Guo et al., 2020). These changes place a greater psychological burden on members of society, which can lead to feelings of anxiety, depression, and despair. The resulting mental health problems adversely affect the physical and mental health of individuals and have therefore attracted widespread attention from society. Social transformations have had a profound impact on all aspects and groups of society (Gilham et al., 2021).

Colleges and universities play a vital role in nurturing talents, advancing scientific and technological development, and contributing to social progress (Bauer et al., 2020). Among the resources within these institutions, college teachers hold a special social status due to their specific

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roles and responsibilities (Wu et al., 2020). They serve as the cornerstone for fulfilling the mission and responsibilities of colleges and universities (Kolenik & Gams, 2021). Within the broader education system, however, college teachers face new challenges and pressures that can lead to psychological issues with significant societal implications (Maltby et al., 2020). The mental health of college teachers has become an increasingly important societal concern (Kaczmarek-Majer et al., 2022). Addressing the psychological crisis among college teachers is crucial for the reform and development of higher education in the country (Dham et al., 2021).

Teachers' occupational stress arises from a combination of external objective stressors and internal subjective perceptions (Saini & Gupta, 2022). While greater objective stimuli typically result in higher pressure (Dimitriadou & Lanitis, 2023), individual personality traits lead to varying levels of perceived stress under the same conditions (Chen et al., 2023). Factors such as needs, motivation, cognitive style, personality characteristics, ability, self-expectation, and experience play key roles in shaping teachers' internal stress mechanisms (Denecke et al., 2021).

Teachers, like individuals in other professions, have diverse needs that encompass physiological and social aspects, aligning with Maslow's hierarchy of needs theory (Molala & Makhubele, 2021). The field of education demands a systematic approach due to its unique operational mechanisms, leading teachers to develop specific needs such as material simplicity, developmental stability, self-esteem urgency, and achievement intensity (Antoniou et al., 2022). Meeting these needs is crucial for motivation and involves a cyclical process of desire, action, fulfillment, and the emergence of new motivations and needs (Kamalov et al., 2023). When needs are consistently unmet, individuals may experience negative emotions such as depression and anxiety, ultimately contributing to occupational stress (Diao, 2020).

A teacher's psychological state has a significant impact on aspects such as job effectiveness, student learning experience, and academic outcomes. Assessing a teacher's psychological state and developing appropriate intervention strategies are necessary in order to understand their mood, stress levels, and job satisfaction, among other things. In recent years, artificial intelligence technology has been widely used in education (e.g., to monitor students' learning progress and comprehension), but it can also be used to assess teachers' psychological states; after which, it is necessary to develop appropriate improvement methods and intervention strategies including measures for emotional regulation, stress management, and work environment optimization. In contrast, combining with AI technology, it is possible to explore personalization-based methods for improving teachers' psychological states in order to enhance their well-being, job satisfaction, and professional development.

Emotion recognition is a significant area of research (Adikari et al., 2021). Despite the rapid development of artificial intelligence, researchers have discovered that computers, in spite of possessing logical reasoning, superior memory capacity, and faster computing power than the human brain, still cannot match human performance (Verma et al., 2023). In a shorter span of time, the brain can make optimal decisions. As a result, failure to recognize emotions not only impairs a computer's decision-making ability but also its communicative capacity with humans (Rajaei, 2024). With technological advancements, human-computer interaction has moved beyond the use of just keyboards and mice; users now anticipate more natural communication with computers, and emotions must be recognized to achieve this goal. Wearable devices, such as wristbands, and miniature portable body monitoring systems are increasingly prevalent in daily life. These devices acquire bodily signals such as heart rate, blood pressure, skin temperature, and respiration, enabling analysis of the wearer's current emotional state and provision of health reminders or recommendations. Similarly, emotion recognition technology can benefit professionals such as drivers, pilots, and doctors whose negative emotions could endanger others. An angry driver or pilot, for instance, poses a threat to themselves and those around them. Emotion recognition systems, through emotion monitoring, can identify such circumstances and alert the driver or pilot in real time, thus reducing the likelihood of accidents.

Emotion recognition technology plays an important role in teacher training. It assesses the level of emotional intelligence of teachers by analyzing their voice along with nonverbal expressions. It tailors personalized training plans, providing targeted training on emotion management, and continuously optimizes the plan through real-time data feedback in order to enhance teachers' emotion management ability and teaching quality and ensure the effectiveness and sustainability of the training. These initiatives will help promote teachers' professional growth and enhance the overall development of the education sector.

In this study, we examined the manifestations of teachers' psychological states and the theories of the causes of psychological crises including need-driven, cognitive dissonance, and attribution theories. Meanwhile, the definition, goals, and application scope of psychological crisis intervention were analyzed. We also described the theoretical foundations of feature extraction methods including time-domain feature extraction, time-frequency domain feature extraction, and empirical modal decomposition. Through experimental simulation using the public wearable stress and affect detection dataset (WESAD), wavelet threshold denoising, and time window segmentation of ECG signals were performed, and different models were used to classify and identify human psychological states. Finally, we evaluated and comparatively analyzed the results of the experimental models including different classification models for internal and external trends and those for two types of depression. Through these studies, we aimed to better understand and assess teachers' mental health and to provide guidance and support for psychological crisis intervention.

RELATED CONCEPTS AND THEORETICAL BASIS

Determination of Related Concepts

College Teachers

With regard to teachers, it is evident that college educators constitute a distinct cohort. In contrast to other societal cohorts, college teachers possess unique social roles, occupational characteristics, and psychological needs. The distinctive attributes of teachers are detailed in subsequent sections.

Psychological Crisis

The theory of crisis was initially introduced in 1944 by Lindemann(Lindemann, 1944), who formulated the notion of "pain work," which served as a significant foundation for crisis intervention theory during that era. Subsequently, Lindemann's theory was expanded upon and refined, leading to the formulation and systematic exploration of the concept of psychological crisis. A psychological crisis occurs when an individual experiences distress or an imbalanced state.

According to the research findings of psychologist Glass (Glass & Wright, 1992), "a crisis refers to the harm inflicted by external stimuli or a forceful impact." He defines a psychological crisis as "the combination of the immediate problem's difficulty, significance, and the resources available to address it." Psychologist posited that "a psychological crisis manifests as a response when an individual is unable to cope with the current external or internal stressors using their customary methods or mechanisms for stress management."

While there is no consensus within the academic community regarding a unified perspective on psychological crises, the aforementioned viewpoints share similar connotations. Psychological crises can be understood as a state of psychological imbalance that emerges alongside crisis events. When individuals or groups confront sudden or significant life adversities, their existing resources and coping mechanisms prove insufficient to address the resulting psychological imbalances. This state exhibits three key characteristics: psychological tension and confusion, short-term and transient duration, and an intractable predicament that lacks a more effective resolution.

Related Theoretical Analysis

The Theory of Causes of Psychological Crisis

The main idea of the theory of causes of psychological crisis is that all human behavior is driven by needs, which can be categorized into different levels. These needs act as a driving force, compelling individuals to continuously seek satisfaction, progressing from lower-level to higher-level needs. When individuals fail to meet or obtain these needs, they experience a change in their mental state characterized by invisible discomfort, loneliness, depression, and despair.

Individuals are constrained by their moral values, social context, historical period, and prevailing conditions. In the present social reality, the ongoing development of socialism is a gradual and perpetual historical process. Cognitive dissonance theory is a fundamental concept in sociological psychology. Failure to resolve cognitive dissonance in a timely and effective manner can lead to a psychological crisis.

Attribution theory primarily assists individuals in identifying internal factors (e.g., abilities) and external factors (e.g., external pressure, weather, or situational factors). According to Weiner(Weiner, 1985), when analyzing the reasons behind a person's success or failure, their personality traits and prior experiences of success or failure influence their attributions and subsequent behaviors. Attribution theory aids in identifying the causes of a crisis when resolving psychological crises.

Psychological Crisis Intervention Theory

Crisis intervention has multiple definitions. It is a technique that offers effective assistance and support to people experiencing a crisis. It aims to mobilize their inner potential, enabling them to regain their psychological equilibrium after a traumatic event. According to Zhai Shutao(Zhai, 1997), "crisis intervention is a brief supportive process that provides care and assistance to individuals experiencing distress or setbacks." The purpose is to restore a person's psychological balance and involves society members implementing measures to aid those in distress in overcoming the crisis and readjusting to life.

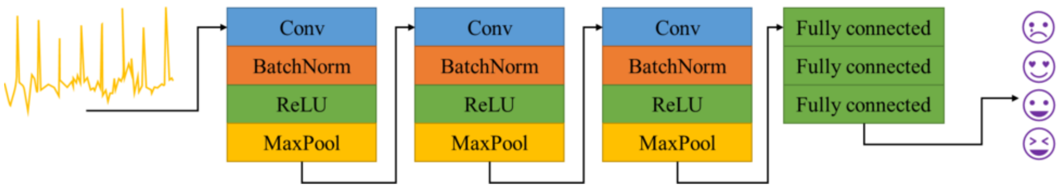
Crisis intervention can be defined as the process whereby the intervener utilizes emergency response techniques to assist the client in relieving the psychological distress associated with the crisis. This process aims to alleviate and eliminate symptoms, ultimately restoring psychological equilibrium. Psychological crisis intervention differs from general psychological counseling and treatment. It provides a distinct form of psychological counseling, serving as a short-term treatment designed for emergency situations. Its primary objective is to help individuals overcome difficulties within a limited timeframe, without seeking radical cures or personality correction. Instead, psychological crisis intervention focuses on problem-solving. It stands out from regular psychological counseling and treatment due to its emphasis on timely and rapid assistance. The effectiveness of the intervention relies on the proactive measures taken, which ultimately determine its success or failure.

Main Manifestations of the Psychological State of College Teachers

Psychological crises may manifest in cognitive, physical, emotional, behavioral, and interpersonal areas. Cognitively, individuals experiencing a psychological crisis may be overwhelmed by sadness, leading to changes in memory and perception, difficulty in distinguishing similarities and differences, and impaired thinking and decision-making abilities. Physically, there are uncomfortable symptoms such as insomnia, headaches, and fatigue. Nervousness, anxiety, emptiness, and loss are common emotional responses, accompanied by emotions such as fear, anger, and guilt. Individuals can also exhibit external behavioral changes in response to psychological stress. Interpersonally, there is a tendency for people to isolate themselves, avoid communication, and they may find it difficult to establish trusting relationships.

Teachers' emotional changes under stress are closely related to expectations and assessments of stress outcomes. Effectively coping with stress tends to result in positive emotional experiences when

Figure 1. CNN-Based Human Mental State Recognition Model



dealing with anxiety, fear, depression, and anger. Moderate anxiety increases alertness and coping skills, but excessive anxiety diminishes the ability to manage environmental change. Generalization of anxiety affects teachers' effective coping strategies.

In this study, we combined artificial intelligence technology and the field of education to explore forward-looking methods for assessing and improving teachers' psychological states. Teachers play a crucial role in the education system, and by examining methods for assessing and improving teachers' psychological states, their productivity and teaching quality can be enhanced, affecting the entire education system. The interdisciplinary nature of this research integrates the fields of AI technology and educational psychology, promoting cross-collaboration and innovation between different subject areas. The final results of this research provide educational institutions and teachers with effective tools for assessing psychological status and methods for improvement, which will help enhance teachers' work, well-being, and teaching effectiveness. With this research, we aim to achieve sustainable development and improve the quality of education.

METHODS AND MATERIALS

To ensure teacher privacy and data security, we anonymized the collected teacher sentiment data and limited access to only authorized researchers and professionals. At the same time, necessary technical measures were taken to secure the data including encrypted transmission, secure storage, and access control measures to prevent the data from being accessed by unauthorized personnel. In addition, emotion-recognizing technologies were used in compliance with relevant privacy regulations and ethical guidelines to ensure that the purpose of data collection and use was transparently communicated to faculty and relevant stakeholders.

Feature Extraction Method

Emotion recognition research, in which features of physiological signals are extracted, has a significant impact on the classification effect. Different features contain different information of the corresponding physiological signals. To study which features contain more signals in different emotional states, as shown in Figure 1, we used four distinct methods. Feature extraction includes time and HHT(Hilbert-Huang Transform)-based features. Although different types of features can reflect the physiological signal changes in different emotional states, too many features are prone to redundancy and optimal set before emotion classification and recognition.

Time Domain Feature Extraction

In the time domain, the corresponding feature extraction is mainly based on the waveform of the physiological signal. In different emotional states, the influence of physiological signals by emotion change the waveform of the signal. For example, when heart rate increases, the distance between the R peak points of the ECG signal will be shortened, that is, the PQRST wave will change at a fixed time, and the segment becomes denser. When the breathing rate increases, the waveform of the respiratory signal becomes narrower, and when the breathing deepens, the peak value of the respiratory signal increases. Therefore, when extracting time-domain features, it mainly extracts its statistical features including mean, mean square error, first-order difference, etc. The mathematical expressions of the extracted specific statistical features follow.

Mean: x_i denotes the value of the ith data point and N denotes the total number of signal data points.

$$\mu_x = \frac{1}{N}\sum_{n=1}^{N} X_n \tag{1}$$

Mean Square: This calculates the average of the squared difference between a signal and its mean, reflecting the degree of dispersion of the signal.

$$\sigma_x = \left(\frac{1}{N-1}\sum_{n=1}^{N}\left(X_n - \mu_x\right)^2\right)^{\frac{1}{2}} \tag{2}$$

First-order difference: The difference between neighboring data points is calculated and used to measure the rate of change of the signal.

$$\delta_x = \frac{1}{N-1}\sum_{n=1}^{N-1}\left|X_{n+1} - X_n\right| \tag{3}$$

Second order difference: Discretizing the data out twice, the correlation and volatility of the data can be further reduced by second-order differencing in the formula.

$$\gamma_x = \frac{1}{N-2}\sum_{n=1}^{N-2}\left|X_{n+2} - X_n\right| \tag{4}$$

The variables represent:

N: the total dimension of the sample points.
X_n: the data of the Nth sample point of the sample.
X_{n+1}: the data of the n+1 sample point of the sample.
X_{n+2}: the data of the n+2 sample point of the sample.

Time-Frequency Domain Feature Extraction

The wavelet transform is based on the short-time Fourier transform. In addition to the idea of localization, the size of the window corresponding to the window function is fixed, but the shape of the window is variable. Different frequencies have different resolutions.

Discrete wavelet transform is a kind that discretizes continuous wavelet transform, and discretizes scale variable and translation variable b. The formula is as follows:

$$b = ka_0^j b_0, j, k \in Z \tag{5}$$

The discrete wavelet function is:

$$\psi_{j,k}(t) = \frac{1}{\sqrt{a_0^j}} \psi\left(a_0^{-j} - kb\right) \tag{6}$$

Therefore, the discrete wavelet transform of f t() is:

$$\lambda_i = \lim_{\tau \to \infty} t \left[\frac{p_i(t)}{p_0(t)}\right] \tag{7}$$

We translated one signal into two signals, then mapped them to different reference spaces and represented the signal with wavelet coefficients including approximate coefficients and detail coefficients. The choice of basic functions in wavelet transform will affect the result of signal decomposition. According to the characteristics of physiological signals and the analysis of related literature, we selected the wavelet basis dbN under the Daubechies system to decompose the corresponding physiological signals, and its properties are as follows:

(1) dbN wavelet bases are mostly asymmetric.
(2) Regularity increases as N increases.
(3) The function is orthogonal.

The Theoretical Basis of Empirical Mode Decomposition (EMD)

The EMD algorithm was used to decompose the components of different frequencies in the signal, and the separated frequency components were different. These components are called "features." The number of zeros and poles in the IMF(Intrinsic Mode Function) are equal or differ by at most one. The decomposition signal is shown in Figure 2.

Step 1: () 1 u t composed of the maximum points () 2 u t composed of the minimum values respectively. The mean is:

$$m(t) = \frac{1}{2}\left(u_1(t) + u_2(t)\right) \tag{8}$$

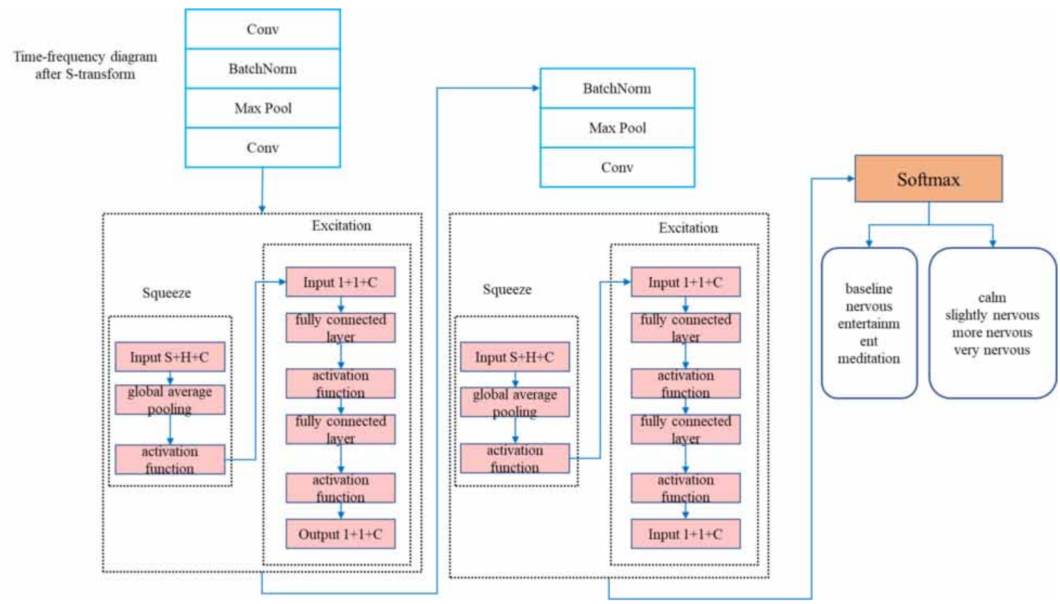
Step 2: Subtract the original signal sequence from equation (9) to obtain a new sequence h(t):

$$h(t) = x(t) - m(t) \tag{9}$$

Step 3: Judge conditions of IMF. If h(t) does not satisfy the conditions of IMF, it is regarded as a new x t(), and it satisfies the conditions of IMF.

In the actual calculation, too much repetition of the above process will lose the practical significance of the signal to a certain extent, so it is necessary to formulate a stopping criterion. The emotional changes of individual teachers under stress are also closely related to their prediction and

Figure 2. Structure Diagram of SE-CNN Human Mental State Recognition Model



evaluation of stress outcomes. Successfully coping with stressors often brings pleasant and happy emotional experiences to teachers. According to the severity of emotional changes, a negative experience can be expressed as anxiety, fear, depression, anger, and so on. Anxiety is the most common emotional response to stress. When the anxiety level is low, it affects the individual's behavior in coping with the environment. The response is often slow, and the efficiency of completing tasks is reduced. Moderate anxiety can improve people's alertness level and improve teachers' adaptability to the environment and coping ability. Excessive anxiety reduces the ability to cope with environmental changes, and this level of anxiety is in danger of generalization, which may affect teachers' ability to cope.

The commonly used stopping criterion is:

$$S_D = \sum_{i=0}^{T} \left[\frac{h_{1(k-1)}(t) - h_{1k}(t)}{h_{1(k-1)}(t)} \right]^2 \tag{10}$$

In the formula, D S is the threshold value; the value range is usually 0.2~0.3. When D S is less than the this, the iteration will be stopped.

Step 4: The IMF component is obtained as C1 = h1k (t), and the remainder after separation is:

$$r_1(t) = x(t) - C_1 \tag{11}$$

Step 5: Repeat the above steps for () 1 r t to get 1 2 C C . . .

Multiple original signals can be reconstructed by summing each IMF component and residual by the above steps. The formula is as follows:

$$x(t) = \sum_{i=1}^{n} C_i(t) + r_n(t) \tag{12}$$

After the above decomposition process, the internal features of the signal can be well extracted. However, it should be noted that the EMD algorithm has a problem that should not be ignored, that is, it has modal aliasing, which leads to the IMF obtained after decomposition losing its physical meaning. Noise is introduced during the EMD decomposition process to eliminate the pattern set. A new decomposition method for the aliasing problem is the overall empirical mode decomposition algorithm.

However, the instantaneous frequency of any time series is not always meaningful. It must meet certain conditions, which is why the signal should be EMD decomposed to obtain IMF before HHT is performed on the signal. After the signal, the formula is as follows:

$$s(t) = \mathrm{Re}\sum_{i=1}^{n} a_i(t)e^{j\phi_i(t)} = \mathrm{Re}\sum_{i=1}^{n} a_i(t)e^{j\int \omega_i dt} \tag{13}$$

In formula (13), the residual function r (t) n is omitted, and Re means taking the real part. The Hilbert time spectrum is:

$$H(\omega, t) = \mathrm{Re}\sum_{i=1}^{n} a_i(t)e^{j\int \omega_i(t)dt} \tag{14}$$

Using equation (14) and the above process, we find that HHT is more general to the instantaneous frequency of the signal and can represent variable frequencies, so the HHT transform is accurate when analyzing nonstationary signals.

$$Z(t) = X(t) + iY(t) = a(t)e^{i\theta(t)} \tag{15}$$

EXPERIMENTAL RESULTS AND ANALYSIS

Experimental Simulation

In our experiment, the public WESAD and the electrocardiographic signal ECG of the self-collected dataset were used to build a model for the four-category recognition of human mental state. The following is an introduction to the two datasets.

The WESAD is a publicly available physiological signaling dataset that includes physiological and self-reported data from 15 subjects. These physiological signal data included electrocardiogram (ECG), electrodermal response (EDA), electromyogram (EMG), skin temperature (TEMP), respiratory signals (RESP), and accelerometer (ACC). Self-reported data included information on subjects' affective states, cognitive loads, and social interactions.

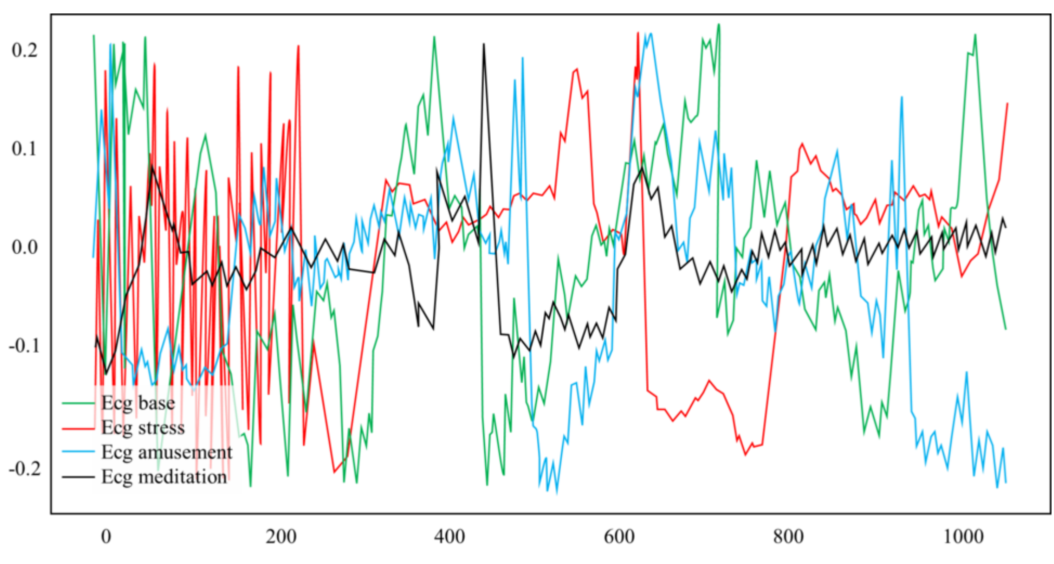
Information from the WESAD was collected to provide a standardized set of physiological signals that could be used to assess changes in affective state and cognitive load in different contexts. It can be used to study the relationship between physiological signals and affective state and cognitive load, as well as for the development of physiological signal-based algorithms for emotion recognition and cognitive load prediction. The opening of this dataset will facilitate research and development in related fields and enhance the application of physiological signals in the fields of mental health, cognitive science, and human-computer interaction.

This study was based on the disclosed WESAD, which uses the ECG signal to identify the psychological state of the human body. The following is an introduction to the acquisition signals and experimental procedures of the WESAD. We used the physiological signal data and mental state labels of 15 subjects, six males and nine females. The average age of the subjects was 27.5 years old, and their personalized physiological characteristics such as height, age, gender, and weight were recorded. Psychological crisis can be manifested in cognitive, physical, emotional, behavioral, interpersonal, and other aspects. In terms of cognition, when an individual is in a psychological crisis, their body and mind are immersed in grief, which leads to changes in memory and perception, manifested as difficulty in distinguishing between the similarities and differences of things and ambiguous relationships between things experienced.

Figure 3 shows the ECG signal data waveform of an experimental subject in the WESAD under different experimental conditions. It can be seen intuitively that the ECG signal waveform characteristics of the four different psychological states of baseline, entertainment, tension, and meditation are quite different, among which is the waveform of the ECG meditation state. Compared with the baseline, the ECG signal in the entertainment state has a steeper slope. This also proves the rationality of human mental state recognition through ECG signals to a certain extent.

The readme.txt of the WESAD recorded the age, gender, height, weight, and other personal information about the subjects. It also recorded detailed information about the dataset including the background of the data collection, the structure and organization of the dataset, and the data preprocessing methods. The quest questionnaire file provided the subjects' subjective scores on their psychological state under the experimental process at each stage using PANAS, SSSQ, and other personal assessment questionnaires. The pkl file provided all physiological signal data and corresponding labels of the two devices of the subjects. In this research, we chose to collect and preprocess ECG signal data based on the pkl file of each subject because the tags and data in the pkl file were stored in an array, which was convenient to establish one-to-one corresponding data and tag pairs. Together, these three files formed an important part of the dataset, providing a wealth of information and data resources.

Figure 3. Data Waveform of ECG Signal in WESAD



Following the settings of the different experimental procedures and conditions described, four different psychological states of the subjects were simulated, which provided the data basis for the construction of the human psychological state recognition model in this paper. The data volume and distribution are shown in Figure 4.

Most of the previous WESAD-based mental state recognition experiments achieved two-category (baseline, nervous) and three-category (baseline, nervous, entertainment), ignoring the meditation state because of the ECG of the meditation state, entertainment state, and baseline state. The characteristics of the signal waveforms are relatively similar, which confused identification. Therefore, completing the four classifications on the basis of the original classification would bring a certain reduction in accuracy. Signals have different meanings. To summarize, it can be seen that the academic circle has not yet formed a unified view of psychological crises, but the meanings expressed by the aforementioned viewpoints are roughly the same. We can understand psychological crises in this way: Its essence is a psychological imbalance that occurs in the event of a crisis.

In addition to denoising processing, before the mental state feature extraction, the physiological signals of the experimental subjects needed to be divided into time windows. The chest device ECG signal of the WESAD has a sampling frequency of 700 Hz. In order to facilitate processing, we it divided into fixed window sizes. We took continuous data every 10 seconds as a single sample point and collected 7,000 samples in total. The sampling frequency of the self-collected dataset MSSFT is 125 Hz. Using the same time window, we collected 1,250 sample points.

Figure 5 shows the number of ECG signal samples of each subject before and after the wavelet threshold denoising operation on the WESAD, and the denoised samples were used as the input for the subsequent model construction in this paper.

Comparative Analysis of Three-Category Human Mental State Models

Four classifications (baseline, nervousness, entertainment, and meditation) were implemented on the WESAD, and the epoch was set to 60. The loss line graph and the accuracy, precision, recall, and F1 score line graph are shown in Figure 6. The accuracy is 87.90%, with an F1 score of 87.71%.

Figure 4. The Amount of Data for Each Mental State of ECG Signals in the WESAD

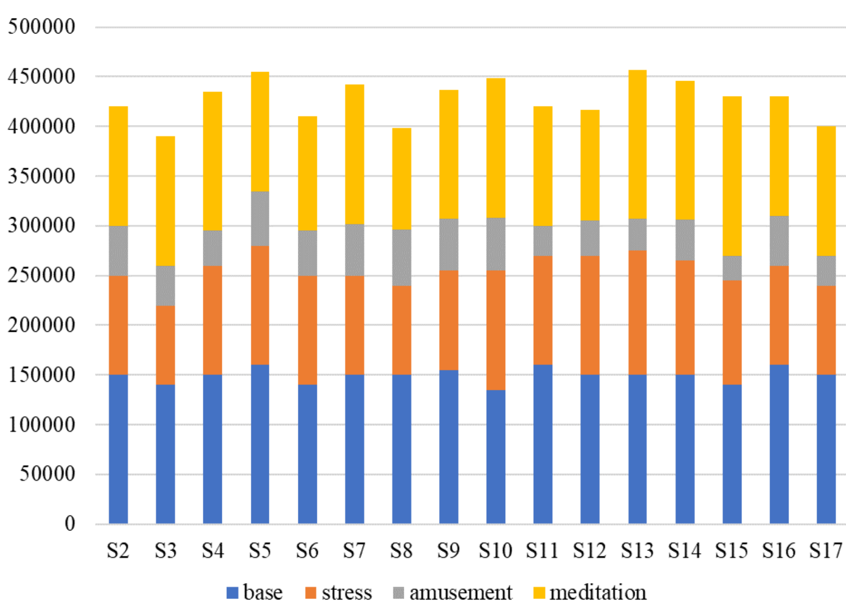
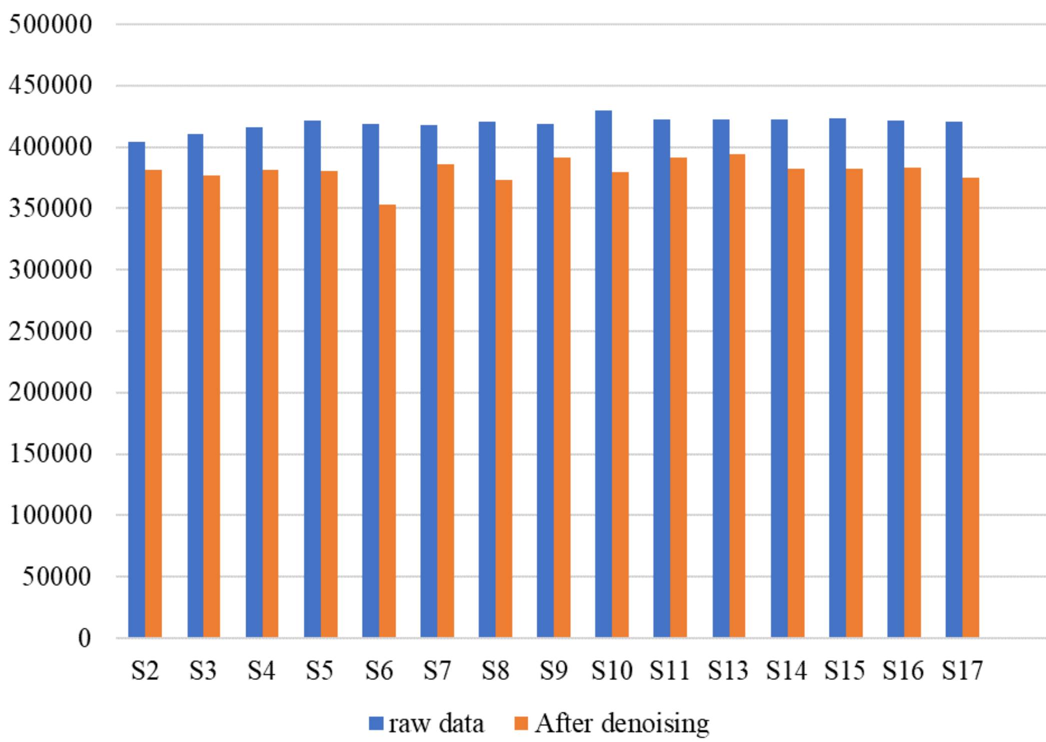


Figure 5. Comparison of the Number of the WESAD Experimental Data Before and After Denoising



Because the source article of the WESAD itself has a three-category mental state (i.e., baseline, entertainment, nervous) recognition model method based on ECG signals, we did not repeat the experiment and directly cited the results of its model as a comparison of the methods proposed in this article. The classification methods in the original text included multilevel dual-channel fusion human mental state recognition model (parallel) and multilevel dual-channel fusion model (composite) built in this article. The first 5 results of building the model in this article are compared to the dual-channel models in Figure 7.

Addressing the above figure, we conclude that compared with the original results, the multilevel dual-channel fusion human mental state recognition model proposed in this article better identifies the three mental states of baseline, entertainment, and nervousness on the WESAD. The effectiveness of the method can be used to further refine the classification of mental states. The following experiments were focused on the study of the four classifications.

Comparison and Analysis of Experimental Model Results

From 1,303 samples, the results of the internal and external propensity classification model in the GA-RF are shown in Figure 8.

Compared with the results of the model without using the genetic algorithm to extract features, the values of the model group using the genetic algorithm improved, which shows that when the internal and external tendency labels are used as the basis, the eight parameters extracted by the genetic algorithm improved. The data of each feature dimension is more representative than the data that has not been processed. From data taken from 1,433 samples, the results of the two-class depression model in the original model group: Decision-tree, SVM, RF and the control group: GA-decision-tree, GA-SVM, GA-RF are shown in Figure 9.

Figure 6. Four Classification Results of the Multilevel Two-Channel Fusion Model (Parallel) in the WESAD

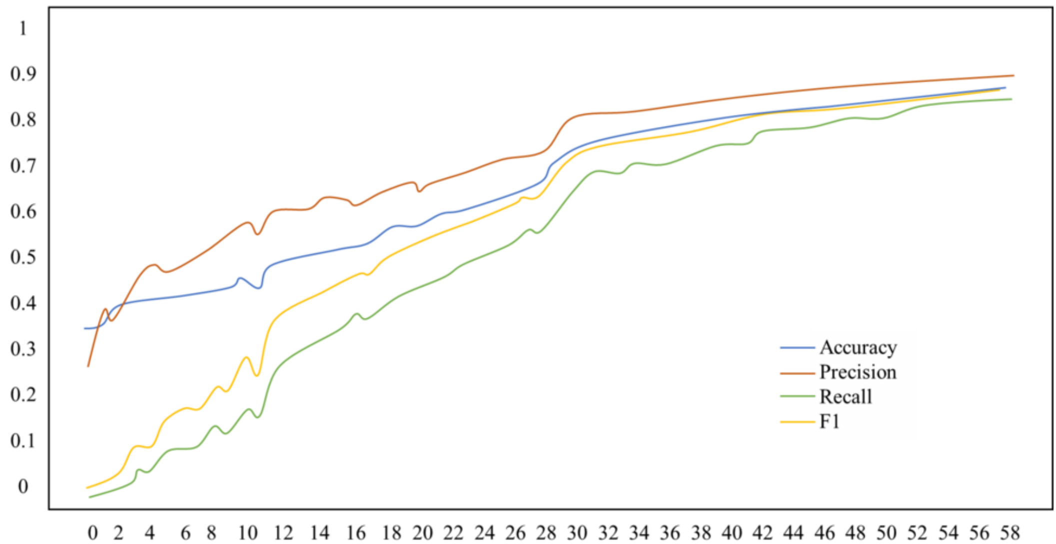
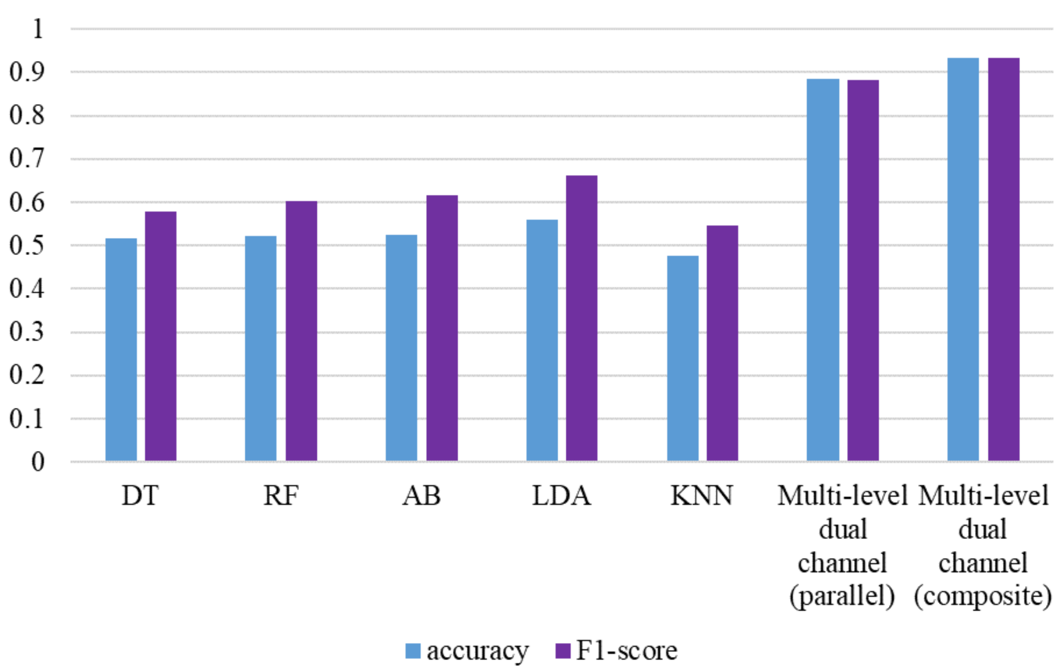


Figure 7. Comparison of the Results of Three-Category Recognition of Mental States Based on the WESAD



The results in Figure 9 show that the *F* score of various model algorithms can reach a score of more than 0.6, and the *F* score of the optimal GA-RF model reaches 0.81, indicating that a teacher's depressive psychological state is indeed predictable and has a relatively large correlation with the characteristics of the network behavior. And the characteristics of the network behavior can realize the

Figure 8. Evaluation of Different Classification Models for Internal and External Tendencies

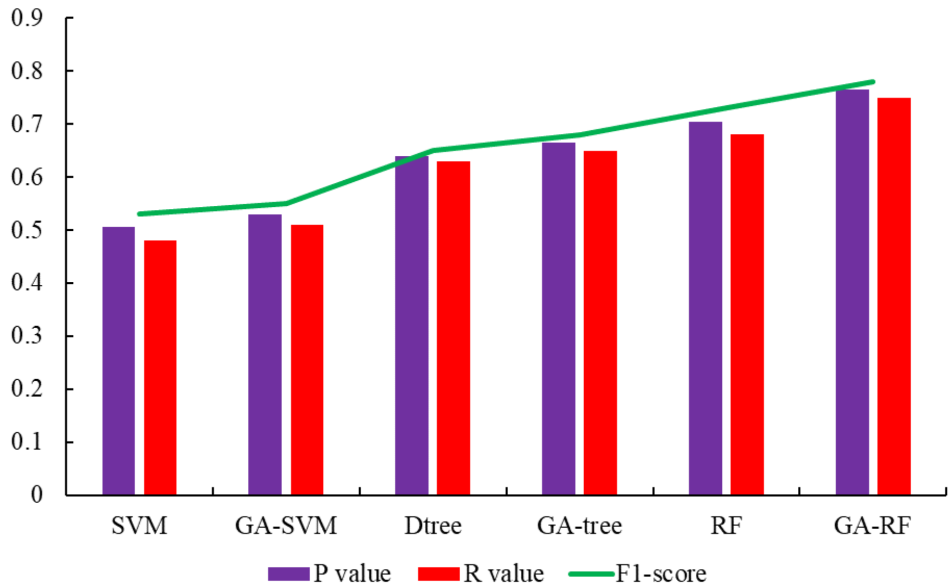
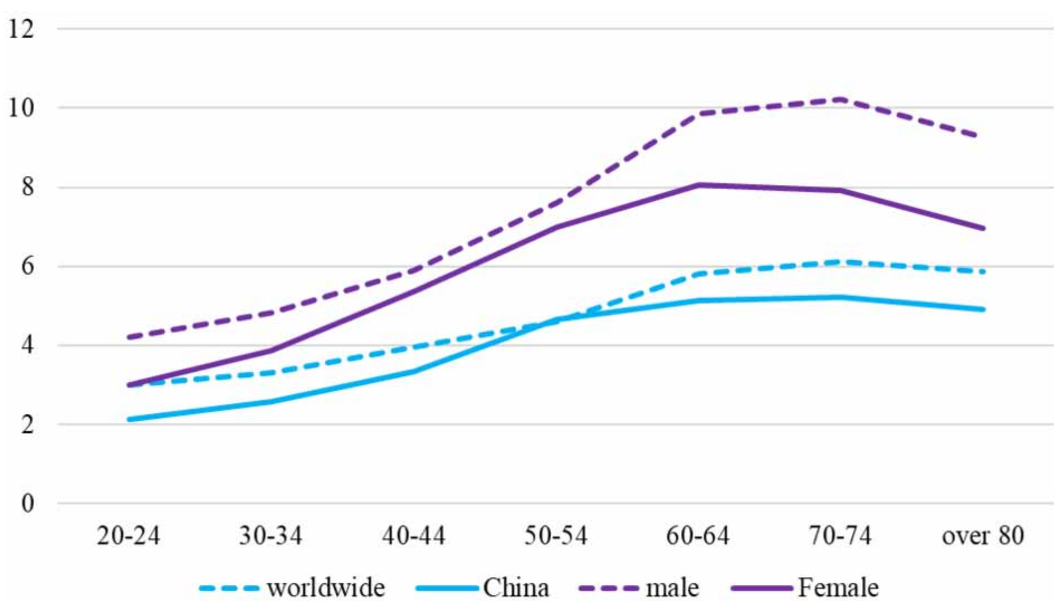


Figure 9. Evaluation of Different Models for Two-Category Depression



real-time perception of the students' depressive psychological states. Next, we compared the results of the model trained with the features extracted by the genetic algorithm and the model trained only with the original data features. It can be the degree of dependence, the degree of WeChat dependence, the regularity of map websites, and the degree of game dependence.

CONCLUSION

In this study, several technical means were used to safeguard the security and privacy of processing teachers' emotion recognition data including anonymization, strict access control, and encrypted transmission. In the emotion recognition study, the time-domain and time-frequency domain feature extraction methods were used, and four types of human mental state recognition models were constructed using the WESAD and self-collected ECG signal data. The experimental results showed that three types of mental states (i.e., baseline, recreation, and tension) can be better recognized on the WESAD using the multilevel two-channel fusion model. The models for psychological states such as internal and external tendencies and depression were also evaluated and analyzed comparatively, showing that feature extraction has a significant effect on model performance. It was found that the emotional state of teachers has a certain correlation with their network behavioral features, and the real-time perception of students' depressed psychological state can be achieved through network behavioral features.

This study has certain limitations as well. For example, the small sample size of teachers may not accurately reflect the diversity of the entire teacher population. Additionally, the subjectivity and constraints of the psychological state assessment criteria may result in assessments that are less thorough and accurate. Finally, additional validation is required to determine whether the methodology is feasible and works in real-world applications. In order to enhance the scientific validity and applicability of the methods in relation to real educational scenarios, future research should focus on increasing the sample size and improving the data collection tools and assessment criteria.

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The figures used to support the findings of this study are included in the article.

CONFLICT OF INTEREST STATEMENT

The author declares that there are no conflicts of interest.

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