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Article

Using wearable technology to optimize sports performance and prevent injuries

Zehao Yang[1,2]

[1] School of Physical Education, North University of China, Taiyuan 030051, Shanxi, China; yangzehao2024@163.com
[2] Yongin University, Yongin 17092, South Korea

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Abstract: Purpose: Wearable devices, as emerging computing platforms, have gradually penetrated into people's daily life, especially in the field of medical health management showing excellent potential. Methods Motion state recognition is performed by deep fusion CNN-LSTM model, CNN is used to obtain the most representative feature information characteristics of the local space of the motion data, while the LSTM layer is used to capture the long-term temporal correlation of these local features, and both of them are combined to obtain the more representative temporal-spatial correlation transportation state feature information implicit in the wearable gait data. An injury prevention method for exercise example parameters is designed, including patient training load characterization, and a Bi-LSTM network structure is used to design lightweight acceleration features to predict abnormalities in exercise physiological indicators. **Results:** Monitoring parameters such as heart rate rise slope, 1-minute heart rate recovery value, blood oxygen drop area, and 1-minute oxygen saturation recovery value, the false alarm rate of wearable device health data warning were kept at 2.55%. After exercise status and detected abnormalities in physiological parameters, personalized breathing training was performed, and the contribution ratio of abdominal breathing increased by 27% after training, and the patient's heart rate decreased by 8.5 bpm and oxygen saturation increased by 2.4% compared to the pre-training period. **Conclusion:** The methodology in this paper can be more comprehensively optimized for sports performance and injury prevention, and is widely applicable in practical applications.

Keywords: wearable devices; motion state recognition; local features; temporal-spatial correlation; exercise physiological metrics

1. Introduction

With the rapid development of science and technology and the deepening of medical research, the application of wearable technology in the field of sports medicine and health management has received increasing attention [1,2]. Traditional medical research methods often rely on doctors' experience and patients' self-description, while traditional manual methods are increasingly limited in terms of sports status monitoring and injury prevention. Currently, with the continuous integration of sensors and advanced algorithms, wearable devices have evolved from the initial basic health monitoring devices, such as smart bracelets and watches, to today's smart sports equipment that integrates complex sensors and advanced algorithms [3,4]. Especially in sports science, rehabilitation medicine, and sports injury prevention, wearable technology helps doctors to more accurately assess patients' exercise status and training loads, and provides a scientific basis for the prevention of sports injuries and the development of rehabilitation programs [5].

The purpose of this paper is to explore the optimization of sports performance and prevention of sports injuries based on wearable technology by combining CNN and LSTM in deep learning. Firstly, the local spatial features of the most data obtained by convolutional neural network and the temporal correlation of the intrinsic features of the data obtained by the long and short-term memory neural network model are utilized to effectively explore the temporal and spatial gait features of wearable sensing time-series gait data that are closely related to the changes of gait patterns, so as to improve the performance of classifying the movement state patterns. Subsequently, an innovative injury prevention method for exercise example parameters is highlighted. By describing the patient training load characteristics in detail and predicting the abnormalities of exercise physiological indexes using the Bi-LSTM network structure, the physiological parameter abnormality warning algorithm based on these characteristics set in the Bi-LSTM network structure realizes the accurate description of the patient training load and the timely warning of the potential injury risk. Finally, the effectiveness of the previously proposed method is verified through experiments. Experimental validation is used to assess the practical effectiveness of the method in optimizing exercise performance and preventing injuries, including the monitored physiological parameters such as heart rate rise slope, 1-minute heart rate recovery value, blood oxygen drop area, and 1-minute oxygen saturation recovery value, etc., and to analyze the false alarm rate of the health data warning of wearable devices. Finally, the potential application potential of wearable devices in the field of medical health management in the future is explored. Through the discussion in this paper, we expect to provide new references and insights for researchers and practitioners in the field of medical exercise science.

2. Related works

In recent years, several scholars have conducted in-depth research on the optimization of practical applications of wearable technology. In particular, significant progress has been made in practical application optimization, health monitoring and disease diagnosis. For example, Lown et al. utilized wearable technology and machine learning algorithms to detect the feasibility and effectiveness of atrial fibrillation, also known as AF, by designing a new AF detection algorithm using a de-correlation Lorenz plot of 60 consecutive RR intervals. Combined with wavelet transform for optimization as input data, the user's ECG signals are continuously monitored by wearable devices such as smart watches and bracelets to identify the occurrence of AF in real time or near real time [6]. Yuan et al. performed a multi-objective optimization considering power density, material consumption and power matching for wearable electronic devices to achieve intelligent power management and data monitoring, which will be used in wearable electronic devices for use in personal health care [7]. Smuck et al. in their study pointed out that wearable devices in clinical care, the potential is very obvious to provide technical support to doctors and personalized experience to patients [8]. Rajinikanth et al. focused on monitoring tic episodes in patients with Tourette Syndrome using machine learning and wearable technology. A wearable wristband device called TSBand, which integrates multiple sensors and machine learning algorithms, was designed to monitor tic attacks and notify caregivers when an attack occurs. The TSBand is used to identify tic attacks by monitoring metrics such as movement, heart rate, sweating, and body temperature, combined with localized abnormality factors and regression algorithms. In addition, the device contains audio tic attack detection mechanism using recurrent neural network with manually activated backup button and audio mechanism to notify the hospital caregivers in the application in a highly efficient manner [9]. Xie et al. stated that the use of Artificial Intelligence to provide intelligent recommendations for diagnosis and treatment of diseases by analyzing the patient's physiological data from the wearable device. Combining organizational and analytical data to achieve the ultimate goal of improving chronic disease management can enhance the efficiency of monitoring, diagnosing, and treating chronic diseases, thereby improving patients' health and quality of life [10]. Ferguson et al. emphasized the importance of wearable technology in monitoring the heart health of older adults through the integration of advanced sensors and semi-structured focus group interviews for a descriptive qualitative study, wearable devices are able to monitor patients' heart rate, step count, exercise intensity and other key indicators in real time. Timely physiological feedback and early warning systems can also effectively prevent sports injuries and safeguard the health and safety of patients [11]. Jin et al. mainly investigated the drawbacks of wearable devices and discussed the feasibility of edge computing to improve the drawbacks from four aspects, namely, computational scheduling, information perception, energy saving and security [12].

In summary, although these research results have made significant progress in the fields of health monitoring, disease diagnosis and personalized medicine, many of them focus on a single type of data, such as heart rate, blood pressure or a single type of features, such as spatial features or temporal features, which leads to the limited generalization ability of the models in complex scenarios. Therefore, in this paper, we propose to solve the limitation of single network in feature extraction in previous studies by deeply fusing CNN-LSTM model, which realizes the comprehensive capture of spatio-temporal features of exercise data. In addition many health monitoring systems fail to fully consider the individual differences of patients, and are unable to provide personalized health guidance and risk warning, and thus this paper designs a lightweight acceleration feature prediction method based on Bi-LSTM, which achieves real-time monitoring and early warning feedback for patients on individual exercise physiological indexes, and improves the pertinence of injury prevention.

3. Theoretical framework

3.1. CNN-LSTM motion state recognition model

The CNN-LSTM deep fusion learning model proposed in this paper aims to make full use of the excellent characteristics of CNN and LSTM models to obtain the spatial and temporal correlation feature information inherent in the data structure, respectively, and deeply fuse the two to obtain more temporal and spatial correlation feature information embedded in the wearable sensing motion state data, which is closely related to the change of motion state, so as to improve the performance of the motion state pattern recognition. It is assumed that the gait pattern to be recognized is data set $V = \{v_1, v_2, \cdots, v_l\}$, where l represents the motion state pattern to be recognized [13]. The wearable sensing motion state time series data is:

$$D = \left(d^1, \cdots, d^j, \cdots, d^t\right) = \begin{pmatrix} d_1^1, \cdots, d_1^t \\ \vdots \\ d_m^1, \cdots, d_m^t \end{pmatrix} \tag{1}$$

where $d^j = \left(d_1^j, \cdots, d_m^j\right)^T$ denotes the wearable sensing data at time point j, m and t denote the number of wearable sensors and the number of motion state pattern time series samples respectively. Each motion state pattern v. the time series data is selected so that each data segment $h_i = (t_{i-1}, t_i)$ contains motion state spatio-temporal feature information, and all the selected data segments are defined as the dataset $h_i = (t_{i-1}, t_i)$, and k is the number of all selected data segments [14]. In order to accurately recognize the motion state patterns, a model plant is constructed to obtain the vector Y_i containing the motion state feature information from each data segment h, i.e., $Y_i = \Gamma(D, h_i)$. Then, the set of confidence values corresponding to each motion state pattern v_i is calculated:

$$P: P(v_i/Y_i, \beta) = \Psi(Y_i, \beta) \tag{2}$$

where β denotes the training parameter set, calculate the following maximum score value $v_i^* = argmax\, P\,(v/Y_i, \beta)$, you can accurately obtain the motion state pattern v_i^*, to realize each motion state pattern v. On this basis, based on the LSTM deep learning model to obtain the temporal correlation of the local spatial features of the motion state data, to obtain more temporal-spatial feature information related to the change of the motion state pattern, the maximum probability of obtaining to the motion state pattern v_i^*, to accurately recognize the motion state pattern v_i.

In this paper, we propose a CNN-LSTM fusion based deep learning of motion state patterns, and the recognition model framework is shown in **Figure 1**, which consists of three parts: the motion state data input layer, the CNN-LSTM fusion deep learning, and the fully connected layer. In view of the time-space correlation characteristics of wearable motion state sensing data, the CNN consists of three convolutional layers CL1, CL2, CL3, one pooling layer MP1, and two dropout layers to accurately obtain the most representative local spatial features inherent in the motion state data. In order to accurately obtain the temporal correlation of the most representative local spatial features inherent in the motion state data, the LSTM model is composed of 32 cells. In order to accurately obtain the temporal correlation of the most representative local spatial features inherent in the motion state data, the full connectivity layer consists of 6 cells to identify the motion state patterns with maximum probability [15].

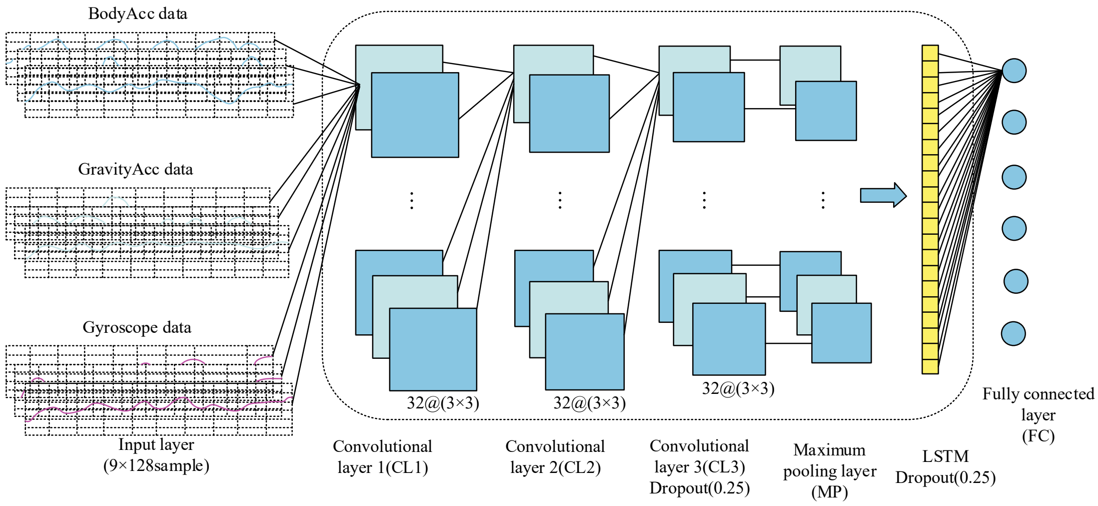

Figure 1. Recognition model framework.

3.2. Spatial characterization of motion state motion data

In order to effectively obtain the motion state feature information, the wearable sensing motion state time series at the moment is defined as:

$$d^t = \left(d^t_{BA\_x} d^t_{BA\_y} d^t_{BA\_z} d^t_{GA\_x} d^t_{GA\_}, d^t_{GA\_z}, d^t_{Gy\_x}, d^t_{Gy\_y}, d^t_{Gy\_z}\right) \tag{3}$$

where, BA-XYZ denotes 3D human motion acceleration data, GA-XYZ denotes 3D gravity acceleration data, and Gy-XYZ denotes 3-axis gyroscope data . For ease of analysis, $t \in \{1, \cdots, 128\}$ is selected [16]. Its sensing motion state data input sequence is defined as:

$$D = (d^1, \cdots, d^t, \cdots, d^{128}) = \begin{pmatrix} d^1_{BA\_x}, \cdots, d^{128}_{BA\_x} \\ d^1_{BA_y y}, \cdots, d^{128}_{BA\_y} \\ d^1_{BA_z}, \cdots, d^{128}_{BA\_z} \\ d^1_{GA\_x}, \cdots, d^{128}_{GA_2 x} \\ d^1_{GA_y}, \cdots, d^{128}_{GA\_y} \\ d^1_{GA_z}, \cdots, d^{128}_{GA\_z} \\ d^1_{Gy\_}, \cdots, d^{128}_{Gy\_x} \\ d^1_{Gy_y}, \cdots, d^{128}_{Gy\_y} \\ d^1_{Gy_z z}, \cdots, d^{128}_{Gy\_z} \end{pmatrix} \tag{4}$$

Assume that the CNN model used to obtain the most representative local spatial features of the motion state has a total of L convolutional layer, each with a convolutional kernel defined as $M_l \times N_l$. The $l \in \{1, \cdots, L\}$rd convolutional layer extracts the local spatial features of the motion state $F^{(l)}$, which is defined as:

$$F^{(l)} = f\left(b^{(l)} + \left\langle w^{(l)}, d^i, \cdots, d^{i+\phi-1} \right\rangle\right), i = 1, \cdots, t - \phi + 1 \tag{5}$$

where $f(\cdot)$represents the activation function, $\langle \cdot \rangle$ represents the inner product, $b^{(l)}$ is the bias term, $w^{(l)}$ is the one-dimensional convolution kernel vector, and ϕ is the length of $w^{(l)}$. Due to the high dimensionality, nonlinearity, randomness and low algorithmic complexity of wearable sensing motion state data, this paper constructs three one-dimensional convolutional layers, each with 32 convolutional kernels, the size of which is defined as 3 × 3, and the step size is defined as 1. A good nonlinear ReLU function is used as the activation function. A Dropout layer is constructed. In order to effectively maintain the intrinsic properties of the motion state features obtained by the convolutional layer and reduce its redundancy information, the pooling layer is used to reduce the feature dimensions and increase its spatial invariance, and the pooling layer of the maximal pooling technique is defined to obtain the local spatial features that contain more information about the changes of the most motion states P [17]. Define:

$$P_j = max\left(F_{(j-1)R+1}, \cdots, F_{jR}\right), j = 1, \cdots, t/R \tag{6}$$

where R denotes the pooling window size.

3.3. Temporal correlation of localized features of motion states

A motion state activity can be considered as a long sequence of time series, and through the autoregressive network architecture characteristic of the long and short-term memory network which is good at dynamically learning the intrinsic temporal correlation of the time series data, we constructed the LSTM cell, including one memory cell C and three gate functions, input i_t, forget f_t, and output o_t, and extracted the intrinsic long-term temporal correlation characteristics of the motion state data in real time.

Assuming that p^t is used to denote the one-dimensional feature map of the motion state data sample processed by the CNN model at the moment of 1 as the input item of the LSTM neuron, the useless extracted data information is firstly discarded by the forgetting gate when passing through the cell of the LSTM [18]. Its output is:

$$f_t = \sigma\left(W_f \cdot [p^t, h_{t-1}] + b_f\right) \tag{7}$$

where σ denotes an activation function Sigmoid, W_f is a weight value, and b_f denotes a bias value, followed by an input gate i_t and a candidate memory unit $\tilde{C}_t$ to determine the updated data information:

$$i_t = \sigma(W_i \cdot [p^t, h_{t-1}] + b_i) \tag{8}$$

$$\tilde{C} = tan(W_c \cdot [p^t, h_{t-1}] + b_c) \tag{9}$$

where W_i and W_c refer to the weights and b_i and b_i refer to the bias values. This is followed by a memory cell C_t indicating the cell update status of this LSTM:

$$C_t = i_t \cdot \tilde{C} + f_t \cdot C_{t-1} \tag{10}$$

Finally, the output data information h_t of the LSTM unit is determined to be:

$$o_t = \sigma(W_o[p^t, h_{t-1}] + b_o) \tag{11}$$

$$h_t = o_t * tan(C_t) \tag{12}$$

where o_t is the output gate and h_t is the output of the current neuron at time. By retaining the information that has experienced forgetting and inputs through the above mentioned memory cell C_t, the LSTM cell is realized to efficiently transmit historical information at long time intervals, thus obtaining the intrinsic temporal correlation features of the data [19]. The proposed LSTM layer consists of 32 cells to process the temporal signals represented as one-dimensional feature vectors:

$$s = \left[h^1, \cdots, h^t\right], t \in \{1, \cdots, 32\} \tag{13}$$

Feature vector s enters the fully connected layer consisting of 6 cells for processing and its output is:

$$h = f[Ws + \varepsilon] \tag{14}$$

where W is the weight matrix of the fully connected layer and ε is the bias term vector. Setting the activation function of the fully connected layer as a Softmax function, the final maximum probability of recognizing the motion state pattern v_i is output as:

$$v_i^* = \frac{e^{v_i}}{\sum e^{v_i}}, i \in \{1, \cdots, 6\} \tag{15}$$

4. Proposed method

The above obtained feature information embedded with rich spatio-temporal correlations, covering the type, intensity, duration of the motion, and how it dynamically changes over time. Further, this value-rich feature information can be used as input or auxiliary information for training the Bi-LSTM network. Parameters include respiration, cardiac, blood oxygen, blood pressure, etc., which are essential for monitoring the training status of the athlete, assessing the risk of potential injuries, and understanding the body's adaptation to training. Then a bi-directional LSTM network is used to extract abnormal internal features of physiological parameters. Bidirectional LSTM is able to utilize both past and future information to learn the internal features of the data by running in both forward and reverse directions, thus improving the accuracy of anomaly detection. Further, a Tensorflow deep learning framework is used to build and train an abnormal early warning model for exercise physiological parameters. During the training process, the generalization ability of the model is improved by introducing dropout technique and regularization term to prevent the occurrence of overfitting phenomenon. Meanwhile, binary cross entropy is used as a loss function to evaluate the performance of the model. Finally, the trained model is transformed into TFLite format for deployment and inference in real applications.

4.1. Characterization of patient training loads

For the use of wearable technology exercise physiological parameters early warning indicators, for which this paper selected 14 indicators covering common physiological parameters during respiratory training, including respiration, cardiovascular, blood oxygen, and blood pressure, end-expiratory carbon dioxide partial pressure. Other important indicators related to body temperature, perspiration, sweating, and lactate concentration were used to monitor and warn of physiological states during exercise [20]. **Table 1** shows the symbols of characteristics related to early warning of exercise physiological parameters to understand the patient's training status, potential risk of injury, and the body's adaptation to training, so as to develop a more scientific training program and preventive measures. Research in the medical field has identified a variety of physiological parameters such as respiratory rate, heart rate, oxygen saturation and other indicators as recognized important monitoring indicators. Among them, parameters such as respiratory rate, tidal volume, and respiratory minute ventilation are important in assessing respiratory system function. Heart rate, heart rate variability, electrocardiogram and other parameters help to understand the health of the heart, oxygen saturation, blood pressure, carbon dioxide partial pressure at the end of expiration and other parameters can reflect the blood circulation and gas exchange, body temperature, sweating, lactic acid concentration and other parameters are closely related to thermoregulation, water metabolism and muscle fatigue. These feature symbols provide a dataset for constructing an injury prevention early warning model for exercise physiological parameters, which facilitates the subsequent extraction of abnormal internal features of physiological parameters using bidirectional LSTM, enabling the understanding of the patient's training status, potential injury risk, and the body's adaption to the training, so as to formulate a more scientific training program and preventive measures.

Table 1. Characteristic symbols related to early warning of exercise physiological parameters.

Characteristic symbol	Characteristic Name	Description
RR	Respiratory rate	Number of breaths/minute, 10–16 breaths/minute for normal adults in quiet state
VT	Tidal volume	Amount of gas inhaled or exhaled during each breath
VE	Respiratory minute ventilation	Total amount of gas inhaled or exhaled per minute
HR	Heart rate	Number of heart beats per minute
HRV	Heart rate variability	The extent to which the heart rate varies over time
ECG	Electrocardiogram	Recordings of the electrical activity of the heart
SpO_2	Oxygen Saturation	The percentage of total hemoglobin in the blood that is oxygenated hemoglobin
BP	Blood Pressure	The pressure exerted on the walls of blood vessels by the flow of blood through the vessels, including systolic and diastolic pressures
$ETCO_2$	Carbon dioxide partial pressure at end-expiration	The partial pressure of carbon dioxide at the end of exhalation
TEMP	Body Temperature	The internal temperature of the body, with a normal adult underarm temperature of 36–37 degrees Celsius
SWEAT	Sweating	The degree of sweating of the body during exercise
EMG	Myoelectric Signal	Signals reflecting the electrical activity of muscles, used to assess muscle fatigue and injury.
LACTATE	Lactate Concentration	Lactic acid level in the blood, reflecting muscle fatigue and metabolic status.

4.2. Bidirectional LSTM to extract abnormal internal features of physiological parameters

The working principle of LSTM is one strand runs from front to back according to the time sequence, learns the internal features of the data, and obtains the final result through the classifier. The use of bi-directional LSTM, which runs in the forward and reverse direction according to the time sequence, and the internal features of the classifier are determined by the 2 uni-directional LSTMs together to determine the final output result, which enables the algorithm to learn the internal features of the abnormal data of the exercise physiological parameters in a better way, and to improve the exercise physiological parameter abnormality detection and classification accuracy. Bidirectional LSTM network structure is shown in **Figure 2**, because through the exercise physiological parameter abnormality detection found that the use of unidirectional LSTM in the exercise physiological parameter abnormality detection occurs more omission or misjudgment. While the two-way LSTM output is characterized by the forward layer and the inverse layer to jointly determine the final output result, which can greatly reduce the situation of missed or misjudgment. Short-term memory neural network) consists of two layers of recurrent neural networks with the same inputs but different timing of information transfer, which use both past and future information to learn the internal features of the sensing data and improve the accuracy of abnormal prediction of exercise physiological parameters. In this case, the forward and backward transmissions are independent of each other, and the final prediction result is determined by the hidden layer that retains the bidirectional information.

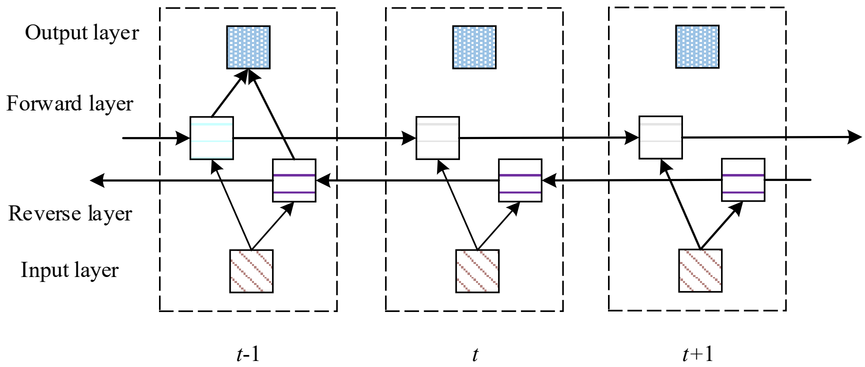

Figure 2. Bidirectional LSTM network structure.

4.3. Bi-LSTM-based early warning of physiological parameters

In order to realize wearable exercise physiological parameter abnormality warning that takes into account both accuracy and timeliness, this paper adopts a deep learning algorithm to end-to-end automatically extract deep features for prediction, and accurately predicts physiological parameter abnormality in real time. The architecture of exercise physiological parameter fall abnormality warning is shown in **Figure 3,** and the exercise physiological parameter abnormality warning algorithm mainly contains three stages. The first is the preprocessing stage, which converts the raw accelerometer data to values in g, then determines the time of peak combined velocity, i.e., the moment of abnormal exercise physiological parameters, and finally intercepts a 1.5s data window as an input based on the moment and the lead time. Second, the training stage, the preprocessed data segments are used to extract deep features through a bidirectional LSTM neural network and return carefully adjusted gradient information to the model. Third, the testing phase, the test set is passed into the trained model for classification via a sigmoid classifier, which outputs a probability value of 0–1, and a probability value greater than 0.5 is recognized as abnormalities of the exercise physiological parameters, otherwise it is recognized as ADLs.

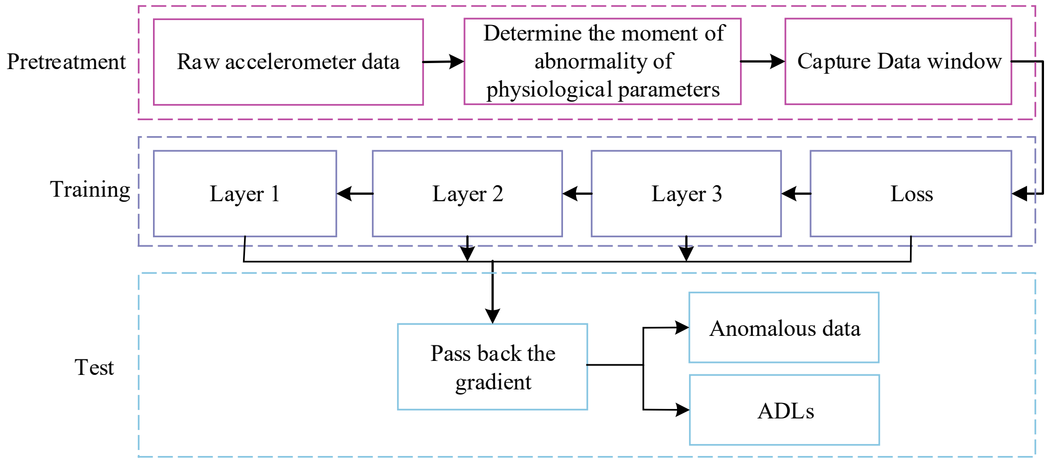

Figure 3. Early warning architecture for abnormal exercise physiological parameters.

4.4. Network training

In this experiment, the deep learning framework Tensorflow2.3.0 is used to build an abnormal early warning model of exercise physiological parameters, and the hardware configuration includes Intel(R)Core(TM)i7-7500UCPU@2.90GHz, with 12.0 GB of RAM, the operating system is 64-bit Windows 10, and the code running environment is Python3.8. loss. Function is calculated as follows:

$$Loss = -\frac{1}{N}\sum_{i=1}^{N} y_i \times \log_2\left[p\left(y_i\right)\right] + \left(1-y_i\right) \times \log_2\left[1-p\left(y_i\right)\right] \tag{16}$$

During training, the dropout term is used to improve the model generalization ability, a regularization term applied to the output is used to prevent model overfitting, and the loss function uses binary cross entropy to evaluate the binary exercise physiological parameter abnormality warning model. where N is the number of samples, y_i denotes the label 0 or 1, and $P(y_i)$ denotes the probability that the output is y_i. To ensure the convergence speed and accuracy of the model, the experiments use the Adam algorithm with adaptive learning rate to optimize the network. At the same time, it is stipulated that the iteration is stopped when the loss value of the validation set does not decrease accordingly within 5 consecutive iterations to prevent overfitting, and finally the trained model is transformed into TFLite format.

4.5. Injury prevention methodology process

To clearly illustrate the proposed method, **Figure 4** shows the motion state recognition and injury prevention flow, which summarizes the whole process from data collection to injury prevention The method combines deep learning techniques, especially CNN and LSTM, with personalized health monitoring strategies, aiming to achieve high-precision, real-time motion state recognition and injury prevention through wearable devices.

Wearable devices are first used to collect data from users' accelerometers, gyroscopes, and physiological sensors such as heart rate monitors and blood pressure monitors. The collected raw data is cleaned to remove noise and outliers. The raw motion data is processed using convolutional neural networks to automatically extract local spatial features from it. These features reflect the unique morphology and variations of the motion patterns. The features extracted by the CNN are passed to the long and short-term memory network, and the LSTM is used to capture the long-term dependence of these features on the time series, and further capture the long-term dependence of these features on the time series, so as to realize the comprehensive recognition of the motion states. Based on the recognized motion states, a motion example parameter set is constructed, including key indicators such as training load, motion intensity, duration and so on. Bidirectional long and short-term memory networks are used to model the exercise example parameters, which are used to predict abnormal changes in physiological indicators during exercise, such as excessive heart rate, sudden rise in blood pressure, etc. Bi-LSTM takes into account both forward and reverse time dependencies to improve the accuracy and robustness of the prediction. Based on the output of the prediction model, personalized injury prevention strategies are developed by combining the patient's historical data and real-time physiological feedback. This includes adjusting the training program, such as reducing training intensity, increasing rest time, and providing health guidance and advice. It can achieve accurate monitoring of the user's exercise status and timely warning of injury risk, providing strong support for personalized health management.

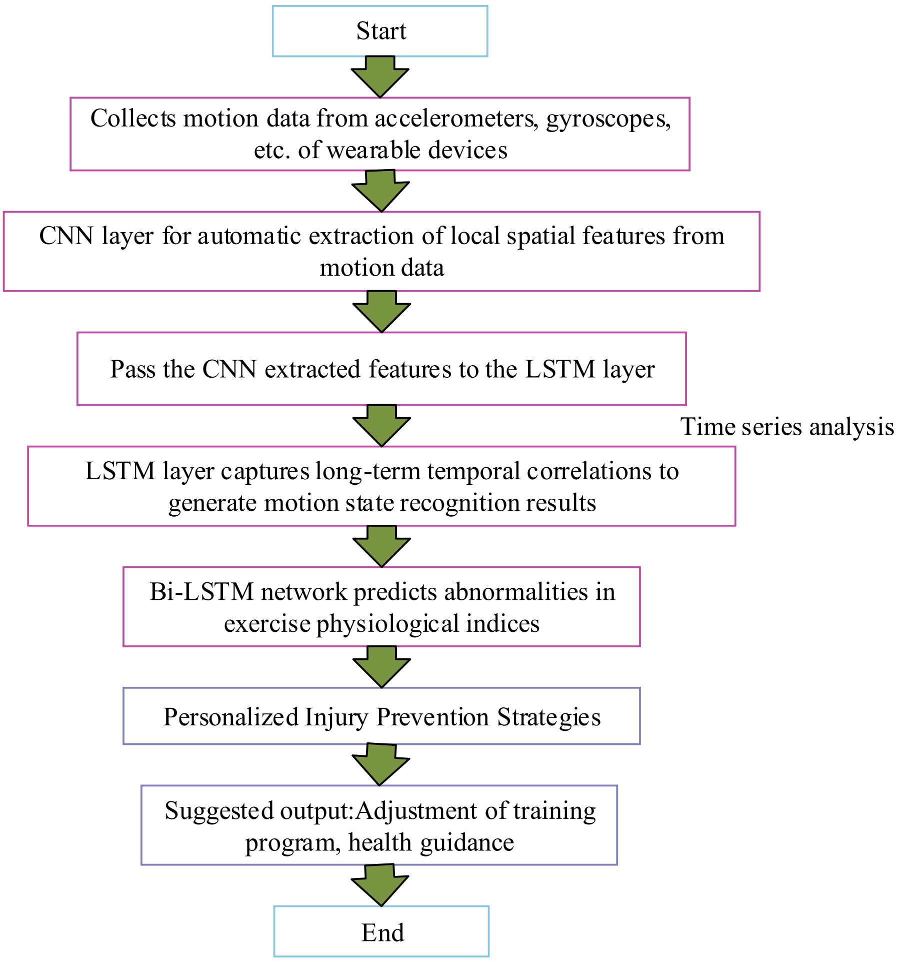

Figure 4. Motion state recognition and injury prevention process.

5. Empirical results and actual campaign performance

5.1. Real-time monitoring and assessment of patient cardiorespiratory function

To validate the accuracy of the 2CNN-LSTM deep fusion learning motion state recognition proposed in this paper, the patient's motion and physiological data were monitored and recorded during the 6-MWT, and key physiological parameters were extracted and quantitatively analyzed to assess the quantitative capability of the method. The Empatica E4 wearable device was selected to monitor patient physiological data. This device was selected because it provided highly accurate real-time monitoring of ECG, respiratory, oximetry, and pulse data, and had a more intuitive user interface and more powerful data export and analysis capabilities than other similar devices. Meet the need for comprehensive physiologic monitoring of patients during the 6-minute walk test. One hundred and five patients with cardiopulmonary diseases were selected to perform the 6-MWT test, and comprehensive ECG, respiratory, oximetry, pulse, body position/movement, and blood pressure data were collected during the test. To ensure the quality and consistency of the data, the collected data were filtered, denoised, and etc. to minimize the effect of noise on the model performance. The preprocessed data were input into a 2CNN-LSTM deep fusion learning model, which subsequently performed motion state recognition and extraction of motion physiological parameters on these data.

Figure 5 shows the physiological parameter changes during the six-minute walk test. The method in this paper is able to monitor and record the patient's exercise and physiological data during the 6-MWT for quantitative analysis, which can extract parameters such as the slope of heart rate increase, 1-minute heart rate recovery value, area of decrease in blood oxygen, and 1-minute recovery value of oxygen saturation, as well as to visualize the changes in cardiorespiratory physiological parameters during the 6-MWT. Regarding heart rate HR, the slope of heart rate increase was 118 at 221/s, the maximum heart rate HRMax was 128.2/bpm at 419 s, the heart rate recovery value at 1 min was 126.1/bpm, and the 75% ΔHR, i.e., the value of the heart rate when it recovered to 75% of the maximum heart rate, was 123/bpm. i.e., the time required from the beginning to the maximal heart rate was between 120 and 240, or 120 s. The heart rate at 1 min after the end, i.e., the value of heart rate at 1 min after the end of the test was 126.1/bpm.In terms of oxygen saturation SpO_2, the method in this paper was able to accurately extract the key parameters, including the time of decrease of SpO_2 in the range of 120/s–150/s i.e., the time required from the beginning of the test to the beginning of the decrease of oxygen saturation, the maximum decrease in the ΔSpO_2 oxygen saturation was 87.4%–92.3%, and 75% ΔSpO_2 oxygen saturation recovery was 91.8%. The average oxygen saturation SpO_2 recovery value 1 min after the end of the session was 92.5. In addition, the patient's horizontal activity could also be monitored in real time, with the patient's activity level at 1.46 at the start time point, around 130 s, and at 480 s after the end time point, which provided accurate information for the comprehensive assessment of the patient's cardiopulmonary function.

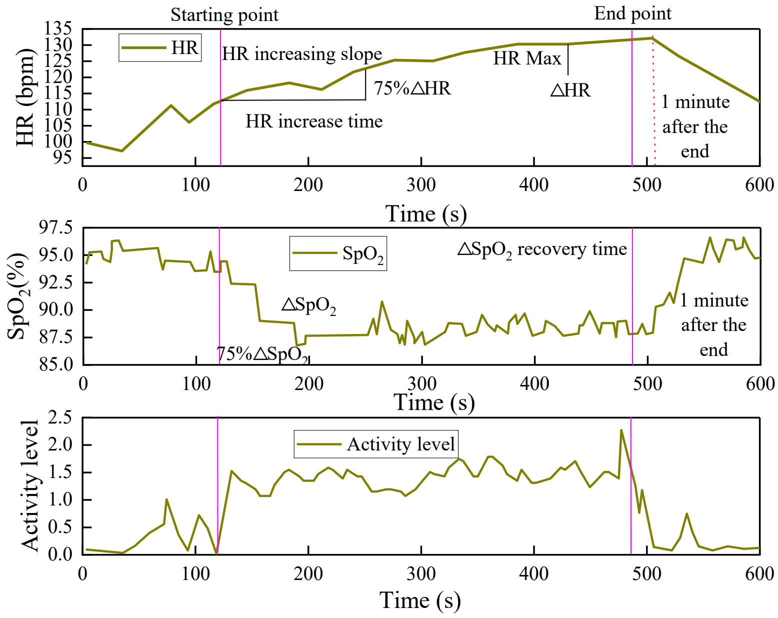

Figure 5. Changes in physiological parameters during the six-minute walk test.

5.2. Validation of early warning for exercise physiological parameters

The performance of different algorithms in physiological parameter abnormality warning is trained and tested by the same physiological parameter abnormality dataset, so as to evaluate the effectiveness of each algorithm in preventing sports injuries. The comparison algorithms include CNN-SVM, which combines the spatial feature extraction ability of CNN and the classification ability of SVM.LSTM-RF is LSTM processing time series and then uses Random Forest for classification or regression.3D CNN is suitable for processing 3D spatial data such as motion capture data, which can capture both temporal and spatial features simultaneously. Transformer based on the self-attention mechanism is suitable for dealing with long distance dependent problems. Model, which is suitable for dealing with long-distance dependency problems.GaitGAN Generative Adversarial Network GAN for gait recognition, which accomplishes cross-view gait recognition. The F1 score is also used as the main evaluation metric, which is the reconciled average of precision and recall, and can comprehensively evaluate the performance of the model.

Figure 6 shows the exercise physiological parameter abnormality early warning F1 score, and the method proposed in this paper achieved a significant advantage in the exercise physiological parameter abnormality early warning F1 score. On the test dataset, at week 22, the early warning F1 score of this paper's method reaches 0.78%, showing its strong ability in capturing complex movement patterns and subtle physiological parameter variations. 3D CNN method early warning F1 score is 0.69%, and the effectiveness of Convolutional Neural Networks in dealing with spatially structured data. In contrast, the CNN-SVM. LSTM-RF and GaitGAN, Transforme methods, although they also showed some early warning ability, had relatively low accuracy rates of 0.46%, 0.35% and 0.30% and 0.33%, respectively. It indicates that it is difficult to adequately capture the complex changes in exercise physiological parameters. This paper's method achieved the best performance on the task of early warning of abnormal physiological parameters in patients, which was significantly better than the other compared methods. This result not only validates the effectiveness of this paper's method in capturing complex movement patterns and subtle physiological parameter changes, but also provides assistance for its application in practical exercise training and health management.

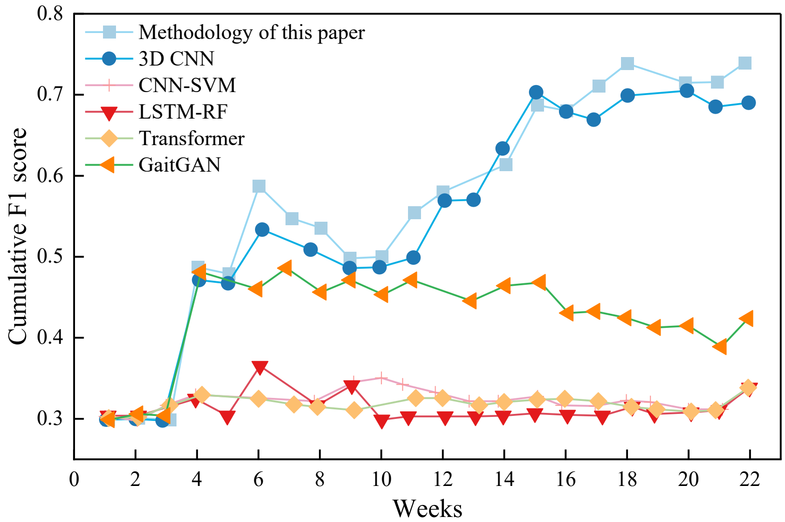

Figure 6. Early warning F1 score for abnormal exercise physiological parameters.

The wearable device health warning false alarm rates are shown in **Table 2**, which shows that during the experimental process of this index, for different wearable devices KCD-01 to KCD-10, the health warning methods proposed in this paper are significantly lower than several other methods in terms of false alarm rates. Specifically, the false alarm rates of all the methods in this paper remain below 2.55%, and the false alarm rate is only 1.98% in KCD-10 wearable device serial no, while the average false alarm rates of CNN-SVM, LSTM-RF, 3D CNN, Transformer, and GaitGAN wearable device health warning are 8.83%, 8.25%, 10.39%, 9.87%, and 11.45%, which are significantly higher than the method of this paper. It indicates that the false alarm rate of this paper's method on all wearable devices is significantly lower than other methods, which can more effectively reduce unnecessary health warnings and improve patient user experience.

Table 2. False alarm rates (%) for wearable device health warnings.

Wearable Device Serial Number	This article Health Alert Methods	CNN-SVM	LSTM-RF	3D CNN	Transformer	GaitGAN
KCD-01	2.55	8.03	7.22	10.36	10.02	11.35
KCD-02	2.12	9.96	9.01	10.56	9.66	11.09
KCD-03	2.01	8.59	8.54	10.21	9.37	11.64
KCD-04	2.26	9.46	7.21	10.15	10.14	11.63
KCD-05	2.32	8.67	7.82	10.59	9.69	11.09
KCD-06	2.13	9.15	9.16	10.76	10.01	11.48
KCD-07	2.06	9.44	8.04	10.24	9.98	11.59
KCD-08	2.14	8.22	8.09	10.61	9.94	11.78
KCD-09	2.34	9.52	8.96	10.19	10.12	11.52
KCD-10	1.98	8.84	7.19	10.08	9.22	11.65

5.3. Application of wearable technology based sports performance optimization

Using the method in this paper after identifying the exercise state and detecting abnormal physiological parameters, this paper will develop corresponding optimization strategies to enhance exercise performance based on these key indicators. For example, for patients with poor breathing patterns, the algorithm in this paper can provide personalized breathing training suggestions. If the patient's breathing is too shallow, a series of deep breathing exercises are designed to help him or her increase lung capacity and improve oxygen utilization efficiency. For patients with irregular breathing rhythm, audio or visual cues can be used to help establish a stable breathing rhythm to better match the exercise rhythm. Provide personalized heart rate training suggestions when the patient's heart rate is detected to be too high. Reduce the load on the heart and prevent overexertion by reducing the intensity of exercise or changing the exercise pattern. Take appropriate breaks, perform relaxing stretches, or provide some relaxing music to help patients lower their heart rate. Provide personalized oxygen saturation training recommendations for patients with poor oxygen saturation. Reduce the duration of high-intensity training or increase the proportion of recovery training. Also, if the environment is hypoxic move to a more oxygenated environment. Recommend training methods that improve blood oxygenation capacity, such as intermittent hypoxic training.

Figure 7 shows the wearable technology training effect of a patient with elevated abdominal respiratory contribution ratio and reduced respiratory rate during training after exercise status and detected abnormal physiological parameters. Respiratory, ECG, and oximetry data during respiratory training were effectively captured, and some of the data records matched the patient's relevant clinical data. It can be seen that before the training, the patient may have relied more on a combination of thoracic and abdominal breathing, which may lead to inefficient respiration during high-intensity exercise and affect oxygen uptake. After specialized respiratory training, the percentage of abdominal breathing increased, with the abdominal breathing signal completely overriding the thoracic breathing signal during the training period, with a maximum signal of 2499. At the same time, the contribution ratio of abdominal breathing increased by 27%. This indicates that the patient is now predominantly ventilating in abdominal breathing and can utilize the abdominal muscles for deep breathing to strengthen lung capacity and oxygen exchange efficiency. Before training, the patient's average respiratory rate was 19 breaths/min bpm. And after training it could be reduced to 8 breaths/min, which is beneficial to the patient's endurance and recovery ability. The patient's heart rate also decreased by 8.5 bpm compared to before training. After training the heart rate was at 75.3, and the decrease in heart rate is a direct reflection of the improved fitness and cardiorespiratory fitness. This indicates that the patient's cardiovascular efficiency has improved and the patient's heart is now able to pump blood more efficiently to provide more oxygen and nutrients to the muscles. The increase in oxygen saturation SpO_2% means that the blood is able to carry more oxygen, and although the oxygen saturation is only increased by 2.4%, it still provides more energy to the muscles, which is critical to the patient's performance during high intensity exercise. This patient made significant progress with respiratory training, not only optimizing breathing patterns, but also improving cardiorespiratory fitness and exercise efficiency, suggesting that the methods in this paper have a significant effect on positive physiological changes in patients.

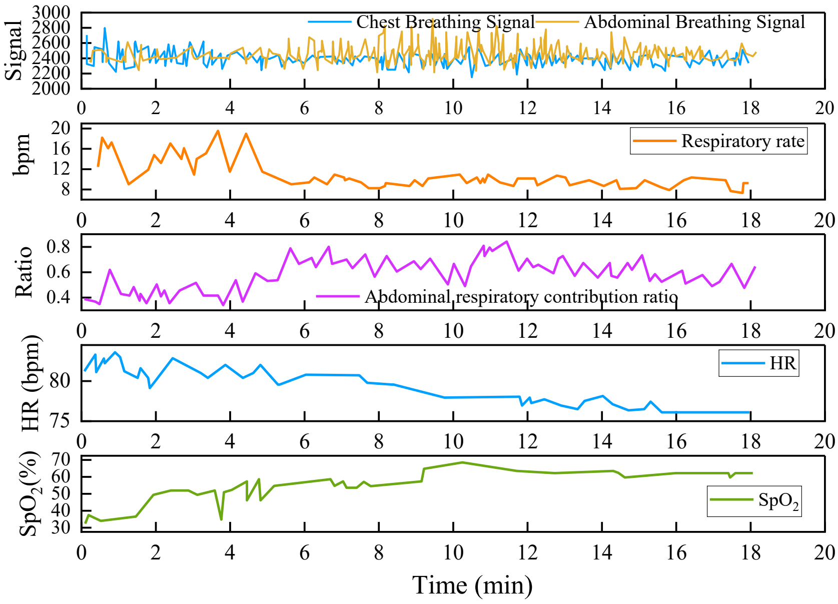

Figure 7. Wearable technology training effects.

6. Conclusion

In this paper, we explore a method to optimize sports performance and prevent injuries based on wearable technology, using a combination of CNN and LSTM, which is able to capture both spatial features and temporal correlation of sports data, and complete the accurate recognition of sports status. On this basis, a lightweight physiological indicator early warning model based on bi-directional long and short-term memory is proposed, end automatically extracting deep features for prediction, and network training is carried out to realize the description of the patient's training load and the timely warning of potential injury risk. The conclusions are as follows:

(1) The method in this paper can monitor and evaluate the patient's cardiopulmonary function in real time by means of wearable technology, and the examination data shows that the heart rate at 1 min after the end of the test, that is, the heart rate value at 1 min after the end of the test, is 126.1/bpm. The average oxygen saturation SpO_2 recovery value at 1 min after the end was 92.5. At the 22nd week, the F1 score of exercise physiological parameter warning reached 0.78%, which could fully capture the data of complex movement patterns and subtle physiological parameter changes.

(2) The contribution ratio of abdominal breathing increased by 27% after training, and the patients' heart rate decreased by 8.5 bpm and oxygen saturation improved by 2.4% compared with the pre-training period. It can help the medical field to more accurately assess the exercise status and training load of people's patients.

Future research needs to review the maintenance of wearable technology in real-world sports and school environments, optimize adherence, modify workloads for other benefits and evaluate rule changes in other sports.

Ethical approval: Not applicable. Informed consent was obtained from all subjects involved in the study.

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

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