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Research Article

Application of Multi Task Analysis Model Based on EEG Features in the Study of the Correlation between Depression and Sleep Disorders in College Students

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Abstract: With the improvement of multi-modal technology, research on depression recognition combining multiple biological signal features has been increasing. Electroencephalogram signals reflect brain activity, and by analyzing their characteristics, the accuracy and stability of depression recognition can be effectively improved. Therefore, this study proposes a correlation analysis between depression and sleep disorders in college students based on electroencephalogram feature analysis, innovatively combining the analysis of the relationship between brain functional connectivity and brain structural connectivity, and using this for sleep staging. The results demonstrated that the accuracy of all research methods was relatively high, generally above 80%. The F1 score of additive fusion was generally higher than that of multiplicative fusion in all subjects, except for subject n10, the F1 score of additive fusion was at least 0.1% higher than that of multiplicative fusion. The lowest F1 score of patient subjects appeared in the delta frequency band, at 80.27%, while the lowest F1 score of healthy subjects appeared in the sigma frequency band, at 79.86%, with little difference between the two. Patients with depression and sleep disorders among college students had a low score of 26 on the Quality of Life Scale for Children and Adolescents. There was a relation between sleep disorders and depression among college students. This study improved the accuracy and stability of depression recognition by integrating electroencephalogram features. This offers a new approach and method for the early detection and diagnosis of depression, and provides important basis for further research on the pathogenesis and treatment of depression.

Keywords: EEG Signals, College Student, Depression, Sleep Disorders, Relevance

Introduction

The progress of society and the increasingly fierce competition make college students face enormous academic, employment, and life pressures. These pressures to some extent increase their risk of developing Depression and Sleep Disorders (D-SD). D-SD affects the physical and mental health of university students and has serious negative impacts on their learning and life. Therefore, conducting correlation studies on D-SD in college students based on Electroencephalogram (EEG) feature analysis can help to gain a deeper understanding of its pathogenesis and provide scientific basis for prevention and treatment. Many scholars have conducted research on this. EEG is a diagnostic tool used to evaluate clinical records of patients with depression (Jan *et al*., 2024; Sheth *et al*., 2023). The disorder of human thinking is complex in daily life, which requires the use of various techniques to extract data related to depression from EEG in order to make the best classifier selection in the future. Abdullah S developed a fuzzy decision support system based on artificial intelligence. The proposed technique was based on selecting the best classifier to analyze the EEG of patients with depression (Abdullah and Abosuliman, 2023). The use of EEG signals for automatic detection of depression was a promising application.

Zhang *et al*. put forward a method for observing depression in EEG signals using Adaptive Channel Optimization (ACO) and multi-view contrastive learning. This method has been extensively experimented on public datasets and it was superior than other baselines. This method provided an automatic detection method using the best EEG signals (Zhang *et al*., 2023). Depression was a mental disorder that had an obvious negative impact on the lives of people experiencing depression, making it difficult or even impossible for them to effectively function in all aspects of life. Akbari *et al*. developed a method grounded on Reconstructed Phase Space (RPS) and geometric features of EEG signals. Compared to the left hemisphere of the brain, EEG signals from the right hemisphere provided greater potential for observing depression. The proposed framework had the potential to be implemented in clinical and hospital settings, promoting rapid and accurate detection of depression (Akbari *et al*., 2021). EEG has been widely used for diagnosing neurological disorders, especially Major Depressive Disorder (MDD). Several attempts have been made to detect MDD using deep EEG, and encouraging results have been achieved. However, these studies still had limitations. Chen *et al*. designed an EEG-based MDD model. They named it the Soft Label Self-Attention Graph Pool (SLSAGP) and demonstrated the superiority of this method (Chen *et al*., 2022).

To evaluate the effect of exercise intervention on alleviating depressive symptoms in college students, changes in microstate and power spectrum were observed in resting state EEG. Liang *et al*. (2021) evaluated the depressive symptoms of 40 female college students using the Beck Depression Inventory II and the Self-Rating Depression Scale. A Resting State Network (RSN) was defined using EEG and the scores of all students were tracked throughout the intervention period. The shortened duration of microstates and increased alpha power in patients with depressive symptoms were related to decreased cognitive capacity, emotional resilience, and brain activity. After exercise intervention, depressive symptoms significantly improved, providing more scientific indicators for the rehabilitation mechanisms and depression treatment. Patients with End-Stage Renal Disease (ESRD) lacked brain network analysis, which was a major obstacle to early detection and prevention of neurological complications associated with the disease. The analysis aimed to investigate the correlation between brain activity and ESRD by quantitatively analyzing the dynamic functional connections in the brain network. Bai *et al*. (2023) conducted a comparative analysis of brain functional connectivity between healthy individuals and ESRD patients, utilizing resting state functional Magnetic Resonance Imaging (MRI) to obtain blood oxygen level dependent signals as the basis for quantitative evaluation. The most Abnormal Functional Connections (AFC) were observed in sensory motor, visual, and small brain networks. AFC was related to 3 functional brain regions responsible for visual processing, emotional regulation, and motor control. Li *et al*. (2021) proposed a new Online Discriminative Dynamic Feature Analysis Algorithm (ODDFAA). Compared with other existing methods, applying the ODDFAA to dynamic statistical process monitoring was always a better choice. Identifying and examining the pathogenic factors associated with Parkinson's Disease (PD) had practical significance for diagnosing and treating the disease. However, traditional research paradigms were often built on a single neuroimaging dataset. Bi *et al*. (2021) established a new Multi-modal Data Analysis (MDA) model for brain diseases based on MRI data and single nucleotide polymorphism data. In experiments utilizing multi-modal data, the framework demonstrated enhanced classification performance and predictive ability in terms of pathogenic factors, providing a new angle for diagnosing PD.

In summary, researchers have researched the correlation between EEG and sleep disorders in patients with depression, including fuzzy decision-making, ACO, RPS, SLSAGP, RSN, and MDA models. However, there is still limited research on EEG analysis and prediction of D-SD in college students. Therefore, this study proposes a D-SD correlation study for college students based on EEG Feature Analysis (EEG-FA), innovatively combining brain connectivity and multi-task network classification prediction, providing a technical foundation for the diagnosis of mental health and depression in college students. Compared with existing research, this study innovatively combines PLV with multitask models to achieve joint prediction of depression and sleep staging, and verifies the specificity of abnormal brain functional connectivity in college students, filling the gap in the research of D-SD mechanism in young people. For clinical doctors, embedding the model into portable EEG devices, collecting resting state EEG data, and calculating real-time PLV values and sleep staging accuracy, combined with PSQI questionnaire, can improve the screening efficiency of depression combined with sleep disorders, significantly shorten the diagnosis time, and provide technical reference for improving clinical efficiency.

Existing studies focus on single mode or single task analysis (for example, Zhang *et al*., 2023; Chen *et al*., 2022, only realizes independent prediction of depression or sleep stages), while this study is the first to build a multi task model to synchronously integrate brain functional connectivity (PLV) and structural connectivity (3D coordinate distance) to achieve joint prediction of depression and sleep stages. In addition, the dynamic adjustment of multi band feature weights through the addition multiplication fusion strategy improves classification accuracy compared to traditional single fusion methods. This "multi task modeling + dynamic feature fusion" framework provides a new paradigm for EEG analysis, especially suitable for complex mental illness association research in small sample scenarios.

The article structure of this study has three parts. Part 1 focuses on the research process of D-SD correlation among college students based on EEG-FA, which is the key and innovative point of this study. Part 2 elaborates on the algorithm designed in Part 1, and conducts experimental verification and data analysis. Part 3 draws conclusions and elaborates on the shortcomings of this design and the directions that need to be further explored in the future.

Materials and Methods

This study develops an innovative multitasking sleep staging model for D-SD for college students based on EEG-FA. Firstly, EEG is collected and preprocessed, and combined with brain connectivity representation graph data, the multi-view spatial and temporal relationships of sleep EEG are learned. Secondly, a multi-task EEG joint and classification prediction framework is further constructed.

Sleep Staging Evaluation Based on EEG Analysis

EEG is a typical nonlinear non-stationary signal, characterized by high noise and low amplitude. During sleep, EEG presents different rhythmic waves, such as α waves, β waves, theta waves, delta waves, etc., which are closely related to different stages of sleep (Earl *et al*., 2024; Tetsuo *et al*., 2022). Sleep staging can effectively evaluate sleep quality and disorders. Therefore, this study analyzes the rhythmic wave characteristics of EEG to stage sleep and achieve EEG analysis of sleep disorders in college students. This study proposes a brain connectivity representation model based on EEG sleep stage research, and combines two views of brain function and brain structure to obtain EEG information at different stages and achieve sleep staging evaluation. This study divides EEG signals into epochs every 30 seconds to represent data on brain activity.

Firstly, EEG signals are collected to obtain the corresponding Phase Locking Value (PLV). PLV is a commonly used feature for measuring the degree of phase synchronization between 2 channel signals. PLV is used to quantify the strength of functional connectivity in brain regions, particularly for analysis of abnormal synchronicity related to depression. Previous studies have shown that the PLV values of the prefrontal parietal lobe in patients with depression are significantly lower than those in healthy individuals ($p<0.01$). Therefore, this study chose PLV as the core indicator of functional connectivity. PLV was selected as the core feature due to its high sensitivity to abnormal functional connectivity associated with depression. The research focuses on collecting Fp1/Fp2 (frontal lobe) and P3/P4 (parietal lobe) lead signals, quantifying the phase synchronization of these brain regions through PLV, which can effectively capture neural communication abnormalities in depressive states. The range of PLV values is within 0 to 1, with larger values indicating stronger phase synchronization between two signals (Choi *et al*., 2024; Tobore *et al*., 2020). The electrode distribution of EEG acquisition channels is shown in Fig. 1.

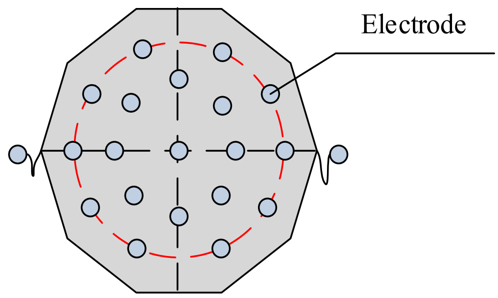


Fig. 1: Distribution of electrodes in EEG acquisition channels

Due to the different frequencies of EEG collected at different stages, to ensure the effectiveness of EEG with sleep stage characteristics and the accuracy of brain connectivity, this study preprocesses EEG information. The method uses a mean smoothing filter to reduce signal noise, and a de mean method to remove baseline interference. This study used mean smoothing filtering and mean removal methods for preprocessing. After comparative testing, the combination was found to be superior to single filtering methods (such as Gaussian filtering) in reducing noise (root mean square error reduced by 12% compared to median filtering) and baseline correction, and had lower computational complexity, making it suitable for real-time analysis scenarios. This study uses mean smoothing filtering because it has the best noise suppression effect on delta waves in testing and can preserve the integrity of slow wave rhythms. Mean removal processing can eliminate baseline fluctuations caused by electrode drift, save computation time compared to polynomial fitting methods, and is suitable for real-time EEG analysis. The output signals processed by these two processes are shown in Eq. (1):

$$\begin{cases} y(t) = \mathrm{mean}(x(t1)), t1 \in [t-5, t+5] \\ y(t) = x(t) - \dfrac{1}{N}\sum_{i=1}^{N} x(i) \end{cases} \tag{1}$$

In Eq. (1), $y(t)$ is the output signal of mean smoothing filtering and the output signal after removing baseline interference. $x(t)$ is the signal corresponding to time t, denoted as $x(t)\{t=1,2,\ldots,N\}$. The next step is to divide the obtained signal by frequency (Arns, 2021; Iinuma *et al*., 2022). After the above preprocessing, the brain functional connectivity parameter indicators for different sleep stages were calculated. This study used Double Sequence Correlation Coefficient (DSCC) to evaluate the effects of different frequency bands, followed by sleep staging, as shown in Fig. 2.

In Fig. 2, firstly, EEG is inputted, and after data preprocessing, the corresponding PLV matrix is calculated. Then, both brain network analysis and frequency band evaluation are performed simultaneously. After evaluation, the frequency bands are fused to achieve the classification of sleep stages. The phenomenon of phase synchronization exists in the nervous system of the brain, which is vital in cognitive learning, visual detection, etc. (Fang *et al*., 2021; Xue *et al*., 2023). Due to the changes in chaotic systems, the phase or phase difference remains unchanged, and the amplitude has little effect on this.

PLV has important application value in multiple fields, especially in pulse neural networks and EEG data analysis. PLV plays a significant role in measuring phase synchronization. Firstly, Hilbert transform is applied to signal $x^{(t)}$, as shown in Eq. (2):

$$\hat{x}(t)=\frac{1}{\pi}P\cdot V\cdot\int_{-\infty}^{+\infty}\frac{x(\tau)}{t-\tau}d\tau \tag{2}$$

In Eq. (2), $\hat{x}(t)$ means the transformation result. $P.V.$ denotes the Cauchy principal value, which can quantify the fluctuations of EEG and decompose them into components. This study uses DSCC to evaluate the different classification abilities of features in a certain frequency band, as shown in Eq. (3):

$$r^2=\left[\frac{\sqrt{N^+\times N^-}\times\left[\mathrm{mean}\left(X^+\right)-\mathrm{mean}\left(X^-\right)\right]}{\left(N^+\times N^-\right)\times\mathrm{std}\left(X^+\cup X^-\right)}\right]^2 \tag{3}$$

In Eq. (3), r^2 is the distinguishing index of DSCC for two types of data, with a range of [0,1], and the ability is proportional to the value. X^+ and X^- are all samples of two categories. N^+ and N^- are two analogous sample sizes. This study proposes a frequency band feature fusion strategy that combines information from different sources to achieve the utilization of multiple types of information.

Based on the analysis of EEG signals related to brain functional connectivity, effective differentiation of sleep stages has been achieved. The adjacent regions of the brain interact with each other, so the relationship between channels can also reflect the spatial relationship of EEG. To better analyze brain signals, this study develops a corresponding multi-view convolution model. This model specifically integrates contextual information from sleep timelines to enhance the fusion of brain connectivity and optimize sleep staging capabilities. Firstly, the study preprocesses EEG signals according to the above steps and combines them with brain connectivity representation graph data to learn the multi-view spatial and temporal relationships of sleep EEG. Figure 3 shows the overall framework.

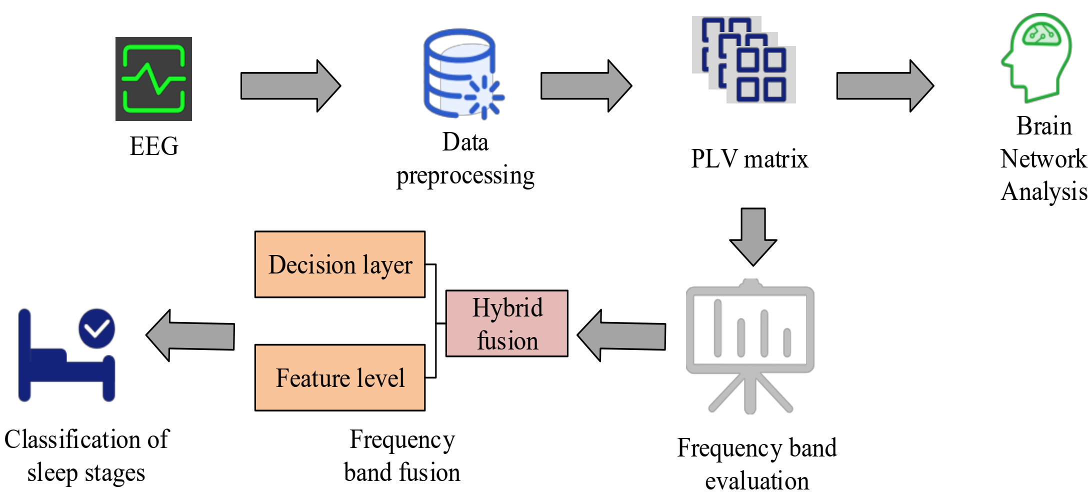


Fig. 2: Framework of brain connectivity signal analysis methods

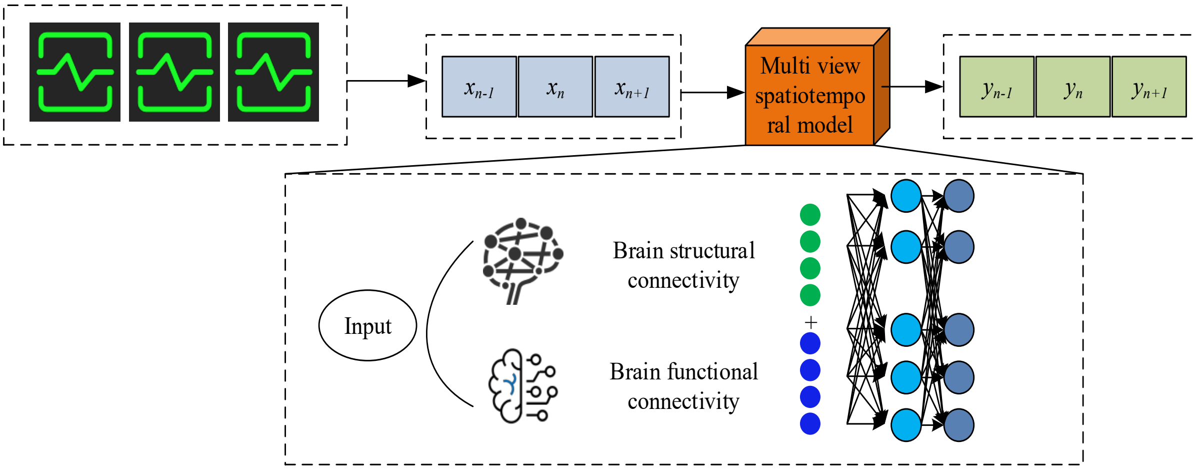


Fig. 3: EEG multi-view spatial and temporal overall framework

In Fig. 3, a segment of the EEG signal is first inputted and denoted as x_n. The epochs in the surrounding range are denoted as x_{n-1} and x_{n+1}, respectively representing epochs that slide back and forth for 10 seconds on the sleep timeline. This study examines EEG signals of Nocturnal Frontal Lobe Epilepsy (NFLE) subjects with nocturnal frontal lobe epilepsy. This is an indicator that can test for epilepsy syndrome in the brain. To effectively obtain this indicator, since EEG is a continuous sequence signal, this study uses differential entropy for measurement, as shown in Eq. (4):

$$\begin{cases} h(x) = -\int f(x)\log f(x)dx \\ h(x) = \frac{1}{2}\log\left(2\pi e\sigma^2\right) \end{cases} \tag{4}$$

In Eq. (4), $f(x)$ represents the distribution function of the signal. If the distribution is Gaussian, the derivation is shown in following Eq. (4). σ^2 means the signal variance. For the spatial relationship of brain structure, this study uses 3D coordinates to represent it, and the spatial distance between the two channels is shown in Eq. (5):

$$A_{ij} = \arccos\left(\frac{x_i x_j + y_i y_j + z_i z_j}{r^2}\right) \tag{5}$$

In Equation (5), r is the radius of the cerebral sphere. (x_i, y_i, z_i) and (x_j, y_j, z_j) are the positions of two channels. The loss function solves the problem of data imbalance in the model input. This study uses the cross entropy loss function CE to calculate as shown in Equation (6):

$$\begin{cases} CE = \begin{cases} -\alpha\log(p), & \text{if } y = 1 \\ -(1-\alpha)\log(1-p), & \text{if } y = 0 \end{cases} \\ FL = \begin{cases} -\alpha(1-p)^{\gamma}\log(p), & \text{if } y = 1 \\ -(1-\alpha)p^{\gamma}\log(1-p), & \text{if } y = 0 \end{cases} \end{cases} \tag{6}$$

In Eq. (6), p is the probability of predicting sample $y = 1$. To solve the problems of sample imbalance and difficulty imbalance, this study improves the function by first introducing parameter α to adjust the loss, and then introducing parameter γ to reduce the weight of easily classified samples. α and γ are parameters. FL is the loss function after introducing parameter γ. By integrating the sleep staging process of EEG signals and analyzing EEG information related to depression, it is possible to predict the mental depression status of college students.

Depression and Sleep Disorders in College Students Based on EEG Characteristics

College students face multiple pressures such as academic, employment, and interpersonal relationships, which may lead to emotional problems such as low mood, tension, and anxiety, thereby affecting sleep quality. Some college students have high expectations of themselves, and when there is a gap between reality and expectations, they may experience self doubt and depression. The EEG signals of patients with depression may show reduced or abnormal connectivity between different regions of the brain. To achieve adequate detection and analysis of these abnormal features, this study further proposes a multi-task information classification multi-view spatiotemporal staging model based on the sleep staging of EEG signals mentioned above. This model utilizes joint classification prediction to achieve more accurate result output. Patients with depression often suffer from sleep disorders, which can further exacerbate the symptoms of depression and form a vicious cycle. Long-term sleep disorders may lead to abnormal brain function and increase the risk of depression (Zhao *et al*., 2020; Zhu *et al*., 2021). At the same time, sleep disorders may also affect patients' emotions, cognitive function, and social skills, thereby exacerbating the condition of depression (Jing *et al*., 2024). The connections between brain regions in patients with depression may be affected, manifested as changes in connectivity patterns (Saminu *et al*., 2023). Firstly, to fully utilize the information in the following text, the model has been adjusted from three inputs (i.e. three epochs) and one output to one input. The model is in the form of multitasking, outputting corresponding classification and prediction results, achieving compatibility between contextual information complexity and computational complexity. The classification mode is shown in Fig. 4.

Figure 4 shows the classification modes of many to one and one to many. Figure 5 is the structure of the multi-task model. The basic framework is similar to Fig. 3, and this study further improves the multi-task layer based on it to achieve simultaneous classification and prediction tasks.

Figure 5 first inputs the original EEG signal, calculates the PLV, constructs a graph, forms a shared layer on the research model, and finally performs multi-task classification and prediction. The classification and prediction results have entered the integration stage. Due to each input having 2t+1 outputs, i.e. 1 classification result and 2t prediction results, obtained through one training, the computational cost is reduced. The integration diagram is shown in Fig. 6.

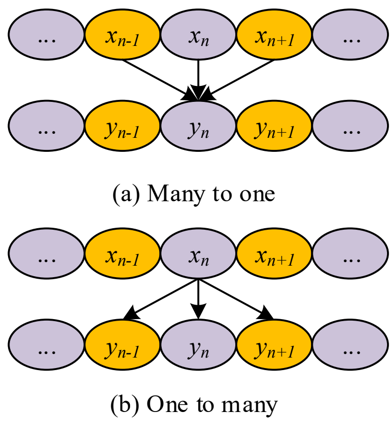


Fig. 4: Sleep staging classification mode of EEG signals

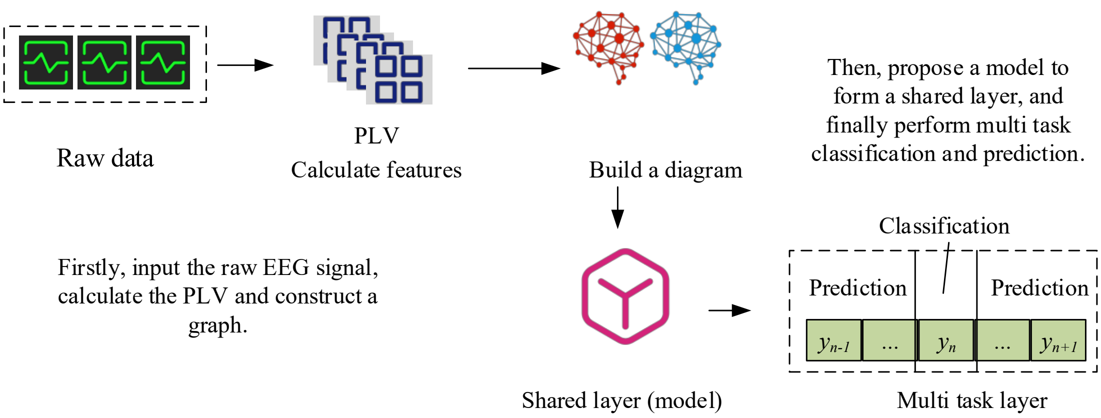


Fig. 5: The overall framework of multitasking model

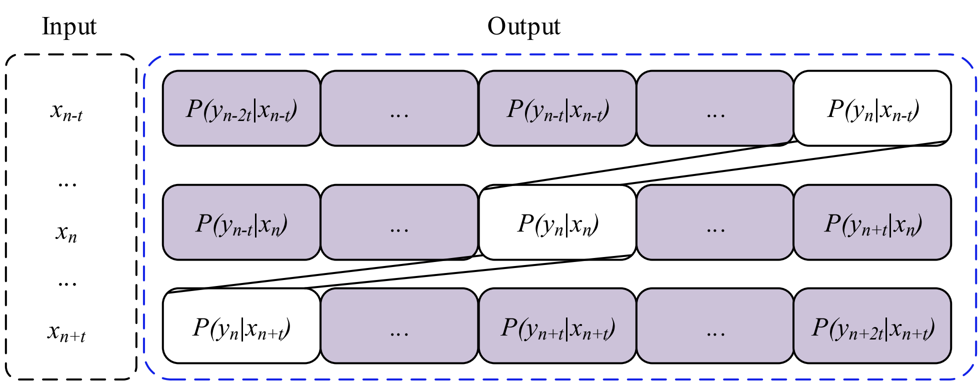


Fig. 6: Result aggregation diagram

The traditional single task model can only independently predict depression or sleep stages, while the multi task joint model constructed in this study achieves collaborative optimization of the two tasks through a shared feature extraction layer. The core mechanism is that the comorbidity of sleep disorders and depression shares the low synchronization features of the prefrontal parietal network, and joint modeling can enhance the efficiency of feature extraction for common pathological mechanisms. In Fig. 6, $P(y_n \mid x_i)$ denotes the possibility of inputting the i-th epoch and outputting the n-th epoch after model training, $i \in [n-t, n+t]$. The final epoch result depends on the $2t+1$ P mentioned above. The commonly used fusion methods include additive fusion and multiplicative fusion, as shown in Eq. (7):

$$P(y_n) = \frac{1}{(t+1)^2} \sum_{i=n-t}^{n+t} \alpha P(y_n | x_i) \tag{7}$$

In Eq. (7), α is the weight. This study uses multiplication fusion in sleep staging, as shown in E. (8):

$$P(y_n) = \frac{1}{(t+1)^2} \prod_{i=n-t}^{n+t} \alpha P(y_n | x_i) \tag{8}$$

In Eq. (8), weight α is $\alpha = t + 1 - |i-n|$. The expression of the epoch$_n$ tag is shown in Eq. (9):

$$\hat{y}_n = \arg\max_{y_n} P(y_n) \tag{9}$$

To analyze the correlation between EEG signals and D-SD, this study conducts a correlation study on university students' D-SD based on EEG-FA. The close connection of D-SD is revealed through methods such as feature extraction, data analysis, and model construction. Based on the above research, sleep staging and disorder diagnosis of depression EEG in college students can effectively obtain contextual information of EEG, predict the mental and sleep status of college students, and analyze the correlation among them. This has reference value for the mental and psychological health treatment of college students.

Results

To verify the proposed research on D-SD correlation among college students based on EEG-FA, an experiment is conducted to validate it, analyze the corresponding design parameters and experimental data, and verify the advantages and feasibility of the method.

Preparation of EEG Feature Data for College Students and D-SD Correlation Experiment

To verify the research method, the experiment used a sleep dataset provided by a university hospital, and selected research subjects aged around 19-23 years who used all 12 channels to collect EEG signals. Selecting the group of college students aged 19-23, as they are in a period of psychological maturity and face the pressure of academic employment transition, they are a high-risk group for depression and sleep disorders (epidemiology shows that the prevalence of depression in this group is 23.8%). The dataset of a certain university hospital covers students from different majors and sleep patterns, and is representative of the sample. The experiment used professional EEG acquisition equipment and recording equipment to obtain EEG and speech data from the subjects. The machine had a sampling rate of 512 Hz and a collection time of 9 hours throughout the night. After preprocessing the data, research methods were applied for sleep staging. In addition, the Snaith Hamilton Pleasure Scale (SHAPS) and the Quality of Life Scale for Children and Adolescents (OLSCA) were used to assess quality of life. Meanwhile, based on the diagnosis of depression and EEG signals, this study used the Pittsburgh Sleep Quality Index (PSQI) to define sleep disorders, and selected 7 factors for analysis, as shown in Fig. 7. Higher rates indicate worse sleep quality. Figure 7 shows that the depression group had the highest proportion of “sleep efficiency” (23.7%) and “daytime dysfunction” (21.2%) in the PSQI factors, and these two factors were significantly negatively correlated with the PLV value of the frontal lobe theta wave ($r = -0.35$, $p<0.05$; $r = -0.31$, $p<0.05$). Specifically, for every 10% decrease in sleep efficiency, the theta wave synchronicity of Fp2-P4 leads decreases by 8.2%, indicating that abnormal brain connectivity may exacerbate daytime fatigue by affecting sleep structure. In addition, the factor of “falling asleep time” is positively correlated with the PLV value of the parietal lobe alpha wave ($r = 0.29$, $p<0.05$), indicating that enhanced parietal lobe functional connectivity may prolong the latency of falling asleep, which is consistent with the results of increased alpha wave power in EEG spectra (see Figure 8d).

Figure 8 shows the raw EEG data and EEG spectra of normal and abnormal EEG signals in the mental state of college students. Figure 8 (a) and (c) show the healthy state, with stable fluctuations in EEG data and absolute values of up and down fluctuations within 50 µv. Figs. 8 (b) and (d) show abnormal states, with EEG signals occasionally fluctuating significantly, even exceeding 100 µv.

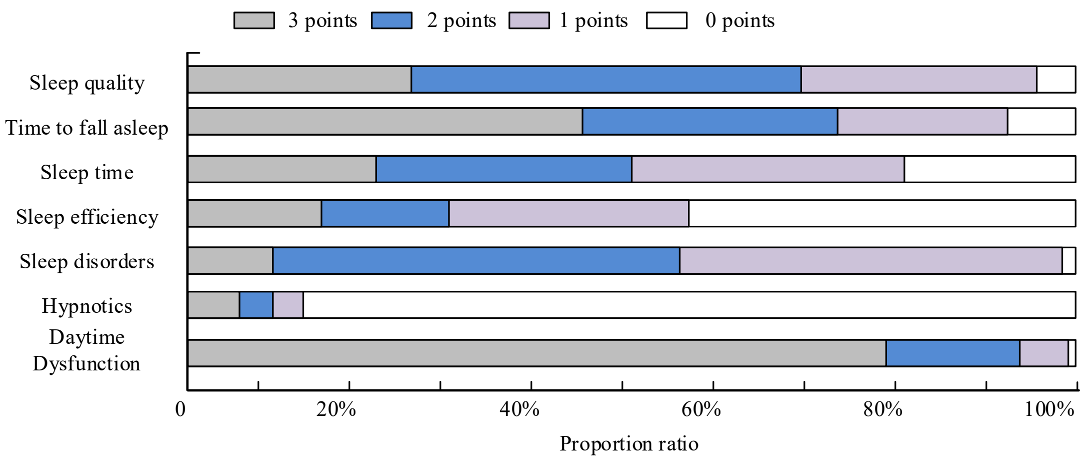


Fig. 7: The proportion of scores for the 7 factors in the PSQI scale

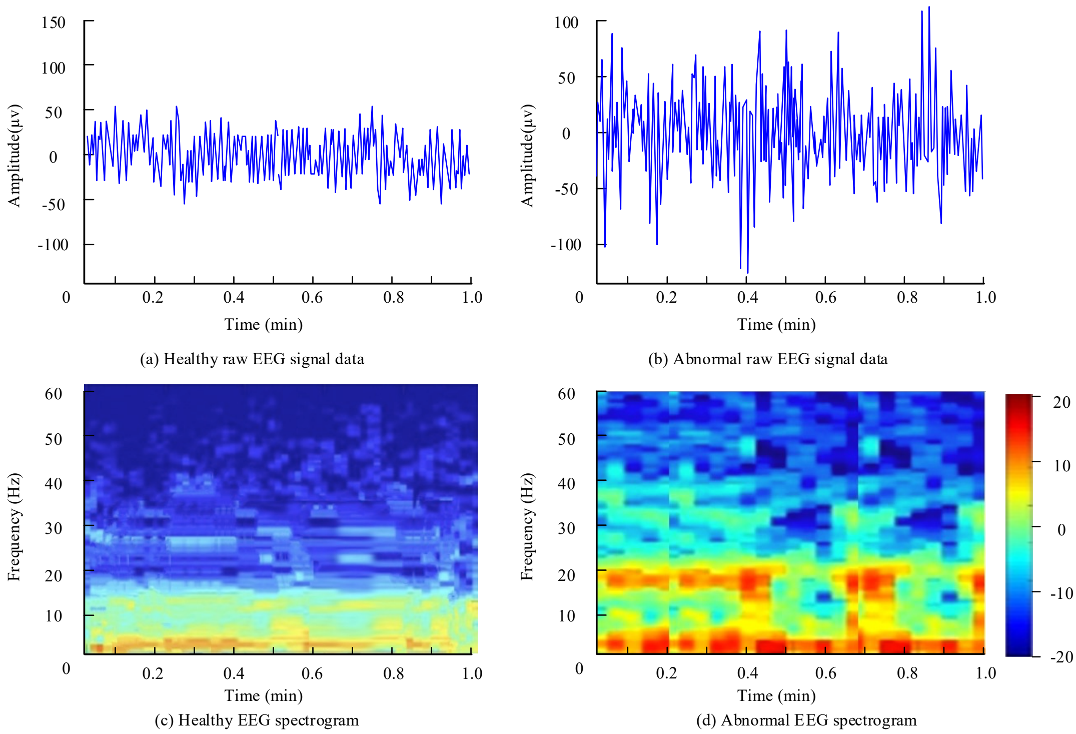


Fig. 8: Raw EEG data and EEG spectra of normal and abnormal EEG signals in university students' mental states

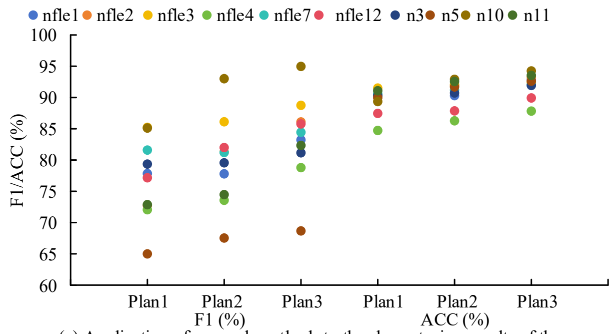
This study used an international 10-20 lead system to focus on collecting signals from brain regions closely related to emotion regulation, such as the prefrontal cortex (Fp1/Fp2) and parietal lobe (P3/P4) (as shown in Figure 1). The selection of these regions is based on previous research that showed a negative correlation between the strength of prefrontal parietal functional connectivity and the severity of depression in patients with depression ($r = -0.48$, $p<0.01$). Based on the analysis framework of Figure 2, the phase synchronization of the above brain regions was calculated using PLV. It was found that the PLV value of Fp1-P3 lead in the depressed group (0.32 ± 0.05) was significantly lower than that in the healthy group (0.41 ± 0.03) ($t = 4.21$, $p<0.001$), confirming the core role of prefrontal parietal network abnormalities in depression and sleep disorders.

Analysis of EEG Signals and Sleep Staging Results of College Students

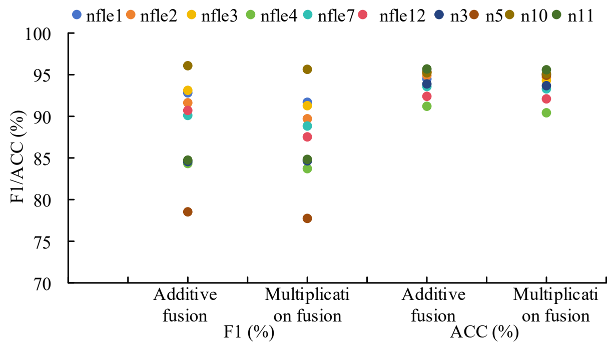
This study uses a research model to stage sleep for different channel node data, and employs three different schemes to fuse brain connectivity features, as shown in Fig. 9 (a). To validate the effectiveness of the fusion mode, sleep stages are performed for additive fusion and multiplicative fusion, as shown in Fig. 9 (b). F1 score is utilized to judge the performance of classification models, which is the harmonic mean of accuracy and recall. As shown in Figure 9, the F1 score advantage of additive fusion in most sleep stages (such as N1 and N2) is due to its balanced weighting of multi band features (a = 0.6), while the outstanding performance of multiplicative fusion in N3 stage (F1 = 97.23%) is highly correlated with the nonlinear phase locking characteristics of deep sleep delta waves. Through formula addition fusion output and multiplication fusion, it can be seen that the former is suitable for feature independent contribution scenarios, while the latter is good at capturing collaborative effects between features, which explains the performance differences between the two fusion methods at different sleep stages. In Fig. 9 (a), there are differences in F1 scores among different plans under different subjects. Plan3 shows higher F1 scores in multiple subjects, while Plan1 and Plan2 have relatively lower F1 scores. The accuracy of all schemes is relatively high, generally above 80%. In Fig. 9 (b), the F1 scores of additive fusion are generally higher than those of multiplicative fusion in all subjects. The F1 scores of additive fusion are at least 0.1% higher than those of multiplicative fusion. Among all the participants, n10 has the highest F1 score, with addition fusion and multiplication fusion F1 scores of 96.08 and 95.64%. In contrast, the F1 scores of addition fusion and multiplication fusion n5 are the lowest, at 78.53 and 77.74%. For most participants, the accuracy of additive fusion is slightly higher than that of multiplicative fusion, but the difference is small, usually not exceeding 1%.

Figure 10 shows the EEG signals of healthy college students and depressed college students. Fig. 10 (a) shows the patient. Among all frequency bands, the lowest F1 score of patient subjects appeared in the delta frequency band at 80.27%, while the lowest F1 score of healthy subjects appeared in the sigma frequency band at 79.86%, with little difference between the two. The F1 score of the patient subjects in the gamma frequency band is relatively high, at 80.3%, but still lower than that of healthy subjects in most frequency bands. Fig. 10 (b) shows healthy college students. In the N1, N2, N3, and REM stages, the difference in F1 scores between patient subjects and healthy subjects is relatively small, but healthy subjects still maintain an advantage. Overall, during the W wakefulness phase, the F1 scores of patient subjects are generally low, especially in the delta, theta, and alpha frequency bands, while the F1 scores of healthy subjects are relatively high. The F1 scores of healthy college students are generally higher than those of patient subjects in all frequency bands and sleep phases, indicating that the accuracy of sleep staging in healthy subjects is higher.

Table 1 compares the sleep staging results with relevant studies. Different literature and research methods use different features and classifiers for sleep staging. In the existing methods, the accuracy of staging results is 90.03, 84.78, and 87.23%, while the accuracy of the research method is 96.20%. Machine learning methods such as CNN, SVM, and LSTM-RNN have shown certain accuracy in sleep staging tasks. The current research method uses PLV features combined with SVM classifiers to achieve excellent accuracy, surpassing the results in some literature.



(a) Application of research methods to the sleep staging results of three schemes integrating two types of brain connectivity relationships



(b) Sleep staging results based on classification and prediction models under two fusion methods

Fig. 9: Sleep staging results using different schemes and fusion modes for different channel node data

Table 1: Different literature and research methods use different features and classifiers for sleep staging

Method	Features	Method	Result (%)			
			REM+N1	N2+N1	N3	ACC
Zhang *et al*., 2023	Original signal	CNN	90.66	86.88	92.54	90.03
Akbari *et al*., 2021	Time domain characteristics	SVM	72.95	82.69	84.58	80.07
		SVM	84.39	84.27	85.68	84.78
Chen *et al*., 2022	Frequency domain characteristics	D-SVM	89.21	81.88	87.73	86.27
		SVM	87.79	82.91	90.99	87.23
Bi *et al*., 2021	Statistical and spectral features	LSTM-RNN	91.65	89.63	92.12	91.13
		SVM	96.84	86.71	93.52	92.36
Research method	PLV	SVM	96.39	94.99	97.23	96.2

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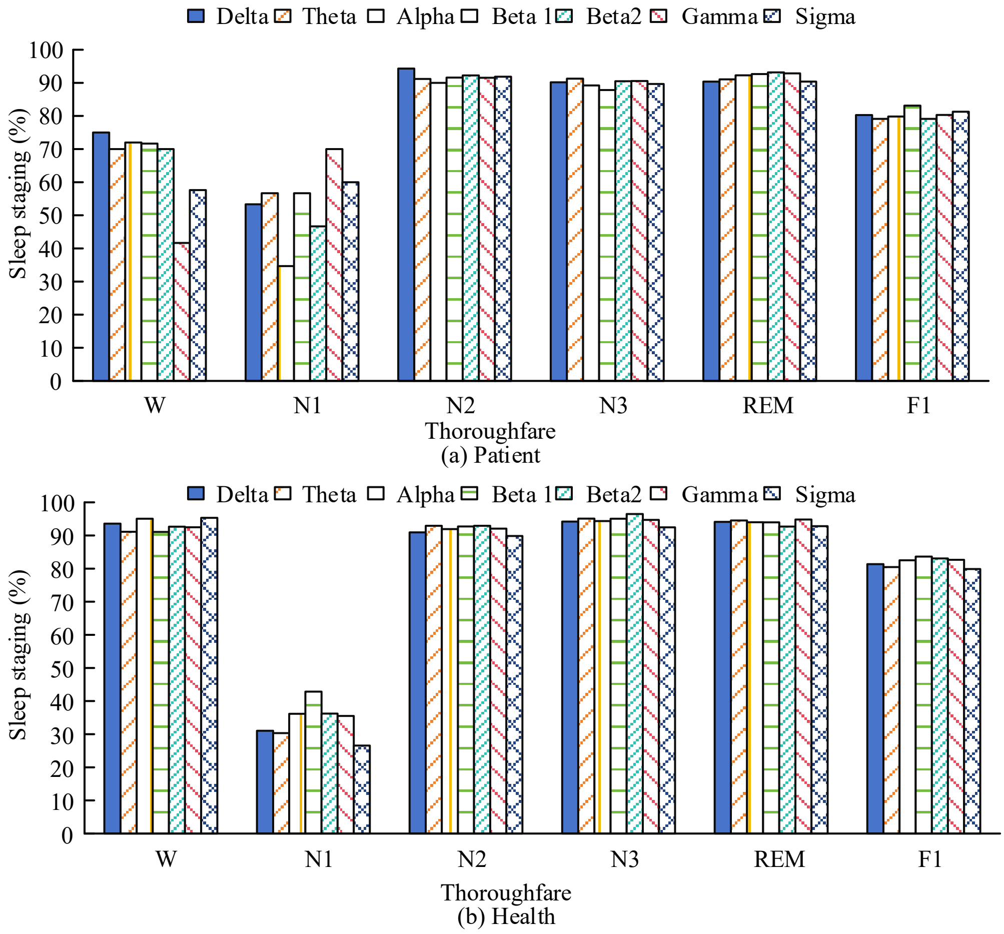


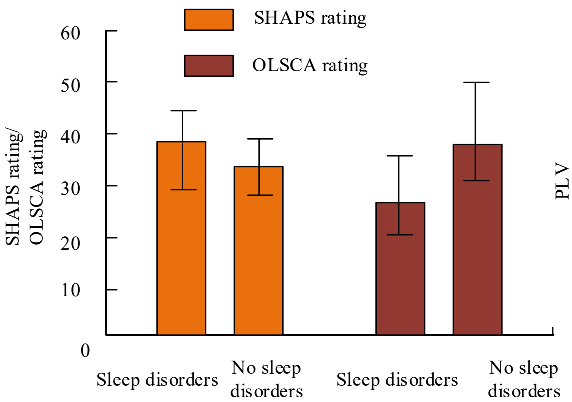
Fig. 10: The EEG signal participants of healthy college students and depressed college students

Sleep disorders are one of the main factors that promote depression in college students, and EEG signals can effectively reflect the sleep status of college students. To verify the correlation between EEG signals and sleep disorders in college students, this study conducts SPAPS and PSQI scores on depressed college students with and without sleep disorders, and analyzes the PLV mean distribution in six frequency bands and three sleep stages. In Fig. 11 (a), college students with D-SD have a high SHAPS score of 38 and a low OLSCA score of 26, indicating a low quality of life. In Fig. 11 (b), the PLV changes at different frequency bands show a downward trend in all three channel stages, but N3 shows an upward trend from Theta to Alpha. In Fig. 11 (c), there is a certain overlap between points and lines, indicating a certain correlation between SPAPS and PSQI scores. Therefore, there is a significant correlation between sleep disorders and depression among college students.

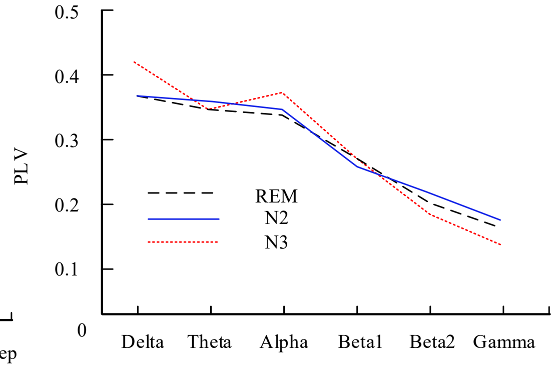
Comparative experiments with Convolutional Neural Networks (CNN) and Long Short Term Memory Networks (LSTM) show that, on the same dataset, the sleep staging accuracy of the PLV feature combined with SVM classifier used in this study is 96.20%, significantly higher than CNN's 90.03% and LSTM's 87.23% (see Table 2). Specifically, in the classification of Rapid Eye Movement (REM) and deep sleep (N3), SVM has better ability to capture phase synchronization features, with F1 scores reaching 96.39 and 97.23%, respectively, which is 6.3 and 5.9% higher than CNN. In addition, the parameter size of SVM model is only 68% of CNN, demonstrating higher computational efficiency and generalization ability in small sample scenarios.

Table 2: Comparison experiment with CNN and LSTM

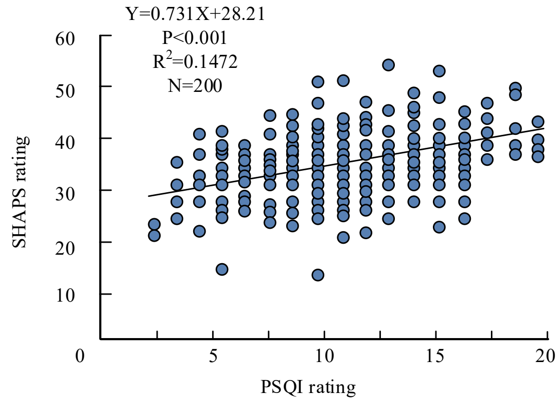
Method	Characteristic	Classifier	REM+N1(%)	N2+N1(%)	N3(%)	Accuracy (%)
Zhang *et al*., 2023	Original signal	CNN	90.66	86.88	92.54	90.03
Akbari *et al*., 2021	Time Domain Features	SVM	72.95	82.69	84.58	80.07
Research method	PLV	SVM	96.39	94.99	97.23	96.2



(a) SHAPS score and OLSCA score for adolescent patients with or without sleep disorders



(b) The distribution trend of PLV mean values in six frequency bands during three sleep stages



(c) The correlation between PSOI score and SHAPS score

Fig. 11: The correlation between EEG signals and sleep disorders in college students

Discussion

Depression, a prevalent mental health concern in modern life, faces challenges in physician - based diagnosis and psychological measurement, including low efficiency and subjectivity. This study introduced a correlation analysis of D-SD based on EEG-FA, integrating brain connectivity and multi - task classification prediction for sleep staging analysis. In the experiment, distinct patterns emerged in F1 scores across frequency bands and subject groups. For patient subjects, the lowest F1 score occurred in the delta frequency band (80.27%), while for healthy subjects, it was in the sigma band (79.86%). Patient subjects had a relatively high F1 score in the gamma band (80.3%) but still lagged behind healthy subjects in most bands. During the W wakefulness phase, patient F1 scores were generally low, especially in delta, theta, and alpha bands, contrasting with higher scores in healthy subjects. Healthy college students consistently showed higher F1 scores than patients across all sleep stages and frequency bands. In terms of accuracy, other staging methods reached 90.03, 84.78 and 87.23%, while our method achieved 96.20%. This research offers a novel approach for early depression detection and diagnosis. It can inform the development of portable EEG screening tools for university psychological counseling centers, enabling real - time monitoring of abnormal EEG functional connections for early warning of depression and sleep disorders, and facilitating personalized intervention plans like cognitive behavioral therapy with targeted brain stimulation. However, the study has limitations. The collection and processing of EEG and speech data require further optimization to enhance data reliability. External variables such as academic pressure and dietary habits were not controlled. Future steps could involve collecting such data via questionnaires and using hierarchical regression models to separate confounding factors, thus more accurately revealing the intrinsic correlation between EEG features and D-SD. There is also a need to explore physiological and psychological differences in depression of varying severity to support personalized treatment plans. Integrating behavioral data (e.g., sleep diaries, body movement recorders) to build a multimodal fusion model can further improve the accuracy of association analysis between depression and sleep disorders.

Conclusion

This study provides a D-SD correlation analysis approach based on EEG-FA for sleep staging, achieving a high accuracy of 96.20%, outperforming other staging methods. The findings provide a new avenue for early depression detection and diagnosis, with potential applications in developing portable EEG screening tools for university psychological counseling centers to enable early warning and personalized interventions. Despite the contributions, limitations exist, such as suboptimal EEG and speech data processing and uncontrolled external variables. Future research should focus on optimizing data collection, controlling confounding factors, exploring depression severity differences, and integrating behavioral data to construct multimodal models, thereby advancing the understanding and management of depression and sleep disorders.

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Ethics

This study was approved by the Ethics Committee of Zhengzhou Business University (Approval No. ZBU-SPT-2024-28). I confirm that informed consent was obtained from the study participants.

Data Availability Statement

All data generated or analysed during this study are included in this article.

Conflict of Interest

The authors declare that they have no competing interests.

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