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Article

Intelligent Algorithm Based Personalized Training Plan Generation and Implementation Strategy for Tennis Physical Education

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Abstract: In the era of mobile internet, data-driven precision training represents a significant trend in the evolution of technical training from traditional experience-based instruction to digital intelligent precision training. The application of intelligent algorithms in the design and implementation of personalized training programs for tennis constitutes the application of data-driven precision training enabled by intelligent technology in tennis instruction and training. The study employs intelligent wearable devices and computer vision algorithms during training to collect parameters such as athletes' physiological data and technical movement parameters. Data is analyzed and mined using swarm intelligence optimization algorithms and deep learning training models, enabling dynamic adjustments and the personalized formulation of scientific training plans. Research findings indicate that intelligent training algorithms can enhance training effectiveness, technical movement standardization, and prevent sports injuries. Athletes in the intelligent training group achieved significant improvements in metrics such as serve accuracy, forehand hitting power, and backhand return success rate compared to those in the traditional training group. Additionally, data on heart rate, blood oxygen recovery time, and the incidence of sports injuries showed a significant reduction. The intelligent video game-assisted training unit designed in this study demonstrates unique effectiveness in cultivating athletes' tactical awareness and the coordination of movements across different body parts. In the comparison of tennis training data, extensive training data confirms the effectiveness of intelligent algorithms in tennis teaching and training, providing new directions for the future development of intelligent algorithms in tennis teaching and training, as well as technical training methods.

Keywords: intelligent algorithms, tennis training, personalized training plans, smart wearable devices, computer vision, swarm intelligence optimization, deep learning

1. Introduction

As human society enters the era of artificial intelligence, technological advancements have posed significant challenges to sports training, particularly in tennis, a sport that places extreme importance on technical movements and tactical strategies [1-2]. Sports training must be scientific and effective, with appropriate interventions tailored to individual differences. However, traditional training models, where coaches primarily rely on their own years of competition and training experience to guide athletes, tend to be subjective, have delayed information response times, and lack consideration for individual differences [3-4]. With the intelligentization of sports education, precise modeling, dynamic optimization, and intervention through big data and algorithmic models have become key research issues [5-7].

On the other hand, the emergence of new technologies such as smart wearable devices, computer vision recognition, virtual reality, and deep neural networks has provided more data and interaction methods [8-10]. Data such as athletes' heart rate, blood oxygen levels, hitting trajectories, and hitting angles can be recorded, fed back, and analyzed in real time, providing a basis for evaluating the effectiveness of training processes and formulating training plans. Intelligent algorithms such as swarm intelligence optimization algorithms, genetic algorithms, and particle swarm algorithms are increasingly being applied in areas such as training plan formulation, fatigue prediction, and technical feedback, gradually transitioning sports training plan formulation from “traditional” to “customized” [11].

Finally, the integration of virtual tennis simulation games and motion simulation systems transforms training environments characterized by high load, high intensity, high injury risk, and lack of feedback into platforms featuring high load, low intensity, low injury risk, and feedback [12]. Liu et al. investigated the impact of virtual reality training environments and wearable sensor technologies on athletes' tennis skill improvement, using personalized learning as an intermediary variable influencing skill enhancement. The validation model showed that virtual reality and other technologies have a significant impact on athletes' tennis skill improvement, while personalized learning did not exhibit a significant mediating effect [13]. Training based on system model data is no longer subject to the subjective judgment of coaches but rather relies on individual data for dynamic responses and precise corrections.

Intelligent algorithms not only revolutionize traditional tennis training systems but also provide scientific support for enhancing athletes' competitive abilities. Chu et al. found that the application of intelligent control technology in specialized tennis training has positive effects, not only enriching the training methods and approaches of tennis teams but also motivating students and improving training efficiency [14]. In training assessment, Wang, Y., and others designed and implemented a real-time human motion assessment algorithm to improve the accuracy and stability of training robots in evaluating tennis athletes' training. Field tests and survey results showed that the algorithm enhances the accuracy of evaluations during tennis training, demonstrating the superiority of the real-time human motion assessment algorithm [15].

Tennis training motion capture and error correction based on intelligent algorithms also hold significant research implications for enhancing athletes' tennis performance. In 2022, Chen utilized data mining technology and deep imaging technology to establish a three-dimensional training data repository for tennis athletes. By combining a three-dimensional skeleton point extraction method based on RGBD images with a dynamic time warping algorithm, the study achieved real-time tracking and analysis of athletes' training movements. This method effectively improved training efficiency and facilitated athletes' training development [16]. Two years later, Li et al. employed a convolutional neural network model to learn from tennis training samples and constructed a tennis error training motion recognition model. Experimental results showed that the constructed model achieved over 90% accuracy in recognizing tennis training motions on the dataset, significantly outperforming comparison models, thereby improving tennis training effectiveness [17].

Intelligent algorithms are not limited to tennis training. Wang, X introduced intelligent algorithms into table tennis training, collecting and analyzing athletes' training data to provide personalized training guidance. Research results indicate that intelligent algorithms can effectively identify athletes' strengths and weaknesses during training and provide targeted training recommendations [18]. Liu et al. utilized artificial intelligence algorithms to predict the spin and trajectory of table tennis balls, experimental results showed that the detection accuracy of the intelligent algorithm after training ranged from 98% to 100%, with a response time of less than 5.3 milliseconds, enabling accurate prediction of the spin and trajectory of table tennis balls [19].

In summary, establishing a personalized tennis training model based on intelligent algorithms, fully utilizing dynamic monitoring, intelligent analysis, and timely feedback systems, not only meets the personalized development needs of outstanding tennis athletes but also pioneers scientific, advanced, and visual methods for university sports training, demonstrating strong applicability and practicality.

This study combines experimental methods with intelligent system modeling to establish an integrated data system that combines data collection, model calculation, and real-time feedback. It proposes the use of intelligent wearable technology and computer vision technology to collect athletes' training data and human condition data in real time, including heart rate variability, blood oxygen saturation, and swing speed. Then, based on swarm intelligence, the training data is optimized to obtain a set of training parameters matched to the individual. Finally, a deep learning model is used to evaluate training effectiveness, with results fed back to the training terminal to adjust the training plan and provide real-time training interventions for athletes. The entire system serves as a scientifically sound and operationally feasible training plan optimizer within a data-driven closed-loop framework, achieving a closed-loop control process of “automatic generation-implementation monitoring-effectiveness assessment-dynamic optimization,” thereby offering new insights for personalized training in tennis sports education.

2. Implementation Strategies for Personalized Training Plans in Tennis Sports Education

2.1. Overall Architecture of Intelligent Training Strategies

Based on the system modeling approach of “data collection-feature extraction-strategy generation-real-time feedback,” this system uses swarm intelligence algorithms combined with personalized behavior modeling strategies to seek the best training results for individual differences. The system obtains training data (heart rate, swing speed, ball strike frequency, etc.) from smart wearable devices that reflect individual differences, processes data in real time before, during, and after training, and dynamically evaluates training load and content.

2.2. Hierarchical Design of Training Strategies

At the strategic level, based on students' physical condition, technical proficiency, and learning needs, three training strategy levels are established according to progressive differences. The beginner-level strategy targets students and focuses on movement pattern training, rhythm training, and basic strength training. The intermediate-level strategy combines data information to update swing trajectories and footwork strategies and restore rhythm. The advanced-level strategy utilizes historical data to analyze training bottlenecks and then uses reinforcement learning to iterate strategies.

2.3. Intelligent Optimization Algorithm Assistance Mechanism

Improved genetic algorithms (IGA) and particle swarm optimization algorithms (PSO) are used for rapid matching and iteration of training parameters [20]. For example, the IGA algorithm's crossover and mutation algorithms are used to combine training content for rapid and effective training. The PSO algorithm is used to correct the pace and intensity of training based on actual data feedback, making the training route more natural and smooth.

2.4. Dynamic Control of Data Feedback Systems

Through the data training function, “self-learning” enables dynamic adjustment of training plans. Every half hour, the system calculates the training load value based on the heart rate during training. When the training load value exceeds the set fatigue value, the load is automatically reduced. When the stability of technical movements exceeds 85%, corresponding tactical exercise content will pop up.

2.5. Integration of Diverse Teaching Tools

The training software also includes an AR-assisted training system, a virtual tactical combat system, and a slow-motion replay system. The AR training mirror system is used to simulate correct movements for comparison, while the virtual tactical combat system is used to increase fun and competitiveness. Slow-motion replays are used to correct movement details and reinforce training memory.

3. Personalized Training Experiment

3.1. Experimental Subjects and Experimental Design

To validate the effectiveness of using intelligent algorithms to generate training plans, the author selected and recruited 60 athletes from the men's tennis team of a certain college for the experiment. The selection criteria were as follows: age 20–24, with 3–5 years of professional tennis training experience, and no significant sports injuries in the past six months. All participants voluntarily signed informed consent forms, and those with a history of cardiovascular disease, unhealed bone or joint injuries, or personal reasons preventing them from attending training sessions on time were excluded. All recruited athletes were male. A random number table method was used to divide the 60 athletes into an experimental group (EC) and a control group (CC), each comprising 30 participants. After grouping, statistical analysis revealed that the differences in age, training duration, and physical fitness between the two groups were minimal, with P-values all greater than 0.05. The baseline characteristics of the two groups were consistent, ensuring good comparability.

The total training duration was 16 weeks, with training conducted 6 days per week, each session lasting 2.5 hours. The experimental group wore smart wearable devices during training, utilizing computer vision and deep learning algorithms to dynamically record movement data. These included heart rate monitoring wristbands, motion accelerometers, and specialized smart rackets, which could real-time record physiological indicators such as heart rate variability, ball-hitting speed, and swing angle, as well as movement indicators. The computer vision system's four high-speed cameras recorded the entire technical process from multiple angles and utilized deep learning technology to analyze the accuracy of athletes' technical movements. The control group employed traditional training methods, with experienced coaches designing identical training plans based on their expertise. The experimental group's training plan was automatically generated using a proprietary swarm intelligence algorithm, which intelligently adjusted intensity based on changes in physiological indicators, technical scores, and fatigue levels, thereby achieving personalized training plans. The control group lacked these self-regulatory mechanisms.

This experiment employed a double-blind design to minimize subjective bias in the experimental process. First, the data collection personnel were unaware of the athletes' group assignments, and second, the athletes' training teams were unaware of the purpose of the experiment. This study systematically designed a training effectiveness evaluation system, divided into physiological indicators (such as resting heart rate, maximum oxygen uptake, blood lactate threshold, etc.), technical indicators (serve accuracy rate, forehand stroke speed, backhand return success rate, etc.), and competitive performance (assessed through simulated match outcomes, key score management, etc.). Comprehensive tests are conducted every two weeks to record changes in these indicators. Additionally, each athlete will have their own electronic file documenting any abnormal conditions and subjective experiences during the training process. The experimental training period spans 16 weeks, divided into three phases (adaptation, intensification, and consolidation) lasting 2, 10, and 4 weeks, respectively. The adaptation phase primarily involves familiarizing experimental group athletes with the smart devices, collecting baseline data, and establishing individual athlete profiles. The intensification phase is the core component of the experiment, where the intelligent algorithm updates the athletes' training content and intensity based on their real-time status, ensuring the personalization and timeliness of the training plan. The consolidation phase primarily involves conducting several simulated competitions to evaluate the stability of training outcomes and the improvement in athletes' abilities. The entire experiment strictly adheres to the ethical guidelines of sports science research. An independent medical supervision team continuously monitors athletes' physical condition to ensure the safety of the experimental training. Additionally, all data is encrypted to protect data privacy and security.

3.2. Data Collection and Analysis Methods

This study employs a data collection and analysis platform to conduct data collection and analysis. Using a smart heart rate wristband equipped with photoplethysmography (PPG) technology, heart rate data is collected at a frequency of 5 times per second. The wristband also incorporates a built-in pulse oximeter for real-time measurement of blood oxygen levels. Through a real-time data transmission platform utilizing Bluetooth technology, physiological metrics of athletes are promptly communicated to coaches. Weekly data checks are conducted using standard medical-grade equipment to ensure the accuracy and reliability of the results. For movement technique data, the collection system is composed of an intelligent sensor system and a high-speed camera system. Accelerometers and gyroscopes are integrated into the intelligent racket, recording relevant information at the moment of impact at a sampling rate of 1000 Hz. Additionally, miniature inertial sensors on the athlete's body measure the movement trajectories of various body parts during the impact process in real time. Using the team's self-developed three-dimensional motion reconstruction algorithm, the complete technical movements are reconstructed. Four 120 frames per second high-definition cameras capture the movement process from different angles, and computer vision methods are used to score the technical standardization of serves, forehand and backhand strokes, and other techniques.

Researchers designed a targeted data processing method for the various types of large-scale data collected. During preliminary data processing, outliers were removed using the Z-score method, and data with unreasonable values were manually verified. For missing data, multiple imputation methods were used to handle the missing values. A minimum-maximum standardization method was applied to normalize incompatible metric data into the range of 0 to 1. In training plan generation, an improved group dynamic particle swarm algorithm was designed to process multidimensional data. The training plan generation model is represented as:

$$Training\ plan = f(Motion\ data,\ Phpysiological\ indicators,\ Indhividual) \quad (1)$$

The model is dynamically adjusted based on real-time feedback data, and the adjustment function is expressed as:

$$Adjustment\ plan = g(Real-time\ data) \quad (2)$$

Statistical software was used to analyze comparisons between groups and within groups, as well as to compare pre- and post-test results within each group. Independent samples t-tests and paired samples t-tests were employed to assess the effects of exercise before and after the intervention. Multivariate analysis of variance (MANOVA) was utilized to analyze the interactions among multiple factors.

The study introduced and established an evaluation system based on indices of technical progress, physical function, and athletic performance. Technical progress was reflected through skill assessments, physical function was measured by heart rate recovery capacity, blood oxygen saturation, and blood lactate threshold, and athletic performance was evaluated through simulated competitions. The three indices were calculated in a 3:3:4 ratio to derive the final training effectiveness index for assessing the efficacy of the training. In analyzing training effectiveness, we utilized data visualization software to create timelines and scatter plots. Additionally, a video motion recognition module was designed to detect athletes' technical movements through the training system, compare them with pre-set movements to determine key differences, and calculate motion quality. Professors of sports statistics and sports physiology were hired to conduct regular data reviews using cross-validation and sampling analysis models. Once the model was stabilized, it was strictly adhered to scientific ethical standards to complete the process.

4. Personalized Training Experiment Analysis

4.1. Experimental Results

After 16 weeks of experimentation, relevant data on the effectiveness of the intelligent algorithm-based personalized training plan generation was obtained. Specific experimental data is presented in Table 1, and a comparison of selected training metrics is shown in Figure 1. The experimental group demonstrated superior performance across various metrics, with significant improvements in both technical movement accuracy and functional adaptability. Through data comparison, it was found that the accuracy of serves in the experimental group improved significantly, rising from 72.3% to 89.6%, an increase of 17.3%. In contrast, the accuracy of serves in the control group only increased from 71.8% to 79.4%, an increase of 7.6%. The average speed of forehand shots in the experimental group increased from 108.5 km/h to 127.3 km/h, an increase of 17.3%, while the average speed of forehand shots in the control group increased from 107.9 km/h to 115.2 km/h, an increase of 6.8%. It can be seen that the intelligent algorithm achieved very good results in optimizing the training plan.

A core advantage of personalized training plans lies in the prevention of sports injuries, as smart wearable devices can help athletes monitor movement parameters in real-time during training. Data shows that the incidence rate of sports injuries in the experimental group was 6.7%, which is 66.5% lower than that of the control group, indicating a significantly lower incidence rate compared to the control group. Observing the physiological data collected by smart devices, the results showed relatively stable heart rate variability values, with a standard deviation slightly lower than that of the control group. Additionally, the average heart rate recovery time for athletes in the experimental group was 21.95% faster than that of the control group, and the blood oxygen recovery speed for athletes in the experimental group was 25% faster than that of the control group. This phenomenon demonstrates the advantages of personalized training plans.

Table 1. Experimental data comparison result.

Evaluation indicators	EC-Early	EC-End	CC-Early	CC-End
Serve accuracy rate (%)	72.3	89.6	71.8	79.4
Forehand hitting speed (km/h)	108.5	127.3	107.9	115.2
Success rate of backhand return (%)	68.9	84.2	69.1	74.6
Heart rate recovery time (min)	4.8	3.2	4.9	4.1
Blood oxygen recovery time (min)	3.6	2.4	3.7	3.2
Sports injury rate (%)	-	6.7	-	20.0
Tactical application score	6.2	8.7	6.1	7.0

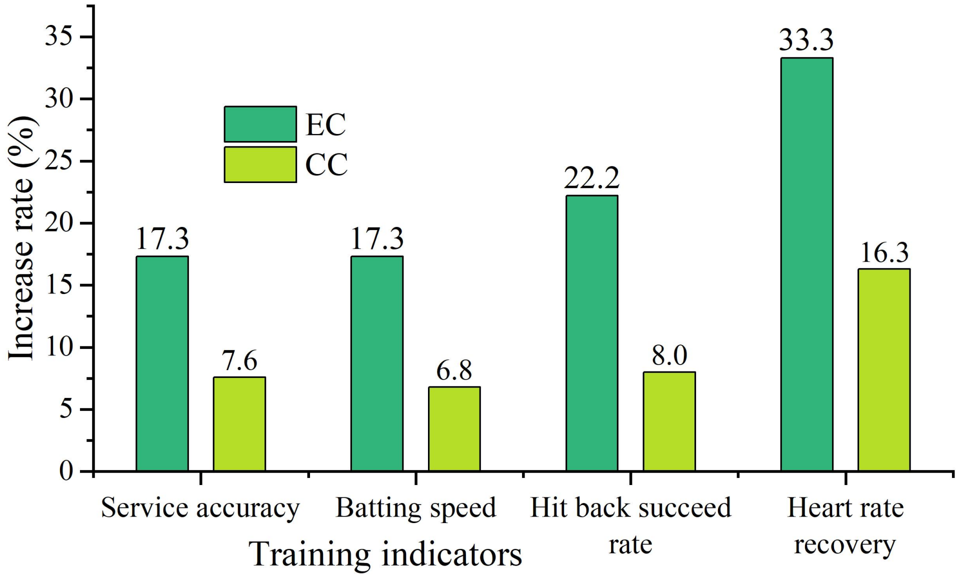

Figure 1. Training effect comparison chart.

Additionally, the use of intelligent video games for auxiliary training has provided athletes with significant advantages in tactical awareness and technical movements. After the training, the experimental group athletes' tactical application abilities improved, with scores increasing from 6.2 to 8.7, representing a 40.3% improvement in tactical application abilities. They demonstrated strong adaptability and response capabilities to complex game scenarios and challenges. Furthermore, in motion-sensing tennis games, the experimental group athletes' swing standardization improved by 31.2%, with more reasonable and accurate timing of ball strikes, resulting in a 26.8% increase in accuracy.

Personalized training plans can dynamically adjust training loads based on real-time physiological indicators and performance metrics, automatically correcting the intensity and volume of training during the supercompensation phase to prevent overtraining. In terms of lactate clearance metrics, personalized training plans significantly enhance training effectiveness, with athletes in the experimental group achieving a 28.5% higher lactate clearance rate after high-intensity training compared to the control group, indicating improved physiological adaptability. Additionally, the system's built-in overtraining and training overload warning features ensure the stability and consistency of athletes' performance capabilities, enhancing training effectiveness when these features are utilized.

4.2. Strategy Comparison

To compare different training strategies, this study conducted an 8-week tennis training experiment involving 50 tennis elective students from a certain school. During this process, the training effects of five different tennis training strategies were validated. After 8 weeks, the specific results are shown in Table 2.

The data in the table indicate that, compared to the four training modes—the unified training plan mode, the level-based training plan mode, the data-feedback-based training plan adjustment mode, and the video game simulation training plan mode—the training mode combining intelligent algorithm-based automatic optimization and simulation training plan achieved the highest training satisfaction score (9.3 points), representing an improvement of 6.9% to 45.3% compared to the other four training modes. Additionally, when applied to tennis training, the injury incidence rate was 6.9%, a reduction of 11.7 percentage points compared to the injury incidence rate of the uniform training plan training mode. Therefore, the tennis sports education training method proposed in this study has higher training efficiency, effectively enhancing training satisfaction while ensuring the safety of trainees.

Table 2. Comparison of the effects of different training strategies.

Training strategy	Implementation difficulty (1~5)	Training satisfaction (1~10)	Injury incidence rate
Unified training plan	2	6.4	18.6%
Train hierarchically by level	3	7.1	14.3%
Fine-tuning based on data feedback	4	8.2	10.7%

Integrate video game simulation training	3	8.7	8.1%
This article	5	9.3	6.9%

5. Conclusions and Recommendations

5.1. Research Conclusions

This study explores the application of intelligent algorithms in personalized tennis training. By constructing a data-driven training feedback system, it effectively enhances training efficacy and safety. Based on data from training experiments, the intelligent algorithm-based training system exhibits characteristics such as training precision, strategic intelligence, and quantifiable outcomes. This research provides scientific technical support for tennis educators and offers empirical evidence and practical pathways for the popularization of personalized sports training in China.

5.2. Training Recommendations

This paper proposes a model for personalized tennis training plans based on intelligent algorithms. Through analysis of experimental data, the feasibility and superiority of the proposed scheme in tennis training can be demonstrated to a significant extent. As such, the introduction of smart wearable devices for real-time monitoring of training status can greatly assist coaches in adjusting training intensity more reasonably, thereby avoiding injuries caused by excessive intensity. The computer vision technology and deep learning algorithms employed in the system design can effectively address the objective basis for motion analysis, and provide training guidance through real-time feedback. However, the intelligent algorithms used in this paper have certain limitations when applied to athletes of different skill levels, particularly under extreme conditions, where algorithm processing requires continuous optimization. Additionally, regarding smart wearable devices, the accuracy of data collection and the stability of the sensors themselves suggest the need to design sensors specifically tailored for tennis.

Looking ahead, future intelligent training systems may incorporate quantum computing to address algorithmic computational speed bottlenecks. Based on our research findings, we propose the following recommendations: policies should provide greater support for the development of such technologies, and the Ministry of Education should establish technical standards for intelligent training equipment. Intelligent training is an inevitable trend in sports education and should be advanced through collaborative efforts across hardware, software, human capabilities, and institutional frameworks. Regarding the role of coaches in intelligent training, our research observed that some coaches have limited ability and proficiency in adopting new technologies. A tiered training curriculum could be used to provide standardized training. Athletes should also develop data awareness and utilize intelligent feedback information to enhance training quality. Research on athletes' physiological states is expected to achieve further breakthroughs in the advancement of biofeedback technology. The application of brain-computer interfaces will enable athletes' subjective intentions to be directly transmitted to the training system, marking a new depth in training research. Although intelligent training methods hold significant application potential, traditional sports training experience should still be prioritized during their implementation. The organic integration of both approaches is essential to achieving breakthroughs in tennis education within the field of physical education.

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