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Article

Design of an epidemic prevention and control bracelet system integrated with convolutional neural networks: Promote real-time physiological feedback and adaptive training in remote physical education

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Abstract: This study aims to design an epidemic prevention and control bracelet system that integrates convolutional neural network (CNN). This system can collect and process the user's physiological index data in real time, especially in the remote physical education scene, and provide learners with immediate physiological index feedback and personalized adaptive training suggestions through accurate human action recognition (HAR) technology. One-dimensional acceleration signal is converted into two-dimensional image, and CNN's powerful feature extraction and classification ability is used to effectively solve the problem that manual feature extraction is complex and nonlinear features are difficult to capture. By considering the joint action trajectory in the time window, a dynamic Recurrence Plot (RP) is constructed to capture the dynamic changes among joints. To input recursive graph data into CNN, it needs to be converted into image form. In the task of HAR, CNN can automatically learn useful features from images without manually designing features. It can not only effectively extract features from images, but also be directly used in classification tasks. Experimental results show that compared with other algorithms, the proposed RP + CNN model has the best performance in action recognition, with an accuracy of 96.89% and a $F1$ value of 86.76%. RP captures the dynamic patterns and periodic behaviors in time series by visualizing the repeated appearance of system states over time. The RP + CNN model is used to extract and classify human action features, which significantly improves the accuracy and efficiency of HAR. This innovative method not only simplifies the complex process of traditional manual feature extraction, but also enhances the system's ability to identify nonlinear and complex action patterns, which provides strong technical support for remote physical education.

Keywords: convolutional neural network; epidemic prevention and control; physical education; physiological indicators; adaptive training

1. Introduction

With the frequent occurrence of global public health incidents, especially the outbreak of COVID-19 epidemic, the traditional education model has been challenged as never before [1]. To ensure the health and safety of teachers and students, remote education has risen rapidly and become an important supplement and reform force in the field of education. During the epidemic period, reducing the gathering of people and reducing the risk of cross-infection are the primary tasks. The bracelet system for epidemic prevention and control can not only monitor students' physical health, but also warn potential health risks through data analysis, which provides strong support for epidemic prevention and control. The bracelet system can also record students' action track and contact history, and provide data support for epidemic traceability and prevention and control [2,3]. In remote education, physical education, as an important link to promote students' physical and mental health and enhance their physique, its effectiveness and interaction are particularly important. However, remote physical education faces many challenges, such as low student participation, difficult evaluation of training effect and insufficient personalized guidance. Therefore, it is of great significance to develop a smart bracelet system that can monitor students' physiological indexes in real time and provide adaptive training suggestions for improving the quality and efficiency of remote physical education. The purpose of this study is to design an epidemic prevention and control bracelet system to collect and process the user's physiological index data in real time. Especially in the remote physical education teaching scene, through accurate Human action recognition (HAR) technology, the study provides learners with immediate physiological index feedback and personalized adaptive training suggestions.

In remote physical education, teachers cannot directly observe students' sports state and physiological reaction, which leads to uncertainty in safety risk and effect evaluation during training [4–6]. More sensors, such as gyroscopes, accelerometers and magnetometers, are integrated in the bracelet to capture the subtle actions and posture changes of the wrist [7,8]. HAR technology mainly captures, analyzes and recognizes human action posture in real time through computer vision, sensor technology and machine learning algorithm. This technology can identify various actions of human body, such as running, jumping, raising hands and turning around, and provide corresponding feedback and guidance accordingly. Each student's physique, athletic ability and health status are different, and the traditional "one size fits all" training mode is difficult to meet the individual needs of students. Based on the physiological data collected by the bracelet system and the powerful learning ability of convolutional neural network (CNN), a personalized training model can be constructed to provide students with tailor-made training plans and adaptive guidance, thus improving the training effect and satisfaction. Through the epidemic prevention and control bracelet system with CNN, students' heart rate, blood pressure, blood oxygen saturation and other key physiological indicators can be collected in real time, providing teachers and students with real-time health monitoring and feedback [9–11].

Traditional HAR methods usually rely on artificially designed features, which are often complex and difficult to fully capture the complexity and nonlinear characteristics of human movements. However, under the background of distance physical education, real-time, accurate and personalized HAR is very important to provide effective physiological feedback and adaptive training. Therefore, this study introduces CNN, which is a deep learning technology with excellent performance in image processing and feature extraction. CNN can automatically learn useful features from raw data without manual design, thus greatly simplifying the process of feature extraction.

In order to further improve the accuracy and efficiency of HAR, the concept of recurrence plot (RP) is also introduced in this study. RP is a technology that transforms one-dimensional time series data into two-dimensional images, and captures dynamic patterns and periodic behaviors in time series by visualizing the repeated appearance of system states over time. The combination of RP and CNN can make full use of

CNN's advantages in image processing and feature extraction, and capture the dynamic changes and periodic behaviors in human movements. This method not only simplifies the complex process of traditional artificial feature extraction, but also enhances the system's ability to identify nonlinear complex action patterns. In the HAR task, CNN can automatically learn useful features from images without manually designing features. It can not only extract features from images effectively, but also be directly used in classification tasks. This means that the whole process from data preprocessing to final classification decision can be completed automatically, reducing the need for artificial feature engineering.

2. Related work

With the rapid development of Internet of Things (IoT), artificial intelligence (AI) and wearable technology, bracelet sensor data is increasingly widely used in the field of action recognition. Action recognition sensors can not only capture, identify and analyze human actions, but also show great application potential in many fields such as smart home, health care, sports training and so on. The acceleration sensor is one of the most common sensors in the bracelet. It can sense the acceleration and convert it into an electrical signal to realize the monitoring of human action [12]. Gravity acceleration sensor can estimate the number of steps, action distance and heat consumption, and is widely used in sports detection and health management. Biomechanics theory can understand the mechanical parameters and changing rules of organisms in the process of movement by analyzing their movements. These parameters include joint angle, muscle activity, and movement speed, which can be used to evaluate the motor function and health status of organisms.

Behavior pattern theory emphasizes the correlation between stimulus and response. When an individual receives a certain stimulus, it will produce a corresponding response, which may be conscious or unconscious. By observing and recording the relationship between these stimuli and reactions, people can summarize the behavior patterns. According to the behavior pattern theory, human behavior is largely formed through learning and habits. In the process of growing up, individuals gradually form a stable behavior pattern by constantly trying and correcting their own behaviors. Once these patterns are formed, they are difficult to change and will be repeated in similar situations.

Tan and Ran [13] mentioned that the key of action capture recognition was to combine sensor technology with computer vision technology. Sensor technology covered many types, such as inertial measurement unit, electromagnetic sensor and optical sensor. These sensors could monitor the state of moving objects in real time and transmit the collected data to the processing system. Davidson et al. [14] emphasized that computer vision technology analyzed and reconstructed the captured image or video through image processing and pattern recognition algorithm to achieve accurate measurement of action trajectory and posture. In sports training and biomechanics field, action capture technology can help athletes optimize their actions, prevent injuries, and deeply understand the internal mechanism of human action. For example, Sun et al. [15] used inertial sensors and action capture systems to record dancers' actions, and used computer vision technology to recognize the posture and reconstruct the actions. The detection of sports fatigues usually adopted two methods: physiological signal monitoring and sports feature analysis. According to the research of Nazaret et al. [16], physiological signal monitoring involved the monitoring of indexes such as heart rate, body temperature and blood pressure. Although these methods can accurately reflect the changes of physical condition, they were not practical in daily life because of their complicated equipment and technology. In contrast, it was easier to detect fatigue by analyzing the action characteristics. This method collected data of gait and other dynamic characteristics through wearable devices such as smart bracelets and smart watches, and used data analysis technology to judge the fatigue state.

In the aspect of sensor data processing, Yang et al. [17] used CNN to study human posture recognition and action state recognition, and achieved remarkable results. Deep learning algorithm can effectively deal with complex datasets and improve the accuracy and robustness of recognition by automatically learning data features. Cosoli et al. [18] proposed a model of limb action intention recognition based on deep learning, and introduced the self-attention mechanism in Decoder to enhance the attention to feature information. Saad et al. [19] discussed the application of blockchain technology in epidemic prevention and control bracelet, and pointed out that this technology could realize data tamper-proof and privacy protection, and at the same time improve the security and credibility of the system. Han et al. [20] emphasized the importance of user experience and pointed out that the design and function of bracelet system should be more in line with users' needs and habits. Meanwhile, with the change of epidemic situation and the adjustment of prevention and control policies, the bracelet system needs to be constantly updated and improved to meet the new needs.

At present, many researches still rely on traditional hand-designed features in feature extraction, and these features are often difficult to fully capture complex action patterns and dynamic changes, resulting in limited recognition accuracy. In addition, the generalization ability for different users and different sports types needs to be improved. In this study, deep learning technology is used to realize automatic feature learning and optimization. This method can automatically extract complex and effective features from the original data, and improve the accuracy and generalization ability of recognition. By reducing the dependence on manual design features, this study has made remarkable progress in feature extraction.

3. Method

3.1. Wireless sensor acquisition system of human body data based on sports bracelet

A complete wireless human body data acquisition system based on sports bracelet usually includes three core parts: hardware layer, software layer and data layer. As the material basis of the system, the hardware layer integrates key components such as the sports bracelet body, various sensors, microprocessor, wireless communication module and power management system. These components work together to ensure that the bracelet can collect and transmit data stably and accurately. The architecture of wireless sensor acquisition system for human body data is shown in **Figure 1**.

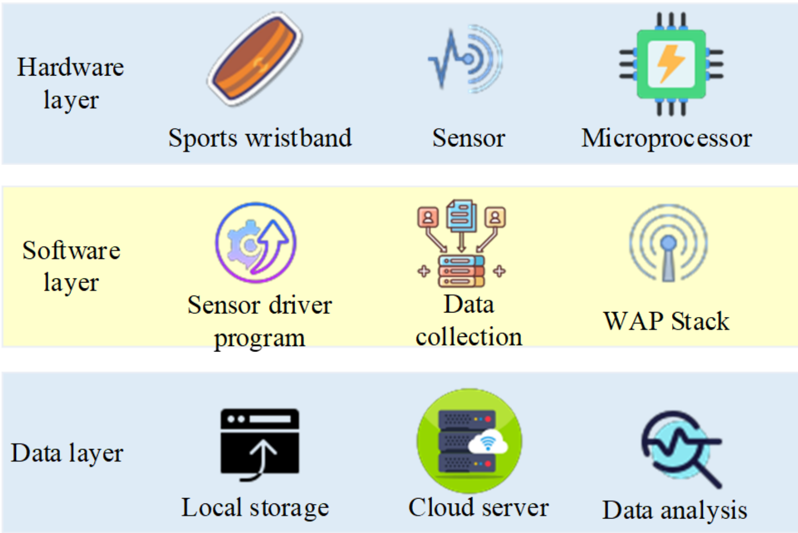

Figure 1. Architecture of wireless human body data acquisition system.

In the hardware layer, the sensor is the core of data acquisition. Common sensors include acceleration sensor, heart rate sensor, optical sensor and gyroscope. They are responsible for monitoring key parameters such as human action state, heart rate, blood oxygen saturation and rotational action. The microprocessor is responsible for controlling the working mode of the sensor, processing the collected data, and transmitting the data to terminal devices such as smart phones and tablet computers through the wireless communication module. The software layer is the control center of the system, which includes key modules such as sensor driver, data acquisition and processing program, wireless communication protocol stack and user interaction interface. The sensor driver is responsible for controlling the operation of the sensor to ensure accurate data acquisition. The data acquisition and processing program preprocesses the original data, extracts feature and compresses them to improve the efficiency and accuracy of data transmission. The wireless communication protocol stack realizes the stable communication between the bracelet and the terminal equipment. The user interface provides a friendly operation experience, which enables users to view data, set parameters and perform other operations conveniently. The data layer is responsible for storing the collected data in the local or cloud server of the bracelet, and deeply analysing and mining the data through big data technology and machine learning algorithm. These analysis results can not only help users understand their own health status and sports performance, but also provide valuable reference information for third-party institutions such as medical institutions and fitness centres [21–23].

To realize wireless data transmission, the system needs to integrate wireless communication modules such as Bluetooth, Wi-Fi, Zigbee and LoRa. These technologies have different advantages: Bluetooth technology is very suitable for wearable devices because of its low power consumption and short-distance communication. Wi-Fi technology is suitable for indoor and outdoor data transmission because of its high data transmission rate and long communication distance. However, Zigbee and LoRa are very popular in IoT applications because of their low power consumption, wide coverage and self-organizing network capabilities.

Based on the existing action sensors such as accelerometers and gyroscopes, the system needs to further integrate biomechanical sensors, such as force sensors for measuring the ground reaction force and surface electromyography sensors for recording the electrical signals generated during muscle activity. These sensors can capture the changes of human mechanics and muscle activity during exercise, thus providing more comprehensive data support for the system. In the acquisition of electrophysiological signals, the key lies in the integration of electrical content. The system needs to design special circuits to receive and amplify the weak electrical signals output by EMG sensors and ECG sensors. To improve the signal quality, preprocessing work such as filtering and denoising is needed. After that, digital signal processing technology is used to extract features and identify patterns of these electrical signals to obtain important information such as muscle activity intensity and heart rhythm.

3.2. The flow of HAR in physical education

The process of HAR is shown in **Figure 2**. According to the acquisition target, choose the appropriate action capture system and sensor. The collected original data often contains noise, outliers and other interference factors, so it needs to be preprocessed to improve the data quality. Pretreatment steps include data cleaning (removing noise, filling missing values, etc.), data calibration (adjusting sensor offset, error, etc.), data segmentation (dividing continuous data into a single action period or event), etc. [24–26]. Regarding video data, the dynamic characteristics and spatial distribution characteristics of human action can be fully captured by human body detection and tracking, key point location and spatio-temporal feature extraction. For sensor data, by analyzing the action parameters such as acceleration and angular velocity, the feature vector that can reflect the action state of human body can be extracted. This feature information will provide strong support for subsequent model training and classification.

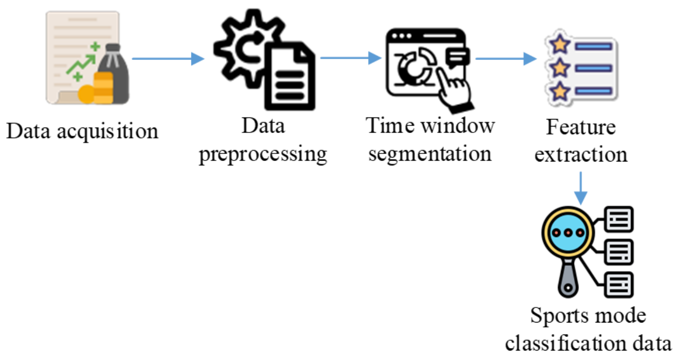

Figure 2. HAR process.

The basic content of action recognition is shown in **Figure 3**. Action detection is the starting point of recognition process, which aims to extract information related to human action from input data. In still images, action detection usually depends on image segmentation technology. These technologies divide the image into different regions or sub-parts based on visual characteristics such as color, texture and shape, in which one or more regions correspond to the human body and its actions. Once the human body and its actions are detected, the next step is to extract features for recognizing and understanding these actions. Action feature extraction involves extracting information that can represent the essence of action from segmented human body regions or action sequences. These features can be based on shape (such as joint angle, limb length ratio, etc.), action (such as speed, acceleration, trajectory, etc.), or appearance (such as color histogram, texture features, etc.). Action feature understanding is the process of mapping the extracted action features to specific action categories or semantic concepts. This usually involves the application of machine learning or deep learning algorithm. By training a large number of labelled data, people learn how to map the input action features to the output action tags.

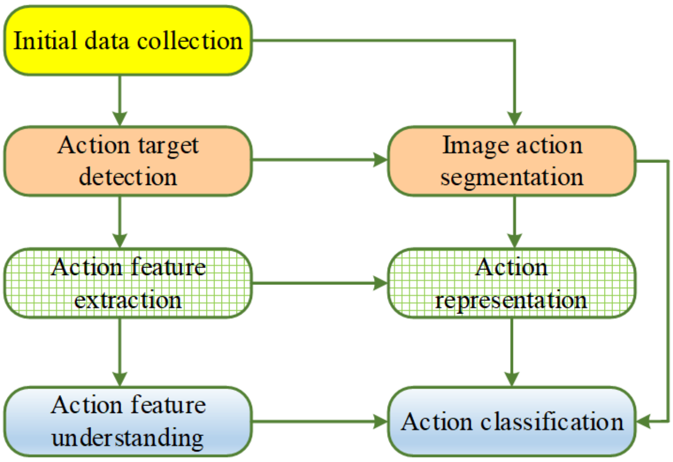

Figure 3. Basic content of action recognition.

Because there may be noise and error information in the original data, it is necessary to preprocess and clean the data. This includes removing blurred video frames and correcting abnormal values in sensor data. Because visual data and sensor data are usually collected by different devices, there may be time inconsistency between them, so data synchronization is needed. This process usually adopts time stamp alignment and interpolation technology to keep the visual data and sensor data consistent on the time axis. To extract human action characteristics, it is necessary to identify the key parts of human body from video data. This can be achieved by using an open-source human posture estimation tool, which can locate the key points of human body and their specific positions in each frame of image. To eliminate the influence of scale and position deviation, it is necessary to standardize the key point data. This includes converting the position of each key point into relative coordinates relative to the center of the human body, and scaling these coordinates to a fixed range. This can ensure the consistency and comparability of data collected by different individuals or different scenarios.

3.3. Sports action recognition based on recursive graph + CNN

Recursive graph is a two-dimensional graph, in which each point represents the relationship between two moments in time series. Specifically, if the distance between the states at time t and t' is less than a certain threshold ε, then draw a point (usually black or white) at time t and t', otherwise, draw nothing. These points in the recursive graph form a series of patterns, which reflect the similarity of the system at different time points. Recursive graph can be regarded as the projection of phase space trajectory, in which the points represent the repeated appearance of system state. An important feature of recursive graph is that it can capture the internal structure of the system, including periodicity, chaotic behavior and other complex dynamic characteristics.

Recursive graph is a matrix drawn on a two-dimensional plane, in which each point indicates whether the states of two moments in the time series are close enough. The calculation equation of recursive graph is:

$$R_{i,j} = \theta\left(\varepsilon - D_{i,j}\right) \tag{1}$$

$\theta(\cdot)$ is the Heaviside function:

$$\theta(x) = \begin{cases} 0, if\ x < 0 \\ 1, if\ x \geq 0 \end{cases} \tag{2}$$

ε is the threshold selected in advance. $D_{i,j}$ represents the distance between two points X_i and X_j in the phase space, and the calculation equation is:

$$D_{i,j} = \left\|X_i - X_j\right\|, i,j = 1,2,\dots,N \tag{3}$$

A static skeleton diagram can be constructed to represent the spatial connection between human joints, and at the same time, a dynamic recursive diagram can be constructed to capture the dynamic changes between joints by considering the joint action trajectory in the time window. In order to input recursive graph data into CNN, it needs to be converted into image form. Specifically, the nodes and edges in the recursive graph are represented by different colors or brightness, in which nodes can represent joints, and the color and thickness of edges can reflect the connection strength and dynamic changes between joints.

CNN models usually include multiple convolution layers, pooling layers, activation layers and fully connected layers [27,28]. The convolution layer is responsible for automatically learning the local features in the image; Pool layer is used to reduce the feature dimension and enhance the robustness of features. The activation layer introduces nonlinear factors to improve the expression ability of the model. After multi-layer convolution and pooling operations, the feature map is gradually abstracted into a higher-level feature representation. Finally, the fully connected layer maps the learned features to the action tag space, and outputs the recognition results of the current human actions.

Convolution operation is a core step to extract features from the input feature map. Given that the size of an input feature map is m × n, and the size of a convolution kernel (filter) is q × q, and the moving step is 1, convolution operation will generate a new feature map, which is usually (m − q + 1) × (n − q + 1). The convolution calculation process can be expressed as:

$$S(i,j) = (I \times K)(i,j) = \sum_{m=0}^{q-1}\sum_{n=0}^{q-1} I(i+m, j+n) \cdot K(m,n) \tag{4}$$

$S(i,j)$ is the element value of position (i,j) in the output feature map. $I(i+m,j+n)$ is the element value of position $(i+m,j+n)$ in the input feature map. $K(m,n)$ is the weight value of position (m,n) in the convolution kernel. This equation describes the core calculation process of convolution operation.

Pooling layer is used to down sample the input data, reduce the amount of data, while retaining important feature information. The general pooling process is shown in **Figure 4**. The 2 × 2 window in the upper left corner contains the numbers 1, 0, 2 and 6. The maximum value is 6, so the first element of the output feature map is 8. Move the window to the right by 2 units, select the maximum value in the window again, and so on, and finally complete the pooling operation to get the feature map.

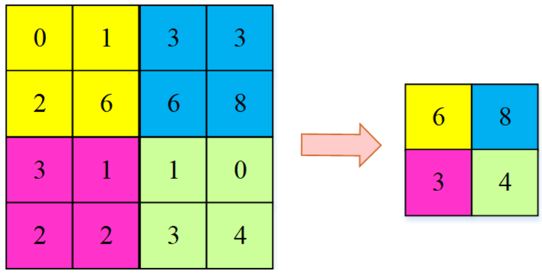

Figure 4. Pool process.

The calculation of the pool layer can be expressed as:

$$M^j = f\left(down\left(M^{j-1}\right)\right) \tag{5}$$

M^{j-1} and M^j represent the characteristic map and new characteristic map output by the upper layer network respectively. $down(\cdot)$represents pooling operation.

Recursive graph, as a powerful time series analysis tool, can transform one-dimensional acceleration signals into intuitive two-dimensional images, revealing the periodicity, repeatability and nonlinear dynamic characteristics hidden behind the data. This transformation process provides abundant feature input for CNN, which enables the model to automatically learn and identify the change patterns of physiological indexes corresponding to various sports actions. Once the model recognizes a specific action or action sequence, such as running, jumping, weightlifting, etc., it can immediately trigger the corresponding physiological index monitoring module to comprehensively evaluate the athlete's real-time physiological state.

The real-time feedback mechanism of physiological indexes depends on the efficient data processing and transmission ability of the system. Through wireless communication technology, the bracelet transmits the collected physiological data to the cloud or mobile application in real time, and the user or coach can view the athlete's physiological index chart anytime and anywhere, including real-time values, changing trends and historical comparisons. This kind of real-time feedback can not only make athletes know their physical condition clearly, but also help coaches adjust the training intensity and content according to the athletes' real-time physiological state to ensure the safety and effectiveness of training.

After the action and physiological signals are captured, they are combined to form comprehensive feedback information. This feedback information not only contains the characteristics of the individual's sports behavior, but also reflects his physiological reaction during the exercise. By training the individual's perception ability, he can understand and use this feedback information to adjust his own sports behavior and realize adaptive training.

When generating adaptive training suggestions, it is necessary to fully consider the individual's personalized characteristics. Based on the individual's movement recognition results and physiological signals, a personalized movement model is established, and a unique training plan is made for everyone, considering factors such as their age, gender and physical condition. This plan not only pays attention to the improvement of individual sports skills, but also pays attention to the maintenance of their physical health. In the process of training, real-time monitoring and evaluation technology is used to adjust the training intensity and difficulty in real time according to the individual's sports performance and physiological reaction. When an individual shows fatigue or discomfort, the training intensity is automatically reduced to avoid the injury caused by overtraining. When individuals show obvious progress, the training difficulty is gradually increased to stimulate their potential and promote continuous progress.

3.4. Experimental design

In this study, the acceleration sensor of Apple Bracelet is used, combined with phyphox application, to realize the acceleration data acquisition of various daily human actions. Through the well-designed experimental scheme, it is ensured that the subtle acceleration changes of different individuals under different actions can be captured, which provides high-quality data support for the subsequent action recognition algorithm.

Eight volunteers (4 males and 4 females), aged between 21 and 35, were selected to ensure that the samples are representative and diverse. Complete five actions in turn: walking, running, jumping, going up stairs and going down stairs. Each action lasts for a certain time to ensure the sufficiency of data collection. The dataset collected in this study is named Action collection database (ACD). While the volunteers are performing actions, the phyphox application records the acceleration data in real time and transmits it to the personal computer via Bluetooth for storage.

From an ethical point of view, this study ensures that all data collection and processing follow the principles of voluntariness, knowledge and consent. Users should be fully informed of the purpose, storage mode and possible risks of their data, and have the right to withdraw their consent at any time. In addition, it also ensures that the collection and use of data comply with the requirements of relevant laws and regulations, especially the legal provisions related to data protection and privacy.

In terms of data protection measures, it is necessary to take a series of technical means and management measures to ensure the security of data. This includes, but is not limited to, the use of advanced encryption technology to protect the security of data transmission and storage, the implementation of strict access control and authentication mechanisms, and regular audits of data security and privacy protection. A transparent data usage policy should also be established to clearly inform users of data collection, use, storage and sharing, and how users can exercise their data rights, such as accessing, correcting, deleting and opposing data processing.

TensorFlow2.4.1 and Python3.6 are adopted as the framework of deep learning. Operating system: Windows 10 64-bit; Memory 8 GB RAM; Multi-core processor Intel Core i7; CUDA 11.1; Graphics card NVIDIA GeForcce GTX 1650.

4. Results and discussion

4.1. Classification results of HAR by RP + CNN

In the ACD collected in this study, the confusion matrix of classification results is shown in **Figure 5**. It shows that walking, running and jumping have achieved 100% classification accuracy. The steady rhythm of walking, the continuous acceleration and deceleration of running, and the sudden acceleration and flight of jumping are effectively captured in the model and used for classification, thus achieving a very high recognition rate.

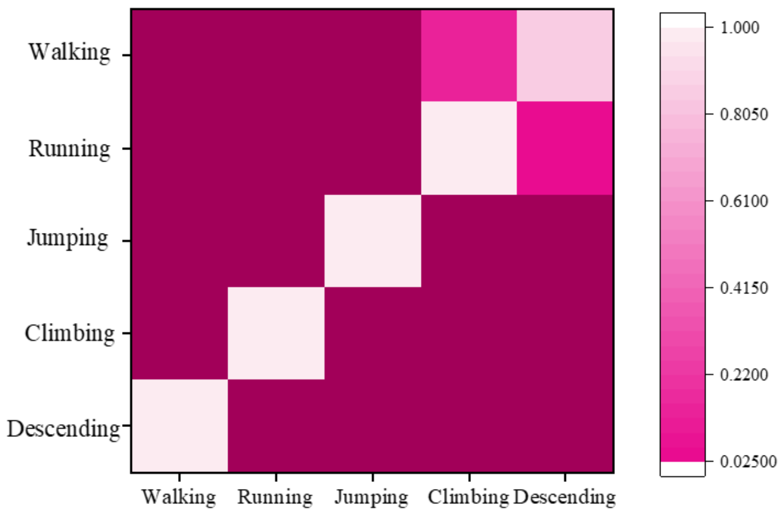

Figure 5. Confusion matrix of classification results under ACD.

4.2. Performance comparison results of different models

In order to verify the validity of the proposed model, further comparative experiments are conducted, and three models, namely, Long Short-Term Memory (LSTM), Graph Convolutional Network (GCN), Support Vector Machine (SVM) and ResNet, are selected for comparison. The evaluation indexes included the accuracy of action recognition and $F1$ value. It shows that with the increase of iteration times, the accuracy and $F1$ value of different models in ACD dataset are on the rise. Compared with other algorithms, the proposed RP + CNN model has the best performance in action recognition, with an accuracy of 96.89% (**Figure 6**) and a $F1$ value of 86.76% (**Figure 7**). RP captures the dynamic patterns and periodic behaviors in time series by visualizing the repeated appearance of system states over time. It is especially good at capturing the time dependence and nonlinear relationship in action sequences, which is very important for understanding the changes in continuous actions. CNN is famous for its powerful spatial feature extraction ability, which can automatically extract local features useful for action recognition from images or video frames. Combining RP with CNN, the model can not only understand the dynamic changes in time, but also capture the spatial information in each frame, thus improving the accuracy of action recognition. Although LSTM is also good at processing time series data, it may face the problem of gradient disappearance or gradient explosion when processing long series, and its computational complexity is high. SVM and GCN perform well in dealing with specific types of data (such as sequence data or graph structure data), but in the face of complex and changeable action recognition scenarios, more data or finer tuning parameters are needed to achieve the best results.

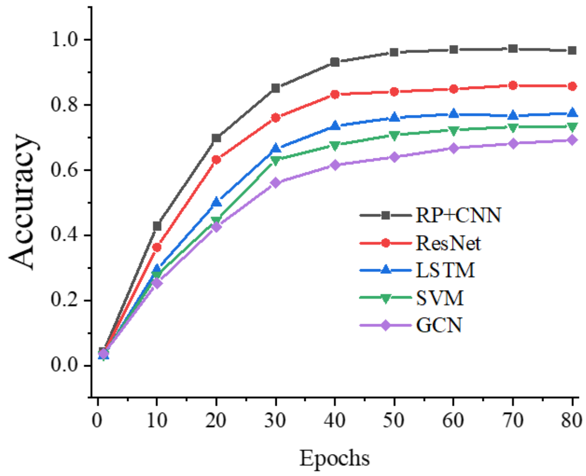

Figure 6. Comparison of the accuracy of action recognition of different models.

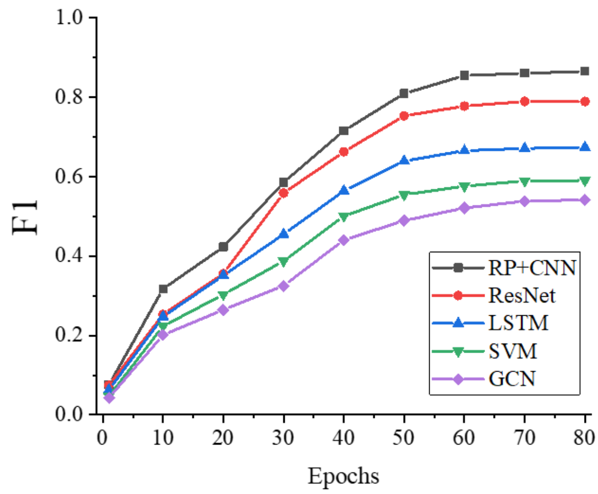

Figure 7. Comparison of $F1$ value of action recognition of different models.

5. Conclusion

In this study, the one-dimensional acceleration signal is successfully converted into a two-dimensional image, and the problem that it is difficult to capture nonlinear features in traditional methods is overcome by using recursive graph technology. Recursive graph can capture the time series characteristics of signals and visualize them as two-dimensional images, which provides convenience for subsequent feature extraction and classification. This conversion method not only improves the efficiency of data processing, but also enhances the algorithm's ability to identify complex action patterns. Secondly, the method of HAR based on CNN has been verified in this study. As a powerful tool in the field of deep learning, CNN can automatically learn features and can effectively extract useful features from images. The bracelet system of epidemic prevention and control designed in this study combines RP technology and CNN's powerful feature extraction ability to realize accurate recognition of human movements and provide strong technical support for distance physical education teaching. The bracelet system collects the user's physiological index data and motion trajectory in real time through the built-in sensor. After preprocessing the collected data, the one-dimensional acceleration signal is converted into a two-dimensional image by RP technology. CNN model carries out feature extraction and classification on the transformed images to realize accurate recognition of human movements. According to the recognition results, the system provides users with immediate physiological index feedback and personalized adaptive training suggestions. But at the same time, it needs to be considered that the research and development and production costs of the bracelet system are high, and it also needs to be maintained and upgraded regularly. This may limit the willingness and purchasing power of some users.

Although some achievements have been made in this study, there are still some limitations in practical application. The dataset used may not be comprehensive enough, mainly from the simulation data in the laboratory environment, lacking the large-scale dataset in the real scene. This may lead to the decline of the generalization ability of the model in practical application, especially in the face of human actions in complex and changeable real environment, the performance of the model may not be as good as expected. It is necessary to further expand the scale and diversity of datasets by collecting more data from real scenes to enhance the generalization ability of the model. In addition, in the expansion of practical application, future research can integrate the epidemic prevention and control system with other wearable devices such as smart watches and VR headsets. Through smart watches, more physiological data can be obtained, such as blood pressure and oxygen saturation to evaluate the health status of users more comprehensively. The integration of VR headphones can provide users with immersive training scenes and interactive experiences, and improve users' participation and training effect.

Author contributions: Conceptualization, YW and ZC; methodology, YW; software, ZY; validation, YW, ZC and SW; formal analysis, YW; investigation, ZC; resources, SW; data curation, ZY; writing—original draft preparation, YW; writing—review and editing, ZC; visualization, SW; supervision, SW; project administration, ZY; funding acquisition, ZY. All authors have read and agreed to the published version of the manuscript.

Ethical approval: Not applicable.

Informed consent: Informed consent was obtained from all subjects involved in the study.

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References

1. Bin S. Construction and simulation analysis of epidemic propagation model based on covid-19 characteristics. International Journal of Environmental Research and Public Health, 2022, 20(1): 132.
2. Luo X, Zhao H, Chen Y. Research on User Experience of Sports Smart Bracelet Based on Fuzzy Comprehensive Appraisal and SSA-BP Neural Network. Computational Intelligence and Neuroscience, 2022, 2022(1): 5597662.
3. Yang C, Chang Y T. Data Collection And Performance Evaluation Of Running Training Sport Using Different Neural Network Techniques. Journal of Mechanics in Medicine and Biology, 2023, 23(04): 2340053.
4. Liang J, He Q. Application of artificial intelligence wearable devices based on neural network algorithm in mass sports activity evaluation. Soft Computing, 2023, 27(14): 10177-10188.
5. Ma B, Nie S, Ji M, et al. Research and Analysis of Sports Training Real-Time Monitoring System Based on Mobile Artificial Intelligence Terminal. Wireless Communications and Mobile Computing, 2020, 2020(1): 8879616.
6. Chidambaram S, Maheswaran Y, Patel K, et al. Using artificial intelligence-enhanced sensing and wearable technology in sports medicine and performance optimisation. Sensors, 2022, 22(18): 6920.
7. Dai X, Li S. [Retracted] Application Analysis of Wearable Technology and Equipment Based on Artificial Intelligence in Volleyball. Mathematical Problems in Engineering, 2021, 2021(1): 5572389.
8. Yang Z. Using wearable technology to optimize sports performance and prevent injuries. Molecular & Cellular Biomechanics, 2024, 21(1): 305-305.
9. Sevil M, Rashid M, Maloney Z, et al. Determining physical activity characteristics from wristband data for use in automated insulin delivery systems. IEEE sensors journal, 2020, 20(21): 12859-12870.
10. Wu Q, Tang P, Yang M. Data processing platform design and algorithm research of wearable sports physiological parameters detection based on medical internet of things. Measurement, 2020, 165: 108172.
11. Sel K, Mohammadi A, Pettigrew R I, et al. Physics-informed neural networks for modeling physiological time series for cuffless blood pressure estimation. npj Digital Medicine, 2023, 6(1): 110.
12. Yong Z. Intelligent system simulation and data accuracy of physical fitness training for sports majors based on real-time status update of wearable Internet of Things. Soft Computing, 2023, 27(14): 10145-10154.
13. Tan L, Ran N. Applying artificial intelligence technology to analyze the athletes' training under sports training monitoring system. International Journal of Humanoid Robotics, 2023, 20(06): 2250017.
14. Davidson P, Trinh H, Vekki S, et al. Surrogate modelling for oxygen uptake prediction using LSTM neural network. Sensors, 2023, 23(4): 2249.
15. Sun W, Guo Z, Yang Z, et al. A review of recent advances in vital signals monitoring of sports and health via flexible wearable sensors. Sensors, 2022, 22(20): 7784.
16. Nazaret A, Tonekaboni S, Darnell G, et al. Modeling personalized heart rate response to exercise and environmental factors with wearables data. NPJ Digital Medicine, 2023, 6(1): 207.
17. Yang L, Amin O, Shihada B. Intelligent wearable systems: Opportunities and challenges in health and sports. ACM Computing Surveys, 2024, 56(7): 1-42.
18. Cosoli G, Antognoli L, Scalise L. Wearable Electrocardiography for Physical Activity Monitoring: Definition of Validation Protocol and Automatic Classification. Biosensors, 2023, 13(2): 154.
19. Saad M, Ahmad M B, Asif M, et al. Blockchain and IIoT Enabled Solution for Social Distancing and Isolation Management to Prevent Pandemics. Computers, Materials & Continua, 2023, 76(1).
20. Han W, Cai H, Lu J, et al. Application of body area network wearable smart bracelet in epidemic isolation scenario. Journal of Translational Internal Medicine, 2024, 12(3): 321-324.
21. Xu Z, Yu B, Wang F. Artificial intelligence/machine learning solutions for mobile and wearable devices. Digital Health: Mobile and Wearable Devices for Participatory Health Applications, 2020, 55.
22. Cui C. Intelligent analysis of exercise health big data based on deep convolutional neural network. Computational Intelligence and Neuroscience, 2022, 2022(1): 5020150.
23. Edriss S, Romagnoli C, Caprioli L, et al. The Role of Emergent Technologies in the Dynamic and Kinematic Assessment of Human Movement in Sport and Clinical Applications. Applied Sciences, 2024, 14(3): 1012.

24. Balkhi P, Moallem M. A multipurpose wearable sensor-based system for weight training. Automation, 2022, 3(1): 132-152.
25. Askari M R, Abdel-Latif M, Rashid M, et al. Detection and classification of unannounced physical activities and acute psychological stress events for interventions in diabetes treatment. Algorithms, 2022, 15(10): 352.
26. Bangaru S S, Wang C, Aghazadeh F. Automated and continuous fatigue monitoring in construction workers using forearm EMG and IMU wearable sensors and recurrent neural network. Sensors, 2022, 22(24): 9729.
27. de Pedro-Carracedo J, Clemente J, Fuentes-Jimenez D, et al. Photoplethysmographic Signal-Diffusive Dynamics as a Mental-Stress Physiological Indicator Using Convolutional Neural Networks. Applied Sciences, 2023, 13(15): 8902.
28. Xu S. Retracted article: BP neural network–based detection of soil and water structure in mountainous areas and the mechanism of wearing fatigue in running sports. Arabian Journal of Geosciences, 2021, 14(11): 920.