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Artificial Intelligence for Tennis Performance Analysis and Match Prediction

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Abstract. Tennis players' technical movements, movements, spatial behavior, and other aspects during matches can already be well analyzed by artificial intelligence, but the data and game predictions obtained from these analyses still need to be integrate. This is the research direction of this narrative review. This review summarizes the relevant data sources, calculation methods, technical features, performance indicators, and prediction methods. Based on technical action information, a comprehensive discussion was conducted around the main line of "from analyzing performance indicators to final prediction", and the relationship between research at different levels was elaborated. At the same time, this review also indicates that videos, Hawk-Eye technology, and wearable devices during matches can provide sufficient information on players' movement and spatial use; These data captured through external devices and analyzed by artificial intelligence need to be combined with the competition context in order to be used as supplementary data for in-game prediction. On this basis, this review proposes research directions for connecting action analysis with whole game prediction, including unified indicators and label definitions, prediction based on standard time series, and comparison using time series validation, probability calibration, and traditional benchmark models. This comprehensive technology provides a clear analytical approach that not only helps to understand the contribution of artificial intelligence in tennis analysis, but also provides new ideas for future game predictions.

Keywords: Artificial intelligence, tennis performance analysis, match prediction

1. Introduction

In the past decade, the development of sports technology, wearable devices, video analysis, and data collection has made sports performance analysis an important part of athlete training, coach decision-making, and competitive performance improvement. Sports performance analysis can describe the characteristics of athletes' technical movements and competition behaviors, and also provide effective basis for adjusting training plans and changing competition strategies [1]. In tennis, Hawk-Eye 、 Video tracking technology and related data collection techniques have significantly improved the volume, granularity, and diversity of competition data. This also creates favorable conditions for data-driven analysis [2].

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Artificial intelligence (AI) technology can extract unobservable patterns from large and complex datasets, and the data that appears in tennis is mostly related to player movements and game performance. Therefore, AI has been applied to identify stroke classification, performance evaluation, and match result prediction in tennis [3]. At present, deep learning research can use videos to classify serving, forehand, and backhand as fine-grained targets, which precisely demonstrates the feasibility of extracting effective information from videos [4]. Moreover, wearable sensors and neural network methods can now distinguish between different types of tennis strokes, achieving an F1 score of 96% for major stroke categories, as reported [5]. In parallel, match-prediction studies have employed logistic regression, decision trees, support vector machines, and Elo-based ratings [6].

Although multiple studies have made progress, most of the current game outcome prediction models rely on player rankings and past game data, rather than indicators of player skill and movement levels. On the contrary, techniques such as action recognition and action analysis are often used to focus on isolated single action performances, and rarely associate action skill levels with higher-level performance indicators or competition results [2, 4]. Therefore, there is still a lack of corresponding technology to link the levels of action recognition, performance evaluation, and game result prediction. So, it is necessary to conduct a targeted review, systematically sorting out available data sources, feature representations, AI methods, outcome indicators, and evidence that can link these links.

This narrative review will discuss how artificial intelligence technology is applied to tennis motion analysis, performance evaluation, and match outcome prediction. The key is how players' movements and spatial information are interpreted as performance indicators, and how to evaluate the potential of these performance indicators for predicting game results. The Section 2 will be used to review the data sources, calculation methods, performance indicators, and predictive models used for these three themes. The Section 3 will summarize the main findings and discuss their significance for game prediction as well as the limitations of current technologies. Finally, important priorities for future research will be given. The final conclusion will be presented in the Section 4 of this narrative review.

2. Methods

2.1. AI-based movement analysis

2.1.1. Data sources and movement representations

Although the movement and orientation of players are crucial in tennis matches, this review mainly focuses on their technical movements, especially the rapid and continuous movements before and after hitting the ball. A ball move should not be limited to the moment when the racket touches the ball, but should include multiple stages such as preparation, pulling, acceleration, touching, and swinging. Videos can preserve the relative positional relationship between players, rackets, tennis balls, and the court, while tracking systems can present changes in position and trajectory over time [2]. Wearable devices can convert the motion information of multiple body joints such as wrists and shoulders into multivariate time series data, thereby supplementing information that video and tracking systems do not directly record. For example, Ganser, Hollaus, and Stabinger used wristband signals, which included inertial testing unit data, to construct a labeled dataset for neural network-based tennis shot classification. These labeled datasets can not only distinguish which type of hit was made, but also identify the changes in action over time [5].

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2.1.2. Detection, tracking, and pose-based approaches

In video based tennis analysis, the extraction of motion information typically begins with identifying relevant targets in the image. Object detection is used to locate players and balls in a single frame image; Tracking associates these positions in consecutive frames to generate motion trajectories. With these trajectories, it is possible to describe the direction of the player's movement, the way they change direction, and the player's position relative to the ball. The pose estimation method further provides joint position or skeletal keypoint information, allowing actions to be described both by the position of the court and by body posture. Huang et al. developed TrackNet, which can locate and track high-speed tennis balls from consecutive game broadcast video frames [7]. A more holistic visual processing flow was demonstrated by AlShami, Boult, and Kalita, who monitored players, balls, and body joints and used Transformer based temporal modeling to predict players' motion paths.These representations provide structured inputs for subsequent models, enabling them to recognize action sequences with technical significance [8].

2.1.3. Stroke and action recognition approaches

Once movement data have been represented in a structured form, action-recognition models can assign labels to temporal sequences, such as serves, forehands, backhands, volleys, or more detailed stroke subtypes. In video-based research, Mora and Knottenbelt [4] represented tennis clips as sequences of Inception-derived deep features and trained a three-layer Long Short-Term Memory (LSTM) network to classify fine-grained tennis actions. Their method can reflect the temporal characteristics of the hitting action, as the relevant information exists in an orderly motion rather than in a single video frame. Wearable sensors also provide a parallel technological route: Ganser, Hollaus, and Stabinger use wristband signals, including inertial measurement unit data, and compare the performance of fully convolutional neural networks and residual neural networks in three class and five class stroke classification [5]. By generating action labels with timestamps, these systems can support comparisons of hitting frequency, hitting sequence, and hitting distribution at different stages of the game. If action labels are combined with trajectory, posture, or motion information obtained from sensors for interpretation, it may help identify technical action patterns related to specific competition contexts. This type of pattern is expected to become a bridge connecting the performance indicators and predictive features discussed in subsequent chapters.

2.2. AI-based performance assessment

2.2.1. Defining tennis performance indicators

Video tracking, Hawk Eye, and wearable sensors enable artificial intelligence to continuously record player movements, ball trajectories, and spatial data. Hawkeye can capture position, trajectory, and speed; The wrist sensor combined with video and manual annotation can be used to identify serving, forehand, and backhand. However, action detection or classification is not equivalent to performance evaluation. The original coordinates, trajectories, and events can only be transformed into meaningful indicators by combining scores, turns, opponent positions, hitting results, and game stages, and through aggregation and interpretation [2, 5]. Coordinates can be summarized as court coverage and repositioning; shot trajectories can be described in terms of speed, direction, and landing points; repeated forehand strokes can be aggregated as usage frequency and reliance under pressure; movement events can generate metrics for distance, speed, acceleration, direction changes,

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and repositioning [2]. Performance indicators are usually divided into three categories: technical, physical, and tactical, and are interrelated [2, 9]. Technical indicators describe the execution and effectiveness of hitting; Physical indicators describe mobility needs and external loads; Tactical indicators describe hitting choices, space utilization, and opponent response. This study mainly focuses on technical actions, as videos, postures, or wearable devices can directly recognize actions and form interpretable predictive features after contextualization [5, 10].

2.2.2. AI applications in technical, physical, and tactical assessment

In technical evaluation, AI combines action labels with game context and turn results to record position, stroke sequence, frequency, and time nodes [2, 5, 10], in order to analyze forehand and backhand usage, serve/receive selection, and key score dependencies. But these actions can be linked to points earned or lost, turn length, and subsequent hits. Detecting an action does not necessarily mean it is valid; The action only has explanatory significance when combined with the landing point, opponent and player positions, turn results, and score [9].

The same technical action may be completed under different physical loads. Wearable devices and AI can record distance, speed, acceleration, direction change, coverage, and return [10]. The two forehand movements may be classified as the same, but one is completed in a stable position, and the other is completed after high-speed lateral movement or being pulled out of the field. By combining hitting and movement information, it is possible to analyze whether players often use a certain technique under imbalance, passivity, or high load. This type of indicator reflects external loads and does not equal physiological fatigue; Fatigue assessment still requires heart rate RPE, Physiological tests or more complete load data [9, 10].

Tactically, AI can analyze the position, trajectory, direction, landing point, and turn sequence of players and opponents. The landing point of tennis itself is just a single event, and can only be interpreted as information about attack, mobilization, control, or defense by combining the opponent's position, previous shot, turn trend, and hitting result.AI can recognize players' choices of attacking gaps, diagonal/straight line selections, baseline defense, and the way they return the ball after being deployed. These patterns cannot directly prove causal relationships, but can provide systematic evidence. If these pieces of evidence can be defined as stable technical, physical, and tactical features, then these features can serve as predictive inputs [2, 9].

In summary, scattered data such as hitting movements, player movements, and spatial decisions can be transformed by AI into structured performance information, which is key to supporting continuous observation and comparison. Its value lies not in being able to judge the good or bad of individual players, but in providing some more valuable information. When this information can be defined and related to the results, it may improve the accuracy of the prediction model.

2.3. AI-based match prediction

2.3.1. Prediction targets and input features

The main objective of this review is to predict the overall probability of winning, including pre match and mid match predictions. Bunker pointed out that machine learning can use historical matches, rankings, and odds for pre match prediction, but many key data only appear after the start of the match [6]. Klaassen proposed a calculation method based on the serve scoring rate [11]. Features include long-term strength (ranking, ATP points Elo、 Historical wins and losses, height, age), recent performance and conditions (recent win rate, match records, tournament level, venue

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type), and real-time status (scores, innings, ball speed, range of motion) [6, 11-13]. Whether the features are applicable depends not only on the correlation, but also on whether they can be obtained before the prediction time point. The current overall forecast still mainly relies on rankings, historical results, and summary statistics; Action, movement, and spatial features still need to be examined [6, 12-14].

2.3.2. Machine learning, deep learning, and rating-based models

Elo, WElo, and statistical probability models are important benchmarks. Elo updates relative strength based on historical results; WElo further adjusts the competition conditions; Statistical models combined with serving ability, score, and serving party are used to calculate the probability of winning [6, 11, 15]. These methods have strong interpretability, so new machine learning models must demonstrate additional value on the same data [6, 15]. Machine learning can learn complex patterns such as logistic regression, random forests, support vector machines, and neural networks [6, 12]. Candila and Palazzo constructed an artificial neural network using historical records, rankings, player characteristics, and serve/receive statistics to output the probability of winning [12]. Its performance still depends on feature quality, training range, and validation design. Deep networks have stronger representation capabilities [16], but they need to be compared with Elo, statistical models, and traditional machine learning on the same prediction time points, input, and test data. The complexity of the model itself cannot guarantee its effectiveness [6, 12].

2.3.3. Evaluation of match-prediction models

Accuracy alone is not sufficient to evaluate probability output. Probability calibration is equally important: if the model predicts that a player will win 70%, the actual winning percentage should be close to 70%. Log loss and Brier score can evaluate probability quality and punish overconfident errors [12, 15]. Similar accuracy may mask unreliable probability. The division of training/testing also affects effectiveness. Past data must be used to predict future matches, and post match data cannot be used, otherwise data leakage may occur. Bunker et al. used an extended time window for time sequence verification [6]. The model performance may not be generalizable to different periods, event levels, venues, or player groups. Comparative research should pay attention to whether the sample, testing period, competition level, and feature sources are comparable [6, 15].

2.4. Linking movement analysis, performance assessment, and match prediction

Action recognition, performance evaluation, and game prediction can form a data chain. Tracking, Hawk Eye, and wearable devices record hitting, movement, trajectory, and spatial information; After identification, summarization, and contextualization, technical, physical, and tactical indicators are formed [2, 5, 10]. If these indicators can be stably extracted in multiple matches, they may be more suitable as predictive inputs than rankings or historical wins and losses.

At present, research on directly incorporating action level information into overall prediction is still limited. Wei et al. used Hawk Eye to extract ball and player positions, hitting speed, distance, score, and turn order, predict scoring probabilities, and demonstrate that recognizing actions alone is insufficient and must be combined with the context [13]. Kovalchik et al. distinguished hitting execution, selection, and field coverage through expected shot values [14]. But predicting within minutes or hitting levels is not equivalent to predicting the entire game. In the future, actions should be aggregated across rounds and competitions to ensure that they can be obtained before the

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predicted time point, and the action/spatial model should be tested and calibrated in chronological order with Elo, ranking, and historical statistical benchmarks [6, 13, 14]. Action information is more suitable as supplementary evidence rather than a proven alternative to traditional predictive features.

3. Results and discussion

3.1. Principal findings from the narrative synthesis

Existing research indicates that AI can capture more specific and continuous movements and spatial information during competitions through videos, tracking systems, and wearable devices. Among them, this information includes hitting type, player and ball position, movement trajectory, ball path, speed, body movement characteristics, and temporal features. People cannot capture or remember many details of this vast amount of information at the same time with human eyes, but AI can. So, AI is no longer just about recording traditional data statistics, but can continuously observe details that are continuous, repetitive, and not easily noticeable to the human eye during competitions. However, detecting or classifying actions correctly does not necessarily mean that a player's performance can be explained, nor does it necessarily mean that this behaviour can improve the chances of winning the game [2, 5, 10].

So far, the prediction of the upcoming game results has been limited to the analysis of historical data before the start of the game. Similarly, although Elo and probability statistical models are not AI technologies, they still play a powerful role in game analysis and cannot be ignored [6, 11, 12, 15]. Although research has begun to predict scoring results based on player position, pitch, speed, and other data, such local level predictions cannot achieve the goal of predicting the entire game [13, 14]. Therefore, this review suggests that player movements and spatial information are currently more suitable as supplementary data, but whether they can provide additional value still needs further validation, rather than being proven to replace traditional data prediction methods.

3.2. From movement detection to meaningful performance assessment

The hitting type, player coordinates, or trajectory identified by AI are essentially output as structural data and cannot be directly used as a judgment of player performance. For example, a forehand stroke can be recorded as a type of stroke. However, recording a forehand stroke alone does not determine whether it is effective or has tactical value. Therefore, recording technical actions alone does not represent the comprehensive inclusion of data such as the background situation and physical conditions into the evaluation criteria [2, 5, 9, 10].

Therefore, technical movements, physical performance, and tactical indicators should not be explained separately. The combination of technical movements and landing points can describe how a player completes a shot; The movement speed, distance, and change of direction frequency can reflect the external movement needs of the player during the turn; The relative position of players and opponents, the order of turns, and the score situation can reflect the intensity and strategy of the game [9, 10, 14]. Even though this multifaceted and situational analysis cannot directly prove that a certain action caused scoring or winning, it can more systematically identify which action patterns, spatial choices, or movement conditions are related to the hitting result, turn development, or scoring result [13, 14]. Whether these local level features can further enhance the prediction of the entire game still needs to be verified through time-series validation and comparison with traditional benchmark models, and can be obtained before the model makes predictions. Verify whether

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predictive information can be provided beyond historical information such as Elo and rankings [6, 11, 15].

3.3. Implications for match prediction

In game prediction, the value of data such as movements, physical performance, spatial information, etc. does not lie in the ability to immediately take state Elo, ranking, or historical data, but in testing whether it can provide supplementary data for traditional game prediction. If the research objective is pre match prediction, the action features should come from historical matches before the target match and be combined with historical data. If the research objective is mid game prediction, the model can only use traditional data information recorded before the prediction time point and combine it with information such as actions and spatial features for analysis. Therefore, the role of action and spatial information is to provide a basis for game prediction by combining historical performance, scoring variables, and other information [6, 11, 13-15].

However, adding action or spatial features to the model does not necessarily mean that the prediction will be more accurate. Its actual value should be judged through direct comparison with Elo, rankings, historical competition statistics, or statistical probability models, and different models must use the same prediction time points, input information, and time sequence to test data [6, 12, 15]. Only when models incorporating action and spatial features exhibit more stable and calibrated winning probabilities in unseen subsequent competitions, can it be concluded that these features may provide additional predictive value. At present, there is still limited evidence to directly verify whether action level information can stably improve the prediction of the entire game; The existing research on position, pitch, and hitting choices provides more support for its potential to explain the game process at the hitting or turn level [13, 14].

3.4. Limitations of current evidence and directions for future research

The current primary limitation is not the lack of recognition technology for hitting actions or movement abilities in AI, but rather the gap between basic information such as action classification and high-dimensional information such as predicting the entire game. There are already enough studies available to recognize and judge tennis movements, but these local level findings cannot directly indicate a direct connection between movement patterns and game outcomes [5, 13, 14]. The choice of action, space, and the outcome of the game may also be influenced by many objective factors such as the opponent's level, score pressure, and venue conditions. Therefore, future research needs to consider objective situational factors while capturing player movements, and then analyze whether movements can improve the predictive level of the entire game.

The second limitation comes from differences between data sources, label definitions, and research samples. Whether it is a video eagle eye system or a wearable device, although they can provide different types of motion and spatial information, their recording accuracy, tag definitions, and adaptability to the competition environment may not be completely consistent [2, 5, 9, 10]. Therefore, future research should establish more consistent action and label scenarios, and build sample libraries in different venues, competition levels, and player groups to determine whether these features have stable generalizability.

The third limitation relates to the evaluation design of predictive models. If actions, movements, or spatial features are recorded or summarized after the target prediction time point, or if the training and testing sets are not strictly divided in chronological order, the model may be exposed to future information, resulting in data leakage and overestimating its true predictive ability [6, 12, 15].

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Therefore, future research should clearly distinguish between pre match and in match prediction tasks, and compare traditional benchmark models with extended models that incorporate action, movement, and spatial features under the same prediction time point, input range, and time sequence test data. At the same time, in addition to accuracy, the calibration of predicted probabilities should also be reported to determine whether these features truly provide stable additional value for predicting the entire game [6, 12, 15].

4. Conclusion

This narrative review has now demonstrated that artificial intelligence can continuously and structurally record the hitting, movement, and spatial information during tennis matches through video tracking, eagle eye technology, and wearable devices. At present, the greatest contribution of existing research is the ability to observe and compare players' technical movements, athletes' movements, and spatial decisions in more detail. However, only by combining the results of action recognition with contextual information such as opponent position, score, and turn status, can these studies have certain reference value for game prediction. The current game prediction method mainly relies on Elo ratings, player rankings, and historical data. Actions and spatial features are more suitable as supplementary variables to assist with existing prediction methods. However, current technology still does not recommend replacing the original prediction method with this analysis. Future research directions should adopt more unified standards, combining traditional prediction methods with the analysis methods being studied. At the same time, different methods of prediction at different time points can also be clarified, and finally predictions should be made in chronological order. This will be a crucial step in driving AI from action recognition to game prediction.

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