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Nengyun Zhang,
Ningbo University, China

*CORRESPONDENCE
Qiang Zhang,
zhangqiang9992023@163.com

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Athlete injury detection and emergency treatment in mobile smart medical system

Yiqiao Zhang[1], Qiang Zhang[2]* and Yuhe Liu[3]

[1]Physical Education College, Hubei University of Arts and Science, Xiangyang, Hubei, China, [2]Department of Common Basic Course, Xinjiang Institute of Technology, Aksu, Xinjiang, China, [3]Department of Student Affairs, Hubei University of Arts and Science, Xiangyang, Hubei, China

Using the sports injury monitoring system to detect injury symptoms in time and take effective treatment measures in time can reduce the damage caused by sports injuries to athletes. However, many current detection methods lack the support of advanced technologies and algorithms, resulting in poor performance in sports injury detection. Based on this, a mobile intelligent medical system is designed in this paper, and an athlete injury detection method based on CNN and sensors is proposed. The method includes three parts: motion region acquisition, motion injury feature extraction, and motion injury detection. In addition, for emergency treatment, this paper proposes a variety of CNN-based image data analysis methods to ensure the accuracy of the processing process. The experimental results show that the athlete injury detection method based on the convolutional neural network improves the detection accuracy by 6.73% compared with the traditional method, which also provides an important reference for the future application of ML in medical treatment. The research confirms that the construction and analysis of mobile intelligent medical system can effectively improve the accuracy of sports injury detection.

KEYWORDS

sports injury monitoring, emergency treatment, sensor information, neural network, mobile smart medical system

1 Introduction

With the continuous development of information technology, intelligent medical treatment is also gradually popular, and athlete injury as an important part of the mobile intelligent medical system, its safety issues have been a topic of concern and discussion. The mature application of ML in the medical field promotes the application of CNN increasingly. At present, many athletes' detection methods are too backward, and they have not timely combined with the new era of technical means to make innovations, which leads to low accuracy of injury detection. In this context, it is an attempt and innovation to apply CNN to athlete injury detection and emergency treatment, which would also promote the development of ML in the medical field.

Athlete injury is a common research topic in sports medicine, and many scholars have joined the research ranks. Hamrin Senorski Eric summarized and discussed

Abbreviations: CNN, convolutional neural network; ML, machine learning; 3D, 3 Dimensions.

relevant methods currently involved in the treatment of athletes with anterior cruciate ligament injury. Research showed that ligament reconstruction was an effective method to treat such injuries [1]. Saini Sundeep S used the medical system to study the movement disorder of the scapula in the injury of athletes and finally concluded that the movement disorder of the scapula was closely related to the shoulder pain of athletes [2]. Zanin Alaina C discussed the tension and discourse generated in the treatment and rehabilitation of athletes' injuries, and finally found that these discourses or emotions created a structural divergence, which constrained the treatment of athletes [3]. Shanley Ellen used the method of logistic regression analysis to evaluate the possibility of athletes not having additional injuries throughout the season. The test showed that the evaluation effect of this method was good [4]. Vellios Evan E applied advanced information technology to the athlete injury prevention program. Practice showed that team doctors could use this technology to provide better and more personalized care for athletes [5]. Fredericson Michael summarized the characteristics of sports injuries among soccer players and volleyball players, and finally concluded that soccer players were more likely to have bone injuries than volleyball players [6]. Morrell Nathan T applied new bone reconstruction technology to restore scapular function. The practice showed that this technology showed a good application prospect in the repair of athletes' bone injuries [7]. These researches on athletes' injuries are relatively specific, but they have not been applied to CNN.

In recent years, CNN has been used increasingly in the field of sports. Liu Yuzhong established the athlete feature recognition model based on the idea of CNN. The research results showed that the recognition effect of this model was good [8]. Hatamzadeh Mehran applied CNN to the expert diagnosis system of anterior cruciate ligament injury. The results showed that the designed expert system had a high accuracy in diagnosing the health status of the anterior cruciate ligament [9]. Wang Xin used the CNN model to classify the photos of marathon athletes with high accuracy. The experimental results showed that the model was feasible and effective [10]. Song Hesheng proposed an optimized CNN model based on depth learning for extracting key sports medical data. The experiment showed that the model had a good effect in multidimensional sports medical data analysis [11]. Martin Pierre-Etienne put forward a new double space-time CNN to be used in the action recognition of table tennis players. Practice showed that this method had a high recognition accuracy [12]. Rahmad Nur Azmina applied CNN to the badminton player's motion tracking system. The research showed that the network model could improve the tracking accuracy of the system [13]. Li Tuojian proposed a new algorithm for athlete action recognition based on convolutional neural network. Research showed that the new algorithm could improve the recognition accuracy [14]. Asghar Zeeshan addresses the biomechanics of swimming through different wave surfaces. This channel (including miniature swimmers) is considered a passive two-dimensional channel filled with viscoelastic liquid. The power transfer velocity of different kinds of wavy swims is compared with the velocity of Oldroyd-4 constant fluid [15]. Asghar Z studied the dynamics of microbes swimming in a channel with undulating walls that is affected by a constant, laterally applied magnetic field. Calculations have shown that optimal swimming conditions (i.e., faster speed and lower energy loss) for microorganisms can be achieved in magnetohydrodynamic environments, including magnetic field assisted cervical therapy [16]. Javid Khurram discusses the mathematical modeling of magnetic fluid flow through complex wave walls and provides a comparison between simple and complex peristaltic waves. It is very useful to design a non-uniform micro-peristaltic pump in which the flow rate can be controlled by electromagnetic force [17]. The above research on CNN in the field of sports is more detailed, but it does not involve athlete injury detection.

With the application of ML in the medical field becoming increasingly mature, the application prospect of CNN is also growing, we use 3D imaging technology to obtain the 3D image of the sports injury, and analyze the characteristics of the 3D image. This paper first summarized the application of ML in the medical field and then proposed an athlete injury detection method based on CNN and sensors from three aspects: the acquisition of motion regions, the extraction of sports injury features, and the detection of sports injury. Finally, it analyzed a number of image data in the emergency treatment of athlete injury.

2 ML and its application in medical treatment

Convolutional Neural Network (CNN), a deep feedforward neural network with local connectivity and distributed weights, is a representative algorithm for deep learning, specializing in image processing, especially in image recognition and other related machine learning problems such as image classification, target detection, image segmentation and various other visual tasks of interest. Tasks. It is one of the most widely used models today, and deep learning is an important research area in ML. The mobile intelligent medical system is a computer network-based system that applies sensor technology and communication technology to the medical field, and is characterized by high real-time and scalability. It can not only analyze and process patient records but also identify disease types and diagnostic solutions through images. The traditional two-dimensional display can only present two-dimensional plane information, and doctors need to adjust the angle of view to obtain more angle and scale information. CNN is a branch of artificial neural network in deep learning, and deep learning is an important research field in ML [18].

2.1 Deep learning

Deep learning can transform simple nonlinear models into high-level abstract expressions, and then combine multiple steps to extract very complex function features, which can be realized in the ML process. The most common deep learning algorithms in the medical field are CNN and recurrent neural networks, which are mainly used for medical diagnosis. During the operation, CNN

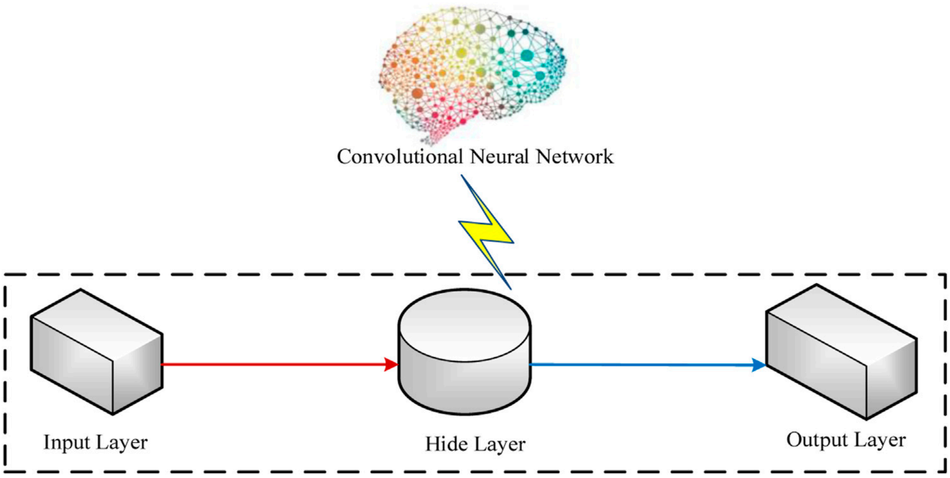

FIGURE 1
Simple Convolutional Neural Network structure.

directly presents the three-dimensional information to the doctor in the form of three-dimensional display, so that the doctor can obtain more comprehensive and accurate information about the shape of the patient's sports injury [19].

2.2 Convolutional neural network

CNN, classified as feedforward neural network, is the most effective network structure in computer vision and has good performance in image recognition, graphics processing, etc. As shown in Figure 1, the simplest CNN structure includes an input layer, a hidden layer, and an output layer; the hidden layer is the core of this kind of network, which is used to extract the convolution kernel of target features, and its number would increase with the complexity of the target. The output layer outputs data, and the input layer inputs data. When CNN is used to detect large data sets and multiple target objects, the higher the parameters of the hidden grid layer, the better the network performance.

The maturity of ML technology makes disease prediction increasingly accurate. For example, many medical experts take the brain imaging data of patients with low cognitive ability and easy to suffer from Alzheimer's disease as samples and apply CNN training model to predict the incidence trend of Alzheimer's disease in the elderly. Its accuracy has been greatly improved than before [20].

3 Athlete injury detection method combining convolutional neural network and sensor

3.1 Acquisition of motion area

As shown in Figure 2, the camera is moving compared to the target athlete, so it is necessary to carry out intra-frame registration processing for image sequences in various sensors through entropy mutual information registration method and then calculate the inter-frame difference. Interframe difference method is a method to obtain the contour of a moving object by the difference operation of two consecutive frames of a video image sequence.

3.1.1 Interframe difference accumulation segmentation

It is assumed that the i th frame image acquired by the sensor is described by O_i and the inter frame difference is described by dO_i. The formula is as follows:

The image collected by the sensor is used to accumulate the inter-frame difference. The specific method is shown in Formula 1. O_i represents the i th frame image, and dO_i represents the inter frame difference.

$$dO_i(y+z) = |O_{i+t}(y+z) - O_i(y+z)| \tag{1}$$

In athletes' movement, the inter-frame difference image has a hole effect, so the hole effect can be eliminated only after the accumulation of frame difference is completed [21].

If lO is used to represent the sub-accumulated value of inter frame difference of N frames, the formula is as follows:

$$lO = \sum_{i=1}^{N} dO_i \tag{2}$$

The motion area of athletes can be obtained only by threshold segmentation for inter-frame differential accumulation. The calculation method is as follows:

$$J = W + a\delta \tag{3}$$

Among them, W is the mean value of differential cumulative image; δ is the image variance; a is a constant.

3.1.2 Determination of athletes' movement area after sensor fusion

Although the athletes' movement area can be obtained through the above methods, there is still a hole phenomenon due to

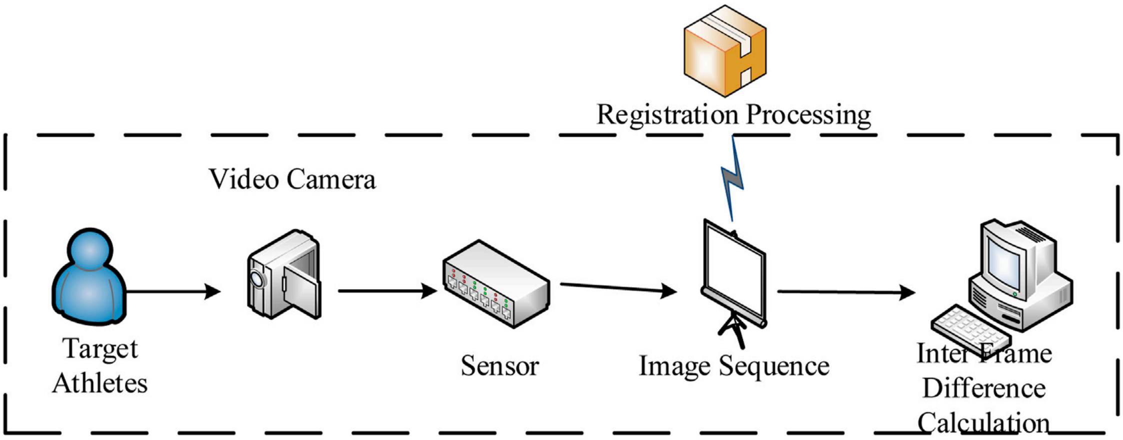

FIGURE 2
Acquisition process of moving area.

insufficient texture. In order to solve this problem, the athletes' motion regions extracted from the two sensors can be fused to improve the accuracy. The athlete movement area detected by the infrared sensor is represented by D_O, and the athlete movement area detected by the visible light sensor is represented by D_l.

The reliability measurement of each pixel belonging to the athlete's sports area in D_O can be expressed as follows:

$$Q[O(y,z) \in D_O] = 1 - e^{-[O(y,z) - \lambda O(y,z)]^2} \tag{4}$$

The reliability measurement of each pixel belonging to the athlete's movement area in D_l can be expressed as follows:

$$Q[l(y,z) \in D_l] = 1 - e^{-[l(y,z) - \lambda l(y,z)]^2} \tag{5}$$

After the reliability measurement is calculated, the adaptive fusion of feature images can be realized through addition rules [22]. The calculation method is as follows:

$$Q[l(y,z)] + Q[O(y,z)] > T \tag{6}$$

Among them, T is the segmentation threshold.

3.2 Feature extraction of sports injury

After the detection of the athletes' sports area, the next thing to do is to extract the characteristics of sports injury. Mobile intelligent medical system is used for feature extraction. In general, when athletes have sports injuries, the sensor signal would have obvious fluctuations. At this time, the signal can be processed by wavelet analysis to obtain the characteristics of sports injuries.

It is assumed that the binary discrete wavelet function is as follows:

$$\phi_{j,k}(t) = 2^{-j/2}\phi(2^j t - k) \tag{7}$$

The discrete wavelet transform of corresponding function $f(t)$ can be expressed as follows:

$$W_f(j,k) = [\phi_{j,k}(t), f(t)] = \int_K f(t)\hat{\phi}_{j,k}(t)dt \tag{8}$$

It is assumed that the discrete wavelet function $\phi_{j,k}(t)$ constitutes the orthogonal normal basis of $L^2(K)$, and the formula is as follows:

$$f(t) = \sum_{j,k} W_f(j,k)\phi_{j,k}(t) \tag{9}$$

In this case, the discrete wavelet is converted into a mapping that guarantees the norm unchanged, and the formula is as follows:

$$[f(t), f(t)] = \int_{-\infty}^{-\infty} |f(t)|^2 dt = \sum_{j,k} |W_f(j,k)|^2 \tag{10}$$

At this time, the quadratic sum of the coefficients after wavelet transformation is consistent with the total energy of the time-domain waveform, and the feature extraction of the sport injury signal can be obtained according to the energy. The specific operation form is as follows:

$$H[\phi_{j,k}(t)] = \frac{1}{2^{-K}N - 1} \sum_{j=1} |W_f(j,k)|^2 \tag{11}$$

Among them, K is the number of energy layers of the time domain waveform.

3.3 Sports injury detection

The new detection method combines sensor information and CNN. First, the motion damage image signal is obtained from the sensor and converted into a wavelet feature vector through wavelet analysis. It is used as the input of CNN to complete the training and fusion calculation. Finally, the motion damage detection results and damage types are obtained according to the maximum probability density function. After the test results, timely intervention and treatment to ensure the health of athletes.

For such problems, such as: error in the test results, a measurement set of m dimensional vector $O = (O_1, O_2, \cdots, O_m)^T$ is set, and the state of $\theta \in \theta_q$ is judged according to Bayesian decision criteria. The specific form is as follows:

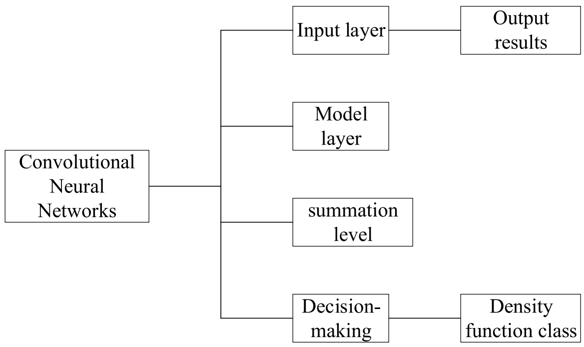

FIGURE 3
Convolutional neural network topology.

$$d(O) \in \theta_q\left[h_q c_q f_q(P) > h_k c_k f_k(O)\right] \quad (12)$$

Among them, $d(O)$ is the decision of test vector O; h_q and h_k are the prior probabilities of θ_q categories and θ_k categories respectively; c_q is the loss that should be θ_q but is wrongly classified into other categories; c_k is the loss that should be θ_k but is wrongly classified into other categories; $f_q(P)$ and $f_k(O)$ are the probability density functions of θ_q and θ_k categories respectively.

The probability density function of the kernel density estimator is estimated, and the formula is as follows:

$$f_q(O) = \frac{1}{n_q (2\pi)^{m/2} \delta^m} \sum_{i=1}^{n_q} \exp\left[-\frac{\left(O - O_{qi}\right)^T \left(O - O_{qi}\right)}{2\delta^2}\right] \quad (13)$$

Among them, n_q represents the number of q categories in the training vector; O_{qi} represents the q th training vector in i categories.

The topology of CNN based on the detection method includes input layer, model layer, summation layer, and decision layer. The training vector is not only the neuron of the input layer, but also the input value of the whole neuron. In the model layer, the point product of the pattern vector and the weighted vector can be obtained through each neuron. The sum layer represents the output of all models associated with each neuron of this class. The output of the decision level is the maximum likelihood density function class of the corresponding level output. The process of implementing this detection method can be summarized as follows: The CNN is used to change the wavelet of the motion injury image signal collected from the sensor and extract the energy characteristics of the signal. It is calculated as the input vector of the CNN, and the final output result is the result of sports injury. This is shown in Figure 3.

4 Image data evaluation based on convolutional neural network in emergency treatment of athletes' injuries

Machine learning is a common research hotspot in artificial intelligence, which mainly focuses on learning algorithms and

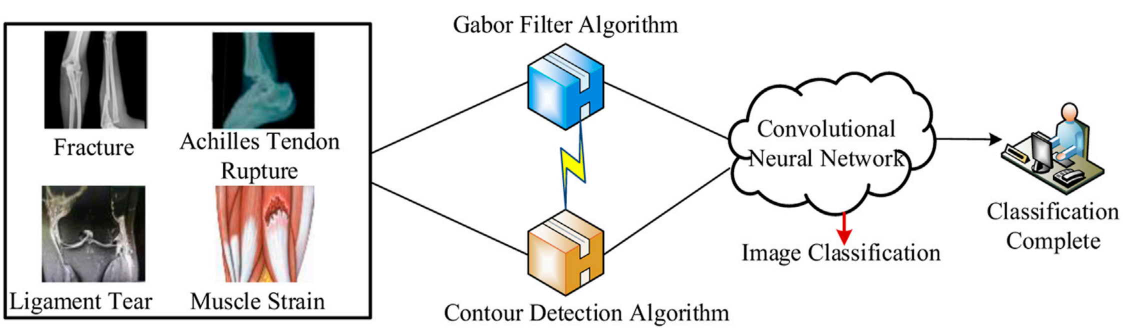

FIGURE 4
Image classification process in limb injury diagnosis and treatment.

TABLE 1 Detection accuracy and false alarm rate under four damage categories under new and conventional methods.

Damage type	New method		Conventional method	
	Accuracy	False alarm rate	Accuracy	False alarm rate
Fracture	89.71%	1.13%	81.25%	7.43%
Ligament tear	95.38%	0.96%	86.21%	3.78%
Muscle strain	91.75%	1.87%	83.43%	4.96%
Achilles tendon rupture	88.47%	1.34%	79.17%	9.64%

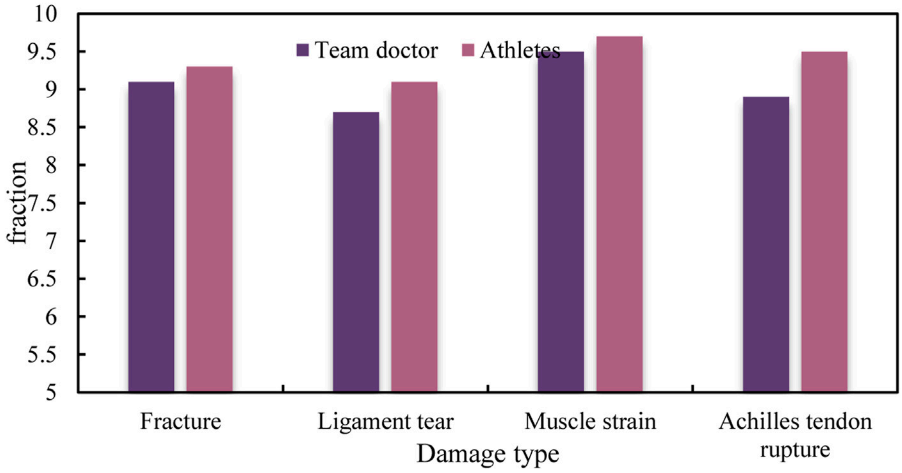

FIGURE 5
Scoring of athletes and team doctors on the effect of the new method.

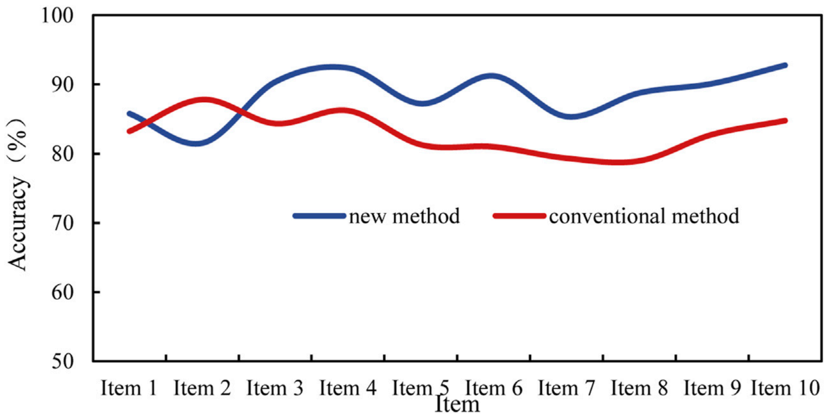

FIGURE 6
Accuracy of 10 damage detection methods.

model construction [23]. Among the learning algorithms, the deep learning algorithm has been widely used. Its application process is to obtain a multilevel neural network structure through training samples. CNN is a very representative network type of deep learning algorithm. It has a good performance in image analysis and graphics processing in the medical field. In the emergency treatment of athletes' injuries, it is very important to analyze and judge the athletes' own state and injury type. In this paper, CNN is used to analyze the image data of athletes' injury treatment. The image types are divided into drug recognition, facial image, pulse data, and limb image.

Drug treatment is a essential item in the treatment of athletes' injuries, and it is easy to misuse drugs due to the lack of understanding of common drugs. To solve this problem, this paper uses up and down shift, brightness adjustment and other data enhancement methods to preprocess the drug images, and then designs a drug recognition model combined with a CNN containing several convolutional layers and full connection layer.

The physique of athletes is an important factor to be considered in the process of injury treatment, but many team doctors have ignored the consideration of athletes' physique and only considered the injury itself. In the aspect of physique analysis, CNN model can be used to process the facial image data of athletes, and athletes with different physiques can be classified. In addition, in order to more accurately understand the injured athletes, this model can also be used to process the pulse signal data.

Diagnosis and treatment of limb injury is a common kind of injury treatment for athletes. As shown in Figure 4, according to the different characteristics of fracture, ligament tear, muscle strain, calcaneal tendonitis, Gabor filter algorithm and contour detection algorithm can be used to preprocess the images of each part respectively. The binary classification model is constructed by adding a normalization layer after each convolution layer of the CNN model to classify such images. In addition, the CNN model can be applied to magnetic resonance imaging and computerized tomography in the identification of the damage location to ensure a more accurate judgment of the damage location.

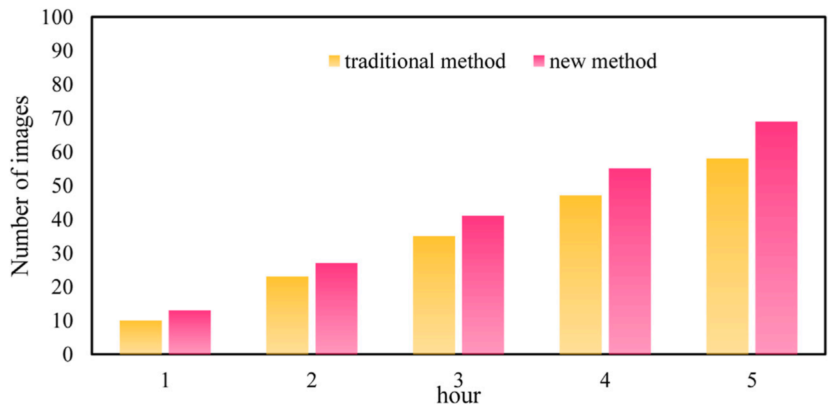

FIGURE 7
Number of image analysis in 5 h under traditional and new methods.

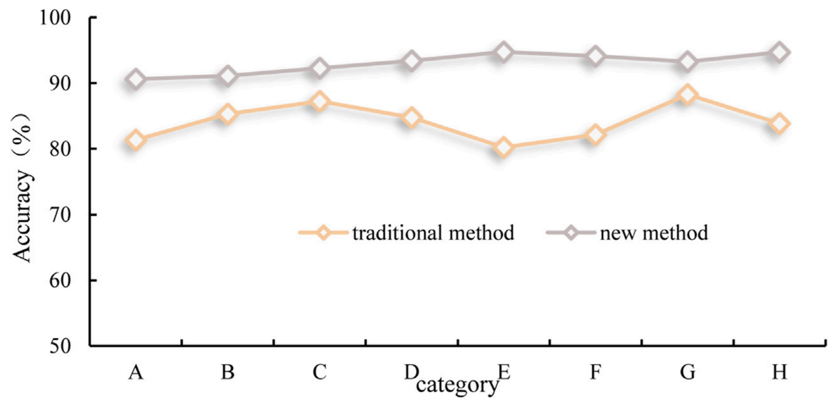

FIGURE 8
Accuracy of two methods for classification of eight kinds of damage images.

5 Evaluation of experimental results of new athletes' injury detection methods and image evaluation methods

In this paper, CNN and sensors are applied to new detection methods. The following experiments are designed to test the effect of the new method. The experimental sample is the injured athlete in a soccer match. The injury categories tested include fractures, ligament tears, muscle strain, and Achilles tendon rupture. The test object is the detection accuracy and false alarm rate under four damage categories under two methods. The specific test results are the data in Table 1.

It can be concluded from the data that the detection accuracy rate of the new method is higher than that of the conventional method in fracture, ligament tear, muscle strain, and Achilles tendon rupture. Especially in ligament tear detection, the accuracy rate exceeds 95%. In terms of false alarm rate, the new methods are generally low, which does not exceed 2%. In contrast, the false alarm rate of the conventional method is higher than that of the new method, and the false alarm rate of Achilles tendon rupture detection even exceeds 9%.

Athlete injury detection is not only related to the athletes themselves, but also has great relevance to the team doctors. A good detection method can provide more accurate and comprehensive medical data for the team doctor, and then facilitate the team doctor to design treatment plans for injured athletes. Whether the new detection method can be recognized by athletes and team doctors, the satisfaction of athletes and team doctors with the implementation effect of the new detection method is investigated. Satisfaction is scored in the form of 10 points. The specific content of the investigation is the detection effect of the new detection method on the injured athletes' fracture, ligament tear, muscle strain, and Achilles tendon rupture. The investigation results are shown in Figure 5.

It can be seen from the scoring in Figure 4 that athletes and team doctors have given high scores in terms of the detection effect of the four types of injuries. In comparison, the score of ligament tear detection effect is the lowest, but it also exceeds 8.5 points. In terms

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of muscle strain detection effect, it obtains more than 9.5 points. The scoring situation fully shows that the new method is relatively effective in the detection of these four common damage species.

In order to make the experiment to verify the practical effect of the new detection method more objective and complete, this paper also investigated the accuracy rate of the 10 most common injury detection in sports under the new method, and compared it with the accuracy rate under the conventional method. The comparison results are shown in Figure 6.

It can be seen that in terms of the accuracy of the first two damage detections, the two methods show an alternating leading phenomenon. From the third item, the accuracy of damage detection under the new method is maintained at 85%–95%, while that under the conventional method is maintained at 75%–85%. By comparison, the new method is 6.73% higher than the conventional method.

In this paper, a new method of sports injury detection is proposed by using CNN and sensors, and a new method of image data analysis in athletes' injury emergency treatment is proposed by combining CNN model. Similarly, in order to understand the image analysis efficiency of the new method, the number of image analysis within 5 h under the traditional method and the new method is tested. The image samples are images of various injury types of a soccer team, and the specific test results are shown in Figure 7.

It is easy to draw from the trend of the histogram that the number of image analysis under the two methods is increasing with time. This is inevitable. If the number of image analysis under this method decreases with time, the image analysis method is doomed to fail. In contrast, whether it is 1 h or 5 h, the number of image analysis under the new method is clearly more than that under the traditional method, and the growth rate is also relatively large.

In the aspect of motion injury image analysis, in addition to the analysis efficiency, the accuracy of image classification is also essential. Figure 8 shows the classification accuracy of eight kinds of damage images by two methods. The eight images are numbered A, B, C, D, E, F, G, H respectively. The test results of classification accuracy are shown in Figure 8.

It can be seen from the line graph in Figure 8 that the accuracy of image classification under the traditional method is maintained between 80% and 90%. The classification accuracy of various images varies greatly and is not very stable. In contrast, the classification accuracy of the new method is kept between 80%-90% and 90%–95%, and the classification accuracy of various images is relatively stable. The size and trend of the data show that the new method has excellent performance in sports injury image classification.

6 Conclusion

The emergence of ML not only provides technical support for the development of medical levels, but also provides method recommendations for detection and treatment. In sports, many athletes' injury detection methods can not keep up with the pace of the development of the times and can not meet the requirements of more precise and accurate detection work, which also has a great impact on the athletes' sports career. Mobile intelligent medical system is a computer network-based sensor technology, communication technology, and other applications in the medical field, with the characteristics of real-time and scalable. It not only analyzes and processes patient records but also identifies disease types and diagnostic solutions through images. Convolutional neural network is used to detect athletes' injuries in sports and carry out emergency treatment. The detection accuracy of athletes' injury detection method based on convolutional neural network has been improved, providing an important reference for the next application of ML in medical treatment. Through intelligent analysis technology, the causes of sports injuries can be analyzed, and sports injuries can be classified and treated effectively.

Currently, the application of convolutional neural networks in the medical field is very mature. Applying this algorithm to athletes' injury detection and emergency treatment is a new attempt and innovation, which will surely promote the application of ML in the medical field.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

YZ and QZ—writing and static analysis of data. YL—experimental operation and check. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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