

Article

Real-time Detection of Psychological Fatigue in Middle-Aged and Elderly Individuals During Physical Exercise Using Wearable Devices

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Abstract: As the global aging population continues to accelerate, exercise-related health management for older adults has emerged as one of the key research priorities in the field of public health. Psychological fatigue incurred during physical exercise is a critical factor contributing to the interruption of exercise activity among older adults, an increased risk of exercise-related injuries, and the development of exercise-related burnout; however, conventional subjective assessment methods and offline monitoring approaches are often inadequate for the continuous and real-time detection of psychological fatigue states. This study develops a real-time detection system for exercise-related psychological fatigue in middle-aged and elderly individuals, leveraging multimodal wearable devices and deep learning technologies. This system collects physiological signals-such as heart rate variability, three-axis acceleration, and skin conductance response-during physical exercise in elderly individuals. Following data preprocessing and feature extraction, it constructs a multimodal deep learning model combining temporal features, namely a CNN-LSTM architecture, to enable quantitative assessment and real-time prediction of psychological fatigue status. Experimental results demonstrate that this model achieves a prediction accuracy of 82.3% for psychological fatigue in middle-aged and elderly individuals, with a root mean square error (RMSE) of 1.25 and a Pearson correlation coefficient (r) of 0.81, significantly outperforming traditional single-feature linear regression models. This system provides an objective technological solution for intelligent and personalized monitoring of exercise-related health in middle-aged and elderly populations, while also offering data support for the development of exercise intervention strategies within the field of smart healthcare.

Keywords: middle-aged and elderly individuals; physical exercise; psychological fatigue; wearable devices; deep learning; physiological signals; real-time monitoring

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1. Introduction

On October ,2024, the official website of the Central People's Government of the People's Republic of China released the "2023 National Bulletin on the Development of Aging Affairs," which showed that by the end of 2023, the number of people aged 60 and above in China reached 296.97 million, accounting for 21.1% of the total population; the number of people aged 65 and above reached 216.76 million, accounting for 15.4% of the total population [1]. On January 17, 2025, Wang Pingping published an article titled "The Decline in Total Population Size Has Slowed, While the Quality of the Population Continues to Improve" on China Economic Net, which indicated that by the end of 2024, the number of people aged 60 and above had reached 310.31 million, accounting for 22.0% of the total population, representing a year-on-year increase of 0.9% compared to the end of 2023; among them, the number of people aged 65 and above reached 220.23 million, accounting for 15.6%, representing a year-on-year increase of 0.2% compared to the end of 2023 [2]. Over the past decade, the proportion of the elderly population in China has

shown a growing trend [2]. According to the "China Aging Development Report 2024-Mental Health Status of Older Adults in China," a blue book released at the 2024 China Annual Conference on Aging Sciences, 23.76% of older adults in China experience varying degrees of loneliness, among whom 4.75% "often feel lonely." Meanwhile, 26.4% of older adults in China exhibit varying degrees of depressive symptoms, of whom 6.2% suffer from moderate to severe depressive symptoms. According to statistics from the World Health Organization, by 2025, the proportion of the global population aged 60 and above will exceed 17%, and the deepening of population aging will impose higher demands on the elderly health protection system. Moderate physical exercise is an effective means of slowing the decline of physiological function in older adults, improving cardiovascular health, and enhancing cognitive function; it also serves as a core intervention strategy in geriatric health management.

Current assessment methods for exercise-induced psychological fatigue primarily fall into two categories: subjective assessment and objective measurement. Subjective assessment, exemplified by the Borg Fatigue Scale and the Rosenberg Fatigue Scale, relies on the subject's subjective reports; however, such approaches are susceptible to influences from factors such as the subject's cognitive level and expressive capacity, and cannot enable continuous monitoring [3]. Objective measurement is typically conducted in laboratory settings, where specialized instruments are used to acquire physiological signals for analyzing fatigue status; although these results are objective, the measurement environments differ significantly from real-world exercise conditions, and these methods lack real-time capability and portability.

Wearable devices, leveraging their advantages of low power consumption, portability, non-invasiveness, and real-time sensing capabilities, have been widely adopted for monitoring physiological functions, exercise status, and cardiovascular health in elderly individuals [4]. Existing research has predominantly focused on the detection of physical fatigue (e.g., muscle fatigue and physical exertion fatigue) in older adults using wearable devices; however, there remain significant gaps in the exploration of physiological indicators specific to psychological fatigue, the development of tailored models, and the consideration of the distinct characteristics of physiological decline in this population [5]. Moreover, many studies directly transfer fatigue detection models developed for younger populations to older adults without adequate accounting for these demographic differences, resulting in suboptimal detection accuracy.

For older adults, physical exercise serves as a crucial means of maintaining bodily functions; however, excessive psychological fatigue-manifested as diminished attention span and depressive moods-can lead to reduced exercise adherence and even increase the risk of injury [6]. In light of this, this study targets healthy middle-aged and elderly individuals aged 60 and above, utilizing multimodal wearable sensing devices to acquire physiological signals under real-world exercise conditions. The study aims to identify physiological features highly correlated with psychological fatigue during exercise in this population, construct a deep learning-based detection model tailored for older adults, and achieve real-time, accurate detection of psychological fatigue during physical activity. This approach provides a novel solution for the intelligent monitoring of exercise-related health in middle-aged and elderly individuals.

2. Related Research

2.1. Current Research Status of Exercise Assessment in Older Adults

Wearable devices have become crucial technological tools for exercise and health monitoring among elderly individuals. Existing research primarily focuses on areas such as activity recognition for older adults, physical fitness status assessment, and early warning of sports injuries [7]. Commercial wearable devices, including the Empatica E4, Apple Watch, and Huawei Band, have already enabled real-time acquisition of physiological signals such as heart rate, acceleration, and skin conductivity [8]. Some studies have utilized these devices to achieve automated recognition of common exercise

types-such as walking, Tai Chi, and square dancing-among older adults, as well as quantitative assessment of exercise intensity [9]. Furthermore, in research on exercise monitoring for frail elderly individuals, physiological signals collected via wearable devices have been used to construct exercise capacity assessment models, providing a foundation for developing personalized exercise intervention plans.

However, existing research still exhibits several notable limitations: first, monitoring efforts predominantly focus on the physical activity status and physiological functions of elderly individuals, while insufficient attention is paid to their psychological states during exercise (e.g., psychological fatigue and exercise-related anxiety); second, most exercise monitoring models fail to adequately account for the physiological specificity of the elderly population, resulting in limited generalization capabilities; third, most studies rely on the monitoring and analysis of single signals, lacking the integrated application of multimodal physiological signals, which hinders a comprehensive assessment of the psychological state of elderly individuals during physical activity.

2.2. Research on Psychological Fatigue Detection Technologies

The core objective of psychological fatigue detection lies in uncovering the correlation between subjective feelings of fatigue and objective physiological indicators. By employing a head-worn mental health monitoring system-comprising an electroencephalogram (EEG) device, a chest-worn heart rate monitor, and a skin electrical impedance sensor-the system integrates a novel wearable eye-tracking device equipped with advanced measurement technologies, as well as embedded sensors and a smartphone-based real-time human-computer interaction interface [10]. This integrated approach provides a theoretical foundation for the objective detection of psychological fatigue using physiological signals.

In terms of subjective assessment, the Borg 6–20 Fatigue Scale has become a widely adopted tool for evaluating exercise-induced fatigue due to its ease of administration and intuitive results, and it is extensively applied for fatigue scoring in diverse sports contexts [11]. Regarding objective monitoring, measures such as heart rate variability (HRV), electrodermal activity (EDA), acceleration signals, and electroencephalography (EEG) have all been demonstrated to be highly correlated with psychological fatigue: the time-domain and frequency-domain characteristics of HRV reflect the regulatory state of the autonomic nervous system; during psychological fatigue, the sympathetic nervous system becomes dominant, and HRV-related indices significantly decrease; EDA signals can capture fluctuations in human emotion and stress levels, with notable changes in both the frequency and amplitude of skin conductance during psychological fatigue; acceleration signals reflect limb movement patterns during exercise, and psychological fatigue may lead to reduced range of motion and diminished motor coordination in older adults [12].

However, existing research on psychological fatigue detection has primarily focused on young adults and athletes, while studies targeting middle-aged and elderly individuals remain relatively scarce; furthermore, some of these studies employ invasive or non-portable detection methods-such as electroencephalography (EEG)-which make it difficult to apply these approaches in real-world sports environments.

2.3. Application of Deep Learning in Fatigue Detection

Deep learning possesses capabilities for feature extraction and temporal data processing, and has already been applied in the field of fatigue detection. Convolutional neural networks (CNNs) can extract local features from high-dimensional physiological data; in research on fatigue detection in elderly populations, some investigators have extracted features from acceleration signals-which reflect altered movement patterns induced by muscle fatigue-and trained CNN models to detect muscle fatigue in older adults [13, 14, 15, 16, 17, 18]. In the field of psychology, researchers have employed various deep learning models-such as large language models (LLMs), deep convolutional neural networks (DCNNs), and hybrid models combining CNNs with long short-term memory networks (CNN-LSTM)-to assess psychological states [19]. Long short-term memory networks (LSTM) are particularly adept at capturing dependencies in temporal data; the

integration of these two architectures allows them to complement each other, and their combined application to physiological signal detection has demonstrated promising improvements in detection accuracy.

The aforementioned studies provide a theoretical foundation and practical reference for this research. In this study, we utilize wearable devices to acquire physiological signals, extract the physiological characteristics of psychological fatigue in elderly individuals, and construct a CNN-LSTM hybrid model for training, thereby achieving real-time detection of psychological fatigue in individuals engaged in physical activity.

3. Methods

The overall approach of this study is as follows: wearable devices are employed to acquire electrocardiogram (ECG), heart rate, and electrodermal activity signals; the acquired physiological signals undergo data preprocessing and feature extraction; a CNN-LSTM model is then constructed, trained, validated, and subjected to feature analysis; ultimately, the goal is to achieve real-time detection of psychological fatigue in elderly individuals during physical exercise. The technical workflow is illustrated in Figure 1.

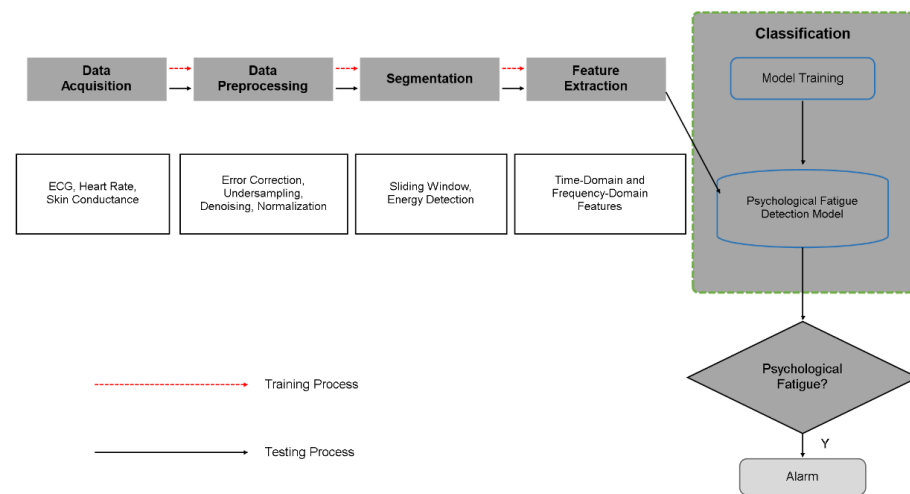


Figure 1. Overall Framework of the Wearable-Device-Based Psychological Fatigue Detection System.

3.1. Introduction to Wearable Devices

In this study, the Empatica E4 smart wristband was selected as the wearable device, which features low power consumption, high sampling rate, and portability. It enables real-time monitoring of heart rate, exercise intensity, limb movement patterns, postural changes, and skin electrical activity during physical activity in elderly individuals; the specific internal sensing modules are as follows:

(1) Photoplethysmography (PPG) sensor: with a sampling rate of 60 Hz, this sensor extracts time-domain and frequency-domain features of the pulse wave signal to derive heart rate (HR) and heart rate variability (HRV); monitoring these parameters reflects the activation status of the autonomic nervous system.

(2) MEMS triaxial accelerometer: with a sampling rate of 32 Hz, it captures acceleration signals along the x, y, and z axes; by monitoring these triaxial accelerations, it reflects the exercise intensity, limb movement patterns, and postural changes of elderly individuals.

(3) Dual-electrode electrodermal activity (EDA) sensor: sampling rate of 4 Hz; measures skin conductance level (SCL) and skin conductance response (SCR). By monitoring the skin conductance response, it assesses the level of sympathetic nervous system activation, thereby evaluating emotional and stress states.

3.2. Data Collection

3.2.1. Experimental Subjects

A total of 60 healthy elderly volunteers aged 60–75 were recruited as study participants, including 32 males and 28 females, with a mean age of 67.2 ± 4.5 years. The inclusion criteria for participants were as follows: (1) absence of chronic diseases that could impair physical activity, such as severe cardiovascular or cerebrovascular diseases, diabetes, or osteoarticular disorders; (2) absence of psychiatric or psychological disorders, including cognitive impairment or depression, and the ability to reliably complete the subjective fatigue scale; (3) possession of basic motor skills, enabling independent performance of physical activities such as walking, Tai Chi, or light jogging; (4) no contraindications related to the use of wearable devices. All participants provided written informed consent, and the study protocol was approved by the ethics review committee.

3.2.2. Experimental Environment

This study captures real-world exercise scenarios of elderly individuals on community fitness trails, outdoor synthetic walking paths, and community Tai Chi squares, thereby minimizing the potential interference of laboratory environments on their exercise performance. The experiment selected three common types of exercise for elderly participants-brisk walking, Tai Chi practice, and light jogging. Prior to each exercise session, participants were required to rest for 10 minutes to prevent the accumulation of physical fatigue.

3.2.3. Data Collection and Annotation

After participants wore the Empatica E4 smart wristband, they sat quietly for 10 minutes to collect physiological signals as baseline data, which served as the basis for subsequent signal normalization. During physical activity, the Empatica E4 smart wristband continuously acquired physiological signals-including heart rate, triaxial acceleration, and skin conductance response-and transmitted them in real time to a mobile device for storage. Upon completion of the exercise, elderly participants completed the Borg 6–20 Subjective Fatigue Scale, with scores ranging from 6 (no fatigue) to 20 (extreme fatigue). These scores were then used as labels for a deep learning model in its training and validation phases.

In this study, a total of 1,800 minutes of valid physiological signal data were collected, along with 180 subjective fatigue scores, thereby constructing a physiological signal dataset on exercise-related psychological fatigue in elderly individuals.

3.3. Data Processing and Feature Extraction

Raw physiological data are affected by factors such as motion artifacts, environmental noise, and device jitter; therefore, the collected data require preprocessing-including data cleaning, denoising, data normalization, and data framing. From the preprocessed signals, features indicative of psychological fatigue are extracted to serve as input data for the deep learning model.

3.3.1. Data Preprocessing

data preprocessing

Apply linear interpolation to fill a small number of removed missing values, and utilize the 3σ criterion to identify and remove signal segments containing more than 10% of outliers.

(2) Electromyographic interference typically spans a broad frequency range, approximately 5–2000 Hz, and exhibits spectral characteristics similar to white noise. To eliminate high-frequency noise, a fourth-order Butterworth low-pass filter with a cutoff frequency of 5 Hz is employed. For PPG-derived heart rate signals, the same fourth-order Butterworth low-pass filter (cutoff frequency: 5 Hz) is applied to remove high-frequency noise; for acceleration signals, the db4 wavelet transform is utilized to perform multi-scale decomposition and reconstruction, thereby eliminating motion artifacts; for EDA-derived

skin electrical signals, a sliding average filter with a window size of 5s is applied to remove baseline drift and environmental noise.

(3) Data normalization involves scaling all physiological signal feature values to the interval [0,1], thereby eliminating the impact of differing scales on model training. The normalization formula is as follows: $x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}$ where x_i denotes the original feature value, and x_{min} and x_{max} represent the minimum and maximum values of the feature values, respectively.

(4) Data framing involves processing continuous physiological signals into time windows, with each window lasting 10s and a step size of 5s, resulting in a total of 10,800 sample frames; each sample frame comprises the physiological signals from the corresponding time window and the subjective fatigue score label for that interval.

3.3.2. Feature Extraction

From the three types of preprocessed signals-PPG heart rate, triaxial acceleration, and EDA skin conductivity-we extracted time-domain, frequency-domain, and statistical features, respectively. In total, 38 effective features were extracted and used as the input feature set for the model; the core extracted features are as follows:

HRV features (12-dimensional): time-domain features of HRV-such as SDNN, RMSSD, NN50, and pNN50-are extracted from the PPG signal, along with frequency-domain features-including LF, HF, LF/HF ratio, and VLF-thereby reflecting the regulatory state of the autonomic nervous system.

Acceleration features (18-dimensional): Extract statistical features from the accelerations along the x, y, and z axes-such as mean, variance, standard deviation, maximum value, minimum value, skewness-and spectral features of the three-axis composite acceleration, including the centroid frequency and energy spectral density; these features collectively reflect exercise intensity and limb movement patterns.

EDA features (8-dimensional): extraction of the mean and variance of skin conductance level (SCL), as well as the peak value, amplitude, frequency, rise time, fall time, and total energy of skin conductance response (SCR), to reflect the degree of sympathetic nervous system excitation.

3.4. Model Construction

In this study, we developed a CNN-LSTM multimodal fusion deep learning model. The CNN layer is employed to extract local spatial features from physiological signals, while the LSTM layer captures long-term dependencies in temporal features, thereby enabling quantitative prediction of exercise-induced psychological fatigue in middle-aged and elderly individuals. The model architecture primarily consists of an input layer, a CNN feature extraction layer, an LSTM temporal feature extraction layer, a fully connected layer, and an output layer; the detailed structure is as follows:

(1) Input layer: The extracted 38-dimensional physiological features are arranged as a time series; the input dimensions are [None, 10, 38] (number of samples denoted as "None", time step set to 10, and feature dimension set to 38);

(2) CNN feature extraction layer: The architecture comprises two one-dimensional convolutional layers. The first layer employs 32 convolutional kernels, each with a kernel size of 3, utilizes the ReLU activation function, and applies max pooling (with a pooling kernel size of 2). The second layer employs 64 convolutional kernels, each with a kernel size of 3, also utilizes the ReLU activation function, and applies max pooling (with a pooling kernel size of 2). Through these convolutional and pooling operations, local features of the physiological signals are extracted, and the output dimension is set accordingly [None, 2, 64] .

(3) LSTM temporal feature layer: A single LSTM layer is configured with 128 hidden units, using the Tanh activation function and a dropout rate of 0.2. This layer is designed to capture long-term dependencies in the temporal features of physiological signals, enabling the modeling of the progression of exercise-induced psychological fatigue, with an output dimension of [None, 128] ;

(4) Fully connected layers: Two fully connected layers are configured; the first layer contains 64 neurons with ReLU activation function and a dropout rate of 0.2, while the second layer contains 32 neurons with ReLU activation function, mapping the temporal features extracted by the LSTM layer into a feature space.

(5) Output layer: A single fully connected layer is configured with one neuron, employing a Linear activation function; the final output is a predicted subjective score of psychological fatigue in middle-aged and elderly individuals, thereby enabling the quantification of the degree of psychological fatigue.

3.5. Model Training and Validation

During the model training and validation phases, this study divided the dataset into a training set, a validation set, and a test set in a 7:2:1 ratio, employing five-fold cross-validation to assess the model's generalization capability. The key hyperparameters configured during model training were as follows: the optimizer used was Adam, with a learning rate set to 0.001, weight decay set to $1e-5$, and the loss function chosen as mean squared error (MSE) to quantify the deviation between predicted values and actual labels; the batch size was set to 32, the number of training epochs was set to 50, and an early stopping strategy was applied—training was halted if the validation set loss failed to decrease for five consecutive epochs—to prevent overfitting. The model was implemented using Python 3.9, with PyTorch 2.0 as the deep learning framework, and was executed on an NVIDIA RTX 3060 GPU to accelerate the training process.

4. Experimental Results and Analysis

In this study, we employed accuracy, root mean square error (RMSE), and Pearson correlation coefficient (r) as evaluation metrics for model performance. Specifically, accuracy refers to the proportion of samples for which the difference between the predicted value and the true label falls within ± 1 point; a smaller RMSE indicates smaller prediction bias of the model, while a Pearson correlation coefficient (r) closer to 1 signifies a stronger linear relationship between the model's predictions and the actual subjective ratings. Additionally, we conducted feature importance analysis to identify core physiological features highly associated with exercise-related psychological fatigue in middle-aged and elderly individuals.

4.1. Model Performance Evaluation

In the test set, we compared the performance of the CNN-LSTM hybrid model, the standalone CNN model, the standalone LSTM model, and the traditional linear regression model; the corresponding performance evaluation results for each model are presented in Table 1.

Table 1. Performance Evaluation Results of Different Models

types of models	precision (%)	RMSE	Pearson correlation coefficient (r)
linear regression model	58.2	2.86	0.45
Single CNN model	69.5	1.92	0.63
Single LSTM model	75.8	1.56	0.72
CNN-LSTM Fusion Model	82.3	1.25	0.81

As shown in Table 1, the CNN-LSTM multimodal fusion model developed in this study outperforms all other models across all evaluation metrics: the accuracy rate reaches 82.3%, representing an improvement of 24.1 percentage points over traditional linear regression models, 12.8 percentage points over standalone CNN models, and 6.5 percentage points over standalone LSTM models; the RMSE is 1.25; and the Pearson correlation coefficient (r) is 0.81. These results indicate that the model's predictions exhibit a high degree of linear correlation with the subjective fatigue scores of elderly individuals, while maintaining relatively small prediction deviations.

The CNN-LSTM hybrid model achieves superior performance due to the synergistic interaction between the CNN layer and the LSTM layer. The CNN layer effectively

extracts local features from physiological signals, while the LSTM layer captures long-term dependencies in temporal features, thereby fully leveraging the associations between multimodal physiological signals and psychological fatigue. Simultaneously, the fusion of multimodal data compensates for the information limitations inherent to individual signals, thereby enhancing the model's detection accuracy.

4.2. Analysis of Key Features

Using the random forest feature importance algorithm, we performed an importance ranking analysis on the 38-dimensional physiological features of the input model, thereby identifying core physiological features strongly associated with exercise-induced psychological fatigue in middle-aged and elderly individuals. The results indicate that heart rate variability (HRV), electrodermal activity (EDA), and the mean value of three-axis acceleration constitute the three core features influencing exercise-induced psychological fatigue in this population, with feature importance proportions of 38.5%, 29.2%, and 21.3%, respectively; the remaining features collectively account for 11.0% of the total importance. The correlation analyses between each core feature and the psychological fatigue score are as follows:

Regarding heart rate variability (HRV), the time-domain features of HRV, including SDNN and RMSSD, exhibited a significant negative correlation with the psychological fatigue score ($r = -0.78$, $p < 0.01$), whereas the LF/HF ratio showed a significant positive correlation with the psychological fatigue score ($r = 0.72$, $p < 0.01$). The study demonstrated that in middle-aged and elderly individuals, higher levels of psychological fatigue during physical exercise are associated with diminished regulatory capacity of the autonomic nervous system, an increased proportion of sympathetic nerve activity, and lower HRV-related indices.

Regarding electrodermal activity (EDA), a positive correlation was observed between the peak amplitude and magnitude of EDA and the psychological fatigue score ($r = 0.65$, $p < 0.01$); similarly, the mean skin conductance level (SCL) also showed a positive correlation with the psychological fatigue score ($r = 0.61$, $p < 0.01$). These findings indicate that in middle-aged and elderly individuals, higher levels of psychological fatigue during exercise are associated with increased sympathetic nervous system activation and more pronounced fluctuations in electrodermal signals.

Regarding triaxial acceleration, the mean value of the triaxial composite acceleration showed a positive correlation with the psychological fatigue score ($r = 0.58$, $p < 0.01$). This indicates that a sharp increase in exercise intensity can exacerbate psychological fatigue in older adults, whereas slower, moderate-intensity exercise is more readily accepted by this population, resulting in lower levels of psychological fatigue. These findings confirm that heart rate variability, skin conductance response, and acceleration signals are effective physiological indicators for detecting exercise-related psychological fatigue in middle-aged and elderly individuals. Additionally, they provide a characteristic basis for the subsequent lightweight optimization of the analytical models.

5. Discussion

5.1. Analysis of the Physiological and Psychological Characteristics of the Elderly Population

The experimental results of this study demonstrate that the association between exercise-induced psychological fatigue and physiological signals in middle-aged and elderly individuals exhibits significant population-specific characteristics, which differ markedly from those observed in young adults and athletes. In older adults, physiological function declines, including reduced autonomic nervous system regulatory capacity; the baseline HRV values are substantially lower than those in young adults; HRV fluctuations induced by psychological fatigue are more pronounced; the response latency of skin conductance responses is prolonged; the duration of signal fluctuations is extended; exercise tolerance is diminished; muscle strength and cardiopulmonary function decrease; even a modest increase in exercise intensity can trigger pronounced psychological fatigue; the correlation between acceleration signal variations and psychological fatigue is

significantly stronger than in young adults; subjective perceptions of fatigue differ, with older adults being more sensitive to fatigue and expressing these perceptions more directly; and Borg scale scores exhibit higher reliability, whereas young adults tend to underestimate the severity of psychological fatigue due to factors such as exercise motivation and perseverance. Therefore, when developing a detection model for exercise-induced psychological fatigue in middle-aged and elderly populations, it is essential not to directly apply models or features derived from young adult populations. Instead, the unique physiological and psychological characteristics of this demographic should be thoroughly considered, and the model should undergo targeted fine-tuning. Additionally, core physiological features highly correlated with psychological fatigue in older adults should be selected to enhance both the detection accuracy and generalization capability of the model.

5.2. Application Scenarios and Practical Value of the Real-Time Detection System

The real-time detection system for exercise-related psychological fatigue in middle-aged and elderly individuals, developed in this study using wearable devices, features real-time monitoring, portability, and objectivity. This system can be widely applied in scenarios such as smart healthcare, community-based elderly care, and home-based exercise monitoring.

For community-based smart health and wellness initiatives, deploying this system at community elderly care service centers or community gyms enables real-time monitoring of collective physical activities among elderly residents within the community. Should the system detect that an elderly individual exhibits excessively high levels of psychological fatigue, it can leverage the vibration and voice alert functionalities of wearable devices to provide recommendations-such as reducing exercise intensity or taking a break-thereby effectively lowering the risk of sports injuries and cardiovascular events. Regarding home-based exercise monitoring, the mobile terminal of the wearable device facilitates real-time tracking of physical activities performed by elderly individuals in their homes. Children can then monitor their elderly parents' exercise status and psychological fatigue levels via this mobile interface, enabling remote monitoring and addressing the challenges faced by "empty-nest" elderly individuals in exercise supervision. In the realm of personalized exercise intervention, the system continuously collects data on physical activity and psychological fatigue levels over extended periods, analyzing how different types and intensities of exercise impact psychological well-being in elderly individuals. This analysis serves as the foundation for developing personalized exercise intervention plans, thereby enhancing both the efficacy and sustainability of exercise regimens. In terms of smart health and wellness product development, the core physiological characteristics identified in this study, along with the established detection models, provide critical technical support for the development of wearable devices tailored to elderly populations. This approach facilitates the evolution of wearable devices from mere "exercise status monitoring" to "exercise-related psychological state monitoring." The application of this system not only fills the technical gap in objective, real-time detection of psychological fatigue among middle-aged and elderly individuals but also drives the advancement of elderly exercise health management toward greater intelligence and personalization, offering essential safeguards for improving the physical health outcomes and quality of life of older adults.

5.3. Limitations of the Study and Future Directions

Although this study has achieved real-time detection of exercise-related psychological fatigue in middle-aged and elderly individuals, it still has certain limitations. Future research will be conducted in the following areas:

5.3.1. Sports Scenarios and Modal Data Supplement

In this study, only three commonly encountered exercise scenarios-walking, Tai Chi, and light jogging-were selected for the research; exercise scenarios in specialized environments, such as high temperatures, cold weather, or rainy conditions, were not

included. Furthermore, the physiological signals collected primarily comprised three categories: heart rate, acceleration, and skin conductance. In future work, we will supplement the exercise data with those from specialized environments and incorporate additional modal data, including respiratory rate, bioimpedance, and body motion signals. This approach will enrich the feature set, thereby enhancing the robustness of the model in complex scenarios.

5.3.2. Model Lightweighting and Edge Deployment

In this study, model training was performed in the cloud, and real-time detection relied on cloud-based computing, which introduced a certain degree of transmission latency. In future work, we will employ lightweight techniques such as model pruning and quantization to optimize the CNN-LSTM hybrid model, enabling direct inference of the model on wearable devices. This approach will reduce reliance on the cloud, thereby enhancing the response speed of real-time detection.

5.3.3. Integrated Construction of Detection and Intervention

In future development, we will integrate the real-time detection system of this study to establish a platform for exercise health management tailored to middle-aged and elderly individuals. This platform will feature an integrated "detection – early warning – intervention" functionality. Upon detecting signs of psychological fatigue, the platform will automatically deliver personalized relaxation intervention protocols-such as music-based relaxation and breathing exercises-therby achieving proactive intervention against exercise-related psychological fatigue and elevating the intelligence level of exercise health management for older adults.

6. Conclusion

Addressing the practical need for detecting psychological fatigue in middle-aged and elderly individuals during physical exercise, this study developed a real-time detection system based on multimodal wearable devices and a CNN-LSTM deep learning model. Physiological signals-including heart rate variability, three-axis acceleration, and skin conductance response-were collected from elderly participants in real-world exercise scenarios. Through data preprocessing and feature extraction, the system achieved quantitative assessment and real-time prediction of psychological fatigue during exercise. Experimental results demonstrate that this CNN-LSTM hybrid model achieves a prediction accuracy of 82.3%, an RMSE of 1.25, and a Pearson correlation coefficient (r) of 0.81 for middle-aged and elderly individuals, significantly outperforming both traditional linear regression models and standalone deep learning models. Furthermore, feature importance analysis identified heart rate variability, skin conductance response, and the mean value of three-axis acceleration as core physiological features highly correlated with psychological fatigue in this population, providing a valuable reference for subsequent model optimization.

By accounting for the physiological and psychological characteristics of older adults, this study develops a sports-related psychological fatigue detection model tailored for middle-aged and elderly individuals, enabling objective and real-time detection of psychological fatigue in authentic exercise environments. This detection system not only provides novel technological solutions for intelligent monitoring of exercise-related health in this demographic, but also offers data support and theoretical foundations for formulating exercise intervention strategies and developing wearable devices within the field of smart health and wellness.

In the future, with the expansion of sample sizes, the incorporation of multimodal data, and the optimization of model lightweighting, this detection system will enable broader application across diverse scenarios. This will propel elderly individuals' exercise health management toward an integrated, intelligent paradigm-characterized by "detection – early warning – intervention" -thereby providing stronger safeguards to enhance the exercise health outcomes and overall quality of life for older adults.

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