Rev.int.med.cienc.act.fís.deporte - vol. 25 - número 100 - ISSN: 1577-0354

Zhou M et al. (2025) RESEARCH ON SPORTS TEACHING AND TRAINING ACTION DETECTION BASED ON DEEP CONVOLUTION NEURAL NETWORK. Revista Internacional de Medicina y Ciencias de la Actividad Física y el Deporte vol. 25 (100) pp. 379-391.
DOI: https://doi.org/10.15366/rimcafd2025.100.024

ORIGINAL

RESEARCH ON SPORTS TEACHING AND TRAINING ACTION DETECTION BASED ON DEEP CONVOLUTION NEURAL NETWORK

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Recibido 11 de junio de 2024 **Received** June 11, 2024
Aceptado 21 de diciembre de 2024 **Accepted** December 21, 2024

ABSTRACT

The aim of this study is to enhance the accuracy and efficacy of error action detection in sports coaching and training by employing a deep convolutional neural network (DCNN)-based approach. This method is designed to minimize the error rate associated with identifying incorrect movements during sports instruction and training sessions. After a thorough review of prior research findings, this study constructs a deep convolutional neural network (DCNN) focused on detecting errors in physical education teaching and training actions. The process begins with establishing feature extraction datasets, which are then fed into the network's input layer. The subsequent convolutional layers generate feature maps, and a normalization layer is integrated to refine the processing of physical education teaching and training samples. The error detection capability is achieved through iterative convolutional operations within the network. Experimental validation of this approach reveals an error rate of approximately 0.034%, indicating that the DCNN-based technique for physical education teaching and training action detection is highly precise in identifying training errors among athletes.

KEYWORDS: Deep Learning; Convolutional Neural Network; Physical Education Teaching and Training; Error Action Detection; Feature Extraction; Batch Normalization

1. INTRODUCTION

Under normal circumstances, after students have experienced physical education teaching, students' own nerves and muscles are difficult to meet the training content in the first time, often because the muscle memory is not formed for the occurrence of inaccurate movements.As for the quality of physical training, standard action is one of the important indicators of a number of teaching activities(Wang et al., 2018). How teachers correct students' movements during physical education teaching and then improve the teaching quality on the whole is the key content in the teaching process.After combing the relevant results of physical education teaching and training movement detection, it is found that most scholars believe that if the wrong movements of students in physical education teaching cannot be corrected in a short time, it will affect the subsequent research activities and reduce the overall quality of international sports.During the training period of the athletes(HU et al., 2019), the relevant practitioners and teachers should carry out the corresponding teaching activities for the athletes according to the premise of the standard movements of physical activities.Subject to the motor nerve problems of some athletes, the understanding degree in the actual training process is insufficient to accurately express the standard movements, which requires the coach to correct the training situation of the athletes, so as to improve the effect of physical education teaching(Shi et al., 2019). Li & Zhu have independently applied two-dimensional wavelet packet analysis and spatial clustering techniques to study human behavior and motion, respectively. Their research focused on enhancing the precision of incorrect action identification through the examination of images from physical education instruction and training. By employing these advanced methodologies (Li & Zhu, 2020), they were able to significantly boost the accuracy of detecting erroneous actions within the analyzed imagery. The extraction process of analyzing the results of the above research obviously cannot accurately understand the characteristics of the data, so that the results of the data analysis have a certain deviation; Spatial clustering techniques, while robust, may overlook the intricate details of image edges, leading to potential inaccuracies in detection outcomes. As the body of scholarly work on physical education teaching and training movements grows, so does the research into deep convolutional neural network (DCNN)-based detection of these movements(YANG et al., 2018). Despite the expanding scope of this research, the hierarchical structure of the analysis model warrants refinement, and a more thorough consideration of data processing depth is necessary(Zhang et al., 2020). To address the limitations in the existing detection processes for incorrect actions in physical education teaching and training, this study proposes an enhancement of the convolutional neural network framework through the incorporation of deep learning techniques. Specifically, it introduces batch normalization layers between convolutional and pooling layers to process erroneous action samples from physical education teaching and training. This approach aims to effectively extract features characteristic of incorrect actions, thereby enabling rapid and precise detection. The ultimate goal is to enhance the athletic performance of sports personnel by improving the accuracy of movement detection(Xu et al., 2020).

2. Wrong Movements in Physical Education Teaching and Training

Deep convolutional neural networks (DCNNs) are an evolution of convolutional neural networks, enhanced by the incorporation of deep learning techniques. These networks feature adjustable depth levels and utilize backpropagation to accurately detect incorrect actions. A significant advantage of DCNNs is the sharing of weights, which streamlines the training process. Their versatility in time series data analysis is noteworthy, and by manipulating the network's depth and complexity, they can significantly enhance the detection capabilities of erroneous actions within physical education instruction and training scenarios(Chen et al., 2019).

2.1 Motion Detection and Recognition

Action recognition is to judge people's action labels. Generally speaking, it belongs to classification problem. The action recognition input can be video or image. When the input is video, it is necessary to use multi frame image sequence information and combined with time-space information to judge the category of a series of continuous actions of people. When the input is still image, there is no action feature in time series, so it is necessary to extract the feature that can express action from the image to judge people's real-time action(Hsu et al., 2019). The early research on motion recognition was limited to a limited number of motion recognition in the laboratory environment, and now it is more committed to the research of motion recognition in natural scenes. The commonly used action recognition databases are collected from real life, and the types of actions covered are more abundant and diverse. People's actions are complex and changeable, which is difficult to exhaust. Sometimes there is little difference between different actions, such as race walking and running(Shan et al., 2023).There may be great difference between the same kind of actions, such as jumping in different ways. People's own appearance characteristics also have many changes, and the scenes are also very different. Sometimes the judgment of people's actions should consider a series of coherent actions of people over a period of time. Moreover, people interact with different objects(Wang & Jiang, 2022). To a certain extent, interactive objects indicate human actions, such as reading books and watching computers. Interactive objects are diverse. Different viewing angles, different distances, or the occlusion of obstacles may also interfere with the apparent model of human action(Zhang, 2022). Generally, action recognition is regarded as a data classification problem. Actions can be classified by using the characteristics that can describe actions and combined with the classification algorithm in machine learning. Motion recognition features include static image features, motion information, dynamic features , optical flow information, spatiotemporal features , descriptive parameter features, etc. . For still image motion recognition, because there is no dynamic feature information, generally only the bottom features of the image can be used, such as target size(Hsu et al., 2019), color, edge, texture, shape, or descriptive features such as human posture parameters. For example, an action recognition method is to recognize actions based on the estimation of human posture, that is, the positioning parameters of various parts or joint points of the human body. However, estimating human posture is a more difficult task than recognizing human actions. Action recognition does not need to estimate human posture as the premise, and taking posture parameters as motion features is not robust enough. In addition, the output of pose estimation is only the human skeleton structure information, ignoring the contextual information contained in the background. When recognizing people's actions, the objects interacting with people play a very important role, such as reading books and using computers, riding bicycles and horses. It is easy to misjudge people's actions without considering the background objects.

2.2 Structure of Deep Convolution Neural Network

Convolutional neural networks (CNNs), evolving from the foundational models of artificial neural networks, present several innovative features that set them apart. By incorporating convolutional and pooling layers, these networks significantly reduce the complexity and parameter interdependencies among layers, thereby diminishing the potential for overfitting and facilitating a more tractable training process. The parameter efficiency in convolutional structures is manifested in two primary dimensions. Firstly, it involves the concept of local receptive fields. Unlike traditional neural networks that establish global connections, convolutional networks restrict connections to a local neighborhood. This means that each neuron is connected to a specific region of the input image, and the relationship between a pixel and its immediate neighbors is emphasized, reflecting the inherent spatial correlation within images. It is unnecessary to process every pixel in an image globally; instead, higher-level neurons can integrate local information to achieve a broader perceptual field. Secondly, the concept of parameter sharing plays a crucial role. Within the realm of local perception, a single set of weights is applied across various regions, indicating that the same parameters are used for convolution operations across the entire input space. This approach not only minimizes the number of parameters but also enables the network to learn spatial hierarchies. Additionally, the pooling mechanism assigns a single value to the output of a group of neurons, effectively reducing the spatial dimensions while retaining critical information. The invariance of convolutional neural networks (CNNs) to certain transformations, such as deformations, translations, and scaling, is largely due to the principles of local receptive fields, weight sharing, and the incorporation of temporal or spatial sampling. These attributes allow CNNs to maintain their functionality across various image manipulations. A deep convolutional network is constructed as a stack of layers, with each subsequent layer receiving the feature map generated by the previous one as input. Through the computations performed at each layer, a new set of feature maps is produced. The lower-level feature maps in this hierarchy are often associated with low-level image attributes like gradients, colors, and edges, while the higher-level feature maps capture more complex and abstract representations. These higher-level features are synthesized from the lower-level details, thereby providing a more comprehensive and task-relevant understanding of the input data. The composition of a deep convolutional neural network is based on three levels, namely, input, implicit, and output layer. The composition of the implied layer is composed of two levels, for the specific structure of the watchtower, see the figure 1 below. After the feature extraction is completed, the data without this step is included in the input layer, and the data of each layer is processed accordingly, and the feature map is formed based on the structure after the data processing; Obtain the corresponding pooling characteristic map by pooling the characteristic map obtained by processing the convolution layer through the pooling layer (S2); By using the hidden layer and C1 data iteration, determine the convolution layer and the pooling data analysis results, thus can get wrong data information, with the data of standard action, determine the wrong movement of athletes in the physical teaching training, improve the resolution of the feature image, and then get the feature data (YU et al., 2019)].

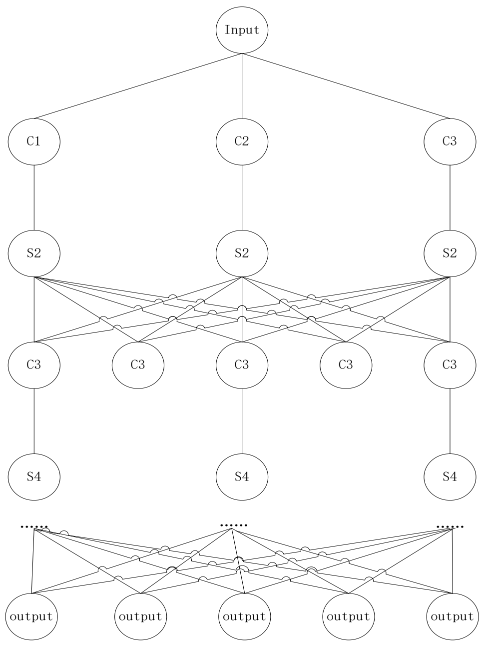

Figure 1: Structure of Deep Convolution Neural Network

2.4 Convolution

The data obtained through the sensor is included in the input data. In this process, X, y and Z will be comprehensively analyzed by preprocessing. To improve the accuracy of the output results, the size of the data should be consistent. What is necessary is that during the processing of the convolutional layer data, the transformation of the convolution kernel cannot affect the weights of the data, and complete the calculation process of the data on the X axis. Through the above analysis content, the relevant data of the deep convolutional neural network can be determined to improve the accuracy of the calculation results(Sun, 2022). In this paper, the training process based on deep convolutional neural network is calculated according to the way of feature extraction. By analyzing the data, the processing process is more rapid, and the sports training result data can be accurately sorted out, and the convolutional kernel is sorted into two-dimensional convolution:

$$y_{m,n} = A\begin{bmatrix} x_{n,m} & \cdots\cdots & x_{n+f_w,m} \\ x_{n,m+1} & \cdots\cdots & x_{n+f_w,m+1} \\ x_{n,m+f_h} & \cdots\cdots & x_{n+f_w,m+f_h} \end{bmatrix} \quad (1)$$

Get the input and output of the total convolutional layer.

$$Y = \mathrm{relu}(\sigma(WB + b)) \quad (2)$$

2.5 Maximum Pool Layer

In this study, the strategy of physical education teaching and training action detection is to analyze the strategy of the maximum pool layer, with the core 22 and the step length. Other dimensions of the data take the maximum pool of the layer as the data sample, and the obtained formula is as shown in (3).

$$y_{i,j} = A\begin{bmatrix} x_{is,js} & \cdots\cdots & x_{is,js+P_w} \\ x_{is+1,js} & \cdots\cdots & x_{is+1,js+P_w} \\ x_{is+P_h,js} & \cdots\cdots & x_{n+P_h,js+P_w} \end{bmatrix} \quad (3)$$

Based on the above formula, it can not only maximize the dimension of the data, but also play a certain constraint role on the training parameters, improving the efficiency of physical education teaching and training movement detection on the whole.

2.6 Full Connection Layer and Output Layer

To mitigate the risk of overfitting that can arise from the limited dataset size in deep convolutional neural network (DCNN) training, regularization techniques are frequently incorporated into the fully connected layers of the network. Incorporating randomness in the regularization approach ensures that the network architecture adapts uniquely to each dataset iteration yet maintains shared weights across the network. This strategy significantly enhances the robustness of the physical education teaching and training error action detection model, simplifying the process of neural adaptation. Leveraging the depth of convolutional neural networks (CNNs) in the context of sports teaching and training action detection, the technology employs a shared parameter approach to fundamentally reduce the computational load. By constraining the structure and parameter dimensions of the neural network, it enables the generalization of data to a lower-dimensional space. Subsequently, through the application of pooling techniques, the accuracy of data analysis outcomes is further enhanced. The characteristics of the neural network change during the calculation process, but it can more effectively cope with the complexity of the computation due to the scalability of the computation mode.

3. Feature Extraction and Test Result Output

Enhancing the precision of erroneous action detection in physical training is contingent upon the depth of the neural network architecture. There is a direct relationship between the depth of a neural network and its capability to represent features. Deep neural networks are designed to analyze and compute the characteristics of erroneous action data comprehensively. The increased depth of the network's final output layer correlates with enhanced feature extraction capabilities. As the depth of neural networks increases, there is a propensity for the vanishing gradient issue, which can adversely affect network performance.

To counteract this challenge, the ResNet101 model is leveraged as the backbone for deep convolutional neural networks in feature extraction tasks. This strategy facilitates the swift and efficient identification of intricate features within sample data from physical education teaching and training. The data is analyzed in the way of batch processing. In the process, the transmission strategy is determined mainly based on the volume base and pool layer data accelerated by RESNET, so as to improve the training speed of neural network, and improve the detection efficiency of data processing from the overall rise. The processing process of the algorithm is normalized in the relevant level, detecting and analyzing the wrong movements of physical education and training movements, and expressing the processing mode as follows:

$$\hat{X} = norm\ (x, X) \tag{4}$$

Where X represents the vector of a certain layer input into the deep convolution neural network. X represents the sample set, and an input group of the overall training set can be described. Based on the above research content, the relevant data optimization of physical education is determined, and the input samples are calculated by algorithm. The formula is as follows:

$$J = A\begin{bmatrix} \frac{\partial u_1}{\partial x_1} & \cdots\cdots & \frac{\partial u_1}{\partial x_n} \\ \frac{\partial u_2}{\partial x_1} & \cdots\cdots & \frac{\partial u_2}{\partial x_n} \\ \frac{\partial u_n}{\partial x_1} & \cdots\cdots & \frac{\partial u_1}{\partial x_n} \end{bmatrix} \tag{5}$$

The amount of computation of batch normalization processing the input of all layers is large, and the time to obtain the covariance matrix is long. Through the above research cross, it is believed that the following centralized treatment methods can further improve the improvement effect. The accuracy of the data can be enhanced by normalization the sample data, and the following formula is obtained by independent normalization processing mode:

$$\hat{X} = \frac{x_i^k - E_x^{(k)}}{\sqrt{var_x}} \tag{6}$$

The formula in the dimension in the input sample, expected value and variance value, through the sports teaching and training action detection technology research results, through the formula to improve research training speed, but on the whole, the neural network of various levels to describe the lack of a certain balance. In order to keep the change of the added batch normalization constant, add parameters in the third dimension of each input sample. Where and are equal, they are variance, after converting the data of physical education, the input sample is k; the data analysis result is the conversion dimension of the input value and the dimension data of the input sample. The network training and detection process are determined by analyzing the analytical parameters in the correlation model, so as to minimize the detection process of the deep convolutional neural network summary and reduce the error value of the calculation results. After converting the data of physical education, the input sample is k; the data analysis result is the conversion dimension of the input value and the dimension data of the input sample. The network training and detection process are determined by analyzing the analytical parameters in the correlation model, so as to minimize the detection process of the deep convolutional neural network summary and reduce the error value of the calculation results. After the above calculation results, the physical education teaching and training movements are detected based on the deep convolutional neural network, and the mean value of the training results is obtained. The reverse propagation of gradient can be realized by using the above operations. The micro batch samples obtained through the calculation process are expressed in B, m represents the sample size description in the network training, X describes the dimension input value in the physical education training data, by normalizing the data as in the formula:

$$BN_{\gamma,\beta}: x_1, \ldots\ldots, x_m \rightarrow y_1, \ldots\ldots, y_m \tag{7}$$

Through the above formula, the wrong movements of physical education teaching are detected, which obtains the wrong movement causes of the athletes during the training, providing the basis for putting forward effective solutions.

4. Experimental Analysis

The effectiveness of deep convolutional neural network is recognized from the theoretical aspect above, but the practical application is lacking. Therefore, the above content is tested in the way of case experiment below. The objects of this test are the students of the School of Physical Education. After sorting, the data values are as follows (Table 1):

Table 1: Parameter Setting of Deep Convolution Neural Network

NUMBER OF LAYERS	FUNCTION	NUMBER OF LAYERS	FUNCTION
1	Input layer	10	Maximum pool layer
2	Convolution layer 3-64	11	Convolution layer 3-512
3	Convolution layer 3-64	12	Convolution layer 3-512
4	Maximum pool layer	13	Maximum pool layer
5	Convolution layer 3-128	14	Convolution layer 3-512
6	Convolution layer 3-128	15	Convolution layer 3-512
7	Maximum pool layer	16	Full connection layer 3072
8	Convolution layer 3-256	17	Full connection layer 1024
9	Convolution layer 3-256	18	Output layer

The detection of errors in physical education and training movements, as detailed in Chapter 2, is aimed at identifying inaccuracies during the teaching and training processes. As the number of experiments conducted increases, a comparative analysis of the efficacy of three distinct methods for detecting these errors in physical education teaching and training is undertaken. During this experiment, in order to more accurately detect the individual training movements in the process of physical education, the relevant data were collected and sorted the non-public data, and then the interference items were removed after calculating the results to enhance the stability of the experiment on a whole(Han & Liu, 2024). After determining the above discussion, the experimental data were divided into two groups in a random way. The experimental group conducted the basic test content, while the control group conducted deep convolutional neural network training, and the experimental results were determined by calculating and comparing the two groups of data.The subjects often have wrong movements during the imitation movement, and the final results of the different mode will also change after testing. The specific content is shown in the figure below.Through the data collection in figure 2 can measure the athletes during training, namely by comparing and standard action to understand the movement of athletes, by comparing the results of three patterns can be seen, based on the depth of the convolutional neural network detection mode can be more accurate understand athletes wrong posture, more effective than the two detection methods (Figure 2)(Wang et al., 2023).

(a) Wrong Movements in Physical Education Teaching and Training

(b) Paper Method

(c) Wpdec2

(d) FMCW

Figure 2: (a) Wrong Movements in Physical Education Teaching and Training (b) Paper Method (c) Wpdec2 (d) FMCW

For the depth of convolutional neural network, FMCW, wpdec2 three modes of detection of the movement of the technology, compare the difference between each action, improve the effectiveness of comparison results, found that the athletes after the training error rate of specific data, by collecting and sorting three methods after data is as follows:

Table 2: Comparison of Detection Error Rates of Different Methods

TEST INDEX	ERROR RATE /%		
	PAPER METHOD	WPDEC2	FMCW
15	0.021	0.078	0.15
25	0.019	0.089	0.143
36	0.045	0.153	0.249
45	0.013	0.124	0.199
55	0.032	0.086	0.132
65	0.075	0.088	0.133

By analyzing the relevant data in the table 2 above, the detection method based on the deep convolutional neural network is relatively high compared with the other two detection techniques. From the specific values, the error rate of the detection method of deep convolutional neural network, wpdec2 and deep convolutional FMCW are 0.034%, 0.103% and 0.168%, respectively, which can clearly show that the detection method in this paper can detect the training movements of athletes more accurately.

That is, using the movement detection technology of this paper, we can understand the wrong movements of the athletes, and then develop an effective improvement scheme. On the basis of the above content, the accuracy of the research results, that is, ACC (accuracy), TPR (sensitivity), fpr (specificity) and PPV (positive prediction rate), by comparing the values of the above indicators to understand the standard degree of training movements.

$$\mathrm{ACC} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}}$$

$$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$

$$\mathrm{FRP} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TN} + \mathrm{FP}}$$

$$\mathrm{PPV} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}$$

The FP in the above formula is the data that is positive in the judgment process but negative in the number of samples; while TP is the number of samples that are both judgment and actually positive; FN is negative in the judgment process but positive in the sample number; FN is the number of samples judged and actually negative.

By comparing the test results of the sample data, when the data is inverse, the test results are more effective. The results of this case test are shown in the following table 3.

Table 3: Test Results of Wrong Movements in Physical Education Teaching and Training

TEST INDEX	PAPER METHOD	WPDEC2	FMCW
ACC	0.984	0.853	0.836
TPR	0.954	0.854	0.853
PPV	0.092	0.254	0.236
FPR	0.017	0.042	0.117

5. Conclusion

Due to the limitations of conventional techniques in precisely capturing the erroneous action characteristics within physical education teaching and training, which leads to a decrease in detection accuracy, this study introduces a novel detection approach for erroneous actions in physical education teaching and training that leverages deep convolutional neural networks. Through the experimental results of cases, it can be seen that the technology of detecting training movements based on deep convolutional neural network can more accurately measure the standardization of athletes' movements of athletes, and then provide powerful conditions to correct the wrong movements of athletes through the judgment results. In the subsequent research content, we can improve the accuracy of the algorithm and the calculation accuracy and efficiency by expanding the sample data, and enhance the standardization of athletes' training movements on the whole.

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