ICA-Enhanced YOLOv5-AdaBoost Framework for Player Localization in Semi-Automatic Offside Detection

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As the rules of football matches become more and more strict, the traditional position information capture technology cannot accurately carry out the problem of athletes' position information capture. To address this problem, this study proposes an adaptive sample size method based on dynamic sample weight optimization. This method focuses on improving the AdaBoost algorithm's sample weighting mechanism and combining YOLOv5's object detection capability with the Empire Competition algorithm's global optimization characteristics to create an athlete position information capture platform. The experimental results showed that in the campus football game dataset, the average absolute error value of the proposed algorithm was 0.086, and the root mean square error was 0.049, which was 0.211 and 0.119 lower than YOLOv4, respectively. Under 100 sets of experimental datasets, the average accuracy of the proposed algorithm reached 96.18%, which is 5.93% higher than the YOLOX Nano algorithm. In the SoccerReplay dataset, the capture platform designed by the research had an occupancy rate of 5.139% and a packet loss rate of 2.367%. These rates were reduced by 19.753% and 35.06%, respectively, compared to YOLOv5s. The above results show that the study of the mention capture technique can capture the positional information of the athletes more accurately and with higher capture accuracy in football SEMI-automatic offside detection.

Povzetek: Predstavljen je nov pristop ICA-YOLOv5-AdaBoost z adaptivnim številom vzorcev za lokalizacijo igralcev vprepovedanem položaju (offside).

1 Introduction

As the times change, people's lives become increasingly prosperous, and more and more people are passionate about sports like football, basketball, and table tennis [1]. As a world-famous ball game, football has the characteristics of strong confrontation and large number of participants, which have led to the increasing audience of football in different age groups [2-3]. As football becomes more and more popular, the rules of football tournaments become more and more strict. However, due to the gradual increase in the size of the football playing field, the referee is not able to make the offside judgment of the player better, and the audience is not able to watch the football events better. Therefore, how to capture the position information of football players has become a great challenge. In today's rapidly developing artificial intelligence technology, machine learning algorithms and new technologies can help referees and audiences capture positional information of football players. It has become a hot research topic how to utilize these new technologies to capture athletes' position information. Numerous researches on the technology used to record athletes' position data have been carried out by academics both domestically and internationally. For example, Ahmad et al. proposed a position coding classification method for hyperspectral images, which improved the classification performance by introducing an implicit conditional scheme and integrated cross attention for global position capture [4]. Gao et al. proposed multilevel feature synthesis for location capture, which increased the information density by spreading multiple output channel features over a single image and expanded the execution data to improve robustness [5]. Li et al. proposed methods to capture image sensors for robot shape capture by using passive tendon displacements for robot bending and twisting calculations and modeling the robot shape [6]. However, these methods are less accurate and efficient at capturing player positions in football stadiums with many parametric targets. These stadiums have complex and diverse personnel, including referees and spectators, in addition to football players. Therefore, a technique to record football players' position information is desperately needed.

In the process of athlete position information capture, it is required to have high accuracy for motion position detection and to be able to capture multi-target position information [7-8]. In athlete position information capture technology, YOLO series of target detection algorithms can accurately identify targets with high recognition accuracy [9-10]. Adaptive boosting (AdaBoost), as an iterative algorithm, does not have to select the target features when performing sample processing and can avoid overfitting during the working process [11-12]. However, AdaBoost algorithm also has the shortcomings of longer training time and more sensitive to noise [13]. Therefore, many scholars at home and abroad have made many improvements to AdaBoost algorithm. For example, Zheng et al. proposed AdaBoost for scene segmentation prediction by combining deep model learning with adaptive enhancement, and interacting with the learning model as well as the data sampler [14]. Kuo et al. proposed an AdaBoost-based approach for chatter cutting data analysis by converting accelerometer data into bandwidths and modeling temporal acceleration and temporal spectral bandwidth learning [15]. Imperialist competitive algorithm (ICA), as a heuristic algorithm, has a stronger ability for global search and is not easy to fall into the trap of local optimal solution. Moreover, its convergence speed to data is faster, and combining with AdaBoost algorithm further improves the ability of capturing athletes' position information [16-17]. Aiming at the problems of low offside detection accuracy and low detection efficiency of football players raised by domestic and foreign research scholars, the study introduces YOLOv5 algorithm for target detection of athletes, and combines with AdaBoost algorithm for position capture of athletes. Finally, ICA is integrated to construct the target position detection platform, which is expected to improve the detection accuracy and efficiency of football players' position information. The research aims to address the insufficient accuracy and efficiency of existing technologies in high-density player scenarios. The core question is whether the YOLOv5-AdaBoost algorithm, based on ICA optimization, can achieve lower mean absolute error (MAE) in such scenarios. To achieve this goal, the research's capture platform must significantly improve the accuracy and response speed of capturing athlete location information while ensuring a low packet loss rate. The proposed method provides a kind of technical support for the field of soccer semi-automatic offside detection, and provides a reference basis for domestic and foreign scholars to carry out research in the field of target detection, and promotes the development of soccer offside detection technology.

The study is divided into 4 sections in total. Section 1 is a review of the current state of domestic and international research on offside position information capture technology for football players. Section 2 is the design of the player position information capturing platform using the adaptive sample number method combined with target detection. Section 3 is an analysis of the empirical effect of football players' position information capturing technology. Section 4 is the summary and discussion of the whole article.

2 Methods and materials

2.1 Improved adaptive sample number method based on YOLOv5 algorithm for location information capture

As science and technology have advanced, semi-automatic offside identification in football has been made possible by the ability to record athletes' positional data [18-19]. However, the existing technology is unable to capture and recognize the specific position information of athletes more accurately. To address this problem, the study introduces the adaptive sample number method that can reduce the consumption of computational resources and effectively improve the performance of the model. It captures and recognizes the position information of athletes in football semi-automatic offside detection to improve the accuracy of position information recognition. The adaptive sample size method is a strategy that optimizes model training efficiency and accuracy by dynamically adjusting sample weights and distributions. Its core mechanisms include adaptive sample weighting, global distribution optimization, and collaborative object detection. Among them, the sample weight adaptive mechanism is based on the AdaBoost algorithm. During iterative training, the weights are dynamically adjusted according to the difficulty of classifying samples, allowing the model to focus on those that are difficult to classify. The global distribution optimization mechanism uses the ICA to globally optimize the sample space, avoiding local optima and improving sample utilization. The collaborative mechanism for object detection uses YOLOv5 to efficiently locate weighted samples and accurately capture location information. The AdaBoost algorithm has high stability and can effectively improve the learning efficiency, which greatly improves the efficiency of target position capture [20-21]. In football semi-automatic offside detection, the AdaBoost algorithm is utilized in the capture recognition of athlete position information. Calculating the cumulative value of the image pixels representing the athlete's position information is the first step. This value can be represented mathematically using Equation (1).

$$Z = z + \left| f\left(x, y\right) - f\left(x-2, y\right) \right| \quad (1)$$

In Equation (1), $f\left(x,y\right)$ denotes the position image and z denotes the initial variable. It is also calculated for the distribution of the pixel points of the position image, as shown in Equation (2).

$$U = \max\left\{cout / 256, u_{\min}\right\} \quad (2)$$

In Equation (2), $u_{\min}$ denotes the distribution slope. Equation (3) is then used to calculate the picture information of the athlete's position.

$$\ln En = -\sum_{i=0}^{255} p\left(i\right) \log_2 p\left(i\right) \quad (3)$$

In Equation (3), $p\left(i\right)$ denotes the pixel point distribution probability. Next, the average degree of the athlete position image is calculated, as expressed in Equation (4).

$$m = \sum_{k=0}^{L-1} r_k p\left(r_k\right) \quad (4)$$

In Equation (4), r_k represents the distance between the positions of the athletes. Then the difference of the average degree of the image is calculated, as expressed in Equation (5).

$$C = abs\left[L_t - L_b\right] \quad (5)$$

In Equation (5), L_t denotes the predicted difference. L_b denotes the actual difference. Finally, the average contrast of the athlete's image is calculated and its mathematical expression is shown in Equation (6).

$$AC = \frac{1}{\sqrt{2}}\sqrt{AC_x^{\ 2} + AC_y^{\ 2}} \quad (6)$$

In Equation (6), AC denotes the average contrast. Through the above steps, the specific flow of capturing and recognizing the athlete's position information using AdaBoost algorithm is obtained. The flow is shown in Figure 1.

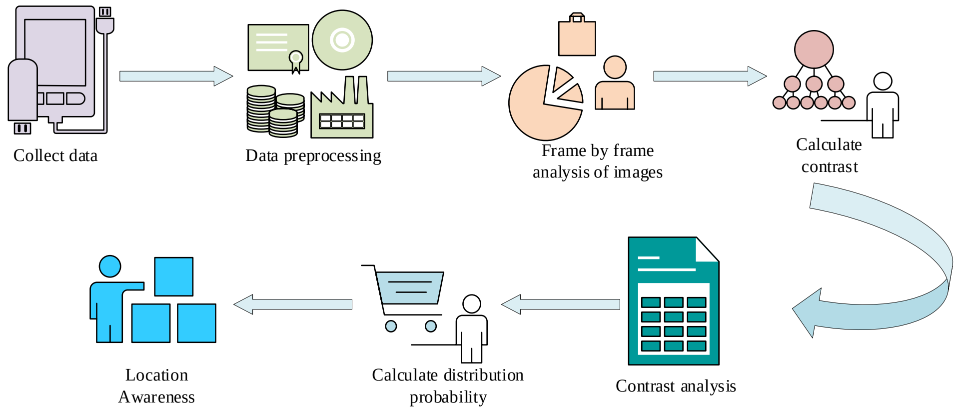


Figure 1: Process of AdaBoost algorithm capturing athlete position information

In Figure 1, the AdaBoost algorithm is utilized in capturing and recognizing the position information of the athlete in football semi-automatic offside detection at first. Then the position image of the athlete is analyzed frame by frame to realize the contrast of the image pixel points. After that, the distribution probability of the pixel points is calculated based on the contrast of the position pixel points. Finally, the position information of the athlete is recognized and analyzed based on the distribution probability and contrast of the position image. The use of AdaBoost algorithm can capture and recognize the position information of athletes, and the recognition accuracy of position information is high. However, when the AdaBoost algorithm is used to capture and recognize the position information of athletes, the AdaBoost algorithm is unable to optimize the parameters of the position information and is easily affected by external noise. The study introduces the YOLOv5 algorithm to make up for the shortcomings of the AdaBoost algorithm. The YOLOv5 algorithm can flexibly tune the parameters and has a high recognition accuracy, which enables target capture with high accuracy [22]. Figure 2 illustrates the YOLOv5 algorithm's basic structure, which can be used to enhance the AdaBoost algorithm.

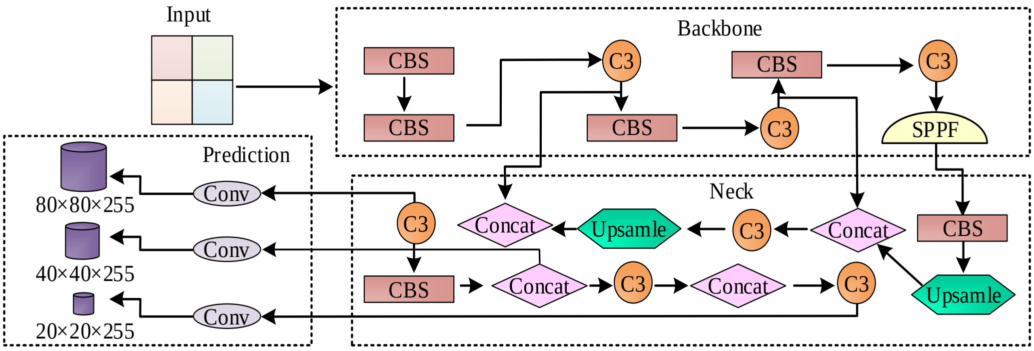


Figure 2: YOLOv5 algorithm structure diagram

In Figure 2, the basic structure of the YOLOv5 algorithm is mainly composed of three parts: the backbone network, the feature fusion layer (FFL), and the detection head [23]. The backbone network is mainly used to preprocess the images collected by the convolutional layer and pooling layer, and to extract and classify the important information in the images. Then the extracted feature information is transmitted to the FFL, and the feature information of the FFL is up-sampled and fused. Finally, the different features of the detected target are fused and converted by the detection head and the final target detection is performed. Based on the basic structure of the YOLOv5 algorithm, the YOLOv5 algorithm is utilized to improve the AdaBoost algorithm. The first step is to calculate the three loss functions (LFs) for classification, targeting and localization. Its calculation formula is shown in Equation (7).

$$Loss = \lambda_1 L_{cls} + \lambda_2 L_{obj} + \lambda_3 L_{loc} \qquad (7)$$

In Equation (7), L_{cls}, L_{obj}, and L_{loc} denote classification loss, target loss, and localization loss, respectively. AdaBoost dynamically adjusts sample weights to focus the model on difficult to classify samples. It is assumed there are N samples in the training set with an initial weight of $w_i, i = 1, 2, ..., N$. Weights are updated through iterative training. In YOLOv5's loss calculation, sample weights directly impact the loss term of each sample. For example, the weighted LF for classification loss is shown in formula (8).

$$L_{cls} = -\sum w_i \left[y_i \log(p_i) + (1 - y_i)\log(1 - p_i) \right] \qquad (8)$$

Similarly, target loss and localization loss are also weighted according to sample weights. Among them, the three LFs are utilized in the recognition of the image pixels of AdaBoost algorithm, mainly through the LF value of its pixels for feature recognition calculation. Its LF values is shown in Equation (8).

$$F_{GIoU\_Loss} = F_{IoU\_Loss} - \left(\frac{C - A \bigcup B}{C}\right) \qquad (8)$$

In Equation (8), F_{IoU_Loss} denotes the value of the intersection and merger ratio LF. A denotes the prediction frame (PF) of the pixel point. B denotes the true frame of the pixel point. C denotes the minimum range frame that contains the A and B. Then the combined loss value is calculated for the pixel points with different location information, as expressed in Equation (9).

$$F_{DIoU\_Loss} = 1 - \left(F_{IoU\_Loss} - \frac{F_{Distance}{}^2}{F_{Distance\_C}{}^2}\right) \qquad (9)$$

In Equation (9), $F_{Distance}$ denotes the position where the PF reaches the center of the distance. $F_{Distance\_C}$ denotes the diagonal distance between the target real frame and the PF. Next, the boundary prediction target of the YOLOv5 algorithm is calculated as shown in Equation (10).

$$\begin{cases} b_x = (2 \cdot \sigma(t_x) - 0.5) + c_x \\ b_y = (2 \cdot \sigma(t_y) - 0.5) + c_y \end{cases} \qquad (10)$$

In Equation (10), b_x and b_y denote the center position. c_x and c_y denote the recognition coordinate points. The YOLOv5 algorithm then primarily computes the similarity between the actual recognition frame and the PF in an attempt to enhance the recognition similarity of the AdaBoost algorithm, as expressed in Equation (11).

$$v = \frac{4}{\pi^2}\left(\arctan\frac{w_t}{h_t} - \arctan\frac{w_p}{h_p}\right) \qquad (11)$$

In Equation (11), w_t denotes the image recognition true width. h_t denotes the image recognition true height. w_p and h_p denote the predicted width and height of image recognition respectively. By improving the AdaBoost algorithm using YOLOv5 algorithm, the improved AdaBoost algorithm, i.e., YOLOv5-AdaBoost algorithm, is obtained. In football semi-automatic offside detection, the YOLOv5-AdaBoost algorithm is utilized in capturing the position information of athletes for identification. The process of capturing its specific position information is shown in Figure 3.

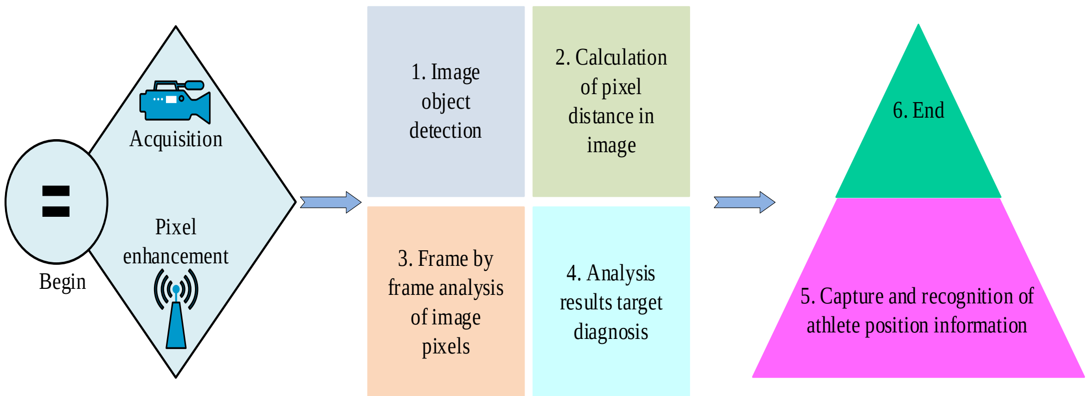


Figure 3: The process of YOLOv5 AdaBoost algorithm capturing location information

As shown in Figure 3, the AdaBoost algorithm is primarily used for denoising and preprocessing the input data to improve the quality of the training data for YOLOv5 when integrated with it. Specifically, the AdaBoost algorithm assigns higher weights to samples that are difficult to classify. This allows YOLOv5 to pay more attention to these samples during training. Additionally, AdaBoost processes the input image to enhance features, highlighting the contours and features of athletes. This enables YOLOv5 to more effectively extract position features, thereby improving detection accuracy. The YOLOv5-AdaBoost algorithm is utilized in the capture of the positional information of the athlete. First, the image of the athlete is collected by using the camera instrument and the image pixel points of the movement are enhanced by using the AdaBoost algorithm. Then the YOLOv5 algorithm is used to detect the target of the image and calculate the distance between the image pixels. After that, the image pixels processed by AdaBoost algorithm and YOLOv5 algorithm are analyzed frame by frame and the results are analyzed for target diagnosis. Finally, the athlete's final position information is obtained. The capturing system captures and recognizes the specific position information to achieve more accurate capture and recognition.

2.2 Athlete position capture platform incorporating ICA's improved number of samples approach

The YOLOv5-AdaBoost algorithm can successfully avoid the interference of external noise components while recognizing and capturing the athletes' position information. However, the YOLOv5-AdaBoost algorithm is unable to accurately capture and recognize the specific position information of each athlete when capturing the position information of the sports hall. To address this problem, the study introduces ICA to improve the YOLOv5-AdaBoost algorithm to make up for the shortcomings of the YOLOv5-AdaBoost algorithm. It is mainly due to the fact that ICA can enhance the population diversity and has a strong global search capability (GSC) [24-25]. Using ICA in the improvement of YOLOv5-AdaBoost algorithm, its specific improvement process is shown in Figure 4.

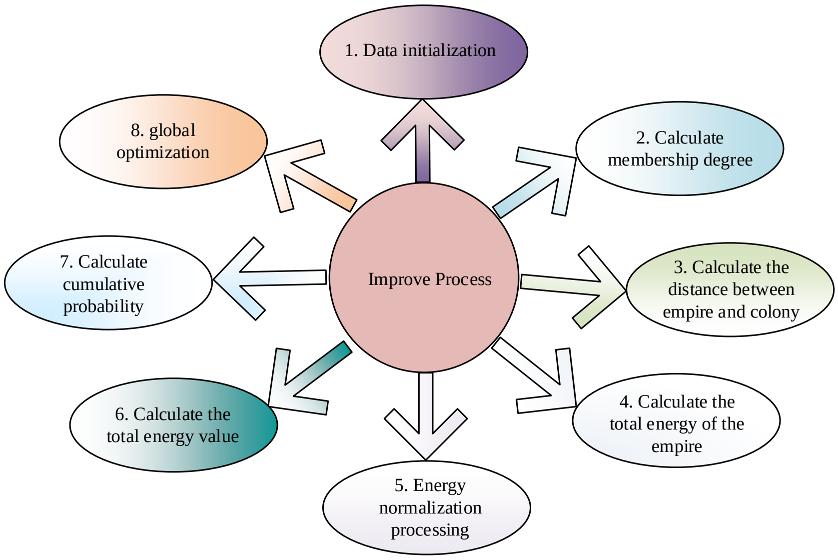


Figure 4: Process of ICA improving YOLOv5 AdaBoost algorithm

In Figure 4, the specific process of ICA improved YOLOv5-AdaBoost algorithm is as follows. First, the empires are initialized and the value of the affiliation function is calculated. Then the distance between empire and colonization is calculated and the total energy of different empires is calculated. Next, the total energy is normalized and the cumulative probability is calculated for the normalized total energy. Finally, the YOLOv5-AdaBoost algorithm is processed for global optimization by the final cumulative probability in an attempt to improve the GSC of the YOLOv5-AdaBoost algorithm. It is assumed the number of empires is n, each empire represents a candidate solution. At the beginning of each empire, M colonies are allocated, which are distributed around the center of the empire and represented the neighborhoods of the solution. First, randomly initialize the position of each empire to ensure population diversity. Subsequently, the fitness values of each empire and its colonies are calculated to measure the quality of each solution. This study uses the objective function value as the fitness indicator. Then, it is iterated and optimized. During the iteration process, each empire expands according to its fitness value. Empires with higher fitness values attract more colonies. Colonies will move according to the location and gravity of the empire. After each iteration, the empire with the lowest fitness will be annexed and its colonies will be assigned to other empires. Meanwhile, the empire with the highest adaptability may split into new empires. The algorithm terminates when either the preset iteration count T is reached or the fitness change is less than the threshold. The combination of the empire and its colonies with the highest fitness is then considered the global optimal solution. Among them, in the initialization process of empire, the first step is to calculate the empire allocation equation of ICA. Its mathematical expression is shown in Equation (12).

$$C_n = c_n - \max\{c_i\} \tag{12}$$

In Equation (12), c_n denotes the target value, and then the distribution equation is normalized. The mathematical expression is shown in Equation (13).

$$P_n = \frac{C_n}{\sum_{i=1}^{N_{imp}} c_i} \tag{13}$$

In Equation (13), P_n denotes the normalized equation. Then the moving distance between different empires is calculated, and its calculation formula can be expressed in Equation (14).

$$X \sim U(0, \beta * d) \tag{14}$$

In Equation (14), β denotes any real number and d

denotes distance. Finally, the combined value between the different imperial forces is calculated, as expressed in Equation (15).

$$T.C._n = \operatorname{Cos}(imperialist_n) + \xi mean\{\operatorname{Cost}(colonies_n)\} \quad (15)$$

In Equation (15), ξ is the weight value and n is the quantity of empires. The improved YOLOv5-AdaBoost algorithm is obtained by ICA, i.e., ICA-YOLOv5-AdaBoost algorithm. Figure 5 illustrates this algorithm's fundamental structure.

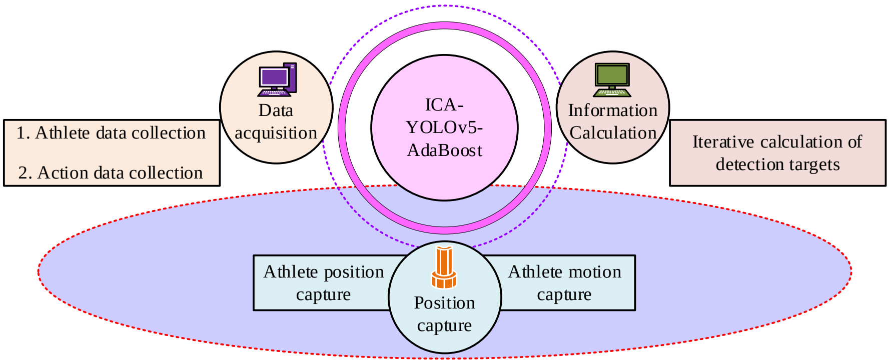


Figure 5: Basic structure of ICA-YOLOv5 AdaBoost algorithm

In Figure 5, the basic structure of ICA-YOLOv5-AdaBoost algorithm is mainly composed of three parts: data acquisition, information calculation, and information capture. The ICA-YOLOv5-AdaBoost algorithm works by firstly capturing the athlete's position information as well as movement information. Subsequently, the information obtained from the acquisition is computed and iterated. Finally, the athlete position as well as movement is captured. The ICA-YOLOv5-AdaBoost algorithm has a better recognition and analysis effect. Therefore, to capture and recognize the position information of athletes more comprehensively, the study applies the ICA-YOLOv5-AdaBoost algorithm in the field of capturing and recognizing the position information of athletes. This can realize a more accurate recognition of the position information of athletes. Among them, for better application of ICA-YOLOv5-AdaBoost algorithm in the field of position information capture and recognition, the study analyzes the process of athletes' position information capture. Its specific process is shown in Figure 6.

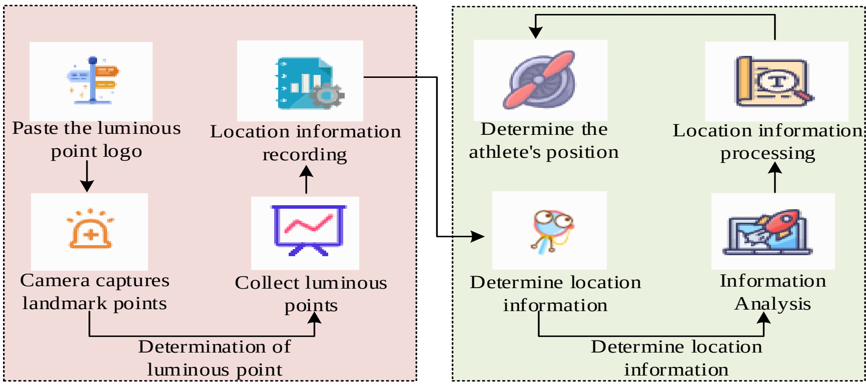


Figure 6: Specific process of capturing athlete position information

In Figure 6, the process of capturing the position information of the athlete is as follows. First, the luminous marking point is pasted on the athlete's body, and the luminous marking point is captured by using a camera instrument with high precision. Then the capturing system is used to collect the recognized luminous marking points in an effort to record the positional changes of the marking points. Then, based on the positional changes of the luminous points, the specific positional information of the athletes in football semi-automatic offside detection is determined. Finally, the final athlete's position information is processed using a computer. To capture and recognize the position information of athletes more accurately and comprehensively, this study constructs a platform for capturing the position information of athletes in semi-automatic offside detection in football. It is based on the process of capturing athletes' position information and combines the recognition advantages of ICA-YOLOv5-AdaBoost algorithm. In constructing the athlete position information capturing platform, the first step is to calculate the weight value of the recognized information. Its mathematical expression is shown in Equation (16).

$$idf(i) = \log \frac{N}{n_i} \quad (16)$$

In Equation (16), N denotes the identification information of the location. n_i denotes the information point. The similarity of the location information is also calculated, as expressed in Equation (17).

$$s(v_1, v_2) = \left| \frac{v_1}{|v_1|} - \frac{v_2}{|v_2|} \right| \quad (17)$$

In Equation (17), v_1 and v_2 denote information vectors. The specific structure of the athlete position information capturing platform is shown in Figure 7.

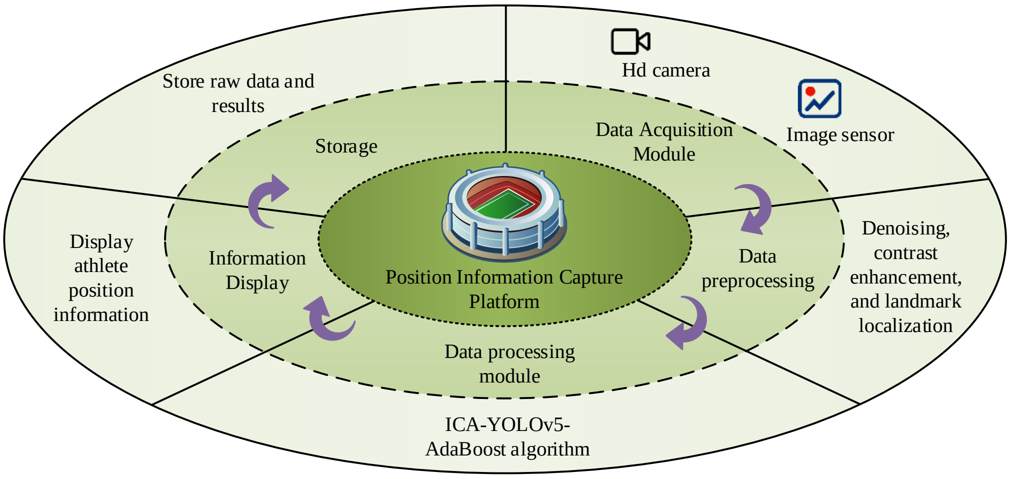


Figure 7: Schematic diagram of the basic structure of the athlete position information capture platform

Figure 7 shows that the athlete position information capture platform uses the ICA-YOLOv5 AdaBoost algorithm and integrates software and hardware components. It consists of five main modules: data acquisition, data preprocessing, data processing, information display, and storage. The data acquisition module consists of multiple high-definition cameras that are deployed in different locations around the football field. Each camera is equipped with a high-precision image sensor. The data processing module uses the ICA-YOLOv5-AdaBoost algorithm to accurately identify and record the positions of the athletes. The information display and storage module present processed athlete position information to users in an intuitive way and stores raw data and results for later analysis. The high-speed HDMI interface protocol is used between the data acquisition and processing modules to meet real-time transmission requirements. The data processing module communicates with the information display and storage module through the computer's internal bus architecture.

3 Results

3.1 Performance validation of YOLOv5-AdaBoost algorithm

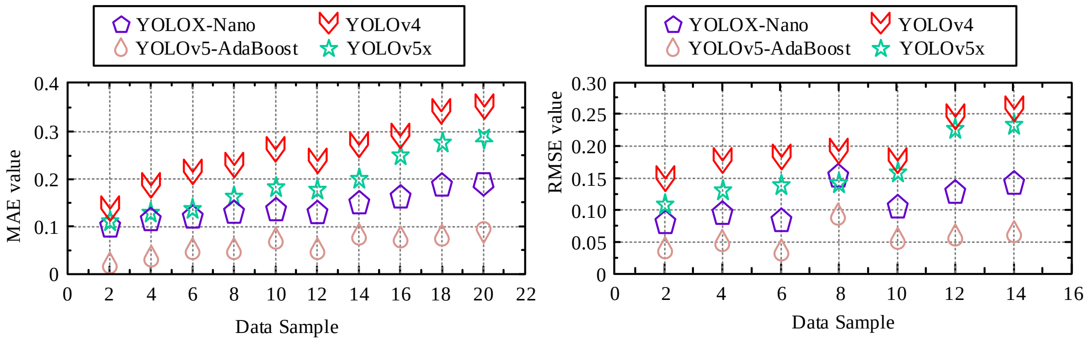
To analyze the performance of YOLOv5-AdaBoost algorithm, the study is conducted in MATLAB software for experiments. Table 1 displays the experimental setup.

Table 1: Experimental equipment environment

Project	Content
Memory	16GB
CPU	Intel Core Ultra 7 265K
Graphics card	GTX 1650 Super
System	Windows 10
ConFigure environment	MATLAB R2022a
Programming language	Python

To verify the effectiveness of the YOLOv5-AdaBoost algorithm, a total of 200 sets of data are collected by collecting data from the 2023 Campus Football Games of Sichuan Agricultural University. The training set consists of 150 data sets, while the test set consists of the remaining 50 data sets. The sports meet is mainly captured by multiple high-definition cameras with a resolution of 1920x1080. These cameras can clearly capture the details of the athletes' movements and the venue. The sports meet is held during the day, so there is abundant natural light. However, due to weather changes and site obstructions, some areas have uneven lighting. This provides diverse lighting conditions for testing the algorithm. In addition, the stadium has complete lighting facilities, providing good basic lighting conditions for image acquisition. Cameras are placed at various locations around the sports field to capture the competition from multiple angles and obtain comprehensive information about the athletes' positions.

YOLOv5s algorithm, CG-YOLOv4 algorithm, and YOLOX-Nano algorithm are introduced. All models are trained using data collected from the 2023 Sichuan University Campus Games, with an initial learning rate of 0.01, batch size of 16, input image size of 640×640, and epoch of 300. The accuracy, MAE, root mean square error (RMSE), accuracy-recall curve, and recall are also used as performance metrics for algorithm performance comparison experiments. The position capture error of the proposed YOLOv5-AdaBoost algorithm is verified and compared with the rest of the algorithms. Figure 8 displays the outcomes of the experiment.



(a) Comparison of MAE accuracy of different algorithms

(b) Comparison of RMSE accuracy of different algorithms

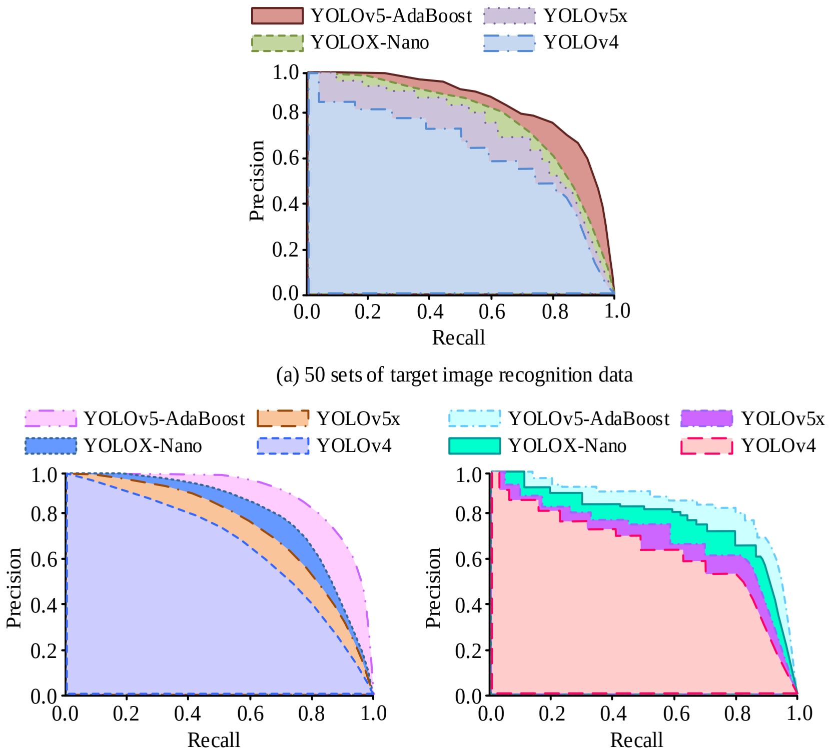
Figure 8: Comparison of error values of different algorithms

In Figure 8(a), the YOLOv5-AdaBoost algorithm shows a significant advantage when the four algorithms capture the position information of the athlete, and the average MAE value of this algorithm is the lowest, with only 0.086. While the average MAE value of YOLOv4 algorithm is the highest of 0.297. The average MAE value of YOLOv5x algorithm is 0.174. Although it is significantly lower than the other two algorithms, it is significantly higher than YOLOv5-AdaBoost algorithm and 0.088 higher than YOLOv5-AdaBoost algorithm. It shows that the YOLOv5-AdaBoost algorithm possesses lower error values than the other three algorithms. In Figure 8(b), the YOLOv5-AdaBoost algorithm possesses a lower RMSE value than the other three algorithms when the comparison of RMSE values is performed. Its average RMSE value is the lowest, with only 0.049. The average RMSE values of YOLOv5x, YOLOX-Nano, and YOLOv4 algorithms are 0.149, 0.107, and 0.168, respectively, which are 0.100, 0.058, and 0.078 higher than that of YOLOv5-AdaBoost algorithm. It shows that YOLOv5-AdaBoost algorithm possesses lower RMSE values than the other three algorithms. It can be concluded that the YOLOv5-AdaBoost algorithm has a lower error value than the other three algorithms when the four algorithms capture the position information of the athletes and the effectiveness of the algorithm is verified. Keeping the original experimental parameters unchanged, the experiment is repeated using 5 different random seeds (seed=0, 1, 2, 3, 4) to ensure random initialization of differences during training. MAE values are recorded for each experiment and the mean MAE and standard deviation are calculated for each algorithm. 95% confidence intervals are calculated based on the t-distribution. The MAE comparison of the above four algorithms is shown in Table 2.

Table 2: Comparison of MAE for four algorithms

Algorithm	MAE	95% confidence interval	*p*-value (And YOLOv5-AdaBoost)
YOLOv4	0.297±0.036	[0.261, 0.333]	0.000
YOLOv5s	0.174±0.022	[0.152, 0.196]	0.000
YOLOX-Nano	0.107±0.014	[0.093, 0.121]	0.034
YOLOv5-AdaBoost	0.086±0.012	[0.074, 0.098]	-

As shown in Table 2, the MAE value of the YOLOv5 AdaBoost algorithm is the smallest at 0.086±0.012, which is significantly lower than those of the other three algorithms (p<0.05). The fluctuation range is the smallest, with a standard deviation of only 0.012. This indicates better accuracy and stability compared to the comparative algorithm. Later, to verify the performance advantages of YOLOv5-AdaBoost algorithm, the study compares YOLOv5-AdaBoost algorithm with YOLOv5x, YOLOX-Nano, and YOLOv4 algorithms. Performance trials with accuracy-recall curves are carried out, and the outcomes are contrasted and examined. Figure 9 displays the outcomes of their comparative experiments.



(a) 50 sets of target image recognition data

(b) 100 sets of target image recognition data

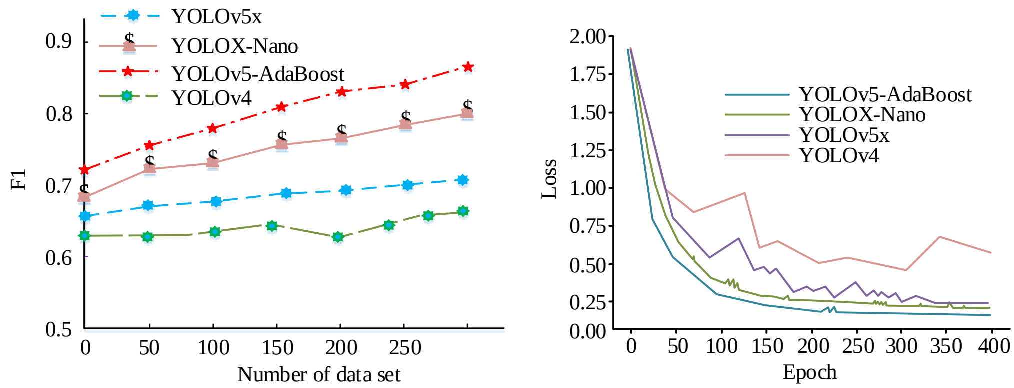
(c) 150 sets of target image recognition data

Figure 9: Comparison of PR curves of different algorithms

In Figure 9(a), the YOLOv5-AdaBoost algorithm shows a significant advantage in the experiment using 50 sets of data. Furthermore, the PR curve area of this algorithm is 0.9782, which is significantly higher than the remaining three algorithms. The YOLOX-Nano algorithm has a PR curve area below the line (ABL) of 0.9024 under this data condition. Its ABL is slightly lower than that of the research mention algorithm by 0.0758, but its ABL is significantly higher than the remaining two algorithms. The area under the line (AUL) of the PR curve of YOLOv4 is only 0.6189, which is significantly lower than the other three algorithms and 0.3593 lower than the YOLOv5-AdaBoost algorithm. In Figure 9(b), under the condition of 100 sets of test data, the AUL of the PR curve for the YOLOv5-AdaBoost algorithm is 0.9628, while the AUL of the PR curve for the YOLOX-Nano algorithm is 0.9204. Although it is significantly higher than the other two algorithms under the condition of this experimental data, it is lower than that of the research proposed algorithm by 0.0424. The YOLOv5x and YOLOv4 algorithms have a PR curve AUL of 0.8615 and 0.7437, respectively. Compared to the YOLOv5-AdaBoost algorithm, the PR curve AUL is lower by 0.1013 and 0.2191, respectively. In Figure 9(c), when 150 sets of data are selected for the experiment, the AUL of the PR curve of the YOLOv5-AdaBoost algorithm with YOLOv5x, YOLOX-Nano, and YOLOv4 algorithms are 0.9538, 0.8072, 0.9104, and 0.6472, respectively. The AUL of the PR curve of the algorithms proposed by the study is significantly higher than that of the remaining three algorithms and is 0.1466 higher compared to the YOLOv5x algorithm. As a result, the AUL of the PR curve of the YOLOv5-AdaBoost algorithm is the highest, and the performance advantage of the algorithm is verified. In addition, to highlight the feasibility of the YOLOv5-AdaBoost algorithm, the study analyzes the comparison of F1 value and loss value between the YOLOv5-AdaBoost algorithm and the three algorithms YOLOv5x and YOLOX-Nano. The comparison results are shown in Figure 10.

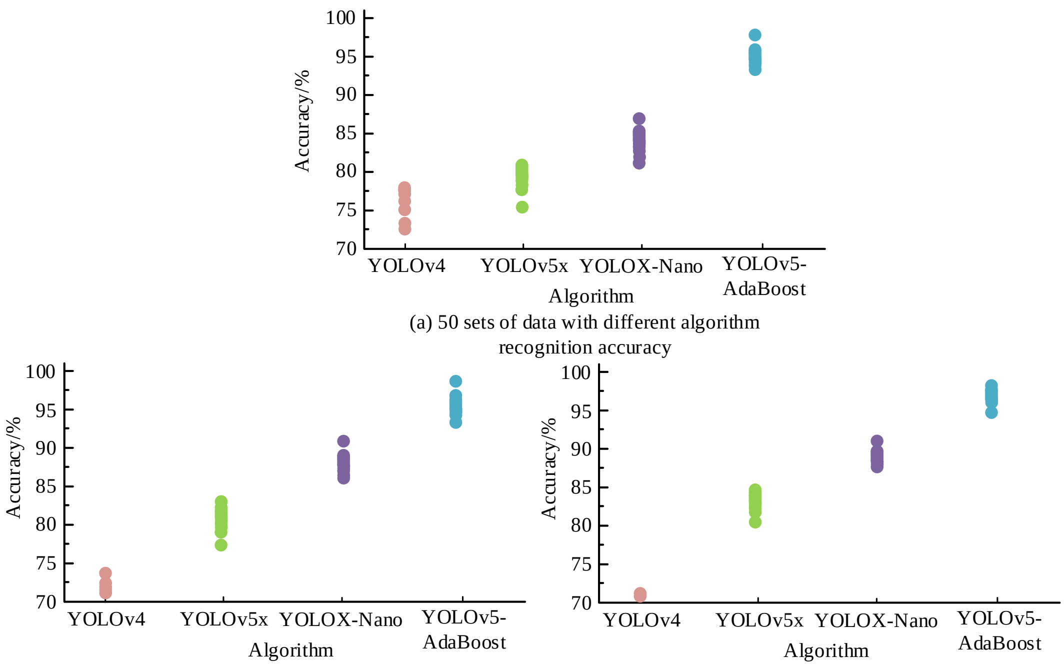
The YOLOv5-AdaBoost algorithm's F1 value change curve in Figure 10(a) is noticeably greater than that of the other three algorithms and does not exhibit major variations. Its maximum F1 value is 0.894. In contrast, the YOLOv4 algorithm's F1 value change curve is far less than that of the other methods. Although its variation is relatively smooth, its highest F1 value is only 0.619, which is significantly lower than the lowest F1 value of the other three algorithms. Although the F1 value variation curve of the YOLOX-Nano algorithm is close to that of the YOLOv5-AdaBoost algorithm, its F1 value is always lower than that of the YOLOv5-AdaBoost algorithm. In Figure 10(b), the YOLOv5-AdaBoost algorithm has a smaller loss value, which is significantly lower than the remaining three algorithms. Furthermore, its loss value curve has no excessive fluctuation, and its average loss value is 0.2357. On the other hand, the YOLOv4 algorithm has a larger loss value, and its loss value curve fluctuates more significantly. Its average loss value is 1.3649, which is 1.1292 higher compared to the YOLOv5-AdaBoost algorithm. The average loss values of the YOLOX-Nano algorithm and the YOLOv5x algorithm amount to 0.4671 and 0.7429, respectively. Compared with the the proposed algorithms, they are

0.2314 and 0.5072 higher, respectively. It can be concluded that the YOLOv5-AdaBoost algorithm has a lower error value, with a higher F1 value, than the other three algorithms. After that, the study compares and analyzes the detection accuracy of the four algorithms. This is to verify that the YOLOv5-AdaBoost algorithm has a higher detection accuracy than the other three algorithms in capturing and recognizing the positional information of athletes, the Figure 11 displays the outcomes of the experiment.



(a) F1 value comparison curve (b) Loss curve comparison

Figure 10: Comparison of F1 values and loss values for different algorithms



(a) 50 sets of data with different algorithm recognition accuracy

(b) 100 sets of data with different algorithm recognition accuracy

(c) 150 sets of data with different algorithm recognition accuracy

Figure 11: Comparison of detection accuracy of different algorithms

In Figure 11(a), for the four algorithms under the condition of 50 sets of experimental datasets, the average detection accuracy of YOLOv5-AdaBoost algorithm is the highest, with 95.67%. Whereas, the average accuracy of YOLOv4 algorithm is the lowest, with 76.84%. It is 18.83% lower than YOLOv5-AdaBoost algorithm. The average accuracy of YOLOX-Nano and YOLOv5x algorithms are 84.31% and 79.62%, respectively, which are 11.36% and 16.05% lower than YOLOv5-AdaBoost algorithm. In Figure 11(b), under the condition of 100 sets of experimental datasets, the YOLOv5-AdaBoost algorithm achieves an average detection accuracy of 96.18%, while the YOLOX-Nano algorithm has a flat accuracy detection accuracy of 90.25%. Although it is the highest, it is much less than the YOLOv5-AdaBoost algorithm and 5.93% lower than the YOLOv5-AdaBoost algorithm. The average detection accuracy of YOLOv5x and YOLOv4 algorithms are 83.16% and 72.38%, respectively, which are 13.02% and 23.80% lower than YOLOv5-AdaBoost algorithm. Figure 11(c) shows the average detection accuracy of the YOLOv5-AdaBoost, YOLOX-Nano, YOLOv5x, and YOLOv4 algorithms for capturing and recognizing the position of athletes in 150 experimental datasets. The respective accuracy is 97.03%, 91.25%, 86.43%, and 71.09%, respectively. The above results indicate that the average detection accuracy of the proposed YOLOv5-AdaBoost algorithm is the highest. It is 5.78% higher than the YOLOX-Nano algorithm and

25.94% higher than the YOLOv4 algorithm. It can be concluded that the YOLOv5-AdaBoost algorithm possesses higher detection accuracy than the other three algorithms when the four algorithms capture and recognize the athletes' position information under different dataset conditions.

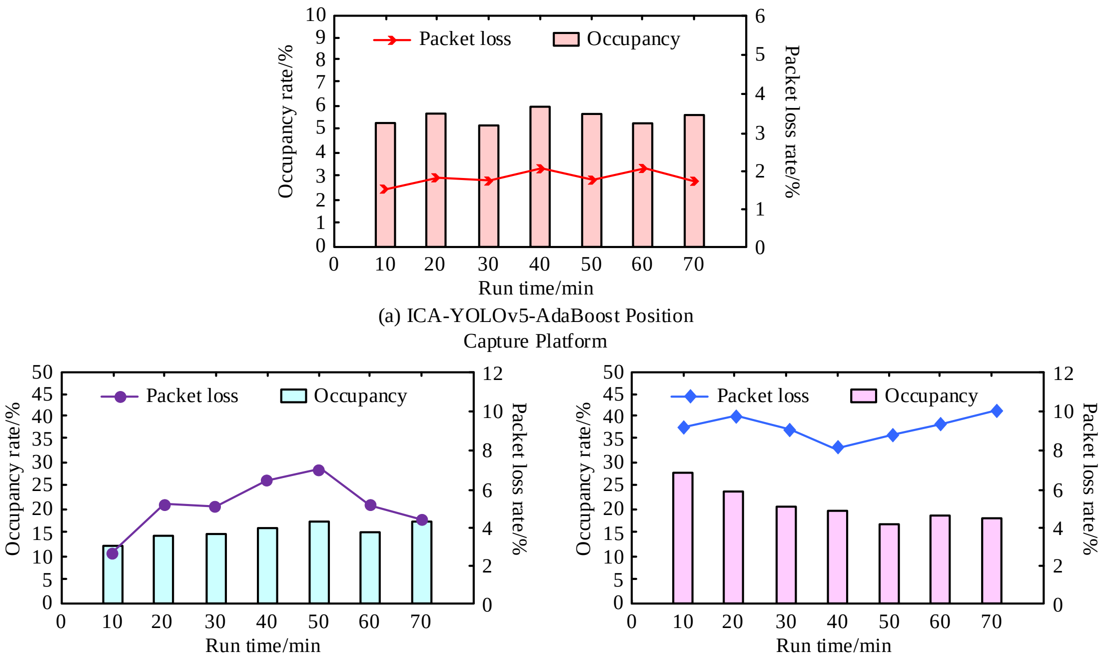
3.2 Practical effects of a football SEMI-automatic offside detection capture platform

To analyze the practical effect of the ICA-YOLOv5-AdaBoost position information capture platform, the study is conducted on the capture platform constructed by introducing the CG-YOLOv4 algorithm as well as the YOLOv5s algorithm. The CG-YOLOv4 capture platform is an athlete position information capture system based on the YOLOv4 object detection algorithm. The main object detection algorithm is YOLOv4, and the detection results are filtered by setting a confidence threshold. The YOLOv5s location information capture platform is built on a lightweight YOLOv5s model. This model performs basic preprocessing operations on images and determines final detection results based on confidence thresholds. The introduction of football event data is also carried out from SoccerReplay data. A total of 500 data sets from 250 test sets and 250 training sets are selected for comparison experiments. To verify the impact of parameters on algorithm performance, this study fixes the number of empires n to 10 and set weights ξ to 0.1, 0.5, and 1.0, respectively. The weight ξ is fixed to 0.5 and the number of empires n is set to 5, 10, and 20, respectively. The sensitivity analysis results of the parameters are shown in Table 3.

Table 3: Sensitivity analysis results of parameters

Number of Empires	Weight	MAE	Training time/h
10	0.1	0.093	3.1
	0.5	0.084	3.3
	1.0	0.089	3.5
5	0.5	0.090	3.0
10		0.084	3.3
20		0.085	3.6

In Table 3, when the number of empires is 10 and the weight is 0.5. The MAE value of the algorithm is the smallest, which is 0.084. The suggested platform's system occupancy rate and packet loss rate are examined and contrasted with those of the other two capture platforms. The packet loss rate can be calculated during data processing by counting the number of frames in the input and output images. The packet loss rate equals the difference between the total number of input frames and the number of successfully processed frames, divided by the total number of input frames. The experimental results are shown in Figure 12.



(a) ICA-YOLOv5-AdaBoost Position Capture Platform

(b) CG-YOLOv4 Position Capture Platform

(c) YOLOv5s Position Capture Platform

Figure 12: Experimental results of occupancy and packet loss rate of the location capture platform

In Figure 12(a), the average packet loss rate of ICA-YOLOv5-AdaBoost position information capturing platform is only 2.367% in football semi-automatic offside detection when the position information of athletes is captured. Moreover, the change curve of packet loss rate shows a small fluctuation, while the average occupancy rate of the platform is only 5.139%. It shows that the ICA-YOLOv5-AdaBoost capture platform is able to capture the position information of the athletes more accurately when it captures the position information. In Figure 12(b), the average occupancy rate of CG-YOLOv4 capture platform reaches 11.659%, which is 6.520% higher than the ICA-YOLOv5-AdaBoost capture platform. Whereas the average packet loss rate of this capture platform reaches 20.473%, which is 18.106% higher than that of the ICA-YOLOv5-AdaBoost capture platform. It shows that the CG-YOLOv4 capture platform is much less capable than the ICA-YOLOv5-AdaBoost capture platform in capturing the position information of the athletes. In Figure 12(c), the average packet loss and occupancy rates of the YOLOv5s position information capture platform are 37.427% and 24.892%, respectively. These rates are 35.060% and 19.753% higher than those of the ICA-YOLOv5-AdaBoost capture platform. This indicates that the YOLOv5s capture platform is much less capable than the ICA capture platform in capturing the position information of the athletes. It can be concluded that among the three capture platforms, ICA-YOLOv5-AdaBoost has a lower packet loss rate and occupancy rate when capturing the position information of athletes, and its capture ability is significantly better than the other two capture platforms. Response time refers to the time required for the model to output the athlete's position information in a frame of input image. To accurately reflect the model's efficiency and real-time performance in processing individual image frames, this study uses a frame-by-frame calculation method to determine response time. The response time is equal to the total processing time divided by the number of frames processed. Afterwards, to verify that the ICA-YOLOv5 AdaBoost capture platform can quickly capture the position information of athletes in semi automatic off side detection of football, the response speed of three capture platforms, ICA-YOLOv5 AdaBoost, CG-YOLOv4, and YOLOv5s, is analyzed. Figure 13 presents the comparison results.

In Figure 13, the ICA-YOLOv5-AdaBoost capture platform exhibits significant advantages in capturing the position information of athletes, with an average response time of only 20.75ms.

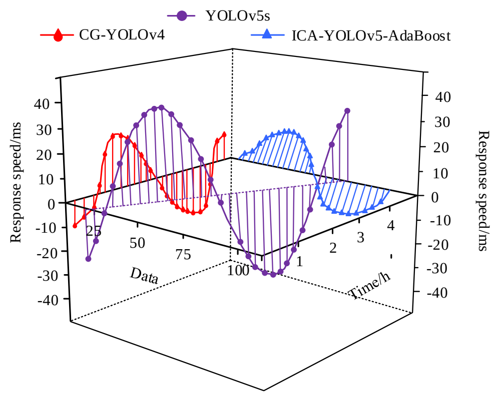
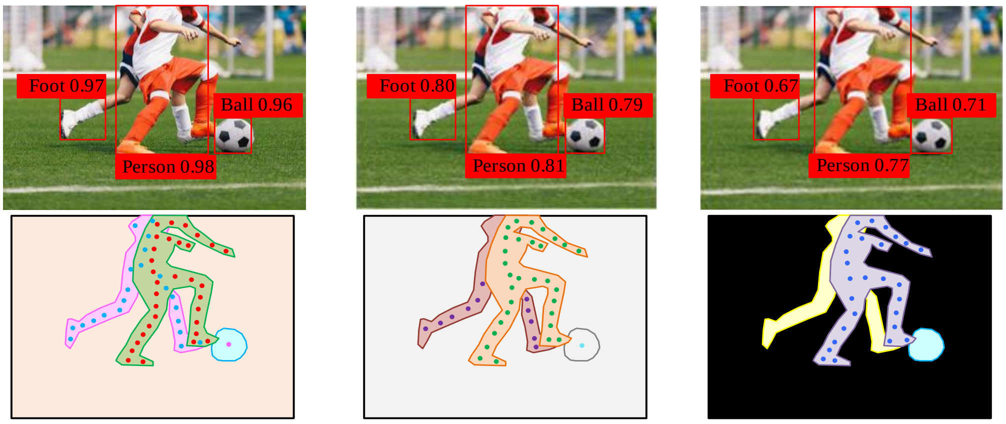


Figure 13: Comparison of the response speed of the three capture platforms

With an average response time of 26.94 ms, the CG-YOLOv4 capture platform is 6.19 ms slower than the ICA-YOLOv5-AdaBoost capture platform. The YOLOv5s capture platform has an average response time of 39.68 ms. This is 18.93 ms slower than the ICA-YOLOv5-AdaBoost capture platform. It shows that the ICA-YOLOv5-AdaBoost capture platform has a faster response speed than the other two capture platforms in capturing and recognizing the position information of the athletes. In addition, in football semi-automatic offside detection, to highlight that the ICA-YOLOv5-AdaBoost capture platform can capture the position information of the athletes more accurately than the other two capture platforms, the study compares and analyzes the capture accuracy of the three capture platforms. The “detection accuracy” in Section 3.1 is an overall performance evaluation based on mean accuracy. This study defines capture accuracy as the proportion of correct detections of a specific target category (e.g., foot, body, or soccer ball) by the model when the intersection-to-union ratio threshold is ≥0.5. In other words, it is the number of correct detection boxes divided by the number of real targets. The comparison results are shown in Figure 14.



(a) ICA-YOLOv5-AdaBoost Position Capture Platform
(b) CG-YOLOv4 Position Capture Platform
(c) YOLOv5s Position Capture Platform

Figure 14: Comparison of the capture accuracy of the three capture platforms

In Figure 14(a), when the position information of the athlete is captured using the ICA-YOLOv5-AdaBoost capture platform, the specific position information of the athlete can be captured more accurately, and the capture accuracy is high. Among them, the capture accuracy for the athlete's feet reaches 0.97, and the capture accuracy for the athlete's body and football are 0.98 and 0.96, respectively. In Figure 14(b), the CG-YOLOv4 capture platform is unable to capture the specific position information of the occluded athlete more accurately. Moreover, the overall capture accuracy is much lower than that of the ICA-YOLOv5-AdaBoost capture platform. Among them, the capture accuracy for football is only 0.79, which is 0.17 lower than that of ICA-YOLOv5-AdaBoost capture platform. In Figure 14(c), the YOLOv5s capture platform is completely unable to capture the position information of the occluded athlete, and the capture accuracy of the unoccluded athlete is significantly lower than that of the other two captured platforms. It can be concluded that the ICA-YOLOv5-AdaBoost capture platform is able to accurately capture the position information of athletes in football semi-automatic offside detection. The capture accuracy is significantly higher than the other two capture platforms. In summary, the comparison table between the proposed ICA-YOLOv5-AdaBoost algorithm and the baseline algorithm is shown in Table 4.

Table 4: Comparison summary table of baseline algorithms

Algorithm	Data set	Accuracy/%	MAE	Advantage	Disadvantage
YOLOv4	Campus Football Games	76.84	0.297	High detection accuracy	High demand for computing resources and long training time
YOLOX-Nano	Campus Football Games	90.25	0.107	Low memory usage	Weak ability to capture small targets
YOLOv5s	SoccerReplay	72.38	-	Fast reasoning speed	Low capture accuracy
CG-YOLOv4	SoccerReplay	83.16	0.195	Strong multi-scale feature fusion capability	Slow training convergence and high hardware costs
ICA-YOLOv5-AdaBoost	Campus Football Games and SoccerReplay	96.18	0.086	High precision and low packet loss rate	The hardware deployment complexity is slightly higher

4 Discussion

The study mentioned that YOLOv5 algorithm combined with AdaBoost algorithm exhibited a better algorithmic performance in the algorithm performance comparison experiments. From the accuracy-recall curve, RMSE, MAE, accuracy, F1 value, and loss value, it was observed that the YOLOv5-AdaBoost algorithm proposed by the study performed better compared to CG-YOLOv4 algorithm, YOLOv5s algorithm, and YOLOX-Nano algorithm. In the experiments of capturing positional information of athletes, the YOLOv5-AdaBoost algorithm could carry out the capture of athletes' positional targets better, and the capture accuracy was higher. The average accuracy reached 95.67%, and the average MAE and average RMSE values for position information capture were 0.086 and 0.049, respectively. Its capture error was significantly lower than the remaining three algorithms. This result coincided with the outcomes obtained from the study done by Guo et al. in 2024 [26]. This is mainly due to the YOLOv5 AdaBoost algorithm's ability to weight sample features through adaptive enhancement algorithms, making the model more focused on important features. YOLOv5 has a certain degree of noise resistance. When combined with the AdaBoost algorithm, the model's ability to resist noise is further enhanced, thereby improving the accuracy of object detection. In addition, in the practical effect experiment of the offside position information capture platform of football players designed by the research, it also showed more excellent capture effect. The capture accuracy of football player position and football position reached 0.98 and 0.96, respectively. The effectiveness and practicality of the proposed method were further verified.

In the practical effect experiment of offside position information capture of football players, the proposed position information capture platform also exhibited better performance. In the process of capturing football players' offside position information, the ICA-YOLOv5-AdaBoost capture platform proposed by the study had a significantly lower occupancy rate and packet loss rate than the capture platforms constructed by using the CG-YOLOv4 algorithm and the YOLOv5s algorithm. This was primarily due to the study's use of the AdaBoost algorithm to increase platform stability and the YOLOv5 algorithm for multi-target detection. These algorithms improved the accuracy of capturing the athletes' position information. In addition, the ICA has a fast convergence speed and is not limited to local optimal solutions, which can search for the optimal sample distribution and weight allocation in a wider range. In capturing the position information of football players, the

ICA helps to more accurately locate the player's position. Moreover, it also ensures the stability of capturing the player's position information in different datasets and scenarios. The performance of the study's suggested strategy for gathering and identifying football players' offside positioning information was noticeably better than that of related studies. For example, it demonstrated higher capture accuracy compared to the localized image block for position information capture experiment proposed by Li et al [27]. In addition, compared to the coupled over-demand feature adaptive position capture model proposed by Lee et al., this study performed complex position localization by utilizing an adaptive target dataset and positional anomaly feature identification by convolutional neural network [28]. Furthermore, Li et al. proposed a position capture method based on pre-detection tracking theory. They studied this method by constructing a theoretical framework for determining and capturing the target's position. However, the method was impractical in scenarios with many parameters [29]. After that, Lai et al. proposed a position capture localization method for distributed multi-input-output radar systems. The study was carried out through the derivation of discrete-time signal model, although the computational complexity of positional capture could be reduced, but it lacked practicality in practical applications [30]. Conversely, the study's suggested approach was able to increase the efficiency of recording the athletes' positions and had a higher capture accuracy in doing so.

The ICA-YOLOv5-AdaBoost capture platform, which was proposed by the research, offers flexibility in hardware deployment. It can run on standard computer hardware and has relatively moderate hardware requirements. During football games, cameras and other collection devices can be set up around the field. The data collected can then be transmitted to a backend server for processing and analysis. However, in practical applications, there may also be issues such as occlusion, insufficient lighting, or excessive lighting, which can affect image quality. When using the proposed method to capture athletes' locations during football matches, it is also necessary to consider privacy ethics issues to ensure the protection of athletes' and other relevant personnel's privacy, and to avoid data leakage or abuse. Additionally, due to the complexity and uncertainty of the competition environment, the proposed model may still be subject to errors in actual competitions. Potential biases in model training may also cause the model to more effectively capture position information for athletes with specific features, such as clothing color and body shape. Therefore, it is necessary to combine the judgment of professionals, such as referees, with a careful review and verification of the model's decision results. Additionally, the dataset must be expanded to ensure sample diversity.

5 Conclusion

In summary, the proposed ICA combined with the improved adaptive sample number method for football players' position information capture platform can solve the problems of low accuracy and low efficiency of traditional position information capture technology, and the practical effect is better. However, the method proposed by the research only focuses on capturing the location information of small soccer players. It is unclear whether this method is effective at capturing the location information of soccer players at large-scale events. In the scene of large sports venues, athletes who are far away from the camera have smaller targets, making action recognition more difficult. Additionally, the capture accuracy of the algorithm will be significantly affected when the camera angle deviates from the front by more than 45 degrees. Therefore, future work should further use transformer-based detectors to enhance data and optimize models for large sports venues. Another possibility is to integrate the perspectives of multiple cameras to improve the algorithm's ability to capture and recognize athlete position information.

Conflict of interest

The authors report there are no competing interests to declare.

Data availability statement

Data will be made available on reasonable request.

References

[1] J. Yun, D. Jiang, Y. Sun, L. Huang, B. Tao, G. Jiang. "Grasping Pose Detection for Loose Stacked Object Based on Convolutional Neural Network with Multiple Self-Powered Sensors Information," IEEE SENS J, vol. 23, no. 18, pp. 20619-20632, September, 2023, doi: 10.1109/JSEN.2022.3190560.

[2] B. T. Naik, M. F. Hashmi, Z. W. Geem and N. D. Bokde. "DeepPlayer-Track: Player and Referee Tracking with Jersey Color Recognition in Soccer," IEEE Access, vol. 10, no. 3, pp. 32494-32509, March, 2022, doi: 10.1109/ACCESS.2022.3161441.

[3] M. Ahmad, M. Usama, A. M. Khan, S. Distefano, H. A. Altuwaijri and M. Mazzara. "Spatial–Spectral Transformer With Conditional Position Encoding for Hyperspectral Image Classification," IEEE GEOSCI REMOTE S, vol. 21, no. 3, pp. 1-5, July, 2024, doi: 10.1109/LGRS.2024.3431188.

[4] Z. Hu, W. Qi, K. Ding, G. Liu and Y. Zhao. "An Adaptive Lighting Indoor vSLAM With Limited On-Device Resources," IEEE INTERNET THINGS, vol. 11, no. 17, pp. 28863-28875, September, 2024, doi: 10.1109/JIOT.2024.3406816.

[5] K. Gao, H. Wang, H. Lv and W. Liu. "Toward 5G NR High-Precision Indoor Positioning via Channel Frequency Response: A New Paradigm and Dataset Generation Method," IEEE J SEL AREA COMM, vol. 40, no. 7, pp. 2233-2247, July, 2022, doi: 10.1109/JSAC.2022.3157397.

[6] J. Li, F. Zhang, Z. Yang, Z. Jiang, Z. Wang and H. Liu. "Shape Sensing for Continuum Robots by Capturing Passive Tendon Displacements with Image Sensors," IEEE ROBOT AUTOM LET, vol. 7, no. 2, pp. 3130-3137, April, 2022, doi: 10.1109/LRA.2022.3144783.

[7] J. He, J. Luo, C. Fu. "The Occlusive Basketball Player Detection Algorithm Based on Posture Recognition Assisted Feature Alignment," Informatica, vol. 48, no. 21, pp. 79-94, 2024, doi: 10.31449/inf. v48i21.6695.

[8] Z. Song, Z. Chen. "Sports action detection and counting algorithm based on pose estimation and its application in physical education teaching," Informatica, vol. 48, no. 10, pp. 35-50, 2024, doi: 10.31449/inf. v48i10.5918.

[9] C. Wang. "Low-cost Badminton Trajectory Recognition and Landing Point Prediction Based on M-YOLOv2 and Kalman Filter for Optimizing the Coordinate System Transformation of Sites," Informatica, vol. 48, no. 23, pp. 73-90, December, 2024, doi: 10.31449/inf. v48i23.6741.

[10] H. Yu, K. Gao, N. Wu, M. Zhou, P. N. Suganthan and S. Wang. "Scheduling Multiobjective Dynamic Surgery Problems via Q-Learning-Based Meta-Heuristics," IEEE T SYST MAN CY-S, vol. 54, no. 6, pp. 3321-3333, June, 2024, doi: 10.1109/TSMC.2024.3352522.

[11] S. Ahmed, S. Mekhilef, M. Mubin, K. S. Tey and M. Kermadi. "An Adaptive Perturb and Observe Algorithm with Enhanced Skipping Feature for Fast Global Maximum Power Point Tracking Under Partial Shading Conditions," IEEE T POWER ELECTR, vol. 38, no. 9, pp. 11601-11613, September, 2023, doi: 10.1109/TPEL.2023.3285243.

[12] F. Shi. "A Motion Capture Framework for Table Tennis Using Optimized SVM and AdaBoost Algorithms," Informatica, vol. 49, no. 6, pp. 191-204, 2025, doi: 10.31449/inf. v49i6.6809.

[13] Z. Liu, X. Gao, Y. Wan, J. Wang and H. Lyu. "An Improved YOLOv5 Method for Small Object Detection in UAV Capture Scenes," IEEE Access, vol. 11, no. 4, pp. 14365-14374, January, 2023, doi: 10.1109/ACCESS.2023.3241005.

[14] Z. Zheng and Y. Yang, "Adaptive Boosting for Domain Adaptation: Toward Robust Predictions in Scene Segmentation," IEEE T IMAGE PROCESS, vol. 31, no. 3, pp. 5371-5382, August, 2022, doi: 10.1109/TIP.2022.3195642.

[15] P. H. Kuo, M. J. Huang, P. C. Luan and H. T. Yau, "Study on Bandwidth Analyzed Adaptive Boosting Machine Tool Chatter Diagnosis System," IEEE SENS J, vol. 22, no. 9, pp. 8449-8459, May, 2022, doi: 10.1109/JSEN.2022.3163914.

[16] B. Hammi, Y. M. Idir, S. Zeadally, R. Khatoun and J. Nebhen, "Is it Really Easy to Detect Sybil Attacks in C-ITS Environments: A Position Paper," IEEE T INTELL TRANSP, vol. 23, no. 10, pp. 18273-18287, October, 2022, doi: 10.1109/TITS.2022.3165513.

[17] Y. Song, Z. Xie, X. Wang and Y. Zou. "MS-YOLO: Object Detection Based on YOLOv5 Optimized Fusion Millimeter-Wave Radar and Machine Vision," IEEE SENS J, vol. 22, no. 15, pp. 15435-15447, Aug, 2022, doi: 10.1109/JSEN.2022.3167251.

[18] C. Chen. "Football Match Analysis and Prediction Based on LightGBM Decision Algorithm," Informatica, vol. 48, no. 16, pp. 137-154, 2024, doi: 10.31449/inf. v48i16.6236.

[19] P. Marimuthu, T. Rajesh, N. Rajeswaran and H. H. Alhelou. "Comparative Performance Analysis of Deregulated Hydrothermal System with Dual Mode Controller and Diverse Source of Generation Employing Imperialistic Competition Algorithm," IEEE Access, vol. 10, no. 1, pp. 51008-51020, May, 2022, doi: 10.1109/ACCESS.2022.3172109.

[20] J. Li, Z. Wang, X. Zhou and X. Liu. "Research on Motion Capture and Phase Segmentation Based on Wireless Body Sensor Networks in Competitive Equestrian," IEEE Transactions on Emerging Topics in Computational Intelligence, vol. 8, no. 1, pp. 840-854, February, 2024, doi: 10.1109/TETCI.2023.3290002.

[21] M. Chen, H. F. Szu, H. Y. Lin, Y. Liu, H. Y. Chan, Y. Wang and W. J. Li. "Phase-Based Quantification of Sports Performance Metrics Using a Smart IoT Sensor," IEEE INTERNET THINGS, vol. 10, no. 18, pp. 15900-15911, September, 2023, doi: 10.1109/JIOT.2023.3266351.

[22] L. Liu, Z. Wang, S. Qiu, H. Zhao, H. Qu and H. Wang. "Kinematic Analysis of Intra-Limb Joint Symmetry via Multisensor Fusion," IEEE T INSTRUM MEAS, vol. 72, no. 4, pp. 1-13, June, 2023, doi: 10.1109/TIM.2023.3282667.

[23] Y. Wang, Y. Qin, X. Chen, Q. Tang, T. Zhang and L. Wu, "Absolute Inductive Angular Displacement Sensor for Position Detection of YRT Turntable Bearing," IEEE T IND ELECTRON, vol. 69, no. 10, pp. 10644-10655, October, 2022, doi: 10.1109/TIE.2022.3148731.

[24] Q. Liang, L. Cheng, J. Long, Z. Li, W. Sun and D. Zhang. "A Force/Position Measurement Method of Surgical Forceps Based on Fiber Bragg Gratings," IEEE SENS J, vol. 23, no. 1, pp. 363-373, January, 2023, doi: 10.1109/JSEN.2022.3224042.

[25] B. Pardhasaradhi and L. R. Cenkeramaddi. "GPS Spoofing Detection and Mitigation for Drones Using Distributed Radar Tracking and Fusion," IEEE SENS J, vol. 22, no. 11, pp. 11122-11134, 1 June1, 2022, doi: 10.1109/JSEN.2022.3168940.

[26] Y. Guo, X. Wang, X. Lan and T. Su. "Traffic Target Location Estimation Based on Tensor Decomposition in Intelligent Transportation System," IEEE T INTELL TRANSP, vol. 25, no. 1, pp. 816-828, January, 2024, doi: 10.1109/TITS.2022.3165584.

[27] Y. Li, Z. Li, Y. Shen and Z. Guo. "Infrared Small Target Detection via Center-Surround Gray Difference Measure with Local Image Block Analysis," IEEE T AERO ELEC SYS, vol. 59, no. 1, pp. 63-81, February, 2023, doi: 10.1109/TAES.2022.3189336.

[28] S. Lee, S. Lee and B. C. Song. "CFA: Coupled-Hypersphere-Based Feature Adaptation for Target-Oriented Anomaly Localization," IEEE Access, vol. 10, no. 4, pp. 78446-78454, July, 2022, doi: 10.1109/ACCESS.2022.3193699.

[29] X. Li, Y. Wang, B. Qi and Y. Hao. "Underwater Acoustic Localization of the Long Baseline Based on Track-Before-Detect," IEEE GEOSCI REMOTE S, vol. 20, no. 7, pp. 1-5, March, 2023, doi: 10.1109/LGRS.2023.3257990.

[30] Y. Lai, L. Venturino, E. Grossi and W. Yi, "Joint Detection and Localization in Distributed MIMO Radars Employing Waveforms with Imperfect Auto- and Cross-Correlation," IEEE T VEH TECHNOL, vol. 72, no. 12, pp. 16524-16537, December. 2023, doi: 10.1109/TVT.2023.3293023.