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Convolutional neural network-based feature extraction and quantification of daily sports data for smart wearable devices

Rong Zhu[1,✉]

[1] Shandong Vocational College of Science and Technology, Weifang, Shandong, 261053, China

ABSTRACT

With the progress of modern technology, smart wearable devices have been gradually applied in the field of sports. This paper focuses on the experiments of motion recognition of the main joints realized by convolutional neural network-assisted smart wearable devices. Using smart wearable devices to feature extraction of a variety of sports signals, using GAF algorithm for sports signal image coding, and using convolutional neural network and gated recurrent unit, a CNN-GRU-based motion recognition method is proposed. Through the training and evaluation experiments of the model, it is found that the average accuracy of the CNN-GRU model training and testing is higher than 96%, and the loss value is lower than 1.5%, and the performance of sports recognition is better than that of CNN and CNN-LSTM models. Meanwhile, it presents excellent performance in the recognition of sports with different classifications and different signal durations, reaching 97.02% and 92.63% accuracy in the recognition of three and four types of sports, respectively, and the distribution of the values of human body indexes in different sports in the case study presents a certain degree of regularity, which verifies the effectiveness and feasibility of the CNN-GRU model in different application scenarios. It also shows that the method has great development potential in the field of intelligent sports.

Keywords: convolutional neural networks; gated recurrent units; motion recognition; smart wearable devices; feature extraction; sports

1. Introduction

With the rise of the sports power boom, people's attention to sports has gradually increased. At the same time, with the development of artificial intelligence technology, big data technology and other advanced technologies and their application in the field of sports, smart wearable devices are being

✉ Corresponding author.
E-mail address: 13371099307@163.com (R. Zhu).
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introduced into various sports, injecting a new impetus for the development of sports. They provide a powerful guarantee in reducing athletes' injuries, monitoring athletes' sports data and health status, and assisting athletes in improving the effect of sports training.

Intelligent wearable devices mainly refer to the sports equipment used to monitor the body state by using artificial intelligence technology and sensors to record relevant data, which can help people understand the data generated during their own exercise [1]. This sports product is the result of people's continuous pursuit of intelligence in sports equipment as well as the realization of scientific sports goals. In smart wearable devices, the most important hardware facilities are wearable kits and physiological information sensors, and the core technology involved in software is artificial intelligence data processing and wireless network transmission. Through the use of machine learning technology, sensor technology and multimedia technology, it provides feedback to the athlete's movement and produces a better interactive experience [2-3]. Intelligent wearable devices are able to collect human physiological parameters during athletes' physical training, and at the same time, analyze the collected data using big data technology, so as to provide athletes with effective suggestions to improve the effect of exercise [4-5]. In addition, the biggest advantage of artificial intelligence wearable devices over previous devices is that they have good convenience, and the extraction and analysis of athletes' body characteristic data do not require the participation of large-scale equipment, reflecting the advantages of good flexibility [6-7]. The rapid development of the Internet of Wisdom and the Internet of Things has also laid a good foundation for the use and development of smart wearable devices, which has great potential and good market prospects in the sports industry.

The main purpose of wearing smart wearable devices is to monitor one's health status, obtain convenient life services and assist in time management and task planning. Literature [8] investigated the application of smart wearable sensors in sports performance tracking, where sensors are attached to relevant parts of the human body to obtain key physiological parameters and analyze the data to provide important feedback for athletes' health status. Literature [9] describes a micro wearable device and system that can detect and record the user's sports data characteristics information, wearing it on the wrist can monitor both skin temperature and pulse rate, but also through the inertial measurement sensors to monitor the arm movement, and transmit the data into the cloud service, which can provide the user with relevant sports services and health monitoring. Literature [10] uses smart wearable devices to monitor the real-time heartbeat data of athletes in different sports postures, and analyzes the health data of athletes by combining intelligent algorithms supported by the Internet of Things system, which can help athletes understand their own health status and thus improve their personal health.

The scale of data collected in the process of sports has become larger and larger, relying only on manual data analysis presents an obvious shortage, and the application of artificial intelligence and deep learning technology to data analysis has become an important research direction. Literature [11] combines the convolutional feature extraction algorithm with sensors supported by smart wearable devices to construct a set of network models for human sports behavior recognition, and introduces the 1D CNN + LSTM algorithm to further improve the sensitivity and accuracy of the sensors, so as to enable them to play an excellent performance in sports event applications. Literature [12] uses motion sensors worn on wrists and ankles to acquire user motion signals, and extracts the short-time spectral features of motion data through deep convolutional neural networks to achieve accurate recognition and classification of sports events. Literature [13] shows that machine learning or deep learning models are able to analyze the time series data generated by wearable sensors to identify specific sports by determining the unique movement actions, and proposes and validates a shallow convolutional neural network for the recognition of sports behaviors, and the proposed model has a high recognition accuracy. Literature [14] established a set of sports prediction model based on big data analysis and convolutional neural network, which is integrated into wearable devices, and can provide users' sports performance analysis based on a large amount of real-time sports data, which strengthens the users' sports health management, and at the same time effectively reduces the risks generated during the exercise process. Literature [15] developed a smart wearable sensor for American soccer catch or drop recordings, using the sensor to capture nine degrees of freedom of movement and audio data from both hands, and subsequently using a convolutional neural network to classify and recognize the movement data, thus providing guidance for high-quality practice. Literature [16] indicates that deep learning has the potential to extend the boundaries of sensor-based activity recognition, and the design of a wearable sensor-based automatic interference-free monitoring system for beach volleyball, which utilizes deep convolutional neural networks to analyze the motion data, can help to identify and understand the risk factors of players' behaviors, and in addition, the performance test results show a significant improvement in the classification performance of the deep convolutional neural network algorithm.

Based on the analysis of the application of smart wearable devices in sports, the study uses flexible fiber optic smart wearable devices to monitor the human knee and elbow joint motion, and the four common motion states captured. The one-dimensional time-series motion signals were converted into two-dimensional feature images by GAF algorithm, and the image coding of motion signals as well as the experimental dataset production were completed. Subsequently, the convolutional layer and GRU recurrent layer are combined to build a CNN-GRU based motion recognition model. Then the motion recognition experiments of CNN and CNN-LSTM models are selected and compared with the CNN-GRU model by analyzing the accuracy and loss values on the training and validation sets. Then the motion recognition performance of the CNN-GRU model is evaluated based on the metrics of accuracy, recall, precision and FI value from the dimensions of different motion types and different signal durations, respectively. Finally, human indicators are selected to characterize four sports, and the feasibility of the CNN-GRU model is explored by recognizing the model and analyzing the motion feature data of each indicator.

2. Smart wearable devices in sports

Intelligent wearable devices, as a kind of electronic devices that can realize the real-time detection of sports data, oriented quantitative development of guidance programs, sports scene human-computer interaction and other functions, have been widely used in sports day by day. The application of smart wearable devices in sports is shown in Figure 1, which is mainly reflected in the following dimensions.

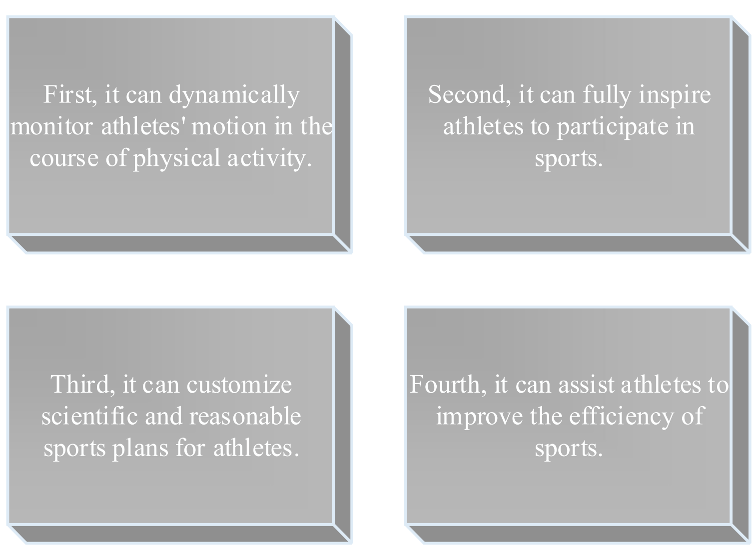


Fig. 1. The application of intelligent wearables in sports

2.1. Monitoring of movement status

Athletes can wear smart wearable devices to monitor their heart rate, sleep and other information in real time, and record the data of athletes in the process of participating in sports. Sports instructors can provide personalized and targeted sports adjustment programs for athletes based on the data recorded by smart wearable devices. At the same time, from the athlete's own point of view, you can always check the data changes in the process of their own sports.

2.2. Stimulating interest in sports

Under the background of the Internet, young people pay more attention to electronic devices, but they usually use these devices for entertainment or games, while their application in the field of outdoor sports is relatively small. By reasonably applying smart wearable devices, we can enhance athletes' interest in smart wearable devices with the help of rich functions and personalized forms, improve their enthusiasm and initiative in wearing smart wearable devices to participate in sports, and maximize the important role of smart wearable devices in the process of assisting the development of sports.

2.3. Customized exercise programs

Through smart wearable devices can realize the monitoring and analysis of athletes' exercise intensity, exercise frequency, heart rate changes and other data, and combined with the athlete's own age, physical fitness, gender, and sports habits for athletes to customize personalized, targeted sports programs. Because it is based on the objective analysis of the athlete's exercise data, the exercise plan formulated is more targeted and reasonable.

2.4. Enhancement of movement efficiency

In the process of sports, athletes need to adopt corresponding training programs according to the different training stages they are in, in order to ensure that sports get better results. Through the application of smart wearable devices can collect a variety of data during the exercise process, such as heart rate, step count, exercise time and so on, in order to analyze the effect of exercise. At the same time, wearable devices can provide real-time exercise guidance for sportsmen, such as changing running speed and adjusting muscle training. Therefore, the efficiency of sports can be effectively enhanced by the assistance of smart wearable devices.

In conclusion, the application of smart wearable devices in sports is of great significance in ensuring the safety of the sports process and enhancing the scientific and personalized aspects of sports. Therefore, in the process of sports implementation, coaches and athletes should pay enough attention to smart wearable devices, and reasonably use the advantages of smart wearable devices to improve sports performance, enhance the safety of sports and promote the scientificization of sports training.

3. CNN-GRU based motion recognition model

Motion recognition refers to the process of judging and recognizing various daily sports by collecting human motion information and analyzing it and then realizing it. In this paper, we use smart wearable devices to collect data during sports and design a CNN-GRU sports recognition model based on convolutional neural network and gated recurrent unit.

3.1. Motion Data Feature Extraction

3.1.1. Motion signal acquisition. In order to facilitate the measurement of daily sports, a wearable sheath was designed that is easy to wear and capable of measuring knee and elbow joint movements.

A flexible D-type plastic optical fiber with high sensitivity was sewn onto the sports sheath, and the direction of the side throw should be consistent with the bending direction of the joint, and the coils at both ends of the optical fiber should be tightened to ensure that the D-POF does not rotate. The optical transmitter and receiver modules are connected to the input and output ends of the optical fiber respectively. The human knee and elbow joint movements drive the flexible fiber optic sensor to produce bending changes with the movement sheath, which causes changes in the output optical power to obtain the motion waveform, realizing the motion recognition of the main joints.

Five healthy female and five healthy male volunteers were selected to participate in this study. In this experiment, the motion of human knee and elbow joints were captured to recognize three common human motions, including: walking, running, low-resistance cycling and high-resistance cycling. In order to obtain more effective, accurate and comprehensive motion signals, the original motion signals were de-baselined and de-noised, normalized, and segmented by sliding window for data fusion.

3.1.2. Motion Signal Image Coding. The data collected through the flexible fiber optic wearable device is a one-dimensional time series motion signal, which presents more depth features in order to capture the temporal correlation in the sensor data. By using the GAF algorithm to image code the original motion signal, more motion features are extracted from the trend and pattern of the signal over time, and the one-dimensional time-series signal is transformed into a two-dimensional image with more focused features.

Gramian Angle Field (GAF) is a method for visualizing time data as images. Its goal is to make the differences between different sequences easier to visualize and identify while maintaining the temporal correlation of time series data.

The conversion process is carried out in several steps:

1) Normalization: first, time series data usually need to be normalized. Normalization is to ensure that all data points fall within a uniform range of values, such as [-1, 1]. This helps to unify the criteria for subsequent processing and facilitates better spatial transformations.

2) Coordinate transformation: after that, the normalized time series data is transformed from Cartesian coordinate system to polar coordinate system. Each data point in the Cartesian coordinate system determines its position according to its value and time stamp, while in the polar coordinate system, the position of each data point is determined by an angle and a radius. Typically the angle represents the timestamp in the time series, while the radius corresponds to the normalized data values. This transformation allows the temporal properties of the sequence to be represented in a new way.

3) Constructing the Gram matrix: the data points after conversion to polar coordinates are used to construct the Gram matrix. In the context of a time series, constructing a Gram matrix involves computing an inner product between two-by-two vectors represented by points in the polar coordinate system (actually complex numbers defined by polar coordinate points). Such an inner product is actually an expression of the relative temporal position between pairs of data points in the time series.

The Gram matrix thus obtained can have two forms of GAF:

Gramian Angular Summation Field (GASF): this matrix is obtained by calculating the cosine values between the points in polar coordinates and contains information about the summation of the time series.

Gramian Angular Difference Field (GADF): this matrix is obtained by calculating the sine value between points and contains information about the summation of the time series.

4) Image representation: finally, the results of the GAF can be visualized as images, which can be used as inputs to machine learning models, in particular Convolutional Neural Networks (CNNs), in order to facilitate classification, clustering, or other analyses of time series data.

Thus, for a one-dimensional time series $X_t = x_1, x_2, \cdots, x_n$, its normalization can be accomplished by the following equation:

$$\bar{X}_t = \frac{X_t - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

When mapped to a polar coordinate system, the polar value is the normalized time series value of the angle cosine and the time value is the radius in the polar coordinate system. Angle θ_i and radius r_i can be calculated using the following equation:

$$\theta_i = \cos^{-1}(\bar{X}_i), 0 \le \theta_i \le \frac{\pi}{2} \tag{2}$$

$$r_i = \frac{t_i}{N} \tag{3}$$

where t_i and N are the time points and constant values, respectively, that equate the time span in polar coordinates.

After mapping the data to polar coordinates, the temporal relationship can be obtained using the triangular sum or difference between the two points, which produces two types of GAFs, GASF and GADF, which are represented by the following equations, respectively:

$$GASF = \begin{bmatrix} \cos(\theta_1 + \theta_2) & \cdots & \cos(\theta_1 + \theta_i) \\ \cos(\theta_2 + \theta_1) & \cdots & \cos(\theta_2 + \theta_i) \\ \vdots & \ddots & \vdots \\ \cos(\theta_i + \theta_1) & \cdots & \cos(\theta_i + \theta_i) \end{bmatrix} \tag{4}$$

$$GADF = \begin{bmatrix} \sin(\theta_1 - \theta_2) & \cdots & \sin(\theta_1 - \theta_i) \\ \sin(\theta_2 - \theta_1) & \cdots & \sin(\theta_2 - \theta_i) \\ \vdots & \ddots & \vdots \\ \sin(\theta_i - \theta_1) & \cdots & \sin(\theta_i - \theta_i) \end{bmatrix} \tag{5}$$

From equations (4) and (5), it can be seen that the GAF matrix is a trigonometric representation of the time series data, and each element of the matrix is the output of the trigonometric sum or difference of the data at two time points. The GAF image mainly shows the temporal correlation between pairs of data points while retaining the spatial location information.

3.1.3. Production of data sets. In order to better analyze the data, the amount of data is the same in each sport for this experiment, 1500 data were collected for each sport, and a total of 6000 data were obtained. The 6000 images generated from each sport were divided in the ratio of 3:1:1, i.e., 3600 images were used as the training set, 1200 images were used as the validation set, and 1200 images were used as the test set.

3.2. CNN-GRU model building

3.2.1. Convolutional Neural Networks. Convolutional neural network (CNN), as one of the representative algorithms of deep learning, is a kind of computer neural network model constructed by scientists inspired by animals. The main structure of the CNN network model includes several parts such as convolutional layer, pooling layer, fully connected layer, etc. The first step of the network is to use convolutional layer to initially extract the features of the input data, and after that, use the pooling layer to further refine the extracted features, and finally output the results through the fully connected layer. Finally the results are output through the fully connected layer.

1) Convolutional Layer. The convolutional layer, as the core part of the CNN, uses sparse connectivity, i.e., the neurons in the previous layer are only connected to the next neuron nearest to its position. In addition, the convolutional layer has the function of sharing weights, where the same line segment types will share the same weights. Compare this to a fully connected network, where each connection weight is different while participating in the training process, which will result in extremely high computational complexity. This feature will be more obvious the larger the number of neurons, the advantage of CNN weights sharing will be more obvious.
2) Pooling layer. The essence of the pooling layer is to reduce the dimensionality of the features, because the convolutional layer is a reduction of the connection weights, and does not reduce the number of connections between the neurons, so the pooling layer is also a secondary screening of the convolutional layer to further simplify the complexity of the model. The general pooling operation is divided into two types: maximum pooling and average pooling. Unlike the calculation of convolution, the sliding window of pooling is a matrix of $n \times n$ to find the maximum or average value of the matrix.
3) Fully Connected Layer. The essence of the fully connected layer is to integrate and further downsize the pooled results. Firstly, the feature influencing factors and load data are used as the input layer, the features of the data are extracted through the sliding function of convolution, and then the feature vector of the convolution layer is extracted through the activation function as the pooling layer. The feature information is extracted again by using the pooling window according to the set average pooling or maximum pooling, and finally the output is performed through the fully connected layer.

3.2.2. Door-controlled circulation units. Gated Recurrent Unit (GRU) is a simplified version of Long Short-Term Memory (LSTM).GRU has a simpler network structure compared to LSTM, and GRU has fewer parameters, which makes it faster to train on tasks containing large-scale data, and also reduces the risk of overfitting, and at the same time the training effect is very good. GRU can solve the long-dependency problem of RNN networks, and therefore is also a currently a very popular network.

The inputs and outputs of the GRU depend on the current input x_t and the hidden state h_{t-1} passed down from the previous node to get the output of the current hidden node y_t and the hidden state passed down to the next node $h^{'}$. Its basic box

GRU forward propagation formula is as follows:

First, two gating values are obtained from the previous state h_{r-1} and the current input x_t:

$$r = \sigma\left(W_r \cdot \left[h_{t-1}, x_t\right] + b_t\right) \tag{6}$$

$$z = \sigma\left(W_z \cdot \left[h_{t-1}, x_t\right] + b_z\right) \tag{7}$$

Where: r - reset gating, z - update gating, σ - sigmoid function to get a gating signal in the range 0-1.

Then h_{t-1} is deflated with input x_t by tanh activation function to get $\tilde{h}_t$ in the range of -1 to 1:

$$\tilde{h}_t = \tan h(W_h \cdot [r * h_{l-1}, x_l] + b_h) \tag{8}$$

Then, $\tilde{h}_t$ and h_{t-1} are connected by updating the gating z_t to find h_t:

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t \tag{9}$$

Finally, with the f function, the current output y_t is obtained:

$$y_t = f(W_p \cdot h_p + b_p) \tag{10}$$

3.2.3. CNN-GRU modeling. The CNN-GRU network structure proposed in this paper has 9 layers, including 3 convolutional layers, 2 pooling layers, 2 recurrent layers and 1 output layer. The network structure of the CNN-GRU is shown in Fig. 2.Firstly, the preprocessed sensor data will be used as the input to the convolutional layer, and then the feature outputs extracted from the convolutional pooling layer will be used as the inputs to the recurrent layer, and finally the outputs of the recurrent layer will be sent to the output layer which is A fully connected layer with the activation function of Softmax, the Softmax layer can calculate the probability that the sample belongs to each class, and it is also convenient to calculate the loss function later by finding the cross entropy.

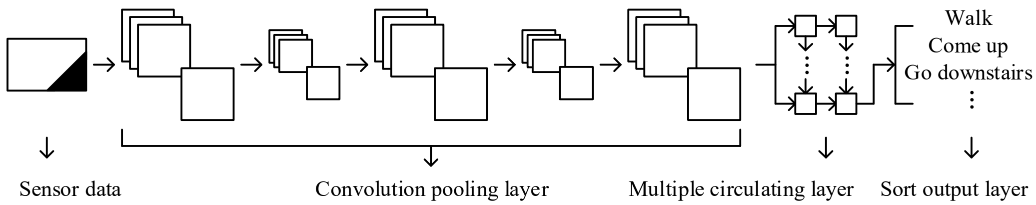


Fig. 2. Structure of the CNN-GRU network

1) Convolutional pooling layer. The convolutional pooling layer part of this network is composed of alternating stacks of convolutional and pooling layers. It includes 3 convolutional layers and 2 pooling layers. The number of convolution kernels of the 3 convolutional layers are 16, 32 and 64 respectively, the size of convolution kernel are 1×8, the step size is 1, and the padding mode is complementary 0. In the convolutional layer, each time, multiple convolution kernels can be used to perform convolution operation on the input information to generate multiple feature maps, and its mathematical model can be described as:

$$x_j^{l+1} = f\left(\sum_{i=1}^{M'} x_i^l \times k_i^l j + b_j^l\right) \tag{11}$$

where: x_j^l is the jnd feature map of layer 1, f is a nonlinear activation function. M^l is the number of feature maps in layer l. $k_j^l j$ is the convolution kernel that maps the ith feature map of layer l to the jth feature map of layer $(l+1)$ by convolution operation. Modified Linear Unit (ReLU) is usually chosen for nonlinear activation. the advantage of ReLU is that it can reduce the dependency between parameters and reduce the generation of overfitting problems. the ReLU is formulated as follows:

$$a_i^{l+1}(j) = f(y_i^{l+1}(j)) = \max\{0, y_i^{(l+1)}(j)\} \tag{12}$$

Where: $y_i^{(l+1)}(j)$ represents the output value of the convolution operation and $a_i^l+1(j)$ is the activation value of $y_i^{(l+1)}(j)$.

The 2 pooling layers are distributed between the 3 convolutional layers, and the pooling filters are all of size 2×1, with a step size of 2 and padding of complementary 0. The pooling layers are sandwiched in the middle of the consecutive convolutional layers, and are used to compress the amount of data and parameters, and to reduce overfitting. The commonly used pooling methods are divided into maximum pooling and average pooling, average pooling can take the average value of all feature points in the window, and maximum pooling takes the largest feature point in the window. In order to extract the most obvious features in the feature map, this network structure uses the maximum pooling strategy.

2) GRU recurrent layer. The 2 recurrent layers of the network both use GRUs as recurrent units with 128 recurrent neurons.

4. Training and evaluation of models

Experiments are carried out on the constructed CNN-GRU motion recognition model, and quantitative analysis is performed through model training and model evaluation to verify the performance of the CNN-GRU model for recognizing motion postures in daily sports activities.

4.1. Model training

In order to avoid introducing too many parameters, the images will be preprocessed first, and the specific steps include on-the-fly cropping, random horizontal flipping, format conversion, and normalization of the training and validation set images. Image coding is performed on the time series, and a total of 6000 GADF images with a size of 400×400 are obtained, which are processed to reduce the size of the images to a standard size of 224×224. The processed images are fed into three models CNN, CNN-LSTM and CNN-GRU for training. The cross-entropy loss function is used during the training process to determine how close the actual output is to the expected output. The parameters were optimized using the AdamW algorithm (β_1=0.8, β_2=0.9) with Batch size=40 and Epochs=80. An Epoch is a process in which the entire training dataset is trained once by the network. The initial learning rate was set to 0.001, in order to prevent the model from oscillating, the training warm-up learning rate method was utilized first, and the cosine descent method was used to dynamically adjust the learning rate after the maximum learning rate was reached. The decay curve of the learning rate is shown in Fig. 3, and the decay of the learning rate tends to be close to 0 after 40 iterations.

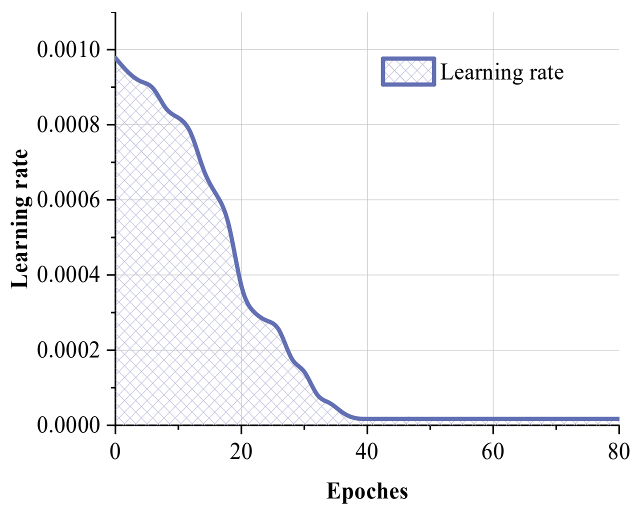
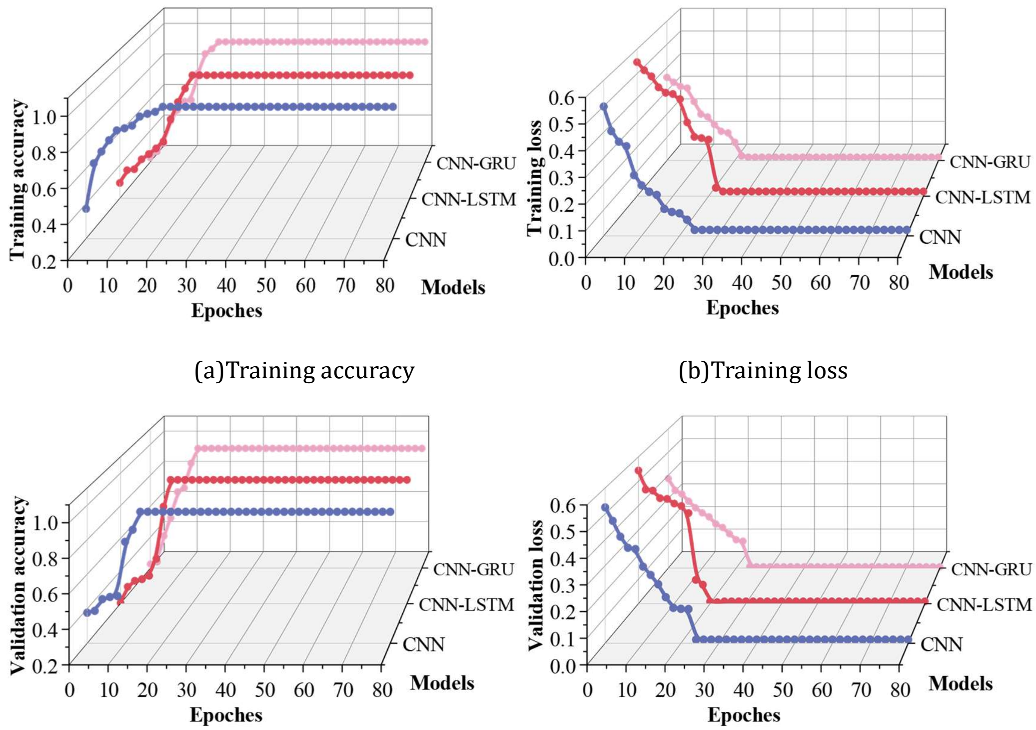


Fig. 3. The decay curve of the learning rate

A total of three models, CNN, CNN-LSTM, and CNN-GRU, are used to train the datasets with different motions collected in this experiment, and Fig. 4 shows the change curves of accuracy and loss during the training and test set training of the three models. Table 1 shows the results of training and validation after the network performance of the three models has stabilized. From the table, it can be seen that the CNN-GRU network is trained with higher accuracy and lower loss, and its accuracy in the training and validation sets is 96.8% and 97.4%, which is an improvement of more than 1.2%, and the loss values are 1.4% and 0.5%, respectively.



(a)Training accuracy

(b)Training loss

(c)Validation accuracy

(d)Validation accuracy loss

Fig. 4. The accuracy and loss curve of the three models of training set and verification set

Table 1. The results of training and validation of three models

Models	Stable training accuracy	Stable training loss	Stable validation accuracy	Stable validation loss
CNN	95.3%	2.3%	96.2%	1.4%
CNN-LSTM	94.4%	1.9%	95.9%	0.9%
CNN-GRU	96.8%	1.4%	97.4%	0.5%

4.2. *Model evaluation*

Samples of 10s and 5s time-length sports signals were obtained by segmenting the collected signals from each of the four types of sports into short-time samples through a sliding window. Four-category classification experiments performed on the four types of sports and exercise recordings contained in the database were conducted to test the feasibility of the proposed model. In addition, due to the similarity between low and high resistance cycling, this study also merged the two cycling datasets into one cycling dataset to perform three-class classification experiments with the other two sports.

The classification results of the CNN-GRU model on 10samples are shown in Table 2. In sport four classification, the classification accuracy can reach 92.63%, and the recall, precision and F1 index reach 91.50%, 92.28% and 91.83%, respectively. When the two cycling sports are combined into the same set, the accuracy of the sport three classification has a significant improvement, reaching 97.02%, and the recall, precision and F1 index have also improved, reaching 97.10%, 97.29% and 97.21%, respectively. At this time, it can be found that the false detection rate of the cycling sport is 0, which can be clearly distinguished from the other two sports. From the experimental results as a whole, it seems that using the CNN-GRU model can better classify the data signals collected from different sports accurately.

Table 2. The classification results of the CNN-GRU model on the 10s sample

Classification	Type	Acc (%)	Rec (%)	Pre (%)	F1 (%)
Three classification	Bike	97.02	100	100	100
	Run		93.61	96.45	94.96
	Walk		97.69	95.41	96.66
	Mean	97.02	97.10	97.29	97.21
Four classification	High resistance biking	92.63	83.75	88.07	85.76
	Low resistance biking		91.18	88.72	90.78
	Run		93.20	96.63	94.47
	Walk		97.85	95.71	96.31
	Mean	92.63	91.50	92.28	91.83

The classification results of the CNN-GRU model on 5s samples are shown in Table 3. In the four-class classification experiment on motion types with 5s signal samples, 91.02% classification accuracy, 89.20% recall, 91.06% precision, and 90.39% F1 index can be obtained. In the sport three classification experiment, 96.23% classification accuracy, 95.39% recall, 96.82% precision and 96.15% F1 index could be obtained. The shortening of the sample length did not affect the recognition rate of cycling sports.

It can be seen that the length of the input sports sample segments has a significant impact on the performance of the CNN-GRU model, in comparison, the 10s time-length sample signal is longer, contains more information, and more features are extracted, and the evaluation indexes corresponding to the classification experiments have a significant advantage, and the recognition effect is better. However, on the whole, the model can still maintain a competitive classification and recognition effect using 5s sample classification.

Table 3. The classification results of the CNN-GRU model on the 5s sample

Classification	Type	Acc(%)	Rec(%)	Pre(%)	F1(%)
Three classification	Bike	96.23	100	100	100
	Run		90.67	95.89	92.51
	Walk		95.51	94.57	95.93
	Mean	96.23	95.39	96.82	96.15
Four classification	High resistance biking	91.02	88.27	86.19	83.75
	Low resistance biking		79.32	87.66	88.03
	Run		92.72	95.51	93.97
	Walk		96.49	94.86	95.82
	Mean	91.02	89.20	91.06	90.39

Figure 5 shows the confusion matrix for different time durations at triple classification. The results of sports recognition for samples of different durations perform similarly, and the difference in recognition accuracy is within 5%, and the difference between cycling and walking and running is more obvious, and the model is able to accurately distinguish cycling and is not affected by the sample durations. As the sample length increases, the recognition rate of running improves, while that of walking is relatively stable.

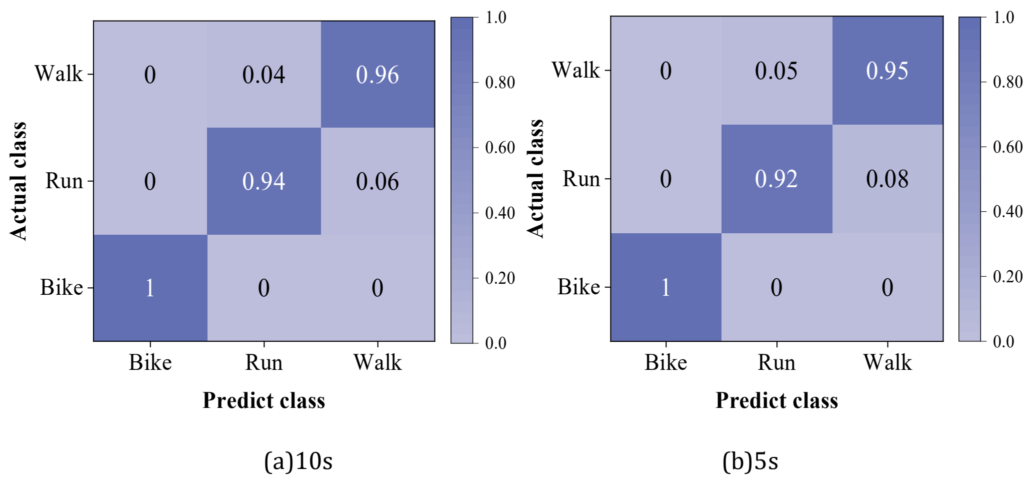


Fig. 5. The confusion matrix of different hours in three categories

Figure 6 shows the confusion matrix for different durations at four classifications. Low-resistance riding and high-resistance riding have more similar features and thus are easily misclassified in the four-class classification, and the recognition rate of low-resistance riding when classifying 5samples is only 81%. The recognition performance of walking and running, on the other hand, is no different from the three classifications and maintains good recognition. Overall, it seems that the recognition rate between the broad categories of sports is high and almost no misrecognition occurs, with the main recognition errors occurring between the more similar sports.

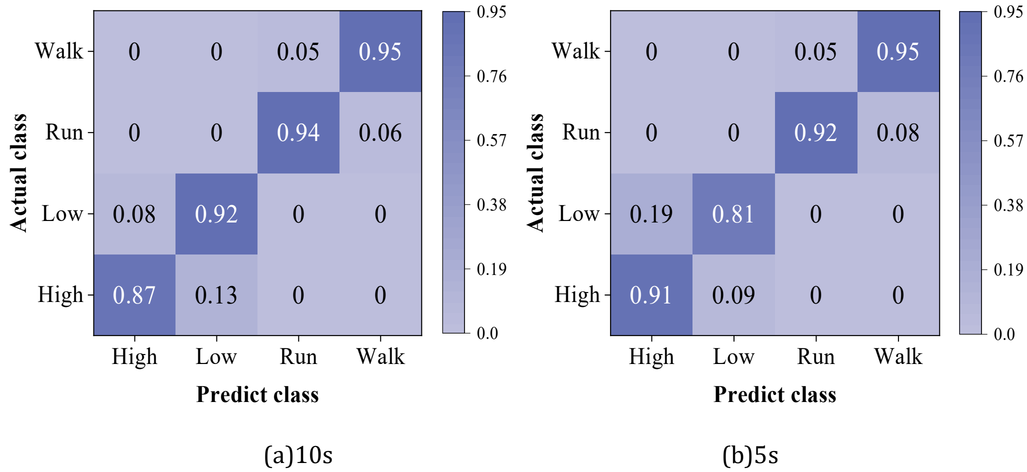


Fig. 6. The confusion matrix of different hours in four categories

5. Analysis of examples

In this chapter, an example analysis is carried out to collect the relevant metrics during sports using a smart wearable device, and analyze its data characteristics using the CNN-GRU model.

5.1. Selection of indicators

In this paper, the optimal features of the four types of motion recognition models are considered comprehensively, and after examination and screening, the following 4-dimensional simple features are selected as the index system for motion recognition quantization. The selection results of the indicators are shown in Table 4. It is worth noting that these indicators are calculated from signals with a time length of 30s.

Table 4. Selection results of the index

Index number	Index name	Meaning
X1	chanel5_min	Minimum respiratory frequency
X2	chanel4_25%	A four-digit number of heart rate
X3	chanel1_kf	ECG signal margin factor
X4	ch3_zerocrossings	The number of times the zero in RR

5.2. Characterization of data

Five volunteers were selected to perform sports such as walking, running, low-resistance cycling and high-resistance cycling, and the indicators in the previous section were collected by using smart wearable devices, and the CNN-GRU model was applied to the indicator-collected data for motion recognition, and the distributions of the motion data features in the different indicators are shown in Figure 7. The range of the four sports in the four indicators from X1 to X4 is [10, 35], [135, 155], [15, 32], and [65, 85], in which the indicator values of running are higher than the other three sports as a whole, followed by high resistance cycling, and the indicator values of walking are all the lowest. With the increase of time, the human metrics of all four sports showed an increasing trend, which is in line with the reality.

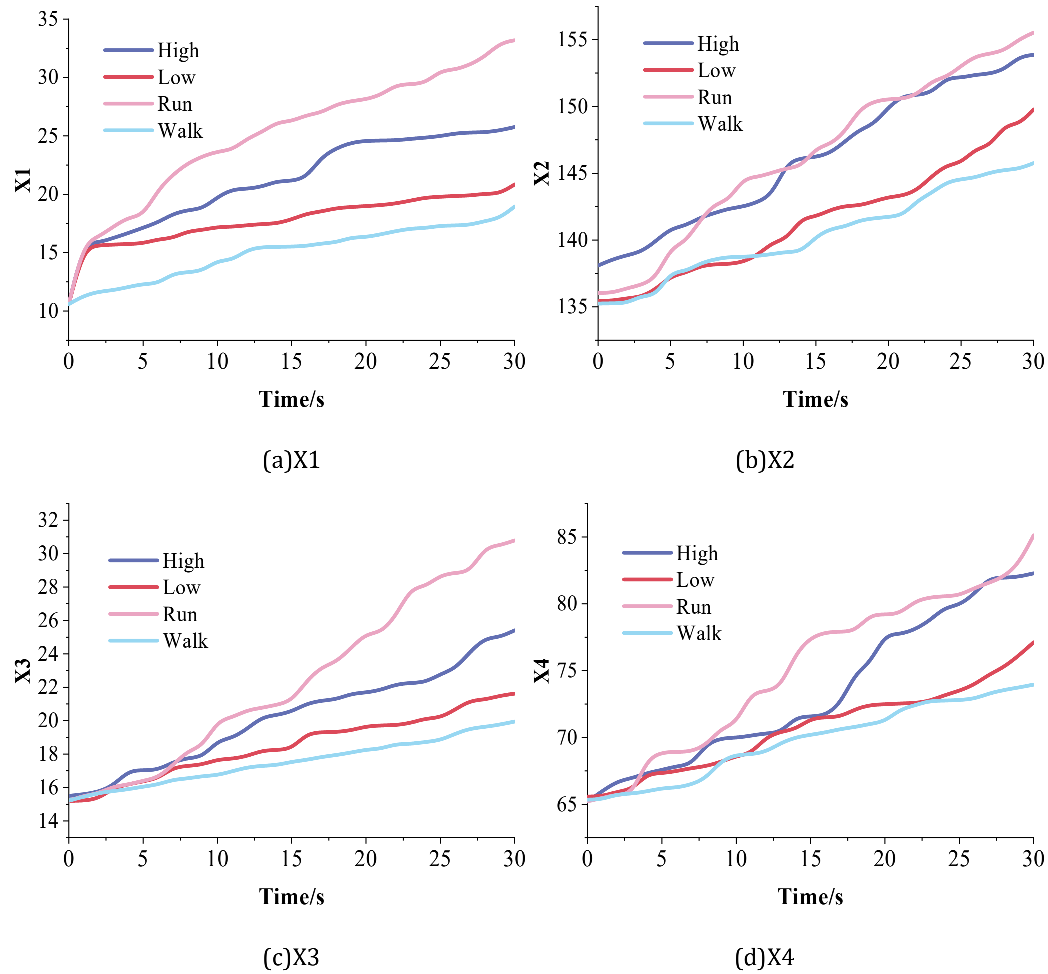


Fig. 7. The movement data characteristics of different indicators

6. Conclusion

The application of smart wearable devices in sports has become one of the main paths to realize smart sports. In this paper, the sensor-based smart wearable device is used to collect the action data with the human body joints as the storage structure, design the image-based coding processing method of sports action data, build the motion recognition model by combining the convolutional neural network and the gated recurrent unit, and explore the effect of its motion recognition through experiments.

The recognition capabilities of the three models, CNN, CNN-LSTM, and CNN-GRU, are compared, and the CNN-GRU model in this paper performs better in terms of accuracy and loss value on the training and test sets, with an accuracy of more than 96% and a loss value of less than 1.5%. Further for different types of sports, the average recognition accuracy of the CNN-GRU model for three-classified and four-classified sports is 97.02% and 92.63% on 10s signal samples, and 96.23% and 91.02% on 5s signal samples, respectively. The longer the signal of the motion sample, the higher the recognition accuracy of the model, and the recognition accuracy of motion three-classification is slightly higher than four-classification. Among them, the recognition effect of cycling motion is the best. The experiments show that the CNN-GRU model has high classification ability and good generalization ability. In addition, the numerical features of the four sports on different human body indexes are obtained through case studies, which proves the effectiveness of the CNN-GRU model.

In this paper, sports recognition based on smart wearable devices is investigated, and the great potential of the devices in the field of sports recognition is verified, and the proposed CNN-GRU algorithm has a strong ability to recognize different joint movements. The application of artificial intelligence technology can provide good service for sports, through the scientific use of smart wearable devices, it can accurately record the athletes' sports performance, monitor the athletes' physical health, timely predict the potential risks that may exist, and then put forward targeted recommendations.

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