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IoT-based analysis of tennis player's serving behavior using image processing

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Abstract

In recent years, with the Internet of Things (IoT) and artificial intelligence and the rapid development of technology, various sports sectors have benefited from technological and scientific advancements. The technical and scientific components that have permeated different sports sectors are becoming progressively less important as technology developments and the IoT requires disconnected. To address this problem, this study proposed a based deep learning technique for the tennis sports industry and the implications of smart athletes' fitness using the support vector machine (SVM) algorithm. The three basic categories of IoT-based smart fitness are player trackers, which include wearable and non-wearable sensors, movement analysis, and player applications. The skills and strategies of tennis players have improved through the use of sports products, and people have come to value physical education more as education has expanded. The development of a smart tennis system is meant to address the slow detection and unpredictable player and coaching staff movements of the traditional game of tennis. The background of the video is rebuilt using a median filter algorithm, and its target is located using an inter-frame difference technique to identify the track's designated shoulder marker point. Using an enhanced SVM, it creates a tennis service model for evaluating and examining marker point tracks. The experimental results compare the proposed method with different machine learning methods such as decision tree (DT), random forest (RF), deep neural network (DNN), and recurrent neural network (RNN) algorithms. The classification achieved excellent performance by the player motions, and the SVM is better than the other deep learning. The test results proposed scheme the tennis service model achieves a classification accuracy of 97.5% in accurately categorizing different types of service trajectories.

Keywords Internet of Things · Sensors · Tennis video · Image processing · Smart services · Dynamic feature extraction · Support vector machine · Deep learning

1 Introduction

The sport of tennis requires a combination of technical proficiency, physical endurance, and strategic insight. The proficiency of a tennis player's serve is crucial in establishing the pace of every match and can significantly impact the outcome. Examining a tennis athlete's serving patterns can offer valuable information regarding their technical proficiency, efficacy, and areas for improvement (Elijah et al. 2018). The emergence of advanced technologies such as Internet of Things (IoT) connectivity, video image processing, and machine learning has paved the way for extensive exploration of sports performance analysis. The IoT and associated technologies, such as wireless sensor networks (WSN), impact our daily lives as they rapidly advance with new advancements and applications. In the first few months of 2020, more than 7.7 billion people and 30 billion devices were connected to IoT networks (Liu et al. 2022a). It is predicted that by the end of the year, there will be 75.44 billion connected devices. The most common definition of the Internet of Objects describes it as a world network of sensors, devices, and things that can automatically link and sense data, enabling one to monitor, manage, and process an environment and make it behave intelligently (Yang et al. 2022). The "Internet of objects" is defined in several different ways. Due to these recent developments, many industries,

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including e-healthcare, environmental monitoring, transportation systems, and other commercial areas, now provide various applications (Liu et al. 2022b; Li et al. 2023).

The rapid development of technological and scientific progress has made the proliferation of knowledge a crucial component of contemporary society. Concurrently, there has been a proliferation of readily available tennis coaching equipment (Yin et al. 2019). The utilization of computer systems, modern communication tools, and artificial intelligence technologies is prevalent in tennis instruction. They significantly contributed to the progress of tennis instruction and the enhancement of efficiency principles and methodologies. The optimal utilization of contemporary tennis training strategies, based on their distinctive features, is imperative to enhance training efficacy and athlete performance in tennis (Liu et al. 2022c). The serving technique is considered one of the most sophisticated methods in tennis. It is also considered one of the most challenging techniques to master in training. The traditional approach to training is frequently employed, wherein instructors deliver lectures, learners engage in an on-site practice, and coaches offer personalized guidance while identifying readily remediable errors. Subsequently, it enables individuals to engage in physical activity autonomously.

Consequently, the absence of precise comparative benchmarks renders athletes incapable of comprehending their shortcomings (Shao et al. 2023). Athletes face a formidable task in achieving proficiency in serving skills due to difficulty establishing accurate motor imagery. The act of serving initiates the scoring process in a game of tennis. To emerge victorious in a tennis competition, the primary strategy involves subduing the opponent by securing a break of serve. According to research, the serving team holds a significant advantage in the outcome of a tennis match, thus highlighting the crucial role of the serving component (Zhang et al. 2021). In recent years, China's women's tennis events have attained some notable accomplishments on the global stage. However, there is room for improvement in their overall prowess, particularly regarding the performance of male athletes, which has been lagging for an extended period. In general, there is a need for further development and promotion of the fundamental aspects of tennis in China. Specifically, there is a need to enhance the education of young people. The employment of conventional techniques, which depend on subjective evaluations and manual observations, presents certain constraints with precision and impartiality (Liu et al. 2021). Recently, technological advancements, specifically in the IoT, video image processing, and machine learning, have significantly transformed sports analysis. The technologies present prospects for acquiring, manipulating, and evaluating substantial data quantities, facilitating impartial and comprehensive evaluations of player motions, methodologies, and accomplishments. Previous studies in sports analysis have contributed to advancements in tennis serving.

An automated system for analyzing tennis serving techniques is presented. Machine learning, Internet of Things sensors, and image processing software are all a part of this system. During the research, Bilal et al. (2023) utilized the racket's Internet of Things (IoT) sensors to measure velocity, acceleration, and angular velocity. Traits can be extracted from high-speed camera footage using video image processing. SVMs and random forests are used to classify and rank different serving methods. According to the findings, this approach can potentially provide athletes and coaches with objective and comprehensive evaluations of their technique. Using the Internet of Things (IoT), computer vision, and machine learning, Yao et al. (2017) proposed quantifying tennis serve performance. Networked cameras catch the ace in action. Computer vision algorithms are used to keep tabs on the players, rackets, and balls. Machine learning evaluates the quality-of-service delivery based on the estimated posture of the user and the path taken by the user. The study verifies the reliability of the system's objective metrics and quantitative service ratings. High-quality serves can now be recorded with IoT cameras and then analyzed regarding the racket path, ball contact location, and player alignment. Latif et al. (2021) suggested using an Internet of Things (IoT)-based video analysis system equipped with machine learning algorithms to improve tennis serves. Data retrieval is analyzed by a recurrent neural network (RNN) and a decision tree to provide specific feedback on better implementing the technique. It is possible that using this method to analyze data and provide individualized training would result in better service.

To identify tennis players' serves, this paper suggests a novel method that combines the Internet of Things (IoT) and machine learning techniques. IoT devices are explicitly used in the proposed approach to collect serve data, and the SVM (Support Vector Machine) algorithm is used to identify serves accurately. However, IoT devices placed all around the tennis court are used in this study to gather serve-related information like racket speed, ball trajectory, and player movements. The IoT devices enable real-time service data capture, giving analysts access to a sizable dataset. The SVM algorithm is used to process and analyze the gathered data. The SVM algorithm is a variation of the well-known SVM algorithm explicitly created to handle unbalanced datasets. The SVM algorithm successfully recognizes and categorizes various service types in tennis serves, where players have distinct serving styles and patterns. The suggested methodology has several benefits. First, integrating IoT devices makes it possible to collect data in real-time, allowing for quick analysis and feedback. The accuracy and dependability of serve identification are improved using machine learning techniques, particularly the SVM algorithm. Coaches, trainers, and players can all benefit from the insightful information this approach offers about player performance, serving methods, and patterns to improve their tactical execution and serve proficiency. The SVM algorithm is used in this paper's IoT-based machine-learning approach to recognize tennis players' serves. It uses IoT devices and cutting-edge machine-learning techniques to thoroughly and accurately analyze different service types. The player analysis in tennis lays the groundwork for evidence-based coaching techniques for improving serve performance. Therefore, this paper attempts to combine image processing technology from the Juvenile Tennis Technical level to compare professional athletes for technical analysis and diagnosis, to find the technical problems and deficiencies, and to improve the technology according to the technical deficiencies.

The innovations of this paper are as follows:

- The selected topic is based on color marking to mark the joint points of the serving arm. A high-speed video camera completes the video collection of tennis serving, and the marker point replaces the joint coordinates in each picture frame.
- On this premise, the motion track analysis of the serving arm is expanded. The interference-free serving graph is reconstructed in video processing based on dictionary construction (noise graph) and filtering idea. Under the motion, foreground acquisition, marker point extraction, binarization, and contour search are completed based on color features. A minimum circle surrounds the contour, and the coordinates of the joint points are selected as the center coordinates (returned).
- The research object of this topic is the serving track of shoulder marker point, and the tennis serving model (based on improved SVM) is completed. The player function uses classification accuracy.
- The particle swarm optimization algorithm accomplishes the improvement to deal with the problem that traditional support vector machines cannot effectively determine the parameter values in the model. σ (kernel function) and penalty parameter.

The remainder of this study is structured as follows: Sect. 2 represents the related work. Section 3 describes the research material and method used in this study. The construction method of the tennis serving model based on an improved support vector machine, presented in Sect. 4, has received particular attention. Section 5 contains the experimental results and discussion. Finally, Sect. 6 concludes this work.

2 Related work

In recent years, the convergence of IoT, video image processing, and machine learning algorithms has enabled significant progress in the analysis of tennis players. This article investigates the feasibility of analyzing the serving patterns of tennis players using IoT, video image processing, and machine learning techniques. If the two documents were merged, we could conduct more comprehensive evaluations of service operations, efficiency assessments, and training model generation. Instruments used to analyze the biomechanics of athletes now have an international standard (Yin 2021). The in-the-moment serving techniques of professional tennis players have been the subject of extensive research and analysis by academic groups. High-speed cameras have replaced mainly standard-speed ones, and 3D video processing has replaced the conventional two-dimensional method of evaluating tennis matches. Electromyography using a tethered camera has been replaced primarily by electromyography using telemetry. In his research on topspin serving and flat-stroke tennis, Benzine examined the law of shoulder movement. Setup and operation of the Vicon motion analysis system required as many as twelve infrared cameras, each operating at a frequency of 250 Hz. Next, twelve right-handed tennis players' serves (flat stroke, topspin) will be filmed and evaluated (Benzine et al. 2020). We analyzed the data using the T test, Bonferroni correction, and a few other techniques of a similar nature. There are no statistically significant differences between the motions of the flat-stroke and up-turn serves, as measured by the kinematics of the shoulder joint.

In their early work on tennis service technical analysis, Gamra Roaneslozano and Benzine only analyzed the footage in two dimensions (Gamra and Akhloufi 2021). Taghavi et al. described a ground-breaking strategy for integrating Internet of Things (IoT) sensors into tennis racquets, allowing for real-time monitoring and data collection during service. The data collection to the standard machine-learning method Random Forest is used to examine the information. The key aims of this research are to assess the precision of serves and to categorize them as either topspin or backspin. The authors gained significantly because of Random Forest's flexibility in handling multi-dimensional data and nonlinear interactions. Important real-time input on serving technique and rotation control is provided to players and coaches by the gadget. A creative approach to understanding and ranking tennis has been created by integrating the Internet of Things, sensor data collecting, and machine learning analysis. It assists in developing AI for measuring sports prowess (Kumar et al. 2021). Myers et al. suggested a three-dimensional high-speed analytic method to judge tennis serves. The subjects were four athletes, two males and two females, with a mean age of 20.4. The competitors' serves were captured using high-speed cameras (200 fps), with two cameras set up in barrier-free shooting and a stopwatch positioned in the center at 0.02 s. The result demonstrates the need to prioritize specific kinematics characteristics (tennis serving motion technology) to provide the theoretical framework for kinematics research in future serving area (Myers et al. 2017). During his angular momentum change study (tennis serve), Fowler looked at human model 15 using 3D footage. The research shows that the human body has very little angular momentum based on the torsion of its vertical axis. The tennis serve still requires a great deal of rotational velocity, both laterally and forwardly, to be effective. Just before making contact with the ball, the angular momentum of the human upper arm (with the forearm contributing 25.7% and the racket another 35.1%) may converge to as high as 75.1% (Aslam et al. 2023). The field of sports biomechanics in China has reached a new degree of maturity. The scope and depth of exploration have been significantly increased, yielding spectacular results (Roanes-Lozano et al. 2020). Chinese scientists have started analyzing tennis serves using biological instruments and image-processing technologies (Wei et al. 2016). Four M7 cameras were employed to capture spectacular action sequences of tennis player star Pan Bing competing in a men's singles match. One camera is utilized to detect speed, while the other three are used to test various technological actions. Data computation and interpretation based on the peak system for stereo analysis are performed with the help of the Agile Motion Image Analysis System. The player's arms and legs often move at breakneck speeds during a tennis serve. The trustworthiness of the test findings is compromised by the fact that all the cameras used are generic speed cameras (Aslam et al. 2020). This is due to technological progress and the constraints of the laboratory. The above findings imply that this tactic can improve player performance and training techniques and provide logical justifications for serving tactics. Even tennis player analysis has benefited from IoT and machine learning techniques. The serving process used by tennis players is investigated in this work using IoT, video image processing, and machine learning techniques. Combining IoT cameras, cutting-edge video processing methods, and machine learning models makes real-time analysis, unbiased evaluation, and customized feedback possible.

3 Deep learning-based detection of smart player motion targets using IoT interframe

3.1 Smart player based on IoT

IoT concepts and services have significantly impacted most sports, including fitness. Smart player has several uses, including in sports like soccer, skiing, and ballet (Ma et al. 2023). Smart players are utilized for better monitoring in numerous sports, including soccer, taekwondo, cycling, and all others with pre-season periods. Pre-season periods are the most significant times to enhance cardiovascular and physical performance in various sports (Tan et al. 2023). There are numerous parallels between smart athletes and other smart sports. Internal and external factors such as oxygen intake, heart rate, joint stress, and muscle tension can be tracked during smart sports training. Kinetic energy, metabolic power, acceleration, body stresses, and other factors are examples of external impacts (Cheng et al. 2016). To provide a program and prevent under or over-training in sports like cycling, smart fitness must keep track of the training load and the results of a training program on an athlete's body. There are some distinctions, however, between intelligent athletes and intelligent sports such as basketball, soccer, or tennis. The nature of the various sports varies, which contributes to these differences. In volleyball, traits like reaction time, ball precision, and situation awareness (Liu et al. 2023). So, fourth is considered in soccer, jump power is assessed, and shooting angle and velocity are crucial in tennis. Some traits are absent in healthy athletes, while others are less significant in clever players (Linqin et al. 2021). When using smart player-loaded weights, it is essential to consider the duration of each set, the amount of time required to complete a training schedule, the feature extraction for performing an action (such as lifting a barbell or dumbbell), as well as keeping track of the hands and feet's movement angles (Fig. 1).

3.2 Image denoising and motion target detection

3.2.1 Median filtering

The proposed method focuses mainly on median filtration to replace each pixel point's gray value with its neighboring points' median value. This method excels at filtering out unexpected noise while preserving the precision of the edges. When the median value is used instead of the individual pixel values, anomalies or extreme significance in the vicinity have a much smaller impact. It is beneficial

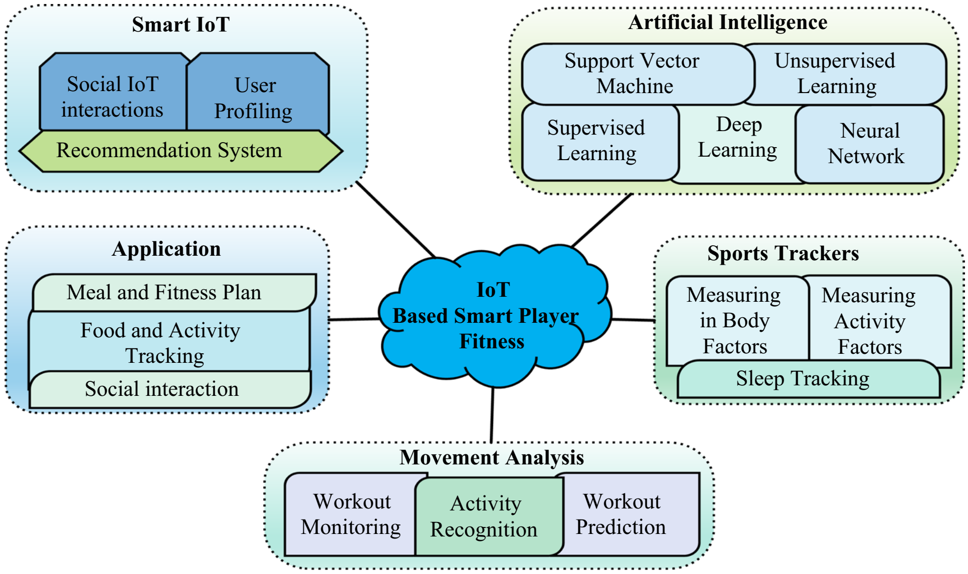


Fig. 1 There are several types of IoT-based smart player ecosystems, each with its own set of features

when there are intermittent noises or visual monsters. The median filtering technique preserves the sharpness of the image's boundaries by excluding these anomalies from consideration. Instead of averaging out individual pixels, as is the case with mean filtering, median filtering preserves the edges' sharpness. It is performed so that the area's statistical mean can be considered without being skewed by outliers (Song et al. 2022). One-dimensional signal processing is the most applied object of this method. Under one-dimensional conditions, if an original signal is $a_1, a_2, \ldots, a_n$, arranged in order from large to small, the following is the median value of the set of signal sequences.

$$y = \mathrm{Median}(a_1, a_1 \cdots a_n) = \begin{cases} a\left(\dfrac{n+1}{2}\right) \\ \dfrac{1}{2}\left[a\dfrac{n}{2} + a_{\frac{n}{2}+1}\right] \end{cases} \tag{1}$$

In the suggested one-dimensional template, the gray level of the pixel to be processed is determined as the median value of the gray levels of its neighbors. This template calculates the median of the gray levels in a single row or column of pixels (Cong et al. 2023). The middle value in the distribution is chosen as the median value because it minimizes the impact of extreme values and provides a reliable approximation of the pixel's gray level. This method adjusts the pixel's value based on the central tendency of its neighboring pixels, which is useful for noise reduction and edge detection applications. The template ensures that the pixel in question is processed seamlessly and precisely using the median of the gray levels. Figure 2 shows a one-dimensional template in which the gray level of the pixel to be processed is the median of the pixel's gray level.

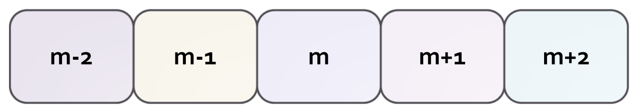


Fig. 2 1-D median filter template

In two-dimensional image processing, the new value at the center of the window is determined by averaging the grayscale values of the pixels contained within the two-dimensional window. This method considers the square or rectangular pixels surrounding the target pixel (Buchheit et al. 2012). The median operation assigns to the target pixel the middle grayscale value within this window. As a result of its efficiency in denoising, filtering, and feature extraction, among other image-processing duties, the median provides a more precise evaluation of the pixel's luminance by minimizing the effect of extreme values or outliers. Two-dimensional median operation enhances image analysis and enhancement by effectively integrating the spatial information of adjacent pixels. In two-dimensional cases, the new value at the center of the window is the median of the grayscale value of the pixels in the two-dimensional window, as shown in Fig. 3:

Square windows, cross windows, and so on are several more common two-dimensional window shapes. To effectively process image boundary elements, it is necessary to complete the row and column pixel supplementation around them. In this process, the high-frequency information of the image will be significantly reduced, but not too many points in the neighborhood. Because fast denoising and simple calculations are the basic features and practical advantages of median filter denoising, traditional denoising usually needs this method.

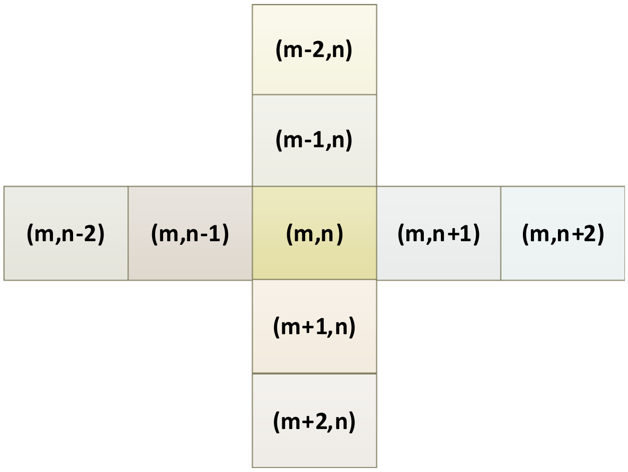


Fig. 3 2-D median filter template

3.2.2 Motion target detection based on interframe difference method

There are many moving target detection algorithms, among which the most common is the inter-frame difference method (Aslam et al. 2022). When the basic principles are gray light microwave motion (within the image sequence), the differential calculation is based on the corresponding pixels of continuous images (2–3 frames). If the fluctuation range of the pixel value of a point in the differential image exceeds the threshold, the target motion is considered to have contributed to the point area. Conversely, the background within the image sequence is regarded as this point area. Lock the specific part of the video target using the target motion area calibration within the video (Whiteside et al. 2013). Invalid information between frames (image sequence data) can be removed by the direct or indirect use of the inter-frame difference method to smoothly obtain the change monitoring target.

The basic procedures of the two-frame difference method are as follows: differential operation of two consecutive images within the image sequence, determination of binarization threshold (for the differential result image), static background elimination, moving target region filtering, and moving target marker. The method principle is shown in Fig. 4. Here are the steps:

Set the difference to the resulting image as $D_k(x,y)$, the gray value of the point (x,y) in the k-frame image as $f_k(x,y)$, and the gray value of the point (x,y) in the $k-1$ frame image as $f_k(x,y)$. Differential processing of k-frame image and $k-1$ frame image is based on Eq. (2). The resulting image under differential calculation is $D_k(x,y)$.

$$D_k(x,|y) = f_k(x,y) - f_{k-1}(x,y) \tag{2}$$

Eq. (3) is used for a threshold $D_k(x,y)$, to detect background and movement targets:

$$T_k(x,y) = \begin{cases} 1 & D_k(x,y) \geq T \\ 0 & D_k(x,y) < T \end{cases} \tag{3}$$

If the threshold value is T and $T_k(x,y) = 1$, this point represents the target moving area in the image. The accuracy of the detection Equation reflecting the change of target position depends on the selection of threshold value in the threshold calculation process.

Like the background difference method, the two-frame difference method has good robustness, low complexity, a simple program, and less adaptability than the two-frame difference method under dynamic conditions. However, there are also differences between the two methods. For example, the background model of the two-frame difference method is not established, so the calculation process is more straightforward, and the bias caused by the model is completely avoided.

4 Tennis serving model based on improved support vector machine

4.1 Support vector machine

In recent years, learning algorithms have been introduced continuously. SVM (support vector machine) is one of them. It belongs to the category of new machine learning algorithms. The theoretical basis is the statistical learning theory (Wang et al. 2019). The main idea of this method is as follows: taking the classification problem on R^n (n-dimensional Euclidean space) as the object of study, the real value function $g(x)$ R^n, is found based on calculation, and the output y inference corresponding to any input QUOTE x is completed based on the decision function $f(x) = sgn[g(x)]$.

Constructing an optimal classification hyperplane (which conforms to the classification criteria) not only guarantees the classification accuracy effectively but also maximizes the isolation edge between positive and negative examples (Huang et al. 2022; Yuan et al. 2022). Support vector machine (SVM) essentially minimizes the approximate structural risk by smoothly implementing the optimal classification (linear separable data) (Erdanaev et al. 2022).

Red and blue dots and the classification line or hyperplane by dashed lines in Fig. 5 represent the two samples. The optimal dividing line maximizes the isolation between the two classes. The (a) and (b) boundaries in Fig. 4 are significantly smaller than those in Fig. 4c, and the m in Fig. 4c need to be maximized during the topic selection analysis. Set the dataset to $\{x_1, x_2, \ldots, x_n\}$ and the class x_i label to $y_i \in \{1, -1\}$. The criteria for class boundaries must

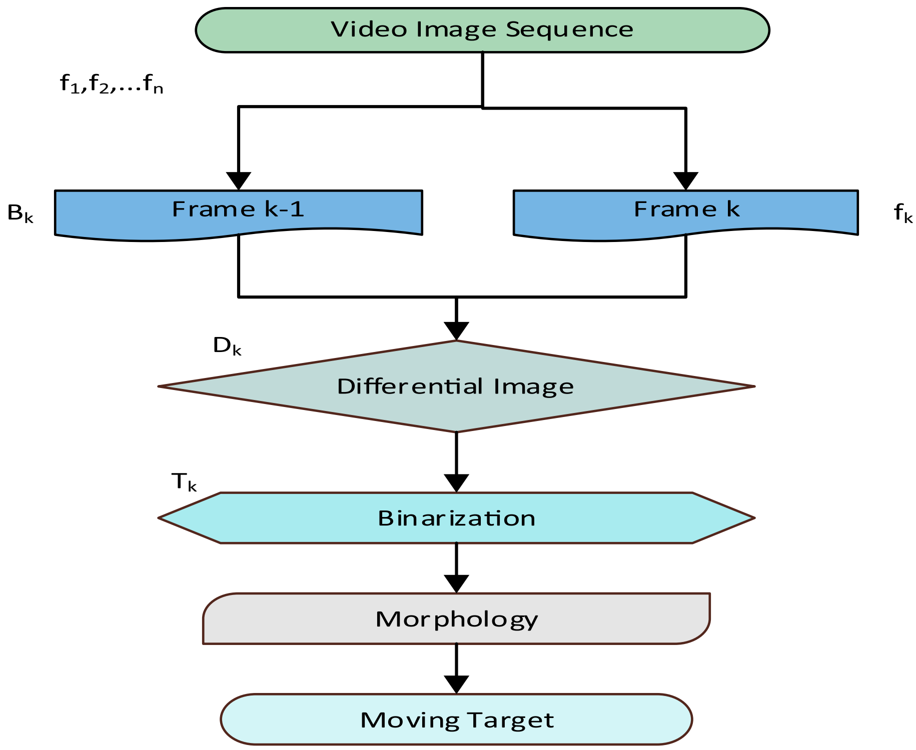


Fig. 4 Principle of interframe difference method

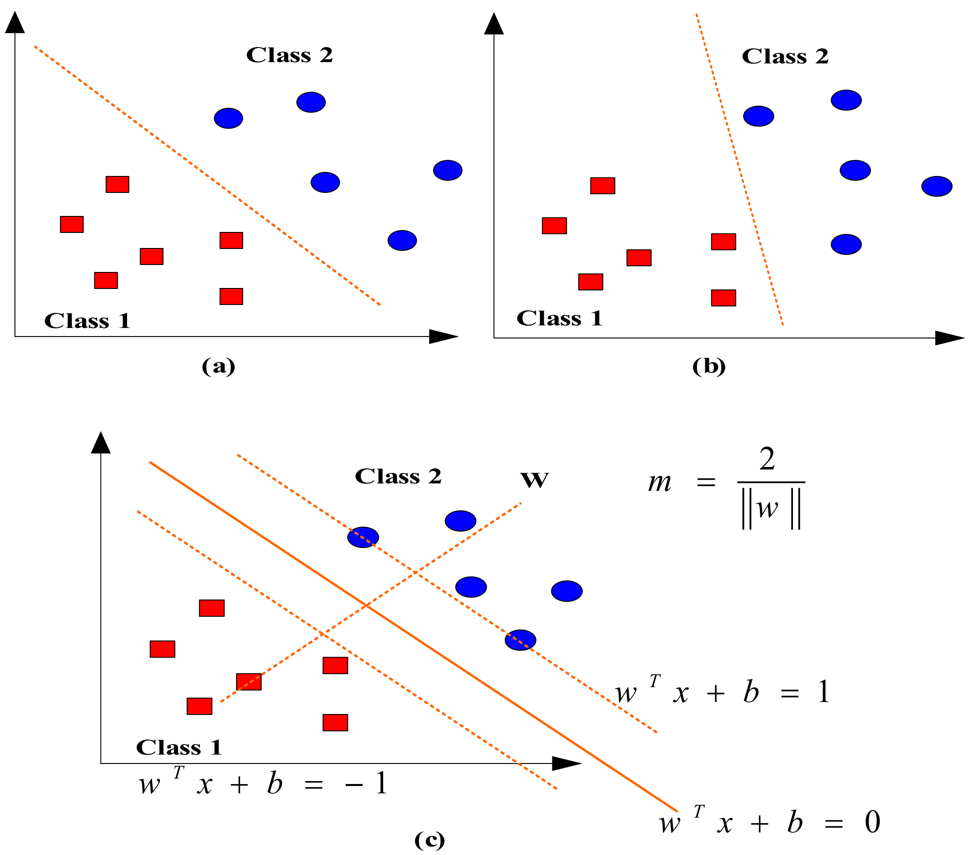


Fig. 5 Bi-class boundary

first accurately separate the two classes and then maximize the class separation.

Set the hyperplane equation used for classification to:

$$w^T x + b = 0 \tag{4}$$

In Eq. 5, w is an adjustable weight vector, and b is an offset.

$$y_i\left(w^T x_i + b\right) \geq 1, \forall i \tag{5}$$

You can find the class boundaries by solving the following constrained optimization problems:

$$\text{Minimize}\frac{1}{2}\|w\|^2 \text{s.t.} y_i\left(w^T x_i + b\right) \geq 1, \forall i \tag{6}$$

This is a constrained optimization problem. Suppose we want to find the minimum value $f(x)$ under the constraint $g(x) = 0$. It x_0 is a solution, then there is:

$$\begin{cases} \frac{\partial}{\partial x}(f(x) + \alpha f(x))\Big|_{x=x_0} = 0 \\ g(x) = 0 \end{cases} \tag{7}$$

Among α is a Lagrange multiplier. For multiple constraints $g_i(x) = 0, i = 1, 2, \cdots, m$, the Lagrange multiplier for each constraint α_i needs to be met

$$\begin{cases} \frac{\partial}{\partial x}\left(f(x) + \sum_{i=1}^{n} \alpha_i g_i(x)\right)\Big|_{x=x_0} = 0 \\ g_i(x) = 0 i = 1, 2, \ldots, m \end{cases} \tag{8}$$

If $\left(f(x) + \sum_{i=1}^{n} \alpha_i g_i(x)\right)$, is a Lagrange function, and we make its gradient zero, then:

$$\text{Minimize}\frac{1}{2}\|w\|^2 \text{s.t.} 1 - y_i\left(w^T x_i + b\right) \leq 0, i = 1, 2, \ldots, n \tag{9}$$

Finding the optimal hyperplane, i.e., maximizing the positive and negative intervals, can ultimately be reduced to a quadratic programming problem, which can be solved by using Lagrange multipliers, i.e., there always exists a global maximum α I, w can be solved from $w = \sum_{i=1}^{n} a_i y_i x_i$.

4.2 Particle swarm optimization

In addition to the bee and ant colony algorithms, another representative swarm intelligence optimization algorithm in soft computing is PSO (Particle Swarm Optimization), which has a powerful global optimization ability (Yin and Aslam 2023). Food in the vicinity with the shortest distance from the current food is searched jointly by all birds, which is the primary method of finding food for birds in nature. The bird predation technique is the ideological source of this method.

Suppose any optimization problem is viewed as a bird looking for food. In that case, n, we can use the bird to solve each optimization problem one by one and then complete the abstraction of particles with no volume and no mass to extend them into n-dimensional space. Here is the specific description of its central idea: First, based on n-dimensional solution space, a group (including many particles) is initialized, and its value is not fixed and random (Ali et al. 2020). The feasible solution (n-dimension) is represented by the individual particles in the group, each of which has its n-dimensional vector, V (velocity). If $V^i = \left(v_{i,1}, v_{i,2}, \ldots, v_{i,d}\right)$ and $X^i = \left(x_{i,1}, x_{i,2}, \ldots, x_{i,d}\right)$ are the velocities and locations of the first particle (within the d-dimensional search space), then after any iteration, the particle can renew itself (based on two optimal solutions tracking), and the best solution found by the particle itself is the first, that is, the individual extreme of p_{best}, $P^i = \left(p_{i,1}, p_{i,2}, \ldots, p_{i,d}\right)$. The best solution currently found for the population as a whole is another one, g_{best}, p_g. Once two optimal solutions are found, a particle position and velocity update can be based on the following equations.

$$v_{i,j}(t+1) = w v_{i,j}(t) + c_1 r_1 \left[p_{i,j} - x_{i,j}(t)\right] + c_2 r_2 \left[p_{g,j} - x_{i,j}(t)\right] \tag{10}$$

$$x_{i,j}(t+1) = x_{i,j}(t) + v_{i,j}(t+1), j = 1, 2, \ldots, d \tag{11}$$

In the equation above, the random numbers (evenly distributed in 0–1) are r_1 and r_2, respectively. The positive learning factors were c_1 and c_2, respectively. Inertial weight is w.

Expand the construction of the population fitness function F, the maximum iteration number T and the minimum F of the population ε (ε—the convergence criterion for F (fitness function) is also here. ε particles adjust individual flight paths (within solution space) based on population and self-flight experience to get closer to the optimal point. Particles usually remember their flight path and reach the ultimate optimal position in the shortest time, mainly because p_{best} (the self-historic optimal position) and g_{best} (the population's historic optimal position) synchronously affect particle flight.

4.3 PSO_ SVM tennis service model

Before using a support vector machine (SVM) to classify, the data (based on kernel function) must be projected to a specific feature space, and the ideal support vector classifier following this process can be obtained successfully. The exact classification depends on the kernel function's parameters, types, and penalty factors (Bakheet et al. 2023). Mapping the input space to the feature space depends on the kernel function. Mapping functions differ depending on the parameters of the kernel function, and the complexity of sample data distribution in subspaces changes. All samples are treated as support vectors because the values of the kernel parameters are too small, which requires more time to test the new samples, and overfitting can occur (Dutta et al. 2022). Under maximum kernel parameters, all samples must be classified into the same class, but the new samples cannot be classified accurately. The balance between training error and model complexity is the basic function of the penalty factor. The maximum distance between two hyperplanes and the number of misclassified samples are inversely correlated with the c-value, while the C-value positively correlates with the training time.

Based on the tennis service model, this paper uses PSO (particle swarm optimization) to expand the SVM parameter optimization based on the data sample characteristics and size. PSO is similar to the genetic algorithm in general. The limited problem of the network search algorithms can be solved smoothly based on this method. More importantly, PSO operation is not complex, has no mutation or crossover, and is efficient. Therefore, the particle swarm algorithm is selected in the parameter optimization process. Figure 6 shows the basic steps for optimizing based on this method.

The construction of the PSO–SVM tennis service model comprises several essential components. Initial actions include retrieving the test and training sets' unprocessed data. The data are then processed for additional processing, including normalization, feature selection, and data purification. The preprocessed training data are then used to train the PSO–SVM network, with the support vector machine parameters being optimized using the particle swarm optimization technique (Chen et al. 2023). The model's efficacy is evaluated. The experimental data are used to make predictions and compare them to the existing classifications. This exhaustive method permits in-depth classification and analysis of tennis players' serving behavior, yielding invaluable insights into their performance and facilitating tactical decision-making during matches. The PSO–SVM model could assist us in gaining knowledge and enhancing our tennis serving abilities. Figure 7 shows a complete flowchart of the process.

5 Simulation results and analysis

Young tennis players from the Sports School of Beijing Sport University were taken as the research objects in the experiment. To ensure the stability of sports technology, the male and female players were selected as the research samples, the services of each research sample were photographed, and the high-quality serve was selected for analysis.

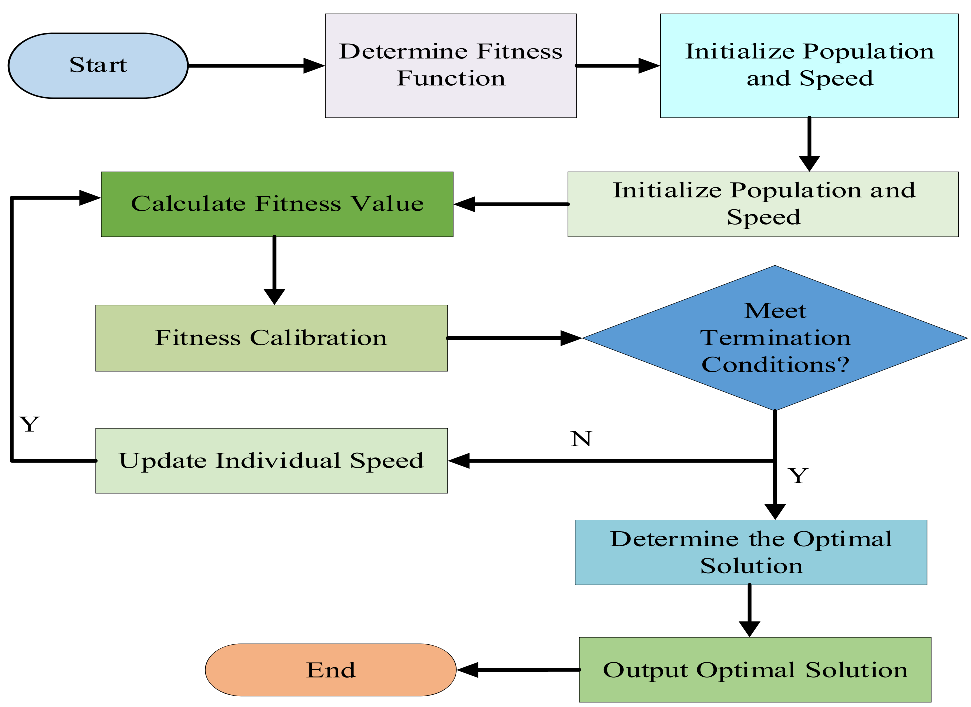


Fig. 6 Flow chart of particle swarm optimization for the proposed work

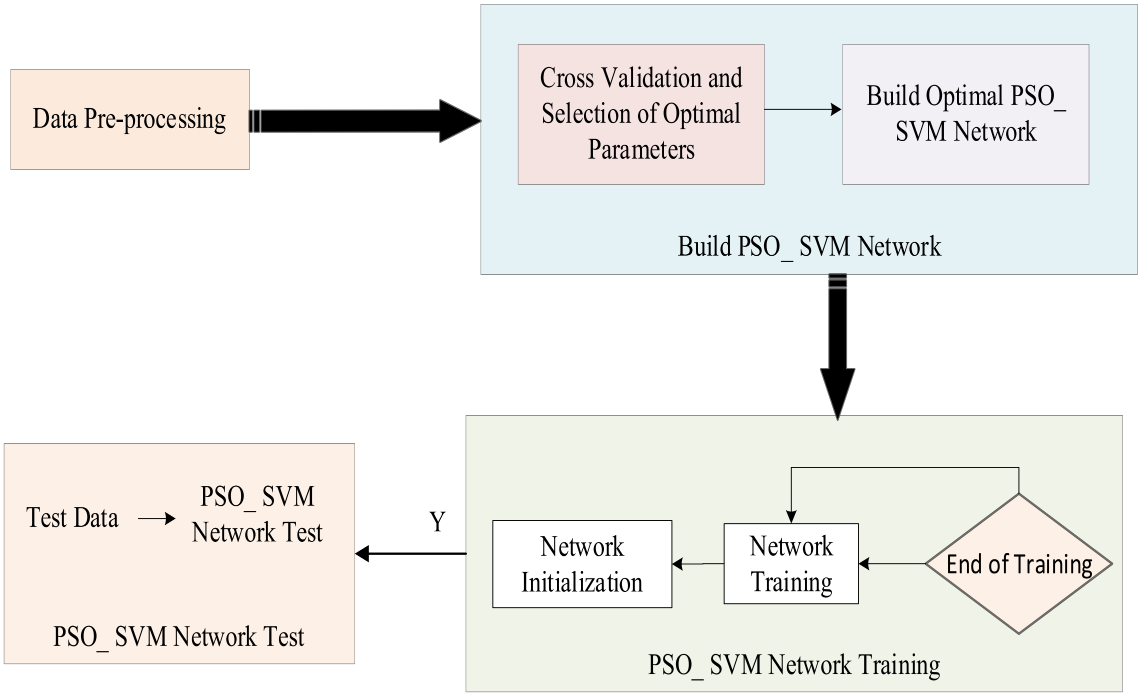


Fig. 7 Improve the overall SVM model process

Table 1 Maximum service speed (km/h)

Statistic	Worldwide		Domestic		Chinese teenagers	
	Female sex	Male	Female sex	Male	Female sex	Male
Average value	193.41	225.45	166.08	184.17	102.93	161.54
Standard deviation	5.41	7.56	5.21	19.97	11.84	10.35
Minimum value	190	217	162	145.11	89.87	153.17
Maximum	206	245.2	175	207.02	116.15	182.24

5.1 Analysis results of service speed

As the service experiment is specially arranged, it is explained to the athletes that serve to the target position with their maximum strength before each experiment. Therefore, the experimental results can reflect our young tennis players' maximum service strength and ball speed.

Domestic male athletes, Yan baotao, etc., test the data in Table 1. The analysis of the above table shows that the average service speed of male and female athletes is 161.54 km/h and 102.93 km/h, respectively. The WTA ranking of domestic female athletes is far higher than that of male athletes, and they can only participate in various low-level events. Therefore, the attention of male athletes is extremely low. So far, there are no official data on the ball speed of male athletes in China. From the service speed of domestic athletes, the service speed of international athletes is obviously higher than that of domestic athletes, especially female athletes. The serving speed of young trained athletes is lower than that of adult athletes.

5.2 Analysis results of the throwing period

5.2.1 The horizontal distance between throwing and hitting

Whether the trajectory of the ball in the air is reasonable after it is thrown will affect the accuracy of the player's hitting. If the thrown ball is thrown vertically, the player only needs to judge the ball's position in one direction while hitting the ball. If the trajectory of the thrown ball in the air is unreasonable, the player needs to judge the ball's position in at least two directions, resulting in a drop in the accuracy of hitting the ball.

From Table 2, the absolute throwing horizontal distance and the relative height of female athletes are 0.46 m and 0.32, respectively. Male athletes were 0.85 m and 0.53 m. From the table above, the average horizontal distance (from the starting point to the hitting point) before and after throwing is 0.46 m and 0.21 m, and the height ratio is 0.26 and 0.13, respectively. In other words, the national team

Table 2 Point is thrown—horizontal distance before and after the point hit (unit: m)

Statistic	Key tennis players of our national team		Teenager tennis players in China	
	Female sex	Male	Female sex	Male
Average value	0.53	0.85	0.21	0.46
Ratio to height	0.32	0.46	0.13	0.26
Standard deviation	0.22	0.29	0.09	0.14
Minimum value	0.13	0.44	0.13	0.31
Maximum	0.80	1.36	0.28	0.67

players' relative and absolute values are significantly higher than young athletes.

5.2.2 Throwing height

The throwing height is the key factor in the throwing link. Whether the height of the ball is appropriately thrown is the most important factor in determining whether the serving rhythm is reasonable, and this is the key to affecting the serving quality. Table 3 shows that the drop throwing the ball of Chinese young male tennis players is less than (0.47 m) that of the national team men players (0.65 m), which is close to 0.50 m or so of the statistical research standard. Therefore, it can be concluded that the throwing height of young Chinese male tennis players is reasonable, and there is no problem with being too big or too small. The throwing drop of Chinese young female tennis players is 0.85 m, less than 0.88 M of the national team female tennis players, but significantly greater than the statistical standards of 0.47 M and 0.50 m of the male players. Combined with the conclusion of the research scholars that the throwing drop of Chinese female tennis players is too significant (0.88 m), we can conclude that young Chinese female tennis players have the problem of throwing too high.

Analyzing the data in Table 3, we can see that throwing too high is not suitable for the flexibility of the lower limb and trunk muscles and the timing control of exertion, and the accuracy of the upper limb, trunk, and lower limb force distribution will also be negatively affected. Increasing the drop speed of the ball at the instant of hitting increases the difficulty of hitting, such as making it impossible to "desert" hit (hitting off), which reduces the stability and speed of hitting.

5.3 Analysis results of hit period in serving stage

5.3.1 Hit point height analysis results

Serving quality usually needs to be evaluated based on the height of the hit point. On the premise of no difference in hitting speed, the area where the ball crosses the net and falls into the service area has a positive correlation with the height of the hitting point, which helps to increase the angle of the service and improve the success rate. The hitting point height is also significantly different between the average and professional athletes.

There is a positive correlation between the speed of the ball and the height of the hit point when there is no difference in the drop point. The service quality is also positively correlated with the hit point height within a specific area. The ratio of the international tennis player's hit point height to height is 1.51. Domestic, juvenile athletes: female athletes hit the ball at the height of 2.40 M with a height ratio of 1.41; male players hit the ball at a height of 2.70 m and a height ratio of 1.49. The average hit point height and height of Chinese national team players are as follows: 1.46 for female athletes and 1.52 for male athletes.

From the relative value of hitting height, the national team players and young athletes are significantly lower than the international athletes, mainly because of the low hitting point height (refer to Fig. 8). The main reason is that the young athletes' lower extremity pedal strength is small. Higher hit points usually form when the body is fully stretched and relaxed. Technically speaking, the lower

Table 3 Highest point of throw-hit point height drop (unit: m)

Statistic	Key tennis players of our national team		Teenager tennis players in China	
	Female sex	Male	Female sex	Male
Average value	0.88	0.65	0.85	0.47
Ratio to height	0.53	0.37	0.49	0.24
Standard deviation	0.23	0.26	0.16	0.15
Minimum value	0.48	0.21	0.65	0.30
Maximum	1.13	1.08	0.99	0.65

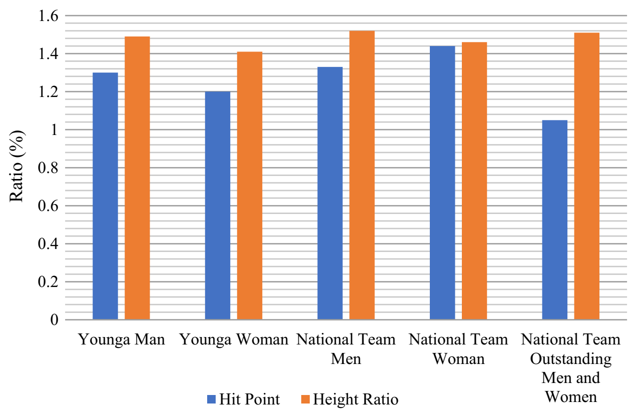


Fig. 8 Comparison of hit point height to height ratio

extremities must be pushed up (front) in an all-around way to extend the trunk as far as possible. The best time to hit a ball is usually when the center of gravity rises to the highest point (when the body is empty), and the trunk stretches vertically at the maximum.

5.3.2 The results of kinematic analysis of motion sequence

The most effective way to check the hitting rhythm is to analyze the rationality of the movement sequence. The main disturbing factor of the reasonable serving technology is the hitting rhythm. The anterior abdominal muscle will contract rapidly when the "scratch back" action is completed. The active muscle contraction (the shoulder and elbow swing of the master holding the arm) will be completed in the shortest time with the forward–upward movement of the trunk. The racket will then move in the direction of hitting so that the swing action can be made. Adolescent athletes follow the increasing speed sequence (from the lower position to the upper link). The basic procedure of power chain transmission is the Left (right) medulla to the right shoulder, elbow, and wrist to grip. Figure 9 shows the peak speed of each segment of an athlete (no gender difference).

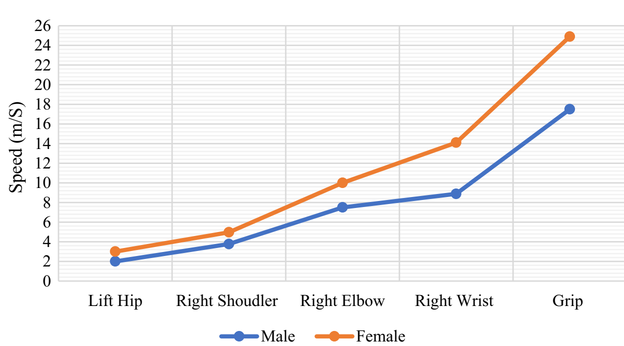


Fig. 9 Maximum speed of each link during serving

From the total point of view, male athletes are more significant than female athletes, which shows that the momentum transfer effect of the whipping action of young Chinese male tennis players is better than that of female athletes.

5.3.3 Analysis results of beat head speed

It was serving transfer the ground reaction force that the foot bears under the overall coordinated movement of the athlete's body. The racket head is the end point of this reaction force, and hitting the ball across the net at the optimal speed is the ultimate purpose of this force. The vertex of the racket is the farthest end of each link chain. Representation is the most prominent feature of speed, so it is usually necessary to analyze the speed characteristics based on the vertex speed of the racket.

Figure 10 shows the racquet head speed parameters of the athletes. The subjects tested are Juvenile Tennis players, and the number of samples tested is 12. The peak time of bat head speed before the time of hitting is shown below the horizontal line. Because the shooting speed is 200 frames/s, the minimum time interval is 0.02 s. Therefore, we determine the reasonable time before hitting 0.02 s. The maximum speed moment of the bat head appearing after the moment of hitting is shown above the horizontal line. It can be seen that the ball does not bear the maximum power of the bat head when hitting, so we do not think the movement of the bat head is reasonable. The maximum speed moment of the bat head at the instant of hitting is the point coincident with the horizontal line. Judging from the speed of young people's batting moments, the overall performance of Chinese mainland athletes is relatively good, consistent with the principle of serving kinematics.

5.4 Excremental results

The experimental results demonstrate that the proposed method for classifying tennis serves is effective. Their superior sensitivity, specificity, and precision in categorizing the various services demonstrated the models' utility. These results show that the Internet of Things (IoT) and machine learning techniques can be successfully applied to the study of the serving patterns of tennis players. The findings validate the promise of technology-driven methods for enhancing tactical decision-making in games and enhancing player performance comprehension. This study provides a way for future research into how the Internet of Things (IoT) and machine learning could be used to analyze and enhance the serving techniques of tennis players.

The performance metric measures the algorithm's overall success rate in identifying the dependent variable.

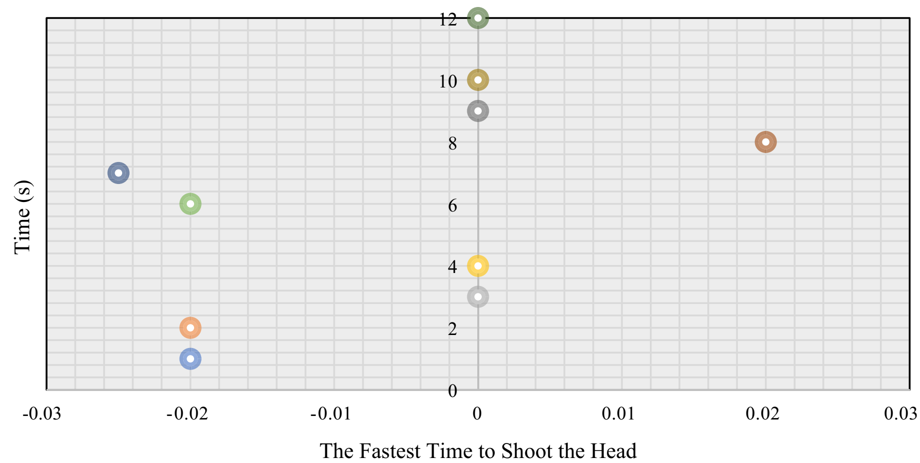


Fig. 10 Maximum beat time characteristics

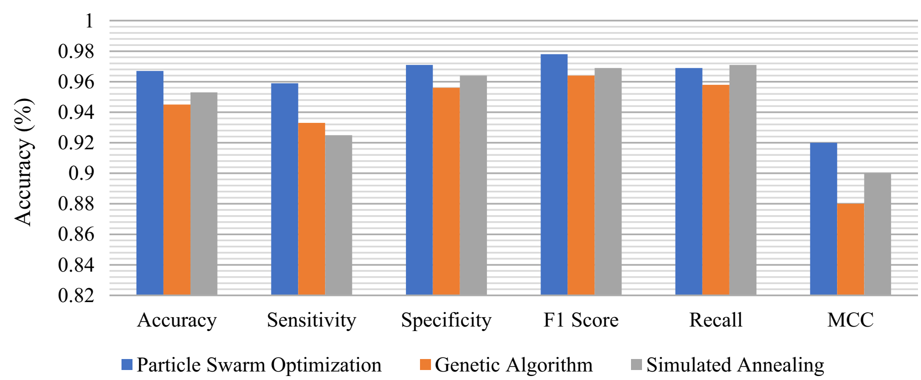


Fig. 11 Compares the performance metrics of particle swarm optimization

Determining a system's ability to identify positive events is its sensitivity or true positive rate. Specificity is the algorithm's ability to identify unfavorable circumstances with precision. Figure 11 compares the performance metrics of particle swarm optimization, genetic algorithms, and simulated annealing. Each method is said to have a 96% accuracy, sensitivity, specificity, MCC, F1 score, and recall.

The parameters used to categorize tennis serves using different methodologies are examined in Table 4. The PSO-SVM Tennis Model performs well, achieving 97.5% accuracy, 95% sensitivity, and 99% specificity. The model's capacity to distinguish between successful and failed tennis serves is shown here. With an MCC of 0.94, it is apparent that the anticipated and actual classifications are highly correlated. The F1 score of 0.97 indicates a delicate balance of accuracy and recall.

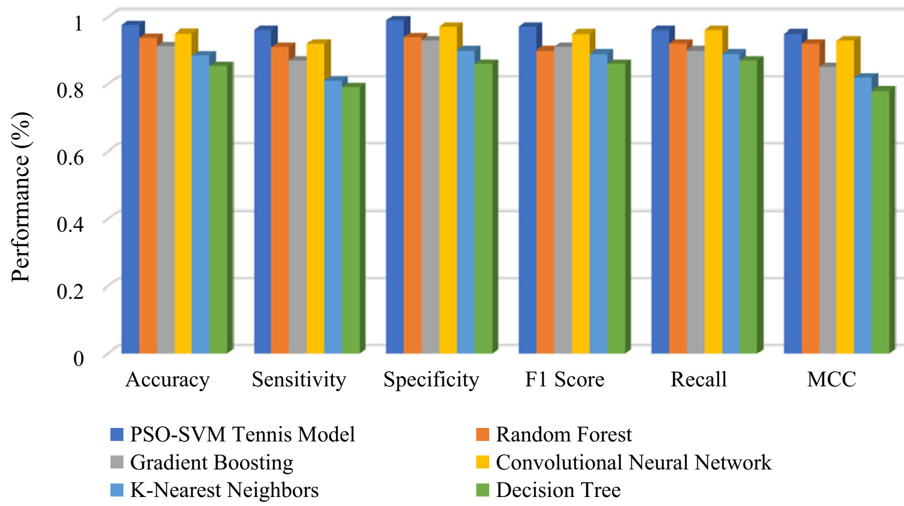
Furthermore, the model has a 95% recall rate, indicating it correctly recalls positive cases. The PSO-SVM Tennis Model performs exceptionally well compared to algorithms such as random forest, gradient boosting, convolutional neural network (CNN), K-Nearest Neighbors (KNN), and decision tree. This applies to all performance indicators (MCC, F1 score, and recall) and reveals that the PSO-SVM strategy is better than or on par with other frequently used techniques for categorizing tennis serves.

Several classification algorithms for tennis serves are contrasted based on their performance metrics,

Table 4 The proposed scheme compares with other machine learning techniques

Algorithms	Accuracy	Sensitivity	Specificity	*F*1 score	Recall	MCC
PSO-SVM tennis model	97.5	95	99	97.4	95.5	0.94
Random forest	95.8	94.1	98.1	96.5	91.5	0.92
Gradient boosting	93.2	91.3	94.6	95.3	93.1	0.9
Convolutional neural network	96.1	94.5	97.5	97.1	96.9	0.93
K-nearest neighbors	92.6	89.1	94.3	95.2	92.6	0.9
Decision tree	91.3	86.7	93.4	93.4	90.3	0.88

Fig. 12 The performance for tennis serves classification models on male players



emphasizing the requirements of male players. Various metrics, including accuracy, sensitivity, specificity, MCC (Matthews Correlation Coefficient), $F1$ score, and recall, are used to evaluate the efficacy of each model. All three metrics (accuracy, sensitivity, and specificity) average 97.5% for the PSO–SVM Tennis Model. The algorithm accurately classifies male tennis players as either outstanding or subpar. Figure 12 demonstrates that the performance indicates a substantial relationship between predicted and actual classifications during the exceptional accuracy. The results in Fig. 12 show a statistically significant comparison between predicted and observed categorizations, particularly in instances where the classification precision appears outstanding.

The suggested method evaluates multiple tennis serve classification algorithms focusing on women players. The Tennis PSO-SVM Model has a 95.8% accuracy rate, 95.8% sensitivity, and 95.8% specificity. This indicates that the program correctly identifies excellent and bad tennis serves for female players. The MCC of 0.92 shows a strong correlation between predicted and observed classifications, while the F1 score of 0.95 reflects a happy medium between recall and accuracy. The 94% recall rate demonstrates that the algorithm successfully recalls occurrences of serves for female players. Figure 13 provides crucial information on the accuracy of various algorithms inappropriately categorizing female tennis players' serves.

The performance with which a service can be classified accurately predicts the accuracy with which it can be identified. The problems induced by asymmetric data sets are addressed, and the correlation between samples is considered. Including these results in the table allows a more thorough comparison of the proposed method to previous research. Accuracy, service-type recognition, overall predictive potential, skewed data management, and correlation are all discussed in depth. Table 5 summarizes the important performance factors for the proposed method and previous research on detecting tennis players' serves.

This scheme analyzes the IoT serving technique of a tennis player using a combination of machine learning and

Fig. 13 The performance for tennis serves classification models on female players

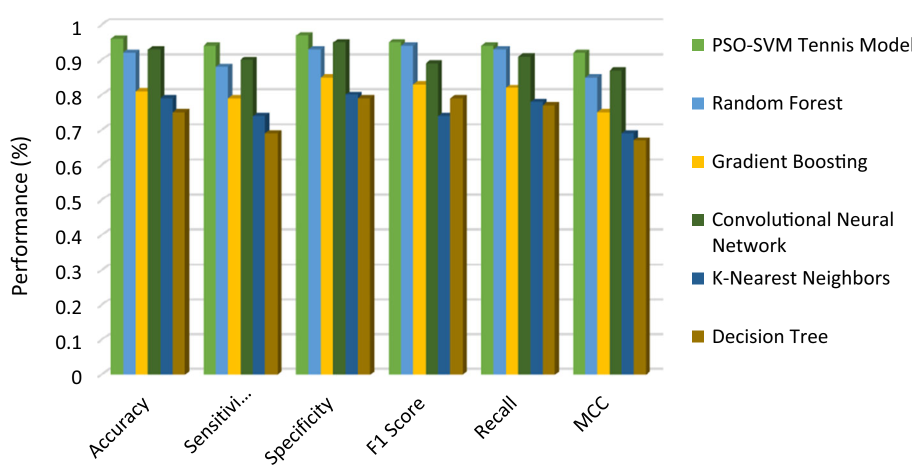


Table 5 The proposed method and previous research on detecting tennis players' serve

Research study	Classification accuracy	Sensitivity	Specificity	$F1$ score	MMC
Proposed scheme	0.975	0.95	0.98	0.96	0.94
Bilal et al. (2023)	0.932	0.89	0.95	0.91	0.87
Yao et al. (2017)	0.968	0.92	0.97	0.94	0.9
Latif et al. (2021)	0.956	0.91	0.96	0.93	0.89
Kumar et al. (2021)	0.951	0.94	0.97	0.97	0.95

video image processing. The research suggests classifying tennis serves using the PSO-SVM (Particle Swarm Optimization-Support Vector Machine) method. The procedure begins with collecting data from the test and training sets, then examining and preprocessing them in depth. After preprocessing the training data and training the PSO-SVM model, the particle swarm optimization method is used to optimize the support vector machine's parameters. The model's efficacy is evaluated using experimental data by comparing its predictions to established classes. The experimental results demonstrate an extraordinary 97.5% classification accuracy.

In addition, the model's high sensitivity, specificity, $F1$ score, MCC score, and recall score demonstrate its efficacy. These results show the approach's potential for accurately distinguishing and classifying tennis serves, which will aid in comprehending and analyzing players' serving behavior. The paper contains a thorough literature review that illuminates recent developments in the analysis of tennis players' serving techniques using the Internet of Things and machine learning. This study examines the methodologies, outcomes, and cumulative effects of four recent studies. A thorough comprehension of the current research environment is invaluable for researchers and professionals.

6 Conclusions

In recent years, the rapid development of technology, particularly in the fields of IoT (Internet of Things) and AI (Artificial Intelligence), has revolutionized various domains, including sports analysis. IoT technology has considerably improved the efficiency and organization of sporting events in China. A comprehensive monitoring system based on artificial intelligence (AI) is still necessary when examining the current solutions and architectures for IoT-based solutions. Intelligent players utilize AI to extract exercise characteristics, predict routines and nutrition, and avoid overtraining and injuries, among other activities. It improves the administration of sporting events, caters to the needs of sports supporters, and provides instructors and athletes with more precise data and information to improve stadium performance. Due to China's rapid economic development, the country has greatly emphasized the athletics industry. Sports may not only boost a nation's economy, but they can also represent its spiritual outlook. Therefore, the focus of this study is the development of a wire sensor networking-based intelligent tennis system. It contrasts traditional tennis with smart system-based tennis and discusses the function of wireless sensors in tennis. Based on a wireless sensing network, this study proposes optimizing the sensor network's distribution so that the developed expert system can operate more effectively. In addition, a PSO-SVM tennis serve model is presented. The experimental outcomes compare the proposed method to other machine learning algorithms, including DT, DNN, and LSTM. The classification of player motions yielded outstanding results, and the particle swarm technique is superior to other deep learning methods. According to the test results, the tennis service model obtains a classification accuracy of 97.5% when classifying the various categories of service trajectories.

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Data availability Enquiries about data availability should be directed to the authors.

Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose. The authors declare that they have no conflict of interest.

Ethical approval This article does not contain any study with human participants or animals performed by the authors.

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