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Intelligent Development Model of Sports Injury Rehabilitation Equipment Integrating Wearable Biomimetic Structures and Adaptive Materials

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Abstract. By collecting and analyzing sports and physiological data, artificial intelligence (AI) technology can detect abnormal sports patterns in real time and provide customized feedback to enhance the safety of sports injury rehabilitation training. With the rapid growth of demand for sports injury rehabilitation, traditional rehabilitation equipment has limitations such as strong passivity, poor adaptability, and lack of real-time feedback, making it difficult to meet the needs of patients. In this context, intelligent wearable devices have gradually entered the clinical diagnosis and treatment field with their portability, real-time data collection and analysis capabilities. This article focuses on the development of sports injury rehabilitation equipment that integrates wearable biomimetic structures and adaptive materials, and proposes a rehabilitation training anomaly detection model based on deep learning (DL) technology. This model collects real-time motion and physiological data of patients through wearable devices, and analyzes the data using DL algorithms to accurately identify abnormal patterns in rehabilitation training and trigger warning mechanisms in a timely manner, providing customized feedback for patients. The results indicate that the model can efficiently and accurately detect abnormal states in rehabilitation training, significantly improving the safety and personalization level of rehabilitation training.

Keywords: Wearable biomimetic structure; Adaptive materials; Sports injuries; Rehabilitation equipment; Intelligent development model y.

1. Introduction

With the continuous emergence of AI technology and algorithm iteration, the ability to analyze and process complex data has been significantly improved [1]. This technological advancement provides a new solution for the prevention, diagnosis, and rehabilitation of sports injuries [2]. Sports injuries are usually caused by excessive load on tissues, leading to excessive depletion of bones, joints, and muscles [3]. If not intervened in a timely manner, these minor injuries will gradually accumulate and eventually lead to serious injury problems. AI technology can provide real-time feedback and avoid secondary injuries caused by improper exercise load by monitoring the rehabilitation training process of patients in real time, thereby minimizing the probability of sports injuries [4]. Among them, wearable devices, as an important carrier of AI technology, are gradually becoming the core tool for sports health monitoring [5]. Wearable devices integrate sensor technology, information technology, and human-computer interaction technology, continuously collecting users' physiological and exercise data through built-in sensors, evaluating rehabilitation effects, and providing health education and feedback functions [6].

Combining AI technology with wearable devices can not only achieve real-time monitoring of patients' movement status, but also further explore the potential patterns behind the data, providing scientific basis for the design of personalized rehabilitation programs [7]. In recent years, numerous scholars have conducted research on health monitoring of sports injuries and have achieved a series of important results. For example, Ikeda et al. [8] designed an intelligent mobile medical monitoring system that utilizes multiple sensors to obtain body indicator data and sends timely warning information to patients. Patel et al. [9] proposed a fall prediction algorithm based on multi-source

convolutional networks, achieving an accuracy of 99.3% on private datasets. However, this algorithm has a high computational complexity and is difficult to achieve real-time prediction and deployment on actual embedded devices. Similarly, Wong et al. [10] constructed the ConvLSTM algorithm and achieved a sensitivity of 99.32% and specificity of 99.01% on the KFall dataset. However, research also indicates that the algorithm has only been validated on the computer side and has not yet been tested for practical applications on embedded devices.

In addition, Sciarrone et al. [11] designed a physiological monitoring system based on WiFi and multiple sensors, including a motion detection module, an ECG signal acquisition module, and a body temperature signal acquisition module. The modules cooperate through serial communication, while the upper computer is responsible for integrating heart rate, body temperature, and exercise data to achieve real-time monitoring, anomaly detection, and posture recognition of users. Eslami et al. [12] studied the impact of gait changes on plantar pressure by building a plantar pressure measurement system, and combined adaptive algorithms to predict and analyze data features, providing new ideas for gait recognition. Although many research achievements have demonstrated the broad prospects of AI technology in the field of sports injury monitoring, there are still some urgent issues that need to be addressed. This article focuses on the development of sports injury rehabilitation equipment that integrates wearable biomimetic structures and adaptive materials, and proposes a rehabilitation training anomaly detection model based on DL technology. This model collects real-time motion and physiological data of patients through wearable devices, and combines advanced DL algorithms to analyze the data and accurately identify abnormal patterns in rehabilitation training.

2. Methodology

2.1 Construction of DL Based Rehabilitation Training Anomaly Detection Model

The human body is a dynamic and complex system, and evaluating its health status through sensor signals is a challenging engineering problem [13]. The motion, environmental, and physiological signals continuously sampled by wearable devices typically manifest as high-dimensional heterogeneous data [14]. These data have nonlinear, multimodal, and temporal characteristics, among which key features reflecting human health status are hidden. How to extract useful information from these complex data and achieve accurate classification is the core issue in the design of rehabilitation training anomaly detection models [15]. The basic idea of neural networks is to complete the classification task of sequence data by extracting and learning these hidden features. In biology, when a region is stimulated, specific neuronal cells perceive the stimulus, and that region is called the receptive field of that cell. Inspired by this mechanism, Convolutional Neural Networks (CNNs) extract local information from upper level feature maps by sharing convolutional kernels, thus possessing rotation, translation, and scaling invariance, while significantly reducing the number of model parameters.

As a commonly used DL model, CNN has a hierarchical structure and strong nonlinear fitting ability, and has been widely used in fields such as image recognition, object detection, natural language processing, and speech recognition. CNN is particularly adept at extracting local features, making it an ideal tool for processing multi-source sensor signals. However, relying solely on CNN is difficult to fully capture long-term dependencies in time series data. Long Short Term Memory Network (LSTM), as a variant of Recurrent Neural Network (RNN), effectively alleviates the gradient vanishing or exploding problem of traditional RNN when processing long time series through gating mechanism, making it more suitable for analyzing data with temporal characteristics. In order to further improve the performance of the model, this paper adopts bidirectional LSTM (BiLSTM), which can not only learn data features from front to back, but also extract information from back to front. The final output is jointly determined by two unidirectional LSTMs, which helps to more comprehensively capture the internal features of fall data or other abnormal patterns, thereby significantly improving classification accuracy.

Compared to unidirectional LSTM, bidirectional LSTM exhibits higher robustness in motion detection and can significantly reduce missed or false positives. Based on the above analysis, this paper proposes a rehabilitation training anomaly detection model that integrates CNN and BiLSTM. The model first aligns and samples the raw signals collected by multiple sensors in time sequence, and then directly inputs them into the model for processing. In the first stage of the model, CNN is used as the primary feature extractor, responsible for extracting local features from the input data; Its output is then used as an input to BiLSTM, which acts as a second level feature extractor, focusing on mining temporal features in the data. Finally, the classification task is completed through a fully connected network. The CNN-BiLSTM network designed in this article consists of two convolutional layers, two pooling layers, and one BiLSTM layer. The overall structure is shown in Figure 1. This two-stage feature extraction design fully utilizes the advantages of CNN in spatial feature extraction and the ability of BiLSTM in temporal feature modeling, thereby achieving efficient anomaly recognition of multi-source sensor signals.

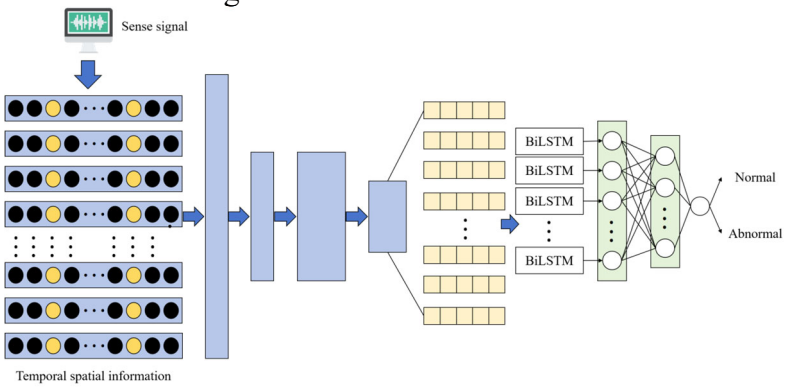

Figure 1 CNN-BiLSTM network

2.2 Algorithm Principle

Discrete Wavelet Transform (DWT) is a method of signal analysis that discretizes the scale and displacement parameters of basic wavelets. In the current construction process of the sports injury database, the data collected by patients through accelerometers in smart wearable devices is usually presented in three-dimensional form, including acceleration information in the three directions of X, Y, Z. The core of the DWT method is to extract features from these three-dimensional acceleration data. Specifically, this method first decomposes the patient's three-dimensional acceleration signal into three axial wavelet components of X, Y, Z, and then converts the original three-dimensional acceleration signal into a discrete wavelet representation by performing translation and scaling operations on each wavelet component. Assuming that the total energy released by the patient during a certain period of time is E_1, this total energy can be further refined into multiple wavelet energy components of different scales through wavelet decomposition. If the total energy is decomposed into i levels of wavelet energy, it can be expressed as the following relationship:

$$E_T = A_i A_i^T + \sum_{j=1}^{i} D_j D_j^T \tag{1}$$

Among them, A_i is the approximate coefficient of the i level wavelet, and A_i^1 is the transpose of A_i; D_i is the detail coefficient of the i level wavelet.

The convolutional layer of CNN performs feature extraction by using convolutional kernels to convolve the input data. In shallow networks, convolution operations can usually capture basic features such as edges and lines of the image; In deep networks, convolutional layers exhibit stronger sensitivity to more advanced and abstract features, which often have a high correlation with the input data. In the field of signal processing, one-dimensional convolution is commonly used to calculate the delay accumulation and other characteristics of signals. Assuming the length of the filter is K, its convolution operation with a signal sequence $s_1, s_2, \cdots, s_t$ can be expressed as:

$$y_t = \sum_{k=1}^{K} w_k s_{t-k+1} \tag{2}$$

Among them, s_t is the signal value generated by the signal generator at each time t, and w_k is the information loss rate.

Mean pooling refers to taking the average of all neurons within the set area $R_{m,n}^d$ as the feature representation of that area. The calculation formula is as follows:

$$y_{m,n}^d = \frac{1}{\left|R_{m,n}^d\right|} \sum_{i \in R_{m,n}^d} x_i \tag{3}$$

Among them, x_i is the value of each neuron parameter within the region. When there is noise or outliers in the region, the performance of maximum pooling may be affected to some extent, while mean pooling can more effectively preserve overall information, thereby improving the robustness of feature representation to a certain extent.

BiLSTM consists of two RNN layers that share the same input data but transmit information in opposite directions: one processes data in chronological order from front to back, while the other processes data in reverse order from back to front. The final prediction result is determined by the input information in both forward and backward directions, thereby achieving more comprehensive feature capture of sequence data. At time t, the operations of each part of the neuron can be expressed as:

$$h_t = f\left(w_1 X_t + w_2 h_{t-1}\right) \tag{4}$$

$$h_t' = f\left(w_3 X_t + w_5 h_{t+1}'\right) \tag{5}$$

$$o_t = g\left(w_4 h_t + w_6 h_t'\right) \tag{6}$$

In the formula: X_t is the input at time t; w_* is the weight matrix; h_{t-1} is the output from the previous moment; h_t is the output of the forward layer at time t; h_{t+1}' is the output for the next moment; h_t' is the output of the reverse layer at time t; o_t is the final output at time t.

3. Result analysis and discussion

To verify the effectiveness of our model in detecting abnormal states during rehabilitation training, we conducted comparative experiments with traditional ConvLSTM based models. Table 1 shows the comparison results of the accuracy of two models on the same dataset. It can be seen that our model has significantly higher accuracy than traditional methods. This outstanding performance is attributed to two key improvements in our model design. Firstly, we introduce DTW to preprocess the collected motion data, converting the original 3D acceleration signal into a discrete wavelet representation to better capture the local features and detailed information of the signal. Secondly, we innovatively combined the CNN-BiLSTM network structure and adopted a two-stage feature extraction strategy. Among them, CNN is responsible for extracting spatial features and fully leveraging its advantages in local pattern recognition; BiLSTM focuses on mining long-term dependencies in time series. This design not only fully utilizes the strengths of CNN and BiLSTM, but also achieves efficient anomaly recognition of multi-source sensor signals, significantly improving the overall performance of the model.

Table 1 Accuracy Comparison/%

Number of tasks/piece	Model in this article	Traditional model
10	90.2	80.5
50	90.8	80.7
100	91.5	81.2
150	92.3	81.7
200	93.1	82.4

Table 2 shows the comparison of the time consumption between our model and traditional ConvLSTM based models in the task of detecting abnormal states during rehabilitation training. The results show that our model has a shorter running time and exhibits higher computational efficiency. This advantage is mainly due to two key optimizations in our model design: firstly, we use DTW to preprocess the collected motion data, which not only effectively reduces data complexity but also significantly reduces computation time. Secondly, we combined the CNN-BiLSTM network structure and achieved efficient anomaly recognition through a two-stage feature extraction strategy. Among them, CNN fully leverages its advantages in capturing local patterns; BiLSTM is responsible for mining long-term dependencies in time series. Compared to unidirectional LSTM, bidirectional LSTM can learn data features from both forward and backward directions simultaneously, significantly reducing missed or false positives and further improving the robustness and accuracy of the model. In summary, our model significantly reduces computation time while ensuring high accuracy, providing a more efficient solution for anomaly detection in rehabilitation training.

Table 2 Time consumption comparison/ms

Number of tasks/piece	Model in this article	Traditional model
10	245	348
50	487	526
100	629	741
150	831	936
200	985	1147

Figure 2 shows the comparison of recall rates between our model and traditional ConvLSTM based models in the task of detecting abnormal states during rehabilitation training. The recall rate is an important indicator for measuring the model's ability to recognize abnormal states. The results show that our model has a higher recall rate and exhibits stronger detection capabilities. This excellent performance is attributed to two key improvements in our model design: firstly, we use DTW to preprocess the collected motion data, thereby more effectively extracting key features of the signal. Secondly, this model combines the CNN-BiLSTM network structure and achieves efficient and accurate anomaly recognition through a two-stage feature extraction strategy. Among them, CNN extracts local features by sharing convolutional kernels, which have rotation, translation, and scaling invariance, while significantly reducing the number of model parameters; BiLSTM, on the other hand, learns time series features from both forward and backward directions simultaneously. Compared to unidirectional LSTM, it exhibits higher robustness and can significantly reduce the occurrence of missed or false positives.

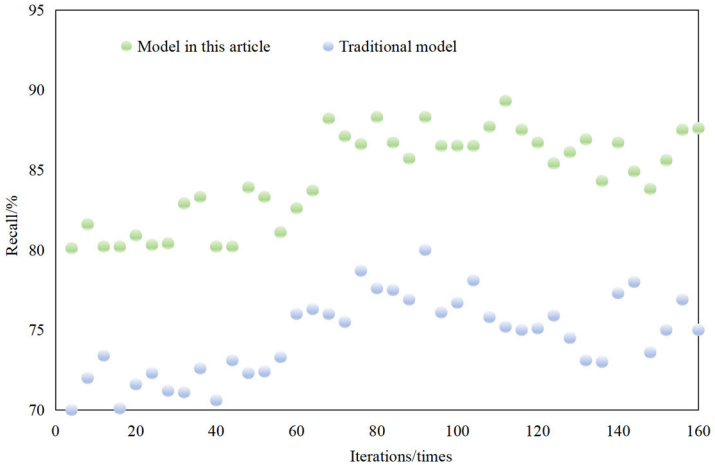

Figure 2 Comparison of recall rates

Figure 3 shows the comparison results of the missed detection rate between our model and the traditional ConvLSTM based model in the rehabilitation training anomaly state detection task. The results show that our model has a lower false positive rate and demonstrates higher detection reliability. Firstly, we use DTW to preprocess the data, effectively extracting key features of the signal

and reducing data complexity. Secondly, this article combines the CNN-BiLSTM network structure with the model. Among them, CNN is good at extracting local features, while BiLSTM learns time series features from both forward and backward directions, which can more comprehensively capture the internal rules of fall data or other abnormal patterns, significantly improving classification accuracy and greatly reducing missed or misjudged cases.

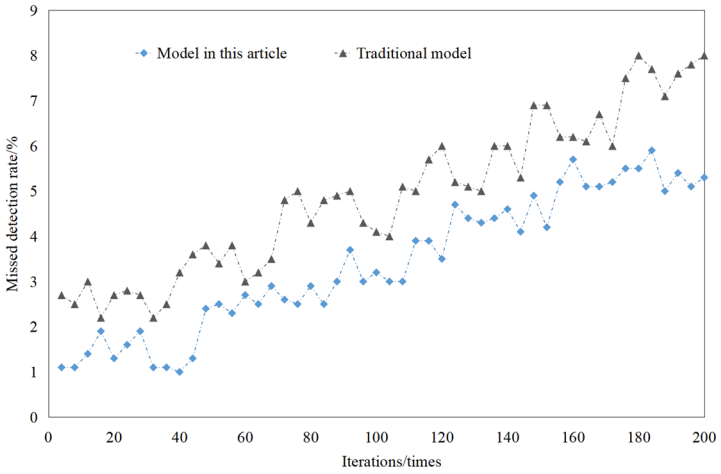

Figure 3 Comparison of missed judgment rate

4. Conclusion

This article focuses on the development of sports injury rehabilitation equipment that integrates wearable biomimetic structures and adaptive materials, and proposes a rehabilitation training anomaly detection model based on CNN-BiLSTM. This model collects real-time motion and physiological data of patients through wearable devices, and combines DL algorithm to analyze multi-source sensor signals, thereby accurately identifying abnormal patterns in rehabilitation training. At the same time, the model can trigger warning mechanisms in a timely manner, providing customized feedback to patients, effectively improving the safety and personalization level of rehabilitation training. The results show that our model performs well in anomaly detection tasks, not only with high accuracy and recall, but also significantly reduces false negatives and computation time, demonstrating its efficiency and reliability in practical applications. However, this study still has certain limitations. Firstly, the performance of the model depends on high-quality sensor data, and there may be issues of noise interference or data loss in practical application scenarios, which puts higher demands on the robustness of the model. Secondly, although CNN-BiLSTM combines the advantages of spatial and temporal feature extraction, the complexity of the model is relatively high, which may pose certain challenges for real-time deployment of embedded devices. Future research will further optimize the lightweight design of the model and explore more efficient algorithm architectures to meet practical clinical needs.

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