J. COMBIN. MATH. COMBIN. COMPUT. 127a (2025) 8879--8893

Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Combinatorial Press

A Deep Learning Model Based Skill Recognition and Evaluation System for Football Sports Players

Changwei Chen[1,✉], Kuanbin Zhang[1], Xiaowen Song[2]

[1] *Basic Department of Qilu Institute of Technology, Jinan, Shandong, 250200, China*
[2] *Baotou Medical College, Inner Mongolia University of Science and Technology, Baotou, Inner Mongolia, 014040, China*

ABSTRACT
As the world's No. 1 sport with wide popularity and high degree of attention, there exists a great application demand and development potential for applying artificial intelligence to soccer sports training. In this paper, Yolov5s-CBAM target detection network is utilized to identify the human body posture of target athletes in soccer sports training, and HRNet network is used to detect the location information of key points of target human skeleton and identify the skill movements of soccer players. Subsequently, the TDS-Fast DTW algorithm is applied to evaluate the skill movements to establish a skill recognition and evaluation system for soccer sports athletes. It is verified that the soccer player skill movement recognition model proposed in this paper outperforms other comparative models, with the checking rate reaching 99.12%, and the evaluation scores of the model on the skill movements of the athletes are not different from those of the manual evaluation scores ($P>0.05$). It is also found that the application of the system in actual soccer training matches can fully meet the needs of soccer training. The system in this paper can accurately assess the technical movements of soccer sports athletes to meet the needs of scientific training, and at the same time, it can meet the needs of coaches to timely grasp the understanding of the level of technical movements of soccer athletes and improve the quality of training.

Keywords: Yolov5s-CBAM, HRNet network, DTW algorithm, FastDTW, soccer skill recognition

1. Introduction

Soccer, as a global sport, the level of competition not only depends on the technical level of the athletes, but is also closely related to the physical quality, physical reserve and psychological quality [1-3]. In secondary school, students' bodies are in a period of rapid development, and physical training during this period plays a crucial role in the skill development of soccer players [4-6]. However, the current research on how secondary school physical exercise affects the skill development of soccer players is

✉ Corresponding author.
E-mail address: 13345125783@163.com (C. Chen).
Received 10 January 2024; Revised 15 March 2024; Accepted 25 December 2024; Published Online 15 April 2025.
DOI: 10.61091/jcmcc127a-493

still insufficient and lacks organized theoretical support and practical experience [7-8]. Therefore, it is important to systematically analyze the content, skills and effectiveness of extracurricular physical training in secondary schools, further study its role in the skill development of soccer players, and provide improvement suggestions and learning directions for secondary school soccer training according to actual needs [9-11].

At present, school soccer is blossoming all over the country, but the level of the soccer representative teams of each soccer specialty school is mixed, and the training level of various soccer training institutions or coaches is naturally difficult to be easily identified by laymen [12-14]. Therefore, there is an urgent need for a set of practical skill assessment system that can be compared across regions (horizontally) and ages (vertically) [15-16]. The traditional few single test items do not accurately reflect the skill level, yet frequent inter-team sparring has bottlenecks in the Chinese context, so developing a set of effective assessment programs about individual skills is necessary for youth soccer development [17-18].

The research on soccer skill assessment and player performance evaluation on the field is more popular nowadays, and the mainstream methods for player skill assessment and identification are soccer skill assessment based on deep learning technology and small tournament evaluation, which are often used to optimize player training and screening of soccer talents. Literature [19] takes deep learning algorithm as the infrastructure, envisions a soccer motion capture system, realizes the two-way motion analysis of the soccer field, and at the same time has a lower cost, and then introduces the network evaluation management technology to reproduce the physical collision of the college soccer teaching, and finally confirms the feasibility of the proposed model through the simulation test. Literature [20] reviewed the research literature on soccer skills, pointed out that most of the soccer skill assessment methods are not applicable to the soccer field, and the direction of skill assessment focuses on soccer attacking skills, and finally emphasized that the variability of the assessment would potentially limit the accurate identification and assessment of soccer players' skills. Literature [21] reviewed journal articles on assessing soccer players' on-field performance and soccer skills, and the research topics included on-field soccer skill performance, off-field skill movement assessment, etc., which contributed to the optimization of soccer players' skill assessment strategies. Literature [22] based on an exploratory approach to soccer mini-match as a screening strategy for soccer skill-based talents, assessed the on-field players' performance and skill level comprehensively through on-field video review, and confirmed that the proposed strategy can assist coaches in screening soccer talents through example analysis.

The enhancement of soccer sports skills requires good sports teaching and training strategies and professional coaching, so many studies on soccer sports skills enhancement have been conducted from the perspectives of teaching, training and coaching. Literature [23] systematically searched the training design and coaching behaviors to improve soccer sports skills, mainly including theory-driven teaching methods, differentiated learning, game teaching and non-linear teaching teaching methods, as well as auxiliary behaviors such as practice task design and coaching guidance, which are of positive significance for consolidating the teaching and guidance work of soccer coaches. Literature [24] carries out professional coaches to carry out soccer training practice, and finds that sports skills show an increasing trend with the training market, in order to explore the problems related to the staging of skills training for professional coaches, it tries to transform the theory of skills acquisition training into the staging framework of skills training, and realizes the variability of sports skills training and the training environment in order to obtain a better training effect. Literature [25] assessed the soccer learning effects of the STAD cooperative learning model and the traditional learning model, and conducted the research by carrying out the method of teaching comparative experimental class, and the research results showed that the STAD cooperative learning model played a more excellent effect in promoting the soccer skill enhancement of the students with low self-confidence, while the traditional cooperative learning model was more suitable for teaching soccer to the students with high self-confidence.

In this paper, the CBAM module is fused with Yolov5s algorithm to get the target detection algorithm for soccer sports players. The skeletal key nodes of the target athlete are detected by HRNet network to realize the recognition of soccer player's skillful movements. Then the lightweight residual module consisting of the fusion of DSC convolution and CBAM module is utilized to replace the Basicblock model in HRNet network to improve the accuracy and performance of the skeletal key point detection method. Subsequently, the DTW algorithm is proposed to analyze the similarity between soccer players' skill movements and standard movements, and the FastDTW algorithm matching strategy is introduced to improve the efficiency of the algorithm, and to construct a skill movement evaluation model based on the TDS-Fast DTW algorithm. Finally, the two models are combined to design a skill recognition and assessment system for soccer sports players. In this study, the training video of a soccer team is selected as a dataset to analyze the accuracy of the skill recognition model and assessment model. At the same time, the system is applied in a game of the soccer team to recognize and evaluate the skill movements of the athletes in real time to verify the application effect of the system.

2. Method

2.1. Athlete Motor Skill Recognition Methods

2.1.1. Targeted human detection methods. Accurate human target detection is very critical in the task of target detection during the training of soccer sports players, and enhancing the effective features of the input data and suppressing their ineffective features can achieve more accurate detection. In order to achieve this goal, this paper fuses the CBAM module with the Yolov5s algorithm [26] to obtain the Yolov5s-CBAM target detection network model, which can focus more attention resources on the key regions of the target.

In the Yolov5s network model, there are three different scales of outputs, and different scales of prediction frames can be generated for different sized targets. In order to avoid a significant increase in the number of model parameters and slower network inference, the CBAM module must not be used too much. At the same time, because the shallow layer can not extract sufficient feature information, then there is no way to better focus on the channel information and key positions, so the CBAM module can not be placed in the shallow part of the network. In summary, in this paper, the CBAM module is added in front of each detection scale of Yolov5s, so that the network can not only extract more adequate feature information and improve the detection accuracy, but also because the number of CBAM modules added is small, the network inference speed will not be greatly affected.

2.1.2. Skill Recognition Method Based on Skeletal Keypoint Detection. After the target detection network for the extraction of the human target region in the process of soccer sports player skill movement training. The next work in this paper is to input the extracted coordinate information containing the human target block diagram into the skeletal key point detection network to detect the location information of the human skeletal key points, so as to realize the recognition of soccer sports players' skill movements. In this paper, HRNet [27] is chosen for human skeletal keypoint detection, and the HRNet network structure is divided into two versions, 32-layer and 48-layer, due to the difference in the number of channels. Fusing feature maps of different resolutions at the same depth can fully utilize the semantic information in the low-resolution features, so that the high-resolution features learn the semantic information in the low-resolution features, and the low-resolution features learn the spatial information in the high-resolution features, and this design allows HRNet to capture both high-resolution spatial information and low-resolution semantic information, which helps to more accurate regression of heat maps.The whole network structure of HRNet is divided into four stages, each containing a different number of parallel multiresolution subnets as well as multiple switching modules.

1) Parallel multiresolution subnetwork. HRNet has two types of residual modules, Basic block and Bottleneck block.The role of residual module is to solve the problem of gradient vanishing due to the network layers are too deep.HRNet uses four Bottleneck blocks for feature extraction in the first stage. The second, third and fourth stages use Basic block module for feature extraction, but the residual module is ineffective when the number of network layers is deeper, and the amount of computation and parameter count is larger.

2) Switching module. The role of the exchange module is to exchange the information between different resolution feature maps and to fuse multi-resolution features, as shown in equation (1):

$$Y_j = \sum_{j=1}^{n} o\left(X_i, j\right) \tag{1}$$

X_i denotes the feature map input to the exchange module with resolution i, Y_j denotes the feature map output from the exchange module with resolution j, and O denotes the conversion operation. The fused result is obtained by converting the input feature map resolution i to the output feature map resolution j and then summing the converted results.

The computational and parametric quantities of the residual module are larger when the HRNet network layers are deeper, which makes the model difficult to train and run. As the computational and parametric quantities of DSC convolution are less, the CBAM module is able to enhance the global feature extraction ability to some extent. Therefore, to address the above problems, this paper designs a lightweight residual module fused with DSC convolution and CBAM module to replace part of the original residual module to obtain the HRNet-DSC-CBAM skeletal keypoint detection network model.

2.1.3. Skill recognition model optimization design. In order to solve the problem that as the number of layers of HRNet network increases, the computational and parametric quantities of its residual module also increase, this paper designs a lightweight residual module to replace part of the residual module in the original network.The lightweight residual module consists of a fusion of the DSC convolution and the CBAM module, which can take into account the detection accuracy and at the same time reduce the computational quantity and parametric quantities significantly. The lightweight residual module consists of two point convolution, a depth convolution and a CBAM module, the introduction of the depth separable convolution can make the network's computational and parametric quantities have been greatly reduced, and the introduction of the CBAM module can make the network's learning ability to be further strengthened.

The activation function after deep convolution of the light residual module uses ReLU6 as shown in equation (2):

$$\mathrm{Re}LU6 = \min(6, \max(0, x)) \tag{2}$$

The function value is x when x is in the range of $(0,6)$. The function value is always 6 when x is in the range of greater than 6. Therefore, the use of this activation function avoids the problem of high activation function which results in poor data resolution of the network on low precision devices. However, the activation function ReLU6 is not used at the point convolution to operate on the output features, this is because the use of the ReLU6 layer in the low dimensional space will destroy the features. When the number of channels is greater than 64, this paper replaces the Basicblock of the HRNet network with a lightweight residual module, which can achieve the purpose of reducing the computational and parametric quantities while ensuring the accuracy of soccer skill action recognition.

2.2. Construction of soccer skill assessment model

2.2.1. DTW-based skill assessment models. The DTW algorithm [28] is a matching algorithm based on the concept of dynamic programming, which is specialized in dealing with time series data. The core idea of the algorithm lies in the computation of two sequences to be matched by flexibly lengthening or cropping the time series in order to find the best matching path between them. This shortest path reflects the similarity between the sequences. In this paper, the DTW algorithm is used to analyze the similarity between soccer sports players' skill movements and standard skill movements to achieve the evaluation of the identified skill movements.

The DTW algorithm matching path has certain constraint rules, such as the following conditions.

1) Starting point and end point. Two DTW time series can be of different lengths, but the matching starting point must be $\left(x_1, y_1\right)$ and the end point must be $\left(x_n, y_m\right)$.

2) Non-retroactivity. Because the time series are monotonically ordered, after x_i is matched with y_i, subsequent matches must be made from x_{i+1} with y_{i+1} and later points.

3) Bounded. The matching path is an integer in the interval $\left[\max(m,n), m+n-1\right]$.

4) Continuous. The distance between neighboring matching time points x_i and y_i cannot be greater than 1.

When the DTW constraints are satisfied, a $m \times n$ cumulative distance matrix D needs to be constructed to store the distance between X and Y. The y axis sequence is calculated as shown in Eq. (3). $D[i,0]$ is the first column distance on the left side of the matrix:

$$D[i,0] = dis\left(A_1, B_0\right) + D[i-1,0] \tag{3}$$

The X-axis sequence is calculated as shown in Equation (4), with $D[0,j]$ being the first row distance below the matrix:

$$D[0,j] = dis\left(A_0, B_j\right) + D\left[0, j-1\right] \tag{4}$$

For other sequence distances, it can be expressed by Equation (5). After calculating the time series one by one, the DTW algorithm searches for the optimal path through the search radius formula as shown in Equation (6):

$$D[i,j] = dis\left(A_i, B_j\right) + MIN(D[i-1,j], D[i,j-1], D[i-1,j-1]) \tag{5}$$

$$\alpha(i,j) = \min\{\alpha(i-1,j-1), \alpha(i-1,j), \alpha(i,j-1)\} + d\left(x_i, y_j\right) \tag{6}$$

Through the above algorithm analysis DTW algorithm computational complexity is $O\left(n^2\right)$, in the processing of large-scale time series data will have a very large amount of computation.FastDTW algorithm matching strategy [29] is an algorithm that accelerates the computational efficiency of the DTW algorithm, the algorithm in the DTW algorithm based on the use of multilevel matching strategy, the time series coarse-grained segmentation, and then use the DTW algorithm for each piece of the sequence matrix for the local matching, and finally fine-grained reduction of all matrices to the initial time series to find the overall optimal path.FastDTW has significant speed improvement in the case of processing large data, but the algorithm coarsely granularizes all the time series, which does not take into account that in the case of acceleration, the features are not equally related to time, and some valuable feature points will be neglected.

2.2.2. Optimizing feature extraction weights

In the process of evaluating the similarity of soccer skill movements, the athlete key point angle transformation can well represent the standard degree of the athlete's skill. However, just directly by calculating the corresponding key point vectors between two frames can't explain the accuracy of the overall movement well, while the key point movement angle information derived in this way contains a lot of noise. Firstly, the angular characteristics of the athlete's legs are derived, as shown in Eq. (7):

$$\alpha = \frac{OA \cdot OB}{\|OA\| * \|OB\|} \tag{7}$$

The dot product of vectors $\overline{OA}$ and $\overline{OB}$ is denoted as $OA \cdot OB$ and is calculated as shown in equation (8). Meanwhile, the modulus of $\overline{OA}$ and $\overline{OB}$ represent their respective magnitudes, and the formulas for their calculation are shown in Eq. (9) and Eq. (10), respectively:

$$OA \cdot OB = x_1 * x_2 + y_1 * y_2 \tag{8}$$

$$\|OA\| = \sqrt{x_1^2 + y_1^2} \tag{9}$$

$$\|OB\| = \sqrt{x_2^2 + y_2^2} \tag{10}$$

Then using the leg keypoint feature, the Euclidean distance between the current frame and comparing the previous frame of that keypoint is found, and finally the feature point is found by normalization using equation (11):

$$D_\varepsilon(i, j) = D(i, j) * \left(1 - norm\left(\sqrt{\left(x_i - x_{i-1}\right)^2}\right)\right) \tag{11}$$

2.2.3. TDS-FastDTW Algorithm Implementation. In order to improve the accuracy of evaluating soccer players' skill movements, this paper proposes an algorithm for dynamic segmentation of time series based on FastDTW (TDS-Fast DTW). Firstly, the soccer skill action to be matched sequence X_u and the standard sequence are derived, then the weighted feature matrix is constructed, the feature sequence is cropped by calculating the ratio of the time duration used in each phase of the soccer skill action to the total time duration, and finally, the Fast DTW algorithm is used to match each segment of the feature matrix with the feature matrix of the standard action.

2.3. Design of Skill Recognition and Assessment System for Football Players

In the overall design phase of the soccer player skill identification and assessment system, various requirement analysis tasks must be integrated in the software system to achieve a common software system design plan. In the overall design of the software system, in order to reduce the logical problems in the development process, the software system will be deployed as a Windows operating system, which defines a unified data and equipment interface standard for the whole system management platform: the application after being added and verified by the background administrators is able to query the training data of volleyball players as well as the analytical reports on the athletes through the interface request. The system mainly realizes data collection and storage, statistical analysis and data display. In terms of functional composition, the system mainly includes four main modules such as athlete information management, training management system, data analysis management, system maintenance, etc. The overall block diagram is shown in Figure 1. The player information module mainly realizes the collection of basic information on soccer players and the analysis of player comparison data. The training management module mainly analyzes data and extracts skills dynamically from individual training videos and group game videos uploaded by users. When uploading individual practice videos, the system will obtain the player's skill dynamic information through the uploaded video, longitudinal comparison data analysis, used as a training aid and basis for coaches and players. Upload. When uploading the video of team competition, the system will automatically collect and analyze the analysis of the skill movement of each player on the field, so as to judge the situation on the field of the players and the characteristics of the skills they are good at, etc., which will provide assistance for the coaches in the analysis of the game strategy and the formulation of the competition strategy. The data analysis management module mainly analyzes and manages the statistics of players and clubs, and classifies them by comparing the historical data, and the analysis report provided by it can also be used as the data source and material for the training and learning of AI algorithms, so as to continuously improve the recognition accuracy of the algorithms. The system maintenance module mainly focuses on the user information management and basic information content of the platform, which involves the basic information content of individual players and teams, training information content, and competition information content.

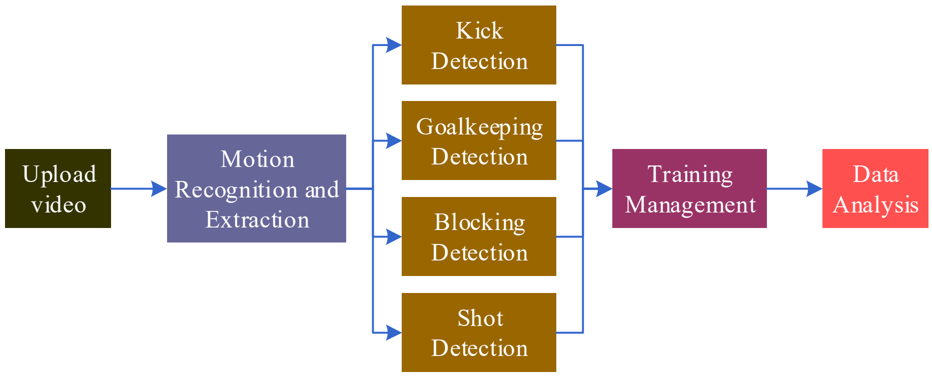

Fig. 1. Football player skills recognition and evaluation system

3. Results and discussion

3.1. Accuracy analysis of soccer skill recognition models

3.1.1. Experimental design:

1) Data set. The soccer sports training data used in this paper is a set of training videos of a soccer team. The soccer sports training videos contain the key action skills of soccer sports, which mainly include 8 skills of passing, shooting, catching, dribbling over the ball, topping the ball, throwing the ball out of bounds, stealing and goalkeeping. The soccer sports player skill action data set is randomly divided into training set and test set, of which 80% is used for training and the rest is test data. For validation as a training model, the batch size was chosen as 300 and the model was subjected to 14000 iterations. In addition, the input data is normalized.Keras library provides several optimization techniques including Stochastic Gradient Descent (SGD), RMSProp, and Adam Optimizer, and Adam Optimizer is selected for model optimization in the experiments.

2) Model evaluation index. When evaluating the performance of the trained model for binary classification problems, Precision, Recall and F1-score are often used to comprehensively evaluate the model performance.

Precision is the ratio of the number of samples correctly classified as positive cases by the model to the number of samples classified as positive cases, and its formula is as follows:

$$\Pr ecision = \frac{TP}{TP + FP} \tag{12}$$

The check rate represents the proportion of the number of samples correctly classified as positive cases by the model to the total number of positive case samples, and its formula is defined as follows:

$$\operatorname{Re} call = \frac{TP}{TP + FN} \tag{13}$$

The value of F1-score is in the range of $[0,1]$, the closer the value is to 1, the better the model effect is, when the value is 1, it means the model effect is the best, and the value is 0, it means the model effect is the worst:

$$F1-score=\frac{2\times \Pr ecision\times \operatorname{Re}call}{\Pr ecision+\operatorname{Re}call} \tag{14}$$

In the above equation, TP represents the number of positive samples correctly identified, FP represents the number of negative samples incorrectly identified as positive samples, FN represents the number of positive samples incorrectly identified as negative samples, and TN represents the number of negative samples correctly identified as negative samples.

In this study, the number of skill movement categories identified for soccer players is set to K, and the accuracy rate is defined as the ratio of the number of samples predicted as correct by the model to the total number of samples. This allows the calculation of the check accuracy rate, the check completeness rate, and the $F1$ metric for each type of movement, which can be noted as $\left(P_1,R_1,F_1\right),\ldots,\left(P_n,R_n,F1_n\right)$. The results can represent the overall metric when the respective mean values for each type of movement are calculated.

Check accuracy rate:

$$\Pr ecision=\frac{1}{K}\sum_{i=1}^{K}P_i \tag{15}$$

Check the full rate:

$$\operatorname{Re}call=\frac{1}{K}\sum_{i=1}^{K}R_i \tag{16}$$

F1-Metric:

$$F1-score=\frac{1}{K}\sum_{i=1}^{K}F1_i \tag{17}$$

3.1.2. Analysis of visualization experiment results. The confusion matrix, also called the error matrix, is an analytical table used to summarize the predictions of a classification model. It consists of an N × N tabular matrix, where N represents the number of categories, the vertical coordinates represent the true labels (actual action categories), and the horizontal coordinates represent the predicted labels (the output action categories predicted by the sample). The value of the grid where the horizontal and vertical coordinates cross represents the number of the category being predicted as the corresponding label. The confusion matrix of the test set of the soccer sports player action recognition model proposed in this paper based on the deep learning model is shown in Fig. 2, where A-H represent the soccer technical actions of passing, shooting, catching, dribbling over the ball, topping the ball, throwing the ball out of bounds, tackling, and goalkeeping, respectively. The colors on the diagonal in the confusion matrix plot visualize the training effect of the model, while the numerical values represent the number of labels that were correctly predicted. The closer to dark blue color indicates that the model performs better on that category and vice versa. It is obvious from the figure that after model optimization, the performance of the soccer sports player action recognition model designed based on the deep learning model in this paper has been significantly improved. In addition to the diagonal values, the remaining values represent the number of incorrectly predicted labels, and it can be seen through the confusion matrix that the soccer action recognition model proposed in this paper has the relatively highest misrecognition rate for the two types of soccer actions, namely throwing the out-of-bounds ball (13.27%) and goal-keeping (13.33%), and has the highest correct rate of recognizing passes of 98.89%. This provides data support for the application of the model in soccer sports players' action recognition and evaluation system.

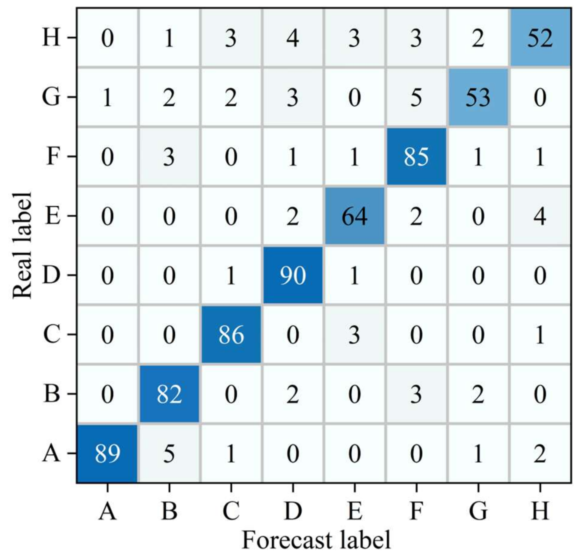

Fig. 2. Model confusion matrix analysis results

3.1.3. Analysis of model comparison results. In this section, ResNet-50, VGG-19 and Inception V3 models are selected as comparison models to further explore the performance of the proposed action skill recognition models based on deep learning. The performance analysis results of each model obtained by analyzing the above proposed model performance evaluation metrics are shown in Table 1. It can be seen that in this experiment, both models, ResNet-50 and Inception V3, have achieved good results, with the checking rate and F1 value reaching 98.92% and 0.953 and 98.23% and 0.948, respectively, but the soccer sports player skill action recognition model proposed in this paper based on the deep learning model performs a little bit better, with the checking rate and F1 value reaching 99.12% and 0.948, respectively. 99.12% and 0.987, which meets the needs of the soccer player skill recognition and evaluation system.

Table 1. Different model performance comparison analysis results

Identification model	ResNet-50	VGG-19	Inception V3	This article
Precision (train)	98.62%	95.42%	97.67%	98.92%
Precision (test)	94.52%	91.26%	93.26%	95.47%
Recall	98.92%	97.52%	98.23%	99.12%
F1-score	0.953	0.924	0.948	0.987

3.2. Validation results of soccer skill assessment algorithm

3.2.1. Analysis of the effectiveness of skills assessment. In this section, the validity of the above proposed soccer skill assessment algorithm was verified by randomly selecting 8 soccer players in this soccer team to perform 8 categories of basic soccer skill movements and scoring them by the assessment algorithm, with the score results retained in two decimal places. The coach assessment scores were the average scores obtained by three professional soccer coaches who scored the athletes' soccer skill movements. The results of the assessment data analysis of soccer sports athletes' skill movements are shown in Table 2. Overall, the assessment scores of soccer coaches on athletes' soccer skill movements are not much different from the assessment scores of the algorithm, and the error scores are within 2 points, and the highest error rate is only 3.28%, which indicates that the effect of the assessment algorithm of soccer skill movements is better.

Table 2. Performance assessment of soccer skills

Skill		Football player number							
		1	2	3	4	5	6	7	8
Passing	Coach	83.42	86.27	85.14	70.56	75.09	82.41	65.83	89.69
	Algorithm	84.78	84.65	83.78	68.98	74.99	82.16	67.6	90.09
Shoot	Coach	81.48	82.6	70.55	70.44	70.02	64.57	68.43	71.81
	Algorithm	79.86	83.86	70.32	72.36	70.81	63.11	67.76	71.89
Catch	Coach	64.53	88.31	86.7	80.2	60.65	89.79	64.1	73.66
	Algorithm	64.37	89.86	86.04	80.72	61.1	90.41	62.15	74
Dribble	Coach	66.93	84.8	62.37	81.26	60.52	80.78	65.78	78.06
	Algorithm	65.18	83.91	60.45	81.29	59.95	79.07	66.22	78.49
Top ball	Coach	72.61	77.41	60.39	89.68	89.03	89.6	89.75	72.74
	Algorithm	74.29	77.02	62.37	91	88.99	91.4	91.34	71.09
Throw-in	Coach	76.11	85.92	75.46	86.31	83.32	73.36	70.69	78.82
	Algorithm	76.22	85.66	74.83	85.37	81.47	73.38	72.46	78.71
Snatch	Coach	84.02	81.5	81.33	66.3	81.39	66.06	79.46	82.43
	Algorithm	85.23	79.78	81.46	66.13	79.79	67.64	80.14	82.3
Gatekeeper	Coach	63.49	84.26	82.11	67.09	77.77	62.75	68.53	77.13
	Algorithm	65.49	83.72	83.48	68.22	76.81	64.7	67.93	77.25

In order to further explore whether the coach assessment scores and the algorithm assessment scores are differentiated, in this section, based on the results of the skill assessment, this paper uses the coach assessment scores and the algorithm assessment scores as the sample variables to conduct the independent samples t-test. In conducting the independent sample t-test, the assumption premise of data normal distribution and variance chi-square needs to be satisfied. In order to conduct the normality test, this paper uses the Shapiro-Wilk test test. In Python, this paper can be calculated using the shapiro() function in the SciPy library. The obtained sequence of coach assessment scores is calculated by the code, and according to the Shapiro-Wilk test, if the p-value is less than the significance level of 0.05, the null hypothesis can be rejected, i.e., the data do not conform to a normal distribution. In this case, the p-value is 0.089 which is greater than 0.05 and hence the null hypothesis cannot be rejected i.e. the data can be considered to conform to a normal distribution. The obtained sequence of algorithmic assessment scores according to the results, the p-value is 0.1462, which is greater than the common significance level of 0.05, therefore the original hypothesis cannot be rejected, i.e. this data set conforms to a normal distribution at a significance level of 0.05. Variance is a statistic that measures the degree of change in a set of data and is obtained by dividing the sum of the squares of the differences between each data value and the mean by the number of data minus one. In order to test whether the variances of the two sets of data are equal, the Levene test can be used. According to the results of Levene's test, the p-value is 0.8725, which is greater than the commonly used significance level of 0.05, and therefore the original hypothesis cannot be rejected, i.e., that the variances of these two sets of data are equal. This paper establishes hypothesis test to determine whether there is a difference between the evaluation scores of the algorithm and the evaluation scores of the coach, H0 is $\mu1=\mu2$, that is, there is no significant difference between the evaluation scores of the coach and the evaluation scores of the algorithm.H1 is $\mu1\neq\mu2$, that is, there is a significant difference between the evaluation scores of the coach and the evaluation scores of the algorithm. The analysis results of the independent samples t-test are tabulated in Table 3. The mean values of the coach assessment scores and the algorithm assessment scores were 76.31 and 76.34, respectively, and the p-value of the F-test was $0.741 \geqslant 0.05$, so the statistical results were not significant, indicating that there was no significant difference between the coach assessment scores samples and the algorithm assessment scores samples, and the Cohen's d-value of the magnitude of the difference was 0.063, which is a very small magnitude of difference. Through the data analysis of the coach's assessment scores and the algorithm's assessment scores, it can be seen that the difference between the two types of assessment scores is not obvious in the assessment scores of 8 types of basic soccer skill movements, and the algorithm's assessment scores of the skill movements of soccer athletes are in line with the coach's objective assessment scores of the movements, and they can satisfy the requirements of the skill identification and the operation of the assessment system.

Table 3. Independent sample t test results

Sample	Coach		Algorithm		Mean difference		T	P	Cohen's d
	Mean value	Total mean	Mean value	Total mean	Mean value	Total mean			
1	74.07	76.31	74.43	76.34	0.36	0.04	1.326	0.741	0.063
2	83.88		83.56		0.32				
3	75.51		75.34		0.17				
4	76.48		76.76		0.28				
5	74.72		74.24		0.48				
6	76.17		76.48		0.31				
7	71.57		71.95		0.38				
8	78.04		77.98		0.06				

3.2.2. Algorithm runtime analysis. Whether the soccer sports athlete skill recognition and assessment system is able to display the athlete's skill assessment score in real time depends on the running time of the algorithm assessment algorithm in the system, so this section analyzes the running time of the skill assessment algorithm, and the results of the algorithm's running time analysis are shown in Fig. 3, the running time of the soccer skill action assessment using the time series dynamic segmentation algorithm based on FastDTW proposed in this paper is is significantly reduced (1.50s on average), and taking into account the characteristics of soccer sub-movements, the judgment of the standard degree of the movement can be more in line with the requirements of soccer skill movements.

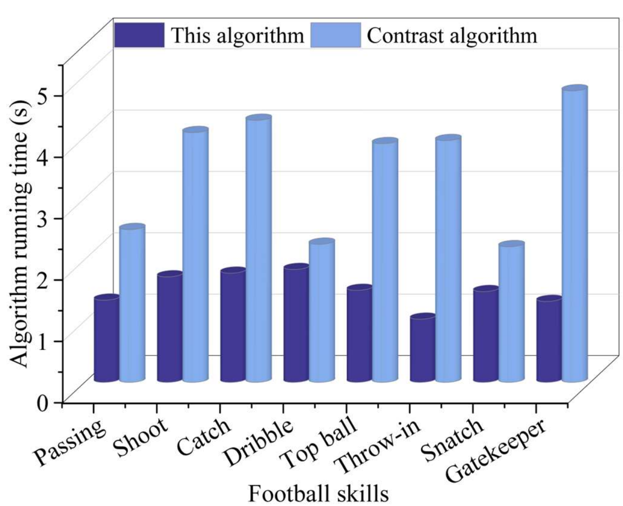

Fig. 3. Algorithm runtime analysis

3.3. Results of the analysis of the empirical application of the system

This paper takes a daily training soccer match of this soccer team as an example, and selects a certain player for soccer skill action data collection to verify the practical application effect of the soccer sports player skill recognition and assessment system. Record all the soccer skill movements of the player in the match by manual means. The results of the skill movement recognition and assessment scores of the soccer player in the game obtained by using the system analysis are shown in Table 4. The average accuracy of soccer skill movement detection situation is 100%, which fully meets the requirements of skill movement recognition. It can be found that the assessment score situation of the player's tackling (99.42 points) in this game is much higher than that of dribbling over the ball (92.35 points), which needs to be instructed by the coaches in the subsequent soccer training. Through the use of the number of soccer skill movements and the actual assessment scores, the subsequent training can be adjusted to make it more suitable for the actual needs of soccer sports players.

Table 4. The results of the system empirical analysis

Action category	Total frequency	Check the correct number of times	Test success rate	Assessment score
Passing	52	52	100%	96.35
Shoot	5	5	100%	97.78
Catch	41	41	100%	96.52
Dribble	16	16	100%	92.35
Top ball	2	2	100%	97.52
Throw-in	0	0	100%	——
Snatch	18	18	100%	99.42
Gatekeeper	0	0	100%	——

4. Conclusion

This paper proposes a method for recognizing and evaluating soccer players' skill movements based on the deep learning model, and combines the two methods to construct a skill recognition and evaluation system for soccer players. The effectiveness and accuracy of the skill movement recognition model and the assessment model are analyzed, and it is found that the performance of the skill movement recognition model for soccer sports players proposed in this paper based on the deep learning model is better than that of other comparative models, with the checking rate and the F1 value of 99.12% and 0.987, respectively. and it is found through the analysis of the data of the coaches' assessment scores and the algorithmic assessment scores that the difference of two types of assessment scores methods in the assessment scores of the 8 types of The difference in the assessment scores of basic soccer skill movements is not obvious ($P>0.05$), indicating that the model meets the operational requirements of the system. After the practical application of the system in soccer training matches, the average accuracy rate of the soccer players' skill movement detection situation is 100%, which fully meets the requirements of skill movement recognition.

The system established in this study can and through the algorithmic model provide soccer sports players and coaches with targeted sports training and athletic management recommendations, effectively improving the efficiency and quality of soccer training.

References

[1] Nusri, A., Prima, A., Ardi, N. F., Ockta, Y., Setiawan, Y., Orhan, B. E., ... & Karaçam, A. (2024). Design of basic football skills test instrument for university students. Retos: nuevas tendencias en educación física, deporte y recreación, (59), 649-657.

[2] Putra, A. N. (2020, August). Developing a Football Basic Techniques Learning Model Through Global Analytical Global Approach. In 1st Progress in Social Science, Humanities and Education Research Symposium (PSSHERS 2019) (pp. 331-334). Atlantis Press.

[3] Sarmento, H., Anguera, M. T., Pereira, A., & Araújo, D. (2018). Talent identification and development in male football: A systematic review. Sports medicine, 48, 907-931.

[4] Yiannaki, C., Carling, C., & Collins, D. (2018). Futsal as a potential talent development modality for soccer–a quantitative assessment of high-level soccer coach and player perceptions. Science and Medicine in Football, 2(4), 299-308.

[5] Vaughan, J., Mallett, C. J., Potrac, P., Woods, C., O'Sullivan, M., & Davids, K. (2022). Social and cultural constraints on football player development in Stockholm: influencing skill, learning, and wellbeing. Frontiers in Sports and Active Living, 4, 832111.

[6] Putra, A. N., Zarya, F., & Bahtra, R. (2023). The Development of a differentiation-based learning model in football school students. Journal of Physical Education and Sport, 23(12), 3282-3291.

[7] Pruna, R., Miñarro Tribaldos, L., & Bahdur, K. (2018). Player talent identification and development in football. Apunts Sports Medicine, 53(198), 43-46.

[8] Sivrikaya, M. H. (2018). The Role of Self-Efficacy on Performance of Sports Skills of Football Players. Journal of Education and Training Studies, 6(n12a), 75-79.

[9] Mahfud, I., & Fahrizqi, E. B. (2023). Development of Soccer Passing Training Models with Play Method for Base School Beginners. JOURNAL SPORTINDO, 1(1), 15-22.

[10] Larkin, P., Mesagno, C., Berry, J., Spittle, M., & Harvey, J. (2018). Video-based training to improve perceptual-cognitive decision-making performance of Australian football umpires. Journal of sports sciences, 36(3), 239-246.

[11] Gledhill, A., Harwood, C., & Forsdyke, D. (2017). Psychosocial factors associated with talent development in football: A systematic review. Psychology of Sport and Exercise, 31, 93-112.

[12] Klingner, F. C., Huijgen, B. C., Den Hartigh, R. J., & Kempe, M. (2022). Technical–tactical skill assessments in small-sided soccer games: A scoping review. International Journal of Sports Science & Coaching, 17(4), 885-902.

[13] Rojas Ferrer, C. D., Shishido, H., Kitahara, I., & Kameda, Y. (2020). Read-the-game: System for skill-based visual exploratory activity assessment with a full body virtual reality soccer simulation. PloS one, 15(3), e0230042.

[14] Koopmann, T., Faber, I., Baker, J., & Schorer, J. (2020). Assessing technical skills in talented youth athletes: a systematic review. Sports Medicine, 50, 1593-1611.

[15] Hendry, D. T., Williams, A. M., & Hodges, N. J. (2018). Coach ratings of skills and their relations to practice, play and successful transitions from youth-elite to adult-professional status in soccer. Journal of Sports Sciences, 36(17), 2009-2017.

[16] Murr, D., Larkin, P., & Höner, O. (2021). Decision-making skills of high-performance youth soccer players: Validating a video-based diagnostic instrument with a soccer-specific motor response. German Journal of Exercise and Sport Research, 51(1), 102-111.

[17] Machado, G., & Da Costa, I. T. (2020). TacticUP video test for soccer: development and validation. Frontiers in Psychology, 11, 1690.

[18] Rechenchosky, L., Menegassi, V. M., Jaime, M. D. O., Borges, P. H., Sarmento, H., Mancha-Triguero, D., ... & Rinaldi, W. (2021). Scoping review of tests to assess tactical knowledge and tactical performance of young soccer players. Journal of sports sciences, 39(18), 2051-2067.

[19] Yin, X., Vignesh, C. C., & Vadivel, T. (2022). Motion capture and evaluation system of football special teaching in colleges and universities based on deep learning. International Journal of System Assurance Engineering and Management, 13(6), 3092-3107.

[20] McCalman, W., Crowley-McHattan, Z. J., Fransen, J., & Bennett, K. J. (2022). Skill assessments in youth soccer: A scoping review. Journal of sports sciences, 40(6), 667-695.

[21] Aquino, R., Puggina, E. F., Alves, I. S., & Garganta, J. (2017). Skill-related performance in soccer: a systematic review. Human Movement Special Issues, 2017(5), 3-24.

[22] Bennett, K. J., Novak, A. R., Pluss, M. A., Stevens, C. J., Coutts, A. J., & Fransen, J. (2018). The use of small-sided games to assess skill proficiency in youth soccer players: A talent identification tool. Science and Medicine in Football, 2(3), 231-236.

[23] Bergmann, F., Gray, R., Wachsmuth, S., & Höner, O. (2021). Perceptual-motor and perceptual-cognitive skill acquisition in soccer: a systematic review on the influence of practice design and coaching behavior. Frontiers in psychology, 12, 772201.

[24] Otte, F. W., Millar, S. K., & Klatt, S. (2019). Skill training periodization in “specialist” sports coaching—an introduction of the “PoST” framework for skill development. Frontiers in sports and active living, 1, 483383.

[25] Atradinal, A., & Ockta, Y. (2024). How do the STAD cooperative learning model, conventional methods, and student confidence affect football learning outcomes?. Jurnal Konseling Dan Pendidikan, 12(3), 112-121.

[26] Jiuxiang Dai,Yangfan Luo,Shenye Shi,Dantong Yang & Zuoxi Zhao. (2024). Design and experimental evaluation of an intelligent sugarcane stem node recognition system based on enhanced YOLOv5s. Multimedia Systems(6),324-324.

[27] Mengchen Liu,Wenbai Chen,Jiajing Cheng,Yiqun Wang & Chunjiang Zhao. (2024). Y-HRNet: Research on multi-category cherry tomato instance segmentation model based on improved YOLOv7 and HRNet fusion. Computers and Electronics in Agriculture(P1),109531-109531.

[28] Changjiang Niu. (2024). The application of improved DTW algorithm in sports posture recognition. Systems and Soft Computing200163-200163.

[29] Hamdi Hassen & Maher Khemakhem. (2013). Large Distributed Arabic Handwriting Recognition System based on the Combination of FastDTW Algorithm and Map-reduce Programming Model via Cloud Computing Technologies. AASRI Procedia156-163.