RESEARCH ARTICLE

A classification model for college students' psychological stress based on sensor data fusion and neural networks

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With the rapid development of information technology followed by information overload and intensified social competition, the psychological pressure of college students has become increasingly prominent, while some students face depression and anxiety. However, traditional single-sensor physiological signal acquisition is prone to motion interference, making it difficult to completely characterize the linkage reactions of multiple physiological systems caused by stress, and lacking objective monitoring methods. To precisely classify psychological stress in college students, this study proposed a "wearable portable + clothing-integrated" dual-scenario sensing solution to collect heart rate variability, respiratory rate, electrodermal signals, and sweat cortisol concentration. The research also introduced an improved adaptive attention-weighted fusion algorithm for processing multi-source data and combined with an enhanced convolutional neural network to construct a fusion model. The results showed that the signal-to-noise ratio after processing with the improved adaptive attention-weighted fusion algorithm ranged from 25.80 dB to 29.60 dB. The improved convolutional neural network achieved an average classification accuracy of 90.53% for psychological stress, which was higher than 83.31% of the traditional convolutional neural network. The fusion model reached an accuracy of 92.02% in daily campus scenarios, which demonstrated that the proposed model could effectively enhance the precision and stability of stress classification. The study provided an objective and real-time monitoring and classification method for psychological stress in college students, facilitating early intervention for mental health.

Keywords: sensors; physiological signal; neural networks; data fusion; psychological stress; classification.

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Introduction

With the rapid development of information technology and intensified social competition, the psychological pressure among college students is becoming increasingly prominent, and some students are facing mental health risks including depression and anxiety [1]. Traditional psychological stress monitoring relies heavily on subjective questionnaires, which have lagging and subjective biases, making it difficult to achieve early intervention [2]. Consequently, there is an urgent need for objective stress monitoring methods [3].

In recent years, physiological signal monitoring has become a research hotspot due to its objectivity. Many studies have been done on multi-sensor fusion and classification models, making significant advances. In terms of sensor data fusion, Rashid *et al*. proposed a context recognition model and integrated machine learning method to accurately monitor the physiological status of patients. The results indicated that the classification accuracy at the wrist was 86.34% [4]. Dogan *et al*. developed a model based on dual early fusion method to capture immediate emotional responses under different levels of mental stress and found that the model could accurately detect physiological signals under different pressures [5]. To detect psychological stress levels more accurately, Zhang *et al*. proposed an end-to-end multi-modal stress detection model based on bidirectional cross-over and self-modal attention mechanisms. Multi-modal physiological signals were fused to detect stress. The results showed that the model could effectively improve the accuracy of stress identification [6]. In terms of psychological stress emotion recognition and classification, Theerthagiri adopted an emotion recognition technology based on deep belief network and transfer learning to carry out effective psychological stress prediction. The results showed that this technology could achieve the recognition and classification of stressful emotions on small-scale emotion and stress datasets [7]. To detect psychological stress in real time, Sağbaş *et al*. used a filter-based method and a standard binary-coded chromosome genetic algorithm for sensor data processing and proved that the algorithm could detect psychological stress data in real time [8]. To determine psychological stress by analyzing physiological signal data, Zhu *et al*. used support vector machines to classify physiological data detected by sensors and found that the method could accurately identify different types of stress emotion data [9]. To accurately classify the psychological stress of college students, psychologically related data should be collected. However, current objective monitoring methods face urgent issues, which include that the single sensor acquisition mode exhibits obvious limitations [10]. Relying exclusively on isolated physiological signals directly introduces high susceptibility to motion interference [11]. It is inherently impossible to fully describe the chain reaction of multiple physiological systems caused by stress [12]. Further, although multi-sensor fusion technology is a breakthrough direction, in dynamic environments, signal interference, feature redundancy (FR), and cross-modal correlation modeling are still difficult problems. The data fusion level lacks a dynamic weight adjustment mechanism and anti-motion interference capabilities. It does not fully explore the correlation of physiological signals. In the classification model, the generalization of deep belief networks is limited, the real-time performance and accuracy of genetic algorithms are difficult to balance, and support vector machines are insufficient to capture complex features.

This research proposed an improved adaptive attention weighted fusion algorithm-improved convolutional neural network (IAAWFA-ICNN) model to accurately classify the psychological stress of college students by fusing sensor data. The study designed dual-scene sensing and three-level fusion architecture, dynamically adjusting weights through error entropy and physiological correlation to form IAAWFA for anti-interference ability and feature effectiveness improvements. It further introduced multi-scale convolution and physiological gated attention mechanisms to strengthen pressure-sensitive feature extraction and form ICNN. A capsule network architecture with classification branches was proposed to accurately determine pressure levels. The proposed model provided not only a reliable, objective, real-time monitoring tool for early intervention of college students' mental health but also a new theoretical framework and practical paradigm for multi-modal physiological signal processing, which was of great significance and influence on the field of intelligent health monitoring.

Materials and methods

Signal acquisition and data fusion technology based on multi-sensors

To accurately obtain all-round data on psychological stress, the research adopted a "wearable and portable + clothing integration" dual-scene sensing solution using three types of easy-to-wear special sensors including Graphene G-Flex flexible wristband sensors (Graphenea S.A., San Sebastian, Gipuzkoa, Spain) for heart rate variability (HRV) and respiratory frequency data collection, BioStamp nPoint electromagnetic meta-surface patch sensor (MC10 Inc., Lexington, MA, USA) fixed on the shoulder strap of a shirt worn daily through Velcro for electrocutaneous signal collection, and the Discovery Patch miniature sweat sensor (Epicore Biosystems, Cambridge, MA, USA) attached to the skin on the inside of the subject's elbow for sweat cortisol concentration data collection. The sensor information collection system would automatically adjust the sampling frequency according to the subject's action status to ensure data accuracy. The data collected by the sensors were processed and fused using IAAWFA. Based on the traditional adaptive weighting algorithm, this algorithm innovatively introduced the physiological modal attention mechanism to achieve dynamic weight allocation and heterogeneous data optimization and fusion. The structure of IAAWFA was divided into three levels of collaborative architecture including preprocessing layer, dynamic weight layer, and fusion decision-making layer. The preprocessing layer differentiated the characteristics of the three types of sensors. The heart rate and respiration signals of the graphene wristband were denoised by Kalman filtering. The skin electrode signals of the shirt shoulder strap were denoised by wavelet transformation. The sweat cortisol signal was denoised by sliding average filtering. The preprocessing layer could effectively suppress motion artifacts and environmental interference, while the dynamic weight layer was the core innovative module and included a dual-channel weight adjustment mechanism, which included the error entropy monitoring channel to calculate the noise distribution entropy value of each signal in real time and the physiological correlation channel. When the error entropy of a certain signal exceeded the threshold, its weight proportion was automatically reduced. By constructing a cross-modal correlation matrix, the Pearson coefficient was used to capture the physiological linkage between HRV and cortisol concentration and strengthen the weight distribution of high correlation signals. The fusion decision-making layer used weighted summation and the feature splicing parallel strategies to dynamically weight fuse time domain features. Meanwhile, frequency domain features of each signal were reorganized through the attention weight matrix. The fusion decision-making layer not only retained the timing characteristics of the original signal but also highlighted key physiological indicators related to stress, providing a high-resolution fusion feature matrix for subsequent neural network classification. The error entropy was calculated as follows [13].

$$H_i = -\sum_{k=1}^{n} p\,(\varepsilon_{i,k}) \cdot ln\, p\,(\varepsilon_{i,k}) \tag{1}$$

where H_i was the error entropy of the i-th sensor signal. $i = 1, 2, 3$ corresponded to heart rate/respiration, skin conductance, and cortisol signals, respectively. $\varepsilon_{i,k}$ was the noise error of the k-th sampling point of the i-th signal. $p(\varepsilon_{i,k})$ was the probability density of $\varepsilon_{i,k}$. n was the number of sampling points for a single signal. The Pearson coefficient was calculated below [14].

$$r_{X,Y} = \frac{\mathrm{Cov}(X,Y)}{\sigma_X \cdot \sigma_Y} \tag{2}$$

where $r_{X,Y}$ was the Pearson coefficient of HRV signal X and cortisol signal Y with a range of [-1, 1]. The larger the absolute value, the stronger the linkage between the two signals. $\mathrm{Cov}(X,Y)$ was the covariance between X and Y. σ_X and σ_Y were the standard deviations of X and Y, respectively. The time-domain feature weighted fusion was shown below [15].

$$F_T = \sum_{i=1}^{3} w_i \cdot f_i^T \tag{3}$$

where F_T was the fused time-domain feature. w_i was the dynamic weight of the i-th signal calculated jointly by error entropy and Pearson coefficient, satisfying $\sum_{i=1}^{3} w_i = 1$. f_i^T was the time-domain feature of the i-th signal. Various physiological information was first collected through the multiple sensors worn by the subjects and then transmitted wirelessly to the IAAWFA. After data differential preprocessing, the dynamic weight layer was used to monitor the noise situation of each signal and adjust the weights before the data entered the fusion decision-making stage and output a highly recognizable fusion feature matrix.

Classification of psychological stress among college students based on ICNN

A multidimensional physiological feature matrix containing signals was constructed through multi-sensor synchronous acquisition, differential preprocessing, and dynamic weight fusion. To transform these fused features into quantifiable stress assessment results, an efficient classification model was established to accurately recognize psychological stress states by using ICNN, which could effectively capture subtle pattern differences related to stress in physiological signals through multi-scale feature extraction and dynamic attention mechanisms. After receiving the fused feature matrix in the input layer of ICNN, a multi-scale convolution block was used to parallelly set up three types of asymmetric convolution kernels as 1 × 3, 3 × 1, and 5 × 1, which were respectively adapted to high-frequency fluctuations of HRV, transient changes of skin electrical signals, and gradual trends of cortisol. A linear deformable convolution (LDConv) was embedded to dynamically adjust the sampling position and improve the flexibility of feature capture. The research innovatively introduced a physiological gating attention module in the middle layer. A gating function based on the physiological laws of stress was designed to enhance the collaborative feature channel weights of heart rate and cortisol. The output layer adopted a dual-branch structure, and the classification branch output pressure levels as none, light, medium, and heavy through a capsule network dynamic routing mechanism. The regression branch predicted the quantified value of pressure intensity, and the total loss function jointly optimized the classification loss and regression error to accurately classify and evaluate pressure states. The multi-scale convolution feature fusion was shown as follows [16].

$$F_{\mathrm{conv}} = \mathrm{concat}\left\{\mathrm{Conv}(F_{\mathrm{in}}, W_{1\times3}, b_{1\times3}), \mathrm{Conv}(F_{\mathrm{in}}, W_{3\times1}, b_{3\times1}), \mathrm{Conv}(F_{\mathrm{in}}, W_{5\times1}, b_{5\times1})\right\} \tag{4}$$

where F_{conv} was the fused feature after multi-scale convolution. F_{in} was the fused feature matrix of the ICNN input layer. $W_{k\times1} (k = 1, 3, 5)$ was the weight parameter of the corresponding size asymmetric convolution kernel. $b_{k\times1}$(k = 1, 3, 5) was the bias term corresponding to the convolution kernel. Conv($\cdot$) was the convolution operation. concat($\cdot$) was a feature concatenation operation that aggregated features of different scales. The weight of physiological gating attention was obtained as below.

$$\alpha_j = \sigma\left(W_g \cdot F_{\mathrm{conv},j} + b_g\right) \tag{5}$$

where α_j was the attention weight with the value range of [0, 1] of the j-th feature channel, and the higher the weight, the stronger the correlation between the channel and the pressure state. $F_{\mathrm{conv},j}$ was the feature of the j-th channel after multi-scale convolution. W_g was the weight matrix of the gating module. b_g was the bias term of the gate control module. $\sigma(\cdot)$ was the sigmoid activation function used to normalize weights to the [0, 1] interval, which met the quantitative requirements of physiological correlation strength. The total loss function was determined as follows.

$$L_{\mathrm{total}} = \lambda \cdot L_{\mathrm{cls}} + (1-\lambda) \cdot L_{\mathrm{reg}} \tag{6}$$

where L_{total} was the total loss of ICNN. λ was the loss weight coefficient with a value range of [0, 1] and was set to 0.6, prioritizing classification accuracy. L_{cls} was the classification loss (cross-entropy loss) and was expressed as follows.

$$L_{\mathrm{cls}} = -\frac{1}{M}\sum_{m=1}^{M}\sum_{c=1}^{4} y_{m,c} \cdot \ln \hat{y}_{m,c} \tag{7}$$

where $y_{m,c}$ was the true label of the m-th sample's m-class pressure level (none/light/medium/heavy). $\hat{y}_{m,c}$ was the corresponding prediction probability. M was the total number of samples. The regression loss (mean square error loss) was shown below.

$$L_{\text{reg}} = \frac{1}{M}\sum_{m=1}^{M}(q_m - \hat{q}_m)^2 \tag{8}$$

where L_{reg} was the regression loss. q_m was the true quantified value of pressure intensity for the m-th sample (0 - 10 points). $\hat{q}_m$ was the corresponding predicted value, collaboratively optimizing classification and regression. The capsule network architecture of the classification branch focused on the precise mapping of physiological features to pressure levels. After receiving the fused feature matrix output from the intermediate layer of ICNN, the input layer first converted it into three sets of physiological feature pressure level capsules through the primary capsule layer, corresponding to HRV, skin electrical activity, and cortisol concentration. Each group of capsules adopted 8-dimensional vector encoding for feature strength and dynamic trend based on the physiological weighted dynamic routing mechanism. The routing coefficient not only included the traditional low-level capsule prediction error but also introduced a stress physiological correlation matrix. By quantifying the synergistic fluctuation law of heart rate and cortisol, the connection weight of high correlation capsules was dynamically improved. The digital capsule layer set four output capsules corresponding to pressure levels (none, light, medium, and heavy). Each capsule was a 16-dimensional vector, compressed by the Squash function, and the vector modulus directly represented the classification probability of that level. Embedding residual connections in the architecture directly transferred the primary capsule features to the output layer, alleviating the feature loss problem of deep networks. Ultimately, by sorting the module lengths of the output capsules, the pressure level was accurately determined, considering the hierarchical characteristics of physiological signals and cross-modal correlation characteristics. The Squash function was determined as follows [17].

$$v = \frac{\|u\|^2}{1+\|u\|^2} \cdot \frac{u}{\|u\|} \tag{9}$$

where u was the original input vector of the capsule, where the primary capsule was 8 dimensions, and the digital capsule was 16 dimensions. v was the compressed capsule output vector of the Squash function. $\|u\|$ was the modulus of vector u, used to characterize the activation strength of capsule features. This function used nonlinear compression to make the output vector modulus of capsules with high activation intensity (larger modulus) approaching 1, and the output vector modulus of capsules with low activation intensity (smaller modulus) approaching 0. The modulus of v eventually characterized the classification probability of the corresponding pressure level directly. To apply IAAWFA and ICNN in practice, an IAAWFA-ICNN combined model was established. The model adopted an end-to-end architecture with "data fusion-feature optimization-stress classification" as the core link, adapting to the real-time and accurate requirements of psychological stress monitoring for college students in practical scenarios. The initial end of the model was the IAAWFA data fusion module, and the input end received raw physiological signals from sensors. The environment and motion interference were first eliminated through targeted preprocessing units, and then the dynamic weight allocation submodule was used to adjust the weight ratio of each signal in real-time based on the correlation between signal noise entropy and physiological indicators. The final output dimension was a unified multi-modal fusion feature matrix. The fused features were directly imported into the backend ICNN classification module, which had multi-scale asymmetric convolution blocks (1 × 3, 3 × 1, and 5 × 1 convolution kernels) in the first layer to capture pressure-sensitive features of different physiological signals. The middle layer embedded physiological gated attention units to

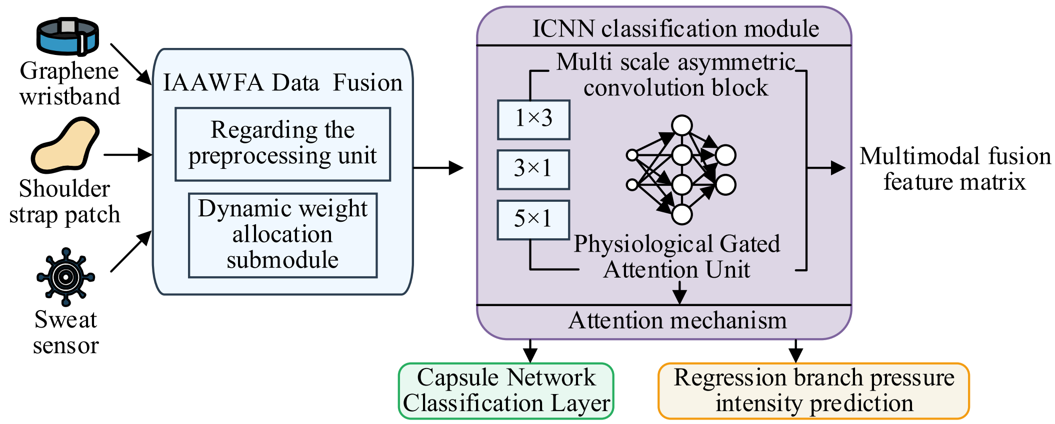

Figure 1. Structure of proposed IAAWFA-ICNN model.

strengthen key feature channels based on the changes in physiological indicators under stress. The capsule network classification layer of the end classification branch mapped features through dynamic routing mechanism to achieve psychological stress classification. The regression branch predicted the quantitative value of stress intensity to assist in the rapid classification of psychological stress and meet the rapid classification needs of actual monitoring scenarios (Figure 1).

Experimental platform and data collection

The sensor data were transmitted to a computer terminal equipped with Intel Core i7-12700H CPU, NVIDIA RTX 3060 GPU, and 16 GB DDR4 3200Mhz memory through Bluetooth 5.0 module. Data acquisition and dynamic sampling rate control were implemented using Python 3.9 (https://www.python.org/) PySerial library. Signal preprocessing was completed using MATLAB R2022b (MathWorks, Natick, MA, USA) and PyWaves library (https://pywavelets.readthedocs.io/), IAAWFA algorithm was implemented using NumPy (https://numpy.org/) /SciPy (https://scipy.org/) libraries. Data visualization was performed by using Matplotlib (https://matplotlib.org/). The fused features were formatted using TensorFlow 2.8 (https://www.tensorflow.org/) to adapt to ICNN input. The input parameters for the IAAWFA module were the Kalman filter Q-values of 0.01 for HRV and 0.02 for respiration with corresponding R-values of 0.1 and 0.15. The skin electrical wavelet transform utilized the db4 wavelet basis with a decomposition level of 3. The cortisol sliding average window was defined as 10 sampling points (10s). The error entropy thresholds were specified as 0.6 for HRV, 0.8 for skin electricity, 0.4 for cortisol, and a Pearson coefficient threshold of ≥ 0.5. The resulting fusion feature dimensions consisted of 6 in the time domain and 4 in the frequency domain. For the backend ICNN module, the input fusion feature matrix dimension was set to N × 60 × 10 (where N was the number of samples). The network utilized multi-scale convolution kernel parameters of 1 × 3 (16 pieces), 3 × 1 (16 pieces), and 5 × 1 (16 pieces) with an LDConv offset range of [-2, 2] pixels. The physiological gated attention module featured a 10 × 10 weight matrix and a 1 × 10 bias. The capsule network architecture was configured to 32 main capsules with a dimension of 8 and 4 digital capsules with a dimension of 16. The dataset used in this study was sourced from data collected by multiple sensors including over 5,200 samples from 120 college students (68 males, aged 18 - 22 years and 52 females, aged 18 - 21 years). All participants were recruited from Guangxi Science & Technology Normal University, Laibin, Guangxi, China under standardized stress tasks and natural scenes. The data of HRV, respiratory rate, skin electrical signals, sweat cortisol concentration, and corresponding pressure levels were collected from each participant. All procedures of this study were approved by Ethics Committee of Guangxi Science & Technology Normal University (Laibin, Guangxi, China). This study adopted "signal quality optimization" and "fusion feature effectiveness" as core indicators with traditional Adaptive Attention Weighted (AAW) algorithm and Improved BP algorithm as comparative methods [18]. To further analyze the performance of the proposed ICNN, the traditional CNN implemented *via* TensorFlow (https://www.tensorflow.org/) and the Improved Multi-label K-Nearest Neighbors (IMLkNN) algorithm implemented *via* scikit-learn (https://scikit-learn.org/) were employed as comparative baseline algorithms. The signal acquisition time was set as 30 minutes, covering natural scenes from 0 - 10 minutes, stress tasks from 11 - 20 minutes, and recovery scenes from 21 - 30 minutes. For signal quality optimization, the study evaluated signal-to-noise ratio (SNR), signal fidelity (SI), and motion artifact suppression rate (MASR). MASR = [(motion artifact energy in pre-processing signal - motion artifact energy in post-processing signal) / motion artifact energy in pre-processing signal] × 100%. The higher the value, the better the motion artifact suppression effect. The effectiveness of feature fusion was evaluated by using intra-inter distance ratio (IIDR) and FR as indicators. IIDR = (average Euclidean distance of samples within all categories) / (average Euclidean distance of samples between all categories), directly measuring the separability of fused features, where a smaller value indicated better performance. FR = 1 - (information entropy of fusion features) / (sum of information entropy of each single modal feature), which evaluated the proportion of duplicate information in the fusion features, where a smaller value indicated better performance.

Statistical analysis

All experimental data were expressed as mean ± standard deviation. Independent student t-test was performed to compare the significant differences between the test groups with *P* value less than 0.05 as statistically significant difference.

Results and discussion

Sensor data acquisition and IAAWFA performance analysis

The SNR, SI, and MASR of signals processed by different algorithms demonstrated that the higher the SNR, the weaker the signal was affected by noise interference and the better the data quality. The SNR of the signal processed by IAAWFA within 30 minutes between 25.80 - 29.60 dB was higher than that of AAW between 21.30 - 25.50 dB, improved BP between 20.10 - 23.90 dB, and initial signal between 16.20 - 19.90 dB throughout the entire process. Especially in stressful scenarios from 11 - 20 min, the initial signal SNR significantly decreased (Figure 2a). The results showed that IAAWFA had stronger anti-interference ability and noise reduction advantages due to the dual-drive weight adjustment of "error entropy + physiological correlation". SI was close to 1, indicating that the processing had not been overly filtered. The key physiological characteristics related to stress were preserved more completely. The SI of 0.90 - 0.96 of the signal processed by IAAWFA was superior to AAW's 0.83 - 0.90 and improved BP's 0.80 - 0.87 throughout the entire time period (Figure 2b). The reason was that IAAWFA adopted adaptive preprocessing for signals such as HRV and skin conductance, which could preserve physiological characteristics such as high-frequency components and transient response peaks. MASR referred to the interference caused by unstable sensor contact due to daily activities of the subjects such as baseline drift of physiological signals and spike noise. The MASR of IAAWFA consistently remained above 90%, indicating a higher proportion of effective physiological information in the signal (Figure 2c), which might be due to its adaptive noise reduction techniques for different physiological signal characteristics through preprocessing layers. The IAAWFA performed better in maintaining features. The IIDR and FR

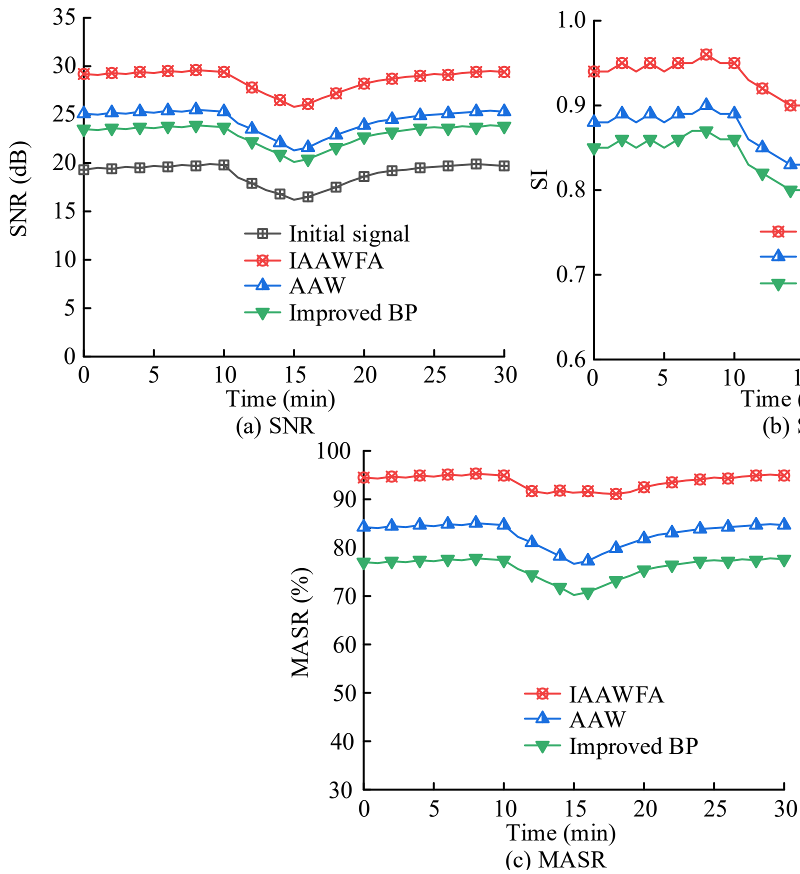

Figure 2. SNR, SI, and MASR processed by different algorithms.

after data fusion showed that the IIDR of 0.32 - 0.38 of IAAWFA was significantly lower than that of AAW (0.45-0.52) and improved BP (0.55 - 0.63) in all scenarios (Figure 3a). IAAWFA enhanced the consistency of similar features and weakened heterogeneous interference through physiological correlation regulation. The results indicated that IAAWFA fusion features had higher intra-class sample aggregation and stronger inter class sample discrimination, which better met the separability requirements of pressure level features. The FR of IAAWFA was 0.21 – 0.25, lower than other algorithms in all scenarios. The FR in pressure scenarios was only 0.25, far lower than that of AAW’s 0.36 and improved BP’s 0.42 (Figure 3b). IAAWFA's error entropy monitoring could accurately identify and filter redundant signals, avoiding information duplication. The results indicated that IAAWFA had a better effect in removing redundant information from multiple sensors and retaining more sufficient complementary physiological information.

The classification effect of ICNN on psychological stress among college students

IAAWFA provided a data quality foundation for ICNN to classify psychological stress. After comparing ICNN with traditional CNN and improved multi-label K-nearest neighbors (IMLkNN) algorithms, the results showed that the classification accuracy of ICNN was significantly optimal. The average classification accuracy of ICNN in stress free type was 94.25 ± 0.24%, which was 6.04% and 9.21% higher than that of CNN (88.21 ± 0.41%) and IMLKNN (85.04 ± 0.31%), respectively. For the mild stress, moderate stress, and severe stress types, ICNN also achieved superior accuracy of 91.07 ± 0.27%, 89.50 ± 0.27%, and 87.30 ± 0.31%, respectively. Overall, the average accuracy of ICNN reached

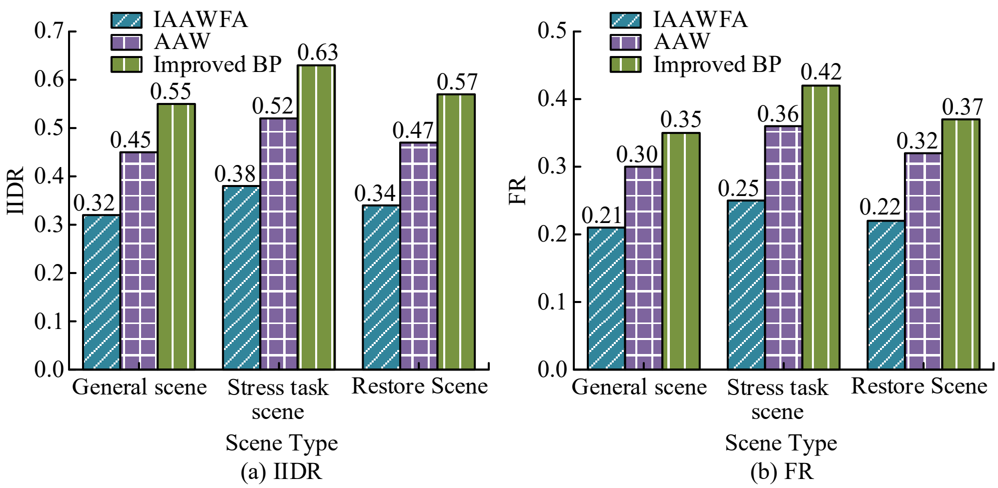

Figure 3. IIDR and FR after data fusion for various algorithms.

90.53 ± 0.25%, comprehensively outperforming CNN (83.31 ± 0.26%) and IMLkNN (80.33 ± 0.20%) ($P < 0.05$). The standard deviation of the accuracy of ICNN for each pressure type was between 0.24% and 0.31%, indicating that it was less affected by experimental random errors and had stable performance. The high-quality fusion features provided by IAAWFA, combined with ICNN's multi-scale feature extraction and physiological gating attention mechanism, could effectively improve the accuracy and stability of psychological stress classification. In terms of sample classification balance, the study used macro- and micro- as indicators. Macro- referred to calculating indicators for four pressure levels separately and taking the arithmetic mean. Micro- was a metric that calculated the total number of correct and incorrect predictions for all levels. Low macro- indicated poor classification for minority classes, while low micro- indicated weak overall classification ability. The results showed that the mean Macro- of ICNN was 0.9044, higher than that of IMLkNN (0.8255) and CNN (0.7948) (Figure 4a), which might be because the physiological gating attention module of ICNN strengthened the weights of minority class features. ICNN could still maintain a stable advantage in handling pressure classification with a small sample size. The mean Micro- of ICNN was 0.9053 and 7.22% higher than that of IMLkNN and 10.20% higher than that of CNN (Figure 4b). The results indicated that ICNN had better overall classification performance.

The practical application effect of IAAWFA-ICNN model

To verify the adaptability, generalization, and reliability of the IAAWFA-ICNN model in actual scenarios of psychological stress monitoring for college students, four core application dimensions were evaluated including scenario adaptability, population generalization, real-time performance, and classification reliability. The results demonstrated that the IAAWFA-ICNN model performed well in the practical application of psychological stress monitoring for college students. In terms of scene adaptability, the average accuracy reached 92.02 ± 0.14% in daily campus scenes, 89.38 ± 0.23% in exam stress scenarios, and 88.54 ± 0.22% in simulated defense scenarios, demonstrating a small standard deviation and strong anti-interference ability. It had effective population generalization with highly stable accuracy rates across demographics as 91.40 ± 0.17% for first-year students, 90.70 ± 0.18% for senior students, 91.59 ± 0.14% for male students, and 92.12 ± 0.16% for female students. The small difference in accuracy among different grade and gender groups proved that it was suitable for diverse populations. Real-time performance met the

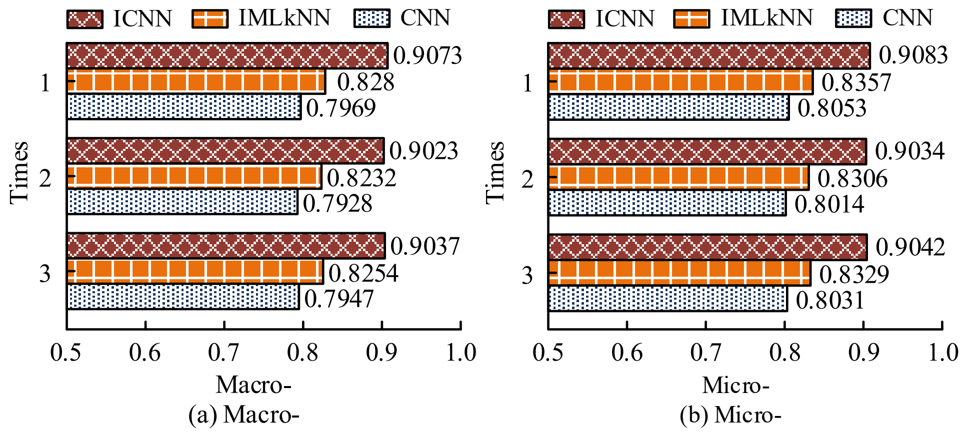

Figure 4. Macro- and Micro- of each algorithm.

requirements with a single sample response delay of only 85.75 ± 0.42 ms and a stable monitoring accuracy of 90.14 ± 0.22% for 1 hour continuously. The classification reliability was high as the Kappa coefficient reached an excellent level of 0.88 ± 0.01, and the severe stress misclassification rate was only 2.24 ± 0.09%. The IAAWFA-ICNN model had outstanding performance in scene adaptation, population coverage, real-time response, and result reliability of psychological stress monitoring for college students and had practical application value.

Conclusion

Aiming at the limitations of traditional single sensors in monitoring the psychological stress of college students, the IAAWFA-ICNN model was proposed to classify the state of psychological stress. The study collected multiple physiological signals through lightweight sensors, then performed data fusion and quality optimization through IAAWFA before combining ICNN to classify psychological stress. The results demonstrated that the proposed IAAWFA effectively improved signal quality by significantly enhancing the SNR and suppressing motion artifacts compared to traditional algorithms. Further, the ICNN model achieved a notably higher classification accuracy and demonstrated superior performance in capturing complex stress features than baseline models. In practical application tests, the integrated IAAWFA-ICNN model exhibited excellent scene adaptability, robust population generalization, low misclassification rates for severe stress, and high overall reliability. Overall, the IAAWFA-ICNN model showed effective performance in classification accuracy, stability, and scene adaptation. However, this study had certain limitations including a limited sample size that resulted in insufficient representativeness of the general population and the exclusion of stress data from specific scenarios that led to incomplete scenario coverage. Future research should expand the sample size, cover different age groups, and supplement the special scenario data. Meanwhile, by combining behavioral data such as facial expressions and speech, a multi-modal classification model could be constructed to further improve generalization ability and practicality.

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