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Article

Research on Image Recognition Technology to Assess the Quality of Badminton Players' Stroke Action and Training Improvement Strategy

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Abstract: This paper establishes a motion agent system based on image recognition to assess the quality of badminton players' stroke techniques, and provides personalized training improvement plans using deep learning and biomechanical analysis. Infrared dot high-speed cameras are used to capture the movements of the athlete's shoulder joint, elbow joint, and wrist joint, among other positions. Convolutional neural networks and long short-term memory networks are employed to classify and evaluate the movements of forehand strokes, pushes, and hooks. The action recognition accuracy rate and feature point detection error rate are 96.2% and 93.2%, respectively. The athletes' technical consistency, movement standardization, and training effectiveness improved by an average of over 30% compared to pre-training levels. This paper effectively overcomes the subjectivity and errors of traditional evaluation methods, providing a quantitative, scientific, and accurate method for evaluating badminton technical movements. This study has practical application value and provides theoretical and methodological guidance for the use of image recognition in research on other sports.

Keywords: image recognition; badminton; biomechanics; deep learning; training improvement

1. Introduction

In recent years, the rapid advancement of artificial intelligence and computer vision technologies has significantly promoted the application of image recognition technology in sports training and tactical analysis, making it one of the key tools for sports training management and research in the current era [1-2]. Badminton, as a relatively complex ball sport, imposes strict requirements on the precision and consistency of every stroke executed by athletes [3-4]. However, the current evaluation of these technical movements still relies primarily on the subjective experience of coaches as the main criterion for assessment, lacking accuracy, universality, long-term effectiveness, and quantitative data-based results.

Visual observation methods, which rely on human eyesight, have inherent limitations when analyzing very fast movements, especially in complex situations involving multiple connected and transitioning actions. They struggle to observe and analyze critical factors such as joint movement trajectories, force distribution, and movement continuity, making it difficult to optimize athletes' technical development and design targeted training plans [5-7]. Especially for novice athletes and non-elite athletes, it is difficult to conduct relevant analyses, which may lead to the continued development of technical errors and negatively impact performance [8].

With the outstanding performance of image recognition and deep learning technologies in capturing movements, analyzing key points, and classifying behaviors in recent years, image recognition combined with deep learning has been applied to badminton technical movement evaluation [9-10]. For example, Wang, Z et al. [11] proposed a badminton training system combining a human sensor network and a two-layer hidden Markov model (HMM) classification algorithm, which can accurately identify 14 different badminton stroke actions. Xie, J et al. [12] developed an intelligent badminton training robot (IBTR) using machine learning algorithms, which can effectively recognize athletes' movements and prevent injuries during badminton training. Lin, K et al. [13] developed a real-time posture recognition badminton training application based on the OpenPose motion recognition algorithm, aiming to improve athletes' badminton smash skills and learning outcomes through scientific training feedback. Ooi, J. H and Gouwanda, D [14] utilized wearable inertial sensors and neural networks to recognize badminton hitting movements. By arranging multiple sensors and focusing solely on the wrist, they achieved a high recognition accuracy rate, demonstrating practical application value in both training and competitive environments. Jiang, X et al. [15] explored the application of feature extraction algorithms and image processing techniques in university badminton movement instruction, aiming to enhance students' movement skills through real-time feedback and personalized teaching recommendations. Based on the above studies, it is evident that image recognition technology can automatically classify and score badminton stroke techniques by capturing the positions and movement changes of key joints during strokes, thereby reducing subjective errors caused by evaluators using different standards [16-18]. Additionally, it can leverage the classification capabilities of motion machine learning algorithms to facilitate process improvements in motion technique refinement and flexible customization of training programs [19].

More importantly, technical movements can be displayed in real-time on images, making the movement state and existing technical issues immediately apparent, significantly enhancing the interactivity and purposefulness of training [20-21]. By conducting quantitative analysis and scientific assessment of technical movements, athletes can understand the strengths and weaknesses of their techniques in various movements, develop corresponding training plans, and strategically address unexpected technical movements during competitions, thereby promoting the further development of China's competitive sports.

Therefore, the objective of this paper is to design an intelligent evaluation and training improvement system for badminton hitting actions that integrates image recognition technology, deep learning, and biomechanical knowledge. Using infrared high-speed camera technology, motion image data of the upper limbs during the athlete's hitting actions are collected, and a standardized action database is established by combining the trajectories of key points in various parts of the upper limbs. Using CNN classification models and STM models to classify and score the athletes' hitting actions, the system achieves intelligent recognition and detection of actions. Based on biomechanical factor analysis of individual athletes, it identifies deficient action segments and patterns, and proposes personalized training improvement plans supported by data. Through experimental comparisons of different training plans after action modifications, the study explores the effectiveness and promotional impact of this method on badminton training. This process, "technical data collection-intelligent recognition-training feedback-evaluation and optimization," ensures the method's practical application while linking theoretical assessment with real-world practice.

2. The quality of Badminton Players' Strokes and Training Improvement Methods

2.1. Experimental Subjects and Data Collection

Any biomechanical experiment in sports requires a comprehensive experimental design and precise data analysis. For this study, the experimental samples selected consisted of 12 male athletes, with an average age of 23.2 ± 1.8 years, an average height of 177.5 ± 4.3 cm, and an average weight of 71.2 ± 3.9 kg. All participants were national-level athletes of grade two or above, with over five years of professional badminton training experience, and are proficient in basic badminton net techniques such as forehand drives, pushes, and hooks. Prior to the experiment, all athletes underwent comprehensive physical fitness tests, had no history of sports injuries, and were in good health. Additionally, all participants were required to avoid intense training the day before the experiment to ensure they were in optimal competitive condition during the experiment. At the same time, standardized and normative assessments of the athletes' technical proficiency were conducted, evaluating their technical proficiency based on the accuracy of their shots, consistency of movements, and completeness of movements, ensuring the representativeness and consistency of the samples.

The data acquisition system utilized an infrared dot high-speed camera system as the core equipment, employing eight Vicon Vantage V16 high-speed cameras to capture the athletes' hitting movements at a sampling frequency of 250 Hz, with synchronized recording. The cameras were arranged in a conventional mode, distributed in an 8-point pattern around the hitting area in a circular shape, enabling comprehensive filming of the entire upper limb movements during the athletes' hitting actions with no blind spots. The athletes' upper limbs were marked with 39 reflective points distributed precisely according to conventional biomechanical calibration methods. Standard reference points include the acromion, inferior angle of the scapula, lateral epicondyle of the humerus, medial epicondyle of the humerus, radial styloid process, ulnar styloid process, and head of the third metacarpal bone. All markers were placed by professional medical doctors in strict accordance with standard biomechanical technical requirements to ensure accuracy and consistency. To further enhance data accuracy, the calibration process employs an L-shaped calibration frame to establish a three-dimensional coordinate system, with a calibration precision of 0.1 mm, meeting the requirements of high-precision motion analysis systems. A dedicated hardware controller ensures that all cameras initiate recording simultaneously, minimizing interference caused by time synchronization issues in the recorded data.

Data collection experiments were conducted within a standard badminton court. During data collection, the environmental temperature was maintained between 22°C and 25°C, with relative humidity between 45% and 55%, ensuring the stability of the experimental data collection environment. Participants in each sport performed three types of technical movements: forehand rubbing, forehand pushing, and forehand hooking, with each type repeated 15 times, totaling 540 valid technical movements. To maintain the natural and authentic nature of the sports environment, data collection was conducted using the actual practice method of participants performing forehand strokes, with professional trainers assisting to complete various hitting scenarios. Team members underwent thorough warm-ups before the formal test, including joint and muscle mobility exercises, stretching, and technical movement warm-ups, to ensure their physical condition was optimized. During real-time recording of the strokes, the visibility and tracking quality of the markers were monitored. When marker occlusion or detachment caused data gaps, supplementary measurements were promptly conducted. The raw data was preliminarily processed using Vicon Nexus software, including marker trajectory recovery, smoothing filtering, and coordinate system conversion, to ensure the data met the requirements for post-processing analysis.

Based on the principles of three-dimensional motion analysis, kinematic parameters are extracted and calculated. Joint angles, angular velocity, and angular acceleration are calculated based on changes in the three-dimensional spatial coordinates between markers. Table 1 shows the results of angle and velocity parameters for the hitting action. The shoulder joint angle is the angle between the upper arm and the trunk, the elbow joint angle is the angle between the upper arm and the forearm, and the wrist joint angle is the angle between the forearm and the hand. All angles are expressed using the right-hand coordinate system and Euler angles. Velocity is obtained by numerically differentiating position data. A 5-point difference method is used to reduce errors generated during numerical differentiation, and a low-pass filter is applied to eliminate the influence of high-frequency signals on velocity calculations. Based on the velocity characteristics of the racket frame, the hitting process is divided into three main stages: the swing-out stage, the backswing stage, and the hitting stage. The duration and motion characteristic parameters of each stage during racket movement are calculated separately. Regarding data quality control, three principles and methods—anomaly detection, data integrity verification, and data repeatability verification—are applied to ensure that the collected data is complete, accurate, and valid, providing an effective and reliable standard dataset for training image recognition algorithms and analyzing motion quality evaluation results in subsequent designs.

Table 1. The ball action data of the badminton player.

Technical action	Rub the ball with the forehand	Forehand push the ball	Forehand hook ball
Shoulder joint Angle (°)	45.2±3.8	52.8±4.5	48.6±3.9
Elbow joint Angle (°)	128.5±5.2	135.7±6.1	132.1±4.8
Wrist joint Angle (°)	165.3±4.1	158.9±5.3	172.4±3.7
Shoulder joint velocity (rad/s)	8.7±1.2	11.4±1.6	9.8±1.4
Frame speed (m/s)	12.3±1.8	18.7±2.4	15.2±2.1

2.2. Image Recognition Technology and Feature Point Extraction

Image-based recognition of badminton stroke actions based on multi-scale feature extraction involves detecting and identifying key body parts of athletes through the spatial positions and trajectories captured from image sequences obtained by high-speed cameras [22]. An improved scale-invariant feature transformation algorithm is used as the feature detector, and a Gaussian difference pyramid is employed to generate extrema points in the scale space for feature identification. A 128-dimensional feature description is constructed for each feature point. Traditional algorithms are prone to losing feature points due to speed limitations, so a multi-scale Harris corner detection method is combined to detect feature points on athletes during critical hitting actions. This method obtains stable corner features by calculating the autocorrelation matrix of image gradients. The response function of the Harris detector is defined as:

$$R = \det(M) - k \cdot trace^2(M) \tag{1}$$

In the equation, M is the structural tensor matrix, and k is an empirical constant with a value of 0.04. This method exhibits good invariance under rotation transformations and can effectively compensate for the shortcomings of the algorithm in certain scenarios.

Based on this, to further enhance the robustness of feature detection, the fast detection component from the accelerated robust feature algorithm is integrated. By using integral images and the Hesse matrix approximation algorithm, the computational complexity of feature extraction is reduced to a level sufficient to meet real-time requirements.

The precise localization and stable tracking of feature points determine the success or failure of an image recognition system. A feature point detection network based on deep learning is designed. This network adopts an encoder-decoder structure, with the encoder using ResNet-50 as the backbone network to extract image features at different scales, and the decoder using upsampling and skip connections to restore spatial resolution and generate feature point heatmaps. The network loss function is a weighted sum of feature point localization loss and descriptor matching loss, with the localization loss using the mean squared error form. That is:

$$L_{loc} = \frac{1}{N}\sum_{i=1}^{N} \| p_i - \hat{p}_i \|^2 \tag{2}$$

In the equation, p_i is the true feature point position, $\hat{p}_i$ is the predicted position, and N is the number of feature points.

The descriptor matching loss uses contrastive learning to optimize the discriminative ability of feature descriptors by maximizing the similarity of positive pairs and minimizing the distance of negative pairs. To address the issues of occlusion during badminton strokes and tracking instability caused by vigorous movement, this study proposes a temporal consistency constraint. By applying Kalman filtering to the feature points of the target in the previous frame, the potential position in the next frame is predicted. Combined with the target motion vector predicted using optical flow methods, this further enhances the robustness of tracking.

Feature point matching and trajectory calculation are key technologies in action recognition. A feature point association algorithm based on graph matching theory is designed to establish the correspondence between feature points in different frames. The similarity matrix between feature points is derived from multiple factors, including spatial distance between feature points, feature descriptor similarity, and motion consistency between feature points. The similarity matrix is:

$$S_{ij} = \alpha \cdot \exp\left(-\frac{d_{spatial}^2}{2\sigma_s^2}\right) + \beta \cdot \exp\left(-\frac{d_{descriptor}^2}{2\sigma_d^2}\right) + \gamma \cdot \exp\left(-\frac{d_{motion}^2}{2\sigma_m^2}\right) \tag{3}$$

In the equation, α, β, γ are weighting coefficients, and $d_{spatial}, d_{descriptor}, d_{motion}$ represent spatial distance, descriptor distance, and motion distance, respectively.

Matching is performed using the Hungarian algorithm to solve the optimal assignment problem, ensuring that each feature point is paired with a target that has the optimal matching degree. To address the situation where new feature points are generated and existing feature points disappear during the ball-hitting process, a dynamic graph update mechanism is proposed. When a feature point appears, it is automatically added to the tracking sequence in real time. If the feature point cannot be matched after a certain period of tracking, it is removed from the tracking sequence. Trajectory smoothing uses a Bézier spline curve to fit a trajectory. By minimizing the second derivative value of the curve, a smooth trajectory is obtained. Under the premise of ensuring the geometric shape and form of the curve, the true form of the curve is reflected as much as possible. This module also proposes to determine whether the feature point is abnormal by analyzing its velocity and acceleration. If it is abnormal, it is determined as tracking failure, and re-matching is implemented.

2.3. Deep Learning Models and Action Evaluation

A hybrid model combining 3D convolutional neural networks with long short-term memory (LSTM) has been proposed. This model uses a 3×3×3 convolutional kernel to simultaneously extract spatial and temporal feature information, achieving the goal of identifying and judging three technical movements: forehand spin, forehand push, and forehand hook. The network encoder uses residual connections to handle deeper parts of the network and avoid the vanishing gradient problem. A residual block consists of two 3D convolutional layers, a batch normalization layer, and a ReLU activation function. The skip connections enable the network to learn deeper feature expressions more effectively. The spatio-temporal attention embedding structure emphasizes the importance of key body parts at critical times during the stroke by assigning importance values to each spatio-temporal point in each feature map. The attention weights are calculated using a self-attention mechanism, with attention distribution maps generated by three matrices: query, key, and value. The network output end is the long short-term memory network section, which only accepts high-order feature sequences transmitted by the network encoder and selectively reads and forgets information through its gate mechanism to establish long-term dependencies and temporal patterns in the hitting action.

The model training employs a fully end-to-end supervised learning method. The loss function design balances the accuracy requirements of classification and regression. For the action classification task, the cross-entropy loss function is used to minimize the classification accuracy for the three types of striking techniques. For the action quality evaluation task, the mean squared error loss function is used to minimize the mean squared error between the predicted score and the expert score. The overall loss function of the model is defined as:

$$L = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{4}$$

In the equation, N denotes the number of training samples, y_i is the true label or score of the i th sample, and $\hat{y}_i$ is the model's predicted output. The L2 regularization term is added to the loss function to prevent overfitting, with the regularization coefficient determined by cross-validation to be 0.001. The Adam optimizer is selected, with an initial learning rate set to 0.001. The learning rate is adjusted during training using a cosine annealing learning rate scheduling strategy, and training is stopped early at the 10th epoch when the validation set loss no longer changes to prevent overfitting. Data augmentation includes random rotation, scaling, mirroring, and random cropping along the time dimension. These data augmentation techniques increase the diversity of the model's training data, helping to enhance the model's robustness to variations in shooting angles, athlete body types, and action execution.

Multi-indicator comprehensive evaluation: We evaluate the system's performance level through accuracy, precision, recall, F-score, RMSE, and MAE. Action consistency refers to the degree of similarity between an evaluated athlete repeatedly performing the same technical action. Model action consistency refers to the degree of similarity between an athlete repeatedly practicing the same action on different training samples. The evaluation of model motion consistency is achieved by assessing the variance in the results of the same athlete repeatedly practicing the same technical motion. In the generalization test, some athletes were not involved in model training at all and were only used as test data. The overall evaluation metrics were applied to the sample data of other athletes, and the final results demonstrated that the system maintained an identification rate of over 90% on athlete sample data that had not been learned.

The improved method for personalized athlete training involves the system conducting a comprehensive analysis of multiple pieces of information, including the athlete's overall performance and scores, technical data, and scoring data, and then using algorithms to calculate and output specific training improvement plans. This method is primarily used for improving athletes' hitting techniques. The strengths and weaknesses of athletes' three-hit techniques are analyzed based on the comprehensive evaluation scores of the quality of the hitting techniques. The system's overall evaluation score is then compared with the athlete's total training data indicators to determine whether similar techniques should continue in the current training session or if there is a need to strengthen the comprehensive evaluation value of these technical indicators, as well as to analyze the technical aspects required to achieve the expected training goals. Based on the specific coach's training objectives, other data models are integrated to generate the next training method, which addresses issues in the athlete's execution of movements by correcting technical movements identified as problematic in the movement quality scoring. Personalized improvement methods are then demonstrated to the athlete in a visual format, allowing the coach to provide reasonable and correct recommendations based on the situation.

3. Analysis and Discussion of the Quality of Badminton Players' Strokes and Training IMPROVEMENTS

3.1. Analysis of Experimental Results

The table showing the extracted feature points is shown in Table 2. As can be seen from the table, the use of image feature point detection algorithms has resulted in good feature point extraction results when identifying badminton stroke actions. Through the analysis of 540 stroke actions performed by 12 people, the system can identify body parts such as the shoulder joint, elbow joint, and wrist joint, and track their feature points. In dynamic scenarios, the target area is relatively complex, but the average detection accuracy reaches 93.2%, enabling the system to precisely detect feature points and determine the movements of different body parts. The detection accuracy for the shoulder joint can reach up to 96.8%, as the shoulder area is relatively stable and lacks obstruction. The wrist joint detection accuracy is slightly lower at 93.9%, but it still meets the requirements for precise motion analysis. The average temporal consistency for high-speed hitting motions reaches 88.4%, and even when motion blur occurs, the system can still stably track the racket's motion trajectory. Precise analysis based on accurate measurement of biomechanical parameters is the precise basis for analyzing hitting actions. Therefore, the differences in the kinematic characteristic patterns of these three hitting techniques are clearly analyzable. The forehand push technique has the highest movement intensity throughout the entire hitting process, with the average angular velocity of the shoulder joint significantly higher than that of the chop and hook techniques, indicating that the push technique requires higher ball speed and force.

Table 2. The results of the stroke feature points.

Feature point	Detection precision (%)	Tracking stability (%)	Processing speed (fps)	Feature dimension	Matching accuracy (%)
Shoulder joint	96.8	94.2	45.3	128	92.5
Elbow joint	95.4	91.7	47.1	128	90.8
Wrist joint	93.9	88.6	48.7	128	89.2
Racket	91.2	85.3	42.8	64	87.6
Badminton trajectory	88.7	82.1	51.2	64	85.4
Average	93.2	88.4	47.0	-	89.1

The effectiveness of deep learning-based classification and quality scoring of hitting actions is satisfactory. By combining a 3D convolutional neural network with a long short-term memory network, the spatio-temporal features of hitting actions are obtained. The quality evaluation of hitting actions is shown in Figure 1, and Table 3 presents the training and testing results of the deep learning model.

As shown in the figure and table, the overall accuracy of the model for classifying the three types of hitting techniques is 96.2%. The recognition accuracy rates for the three actions—flipping, pushing, and hooking—on the test set are 96.2%, 95.8%, and 96.5%, respectively, with F1 values all exceeding 0.95. This indicates that the model has good classification performance and balanced classification. The model scores for action quality are all above 6.5 points (out of 10), and the model's mean square root error (MME) and mean absolute error on the test set are 0.23 points and 0.18 points, respectively. This level of precision is consistent with the assessment of expert coaches.

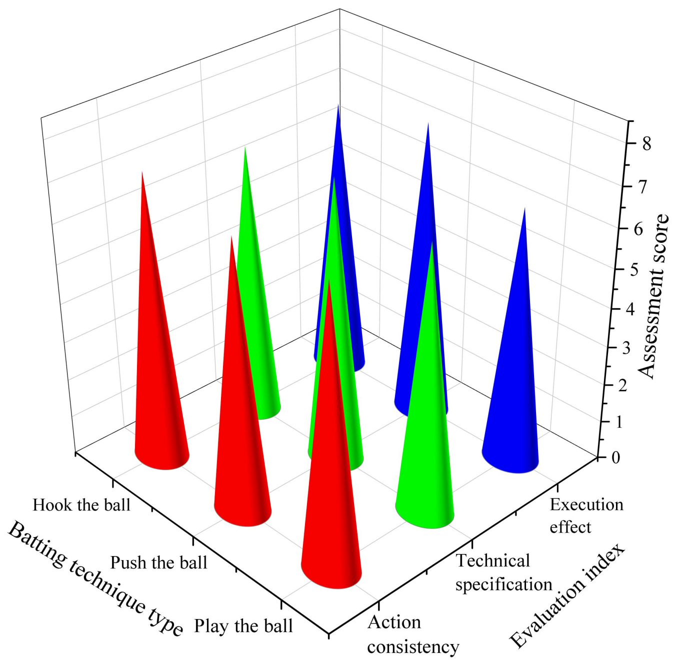

Figure 1. Assessment of stroke action quality.

Table 3. Model training and test results.

Datasets	Training set	Verification set	Test set	Total
Sample quantity	1620	324	216	2160
Action type	Play the ball	Push the ball	Hook the ball	Mixed action
Training accuracy (%)	98.7	97.9	98.2	98.3
Test accuracy (%)	96.2	95.8	96.5	96.2
$F1$ score	0.961	0.957	0.964	0.961
MME	0.27	0.25	0.23	0.18

3.2. Evaluation of the Effectiveness of Training Improvement Strategies

The effectiveness of personalized training improvement strategies was evaluated through a 12-week simulated trial. Twenty-four participating athletes were randomly divided into two groups: a personalized training group and a traditional training group. The personalized training group utilized image recognition technology to provide personalized training methods for the athletes. The traditional training group followed a conventional training program, with the same training intensity and frequency as the personalized training group, and the same specific training methods. The two training groups were completely independent of each other. The personalized training improvement strategy should be tailored to the actual weaknesses of badminton athletes, with technical weakness control parameters proposed for each athlete. These parameters are evaluated through image recognition analysis of the quality of the athletes' stroke movements. Specifically, three key parameters were identified: shoulder joint angle control, wrist joint stability, and technical movement rhythm coordination ability. Specialized training improvement strategies were then designed based on these key parameters. The personalized training group conducts three specialized technical exercises per week, each lasting 90 minutes. The exercise schedule includes several components such as action pattern reinforcement, muscle memory establishment, and technical detail correction. The traditional training group follows the traditional training outline.

To ensure the fairness and objectivity of evaluation results throughout the experiment, all athletes' technical action evaluations are conducted by the same image recognition system. Technical movement scoring was evaluated across three dimensions: movement consistency, movement standardization, and movement execution effectiveness, with each dimension scored out of 10 points. Evaluations during the training process were conducted in two-week cycles, with records kept of athletes' technical movement improvements in each cycle. Additionally, athletes' subjective opinions and coaches' observational evaluations were collected to form a multi-dimensional evaluation system. The comparison of movement quality evaluations before and after training improvements is shown in Table 4.

Table 4. Comparison of movement quality before and after training improvement.

Index	Before	After	Lifting amplitude	t	P
Action consistency	5.8	7.6	31.03%	6.784	0.000
Technical specification	6.2	8.1	30.65%	6.951	0.000
Execution effect	5.9	7.8	32.20%	5.832	0.001

The application of personalized training methods in sports technique improvement can significantly enhance athletes' technical proficiency. Pre- and post-intervention experimental groups demonstrated notable improvements in three technical evaluation metrics: movement accuracy, technical coordination, and movement effectiveness. Movement accuracy increased from 5.8 to 7.6, representing a 31.03% improvement. This improvement is attributed to the targeted identification and specialized refinement of athletes' technical movements through personalized training, particularly through analysis of technical challenges and specialized training on wrist angles. Technical coordination scores increased from 6.2 to 8.1, representing a 30.65% improvement, indicating a significant enhancement in athletes' racket-holding execution. This technical advancement is closely linked to real-time dynamic feedback, which enables dynamic capture of athletes' racket-holding movements and immediate correction of errors. The action effectiveness score increased from 5.9 to 7.8, representing a 32.20% improvement, indicating a notable increase in athletes' racket-holding action effectiveness and practical competition capabilities. Statistical analysis revealed that the p-values for all improved technical indicators were <0.001, indicating significant training effects. The control group's training effects over the same 4-week period were less than 8–12% of the improved technical indicators post-training. These results demonstrate the timeliness of personalized training, and the athletes' technical improvements are a gradual process. In the first 4 weeks, there was a significant improvement in the athletes' movement coordination, in the next 4 weeks, there was a significant improvement in the athletes' movement consistency, and in the final 4 weeks, there was a significant improvement in the athletes' movement effectiveness.

In terms of practicality, the effectiveness of the training improvement strategy was highly affirmed by coaches. The motion analysis report based on image recognition technology enabled scientific and efficient training guidance, effectively addressing the shortcomings of training guidance models that rely solely on subjective experience. Athletes in the experimental group generally showed increased training motivation, with 87% of athletes demonstrating improved training motivation due to more targeted training content and clear improvement goals. Under the same training volume, the rate of technical improvement increased by 35%, and the average time required to achieve technical goals was reduced by nearly 25%, which is of great significance for improving training efficiency. Long-term follow-up results showed that six months after the experiment, athletes in the experimental group maintained a high level of technical proficiency, demonstrating the long-term sustainability of training effects.

4. Conclusion and Outlook

From the experimental results presented in this paper, it can be concluded that image recognition technology can indeed be used to quickly and accurately assess the quality of badminton stroke techniques. This technology aligns with the direction of sports performance analysis and represents a significant breakthrough in its application to stroke techniques. Meanwhile, traditional analysis techniques for badminton stroke techniques primarily rely on the personal experience and subjective judgment of badminton coaches. While this method does have its practical significance, it inherently involves human subjectivity, resulting in issues such as poor objectivity, low consistency, and insufficient accuracy. However, analyzing using image recognition technology can precisely and quickly detect and track stroke movements, effectively avoiding issues such as poor objectivity, low consistency, and insufficient accuracy. It can also accurately capture and judge hitting actions, while providing quantification and repeatability in the assessment of athletes' hitting actions. This method eliminates human judgment factors, thereby providing an accurate and scientific direction for improving badminton technical levels.

The conclusions of this study on training reform methods demonstrate significant success. In terms of personalized training, comparisons of experimental data reveal that the reformed methods offer substantial advantages. In comparative experiments, the experimental group achieved improvements of over 30% in three areas—action consistency, technical standardization, and action effectiveness—after 12 weeks of training, while the control group achieved improvements of only 8% to 12%. The specific data clearly indicate the superiority of the reformed methods. The advantage of the training reform method lies in diagnosing technical errors in athletes' movements and proposing corresponding improvement training methods for different technical issues. The intelligent assistance system can analyze each athlete's technical movements, identify technical weaknesses, and develop personalized technical improvement plans for each athlete. This reduces athletes' blind training time. Meanwhile, training motivation has also been significantly enhanced, with 87% of athletes indicating that the personalized training content and clearly defined improvement goals have stimulated their training motivation. After tracking the results for six months, it was found that the experimental group athletes' technical skills remained stable at a high level after six months, demonstrating the stable long-term effectiveness of the intelligent system's training.

In summary, this study utilized image recognition technology to effectively assess athletes' technical skills, not only demonstrating the effectiveness of this technology but also providing a new direction for sports science and training. It also represents a novel approach to evaluating technical skills by integrating biomechanical technology with deep learning models, further illustrating the powerful synergy between technology and sports development. In the future, as technology continues to advance, it is anticipated that image recognition technology will be applied in more sports disciplines, providing athletes with more comprehensive technical support for scientific training and skill development. Under the trend of artificial intelligence development, image recognition technology is expected to exert an even greater influence in the field of competitive sports, providing more energy for the future development of sports.

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