Insight Analysis for Tennis Strategy and Tactics

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***Abstract*—Nowadays there are a wealth of devices and cameras at sports venues and facilities that collect different forms of data. Mining useful insights from such data are crucial for improving the performance of professional athletes. In this paper, we introduce a new interactive tennis analytics framework that can realistically simulate tennis matches using parameters mined from past match data and help reveal in-depth knowledge about tennis strategies. Our approach uses probabilistic model checking to formally evaluate the effectiveness of various strategies and tactics and recommend the best ones for improving players' chances of winning. Our framework is easily understandable and actionable by players and coaches at any level. We have performed evaluations on tennis matches over the past decade to show the effectiveness of our strategy analytics framework.**

***Index Terms*—sports analytics, tennis, strategy, match prediction, Markov decision process, probabilistic model**

I. Introduction

Two days before the 2018 US Open fourth round, John Millman, ranked No.55 at the time, was facing the then world's No.2 and 20-time Grand Slam winner Roger Federer. Given Federer's 40-0 record against players ranked below NO.50 and Millman's 0-10 record against the top 10, the media thought Millman had no chance. We sent Millman an analytics profile, highlighting Federer's serving and returning patterns in crucial, high-pressure situations like breakpoints, as well as his strengths, weaknesses, and preferred playing patterns. Against all odds, Millman won 3-1 to secure his first-ever Grand Slam quarterfinal appearance. This paper describes the research behind the analysis and beyond.

The key challenge in sports analytics is how to extract valuable information from limited historical data and gain insightful knowledge to improve winning chances. This is especially crucial in racket sports like tennis, where opponent-specific strategies are vital. Sports *tactics* involve adjusting playing patterns and training on specific sub-skills . A *strategy* comprises a collection of tactics employed to gain an advantage in a match, and an effective strategy can aid players in defeating stronger opponents.

Compared to existing works, our paper focuses on providing *opponent-specific* strategy recommendations that are easily understandable and applicable. Additionally, we employ formal verification to evaluate the effects of these recommendations. In contrast, prior works often evaluate individual actions based on their impact on game outcomes, considering contextual factors such as player positions, speeds, and ball velocity [1], [2]. Some studies also provide insight analytics such as decision analysis [3], finding optimal policies [4], and player ratings [5]. However, the application of these strategies in real-world sports games can be challenging due to their complexity or the absence of formal verification. Consequently, it is hard for players and coaches to trust and apply these analytics.

In tennis, a player's winning chance depends on the reliability of his sub-skills (e.g., serving, returning) [6]. Moreover, a player may have different playing patterns against different opponents. Our approach employs Markov Decision Processes (MDP) to model tennis matches, which incorporates various match information such as player types and possible actions. The probability distributions and success rates of these actions are mined from historical data. With the learned model, we can conduct deep strategy analytics, including identifying optimal actions for improvement, via the PAT (Process Analysis Toolkit) model checker [7]. To our knowledge, our approach is the first to apply probabilistic model checking (PMC) to tennis analysis.

To assess the effectiveness of our proposed strategies, we use the MDP model to predict match outcomes and examine the changes in winning probability when different strategies are applied. We validate our predictions using a decade of ATP and WTA tennis matches. Additionally, we conduct experiments comparing our recommended strategies to real player adjustments based on historical data. Our findings demonstrate strong alignment between our recommendations and strategy changes made by top players who have significantly improved their games. This work makes the following contributions.

- We introduce a novel tennis analytics framework that utilizes MDP and PMC. This framework strikes a balance between model accuracy and explainability, making it accessible and useful for players and coaches.
- We conduct a comprehensive evaluation using tennis matches over the past 10 years to validate the performance of match outcome predictions as well as the effectiveness and insightfulness of the recommended strategies.

II. Related Work

A. Sports analytics in racket sports

Previous works have employed computer vision and video analytics techniques to detect the court [8], track players and the ball [9], and detect key events [10] in broadcast videos. Other studies have aimed to predict the next shot location based on the current context and historical data [11]. In the field of strategy analytics, Terroba et al. [4] presented an MDP-based framework using the Monte Carlo tree search to

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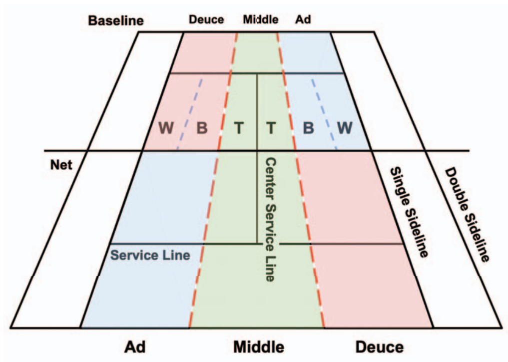

Fig. 1. Tennis court and related terminologies.

find optimal policies. Wang et al. [12] focused on evaluating individual actions by determining the expected probability of winning a rally, considering various contextual features such as player locations, movement speeds, and ball speed in continuous space. Wang et al. [13] evaluated actions by categorizing table tennis shots as "good" or "bad" based on expert knowledge and evaluated actions using video clips. However, these works can hardly be applied in real-world due to their complexity and the lack of formal verification.

B. Winning probability prediction

Kovalchik [14] classified prediction models into three categories: regression-based, point-based, and paired comparison. These models have been compared with bookmaker odds. Regression-based models aim to find features that are highly correlated with match outcomes and predict winning probabilities using regression algorithms. Point-based methods estimate the probability of winning a match by first estimating the probability of winning a single point and then using Markov chains to compute the probability of winning the entire match. Paired comparison methods aggregate past matches between players to determine their relative strength rankings and forecast future match results. However, existing methods primarily concentrate on predicting match outcomes and lack the capability to perform strategy analysis. In contrast, our approach not only accurately predicts match results, but also provides insightful analysis of players' strategies.

III. Preliminaries

Here we introduce tennis technical terms from the USTA[1]. A standard tennis court is depicted in Fig. 1. Each side of the court can be divided into three regions: the deuce court (**De**), the middle court (**Mid**), and the ad court (**Ad**). Additionally, the service box is defined by the boundaries of the net, service line, center service line, and single sideline. It includes three sub-regions, the **T**, **B**ody, and **W**ide. The initial shot of a point is called a "serve". The server can serve to either the receiver's right-hand side, named "deuce court serve" (**De_Serve**), or the left-hand side, named "ad court serve" (**Ad_Serve**). The server can hit the ball to T, B, or W area of the service box. If the first serve fails, the player will have a second chance **(De/Ad_Serve_2nd)**. The shot taken by the receiver after a serve is called a "return" (**R**). Subsequent shots are referred to as "strokes" (**Stroke**). Players can hit the ball cross-court (**CC**), down the line (**DL**), down the middle (**DM**), inside-in (**II**) or inside-out (**IO**) using either their forehand (**FH**) or backhand (**BH**).

[1]https://www.usta.com/en/home/improve/tips-and-instruction.html

IV. The Proposed Approach

Our tennis strategy analytics method is outlined in Fig. 2. We start by collecting data from online sources using video analytics, streamlining the data collection process. Subsequently, we model a tennis match as an MDP, enabling simulations for any pair of players. The constructed MDP model is implemented in the PCSP# language and can be used to predict match outcomes and perform strategy analytics through probabilistic model checking.

A. Mining data from online sources and videos

The dataset employed in our study consists of detailed shot-by-shot descriptions of both players, which are fundamental in constructing tennis models. To collect the data, we gather information from diverse sources. We first obtained our dataset from tennisabstract.com, which is an online data source that collects and manually labels more than 10,000 ATP and WTA matches since 1959 with detailed match information. However, there is still a shortage of detailed shot-by-shot information for many matches. To enhance data coverage, we have applied deep learning based video analytics techniques to automatic extraction of detailed shot-by-shot data from broadcast videos. Overall, we have collected data for the past 12 years (2011-2022), encompassing 8,076 professional matches, 1,073 players, and a total of 6,036,382 shots.

B. Modeling tennis matches in MDP

Modeling tennis matches requires a delicate balance between precision and efficiency. Our modeling approach addresses these needs by providing an expressive representation and powerful analytical capability. In this paper, we focus on singles tennis matches featuring two players, denoted as $P1$ and $P2$. To predict match outcomes, we analyze the winning probability in a simplified **tiebreak game**, serving as an abstraction of the entire match. In this simplified tiebreak game, the first player to reach 7 points wins. We operate on the premise that the player most likely to win the tiebreak game is also favored to win the overall match. This abstraction facilitates efficient performance verification using PAT.

We model a tennis match using a MDP based on expert tennis knowledge. States and actions are defined using tennis terminology (as detailed in Section III), ensuring the model's accessibility to players and coaches for strategy analysis. The model considers various factors such as court location, player type (right-hander or left-hander), and diverse shot types. The individual components of the MDP are outlined below.

State space. A state represents the moment when a player hits the ball. The states are categorized into 4 types: serve,

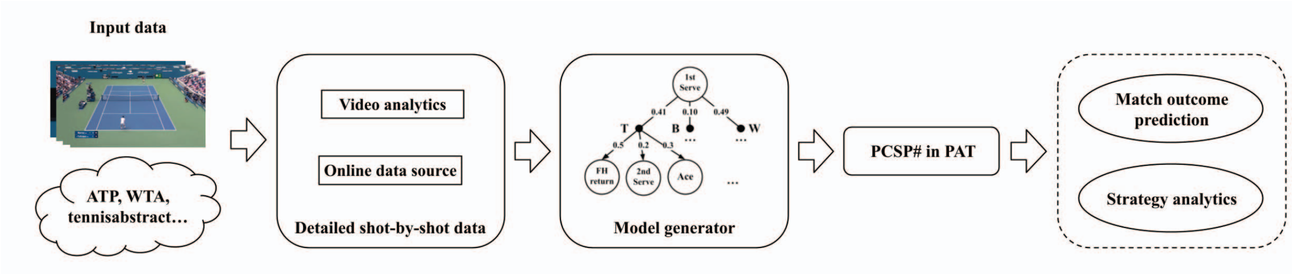

Fig. 2. The system pipeline of our approach.

return, stroke, and termination. Serve states encompass four types: first deuce court serve, second deuce court serve (if the first serve fails), first ad court serve, and second ad court serve. Return states also have 4 types: forehand/backhand return of a deuce/ad court serve. Stroke states encompass deuce/middle/ad court stroke. A termination state signifies that either player has won the tiebreak game, with possible scores such as 7-1 ($P1$ wins), 5-7 ($P2$ wins), and 7-6 ($P1$ wins).

Action space. For each state s, there are a set of possible actions that can be taken by a player based on his location at the court as well as the handedness. There are in total 16 actions, including:

- First/Second serve to T, B, W;
- Fore/Backhand (FH/BH): cross-court (CC), down the line (DL), down the middle (DM), inside-out (IO), inside-in (II).

Transition function. The transition function $P : S \times A \times S \to [0, 1]$ denotes the probability of going to a new state. There are 3 possible outcomes for each state-action pair: **in** (action succeeds but does not directly lead to winning a point), **winner** (action directly leads to winning a point), or **error** (action fails). If an action is **winner** or **error**, the process will transition to a new state for the next serve and add a point to the winner of the rally. If one of the players reaches 7 points, it will transition to the termination state. While if an action is **in**, it will transition to a non-termination state based on the current state and action taken.

Policy. The policy π denotes the probability distribution over all possible actions for each state: $\pi(a|s) = Pr(A = a|S = s)$. It represents how players choose different actions in each state. For example, a serving policy could be 60% serve to T, 30% serve to W, and 10% serve to B.

We learn the policy and transition probabilities for MDP from historical data. The policy is computed by $Pr(a|s) = \frac{N(s,a)}{N(s)}$; while the transition probability is computed by $Pr(s'|s, a) = \frac{N(s,a,s')}{N(s,a)}$, where $N(s)$ denotes the number of times a player has visited state s, $N(s, a)$ is the number of times a player has performed action a in state s, and $N(s, a, s')$ is the number of times a player has performed a from state s and resulted in state s'.

Alternative models. There are alternative methods for modeling a tennis match. For instance, we have built models[2] that incorporate front/backcourt distinctions and strategic choices like approach shots, drop shots, and volleys. Additionally, we also have models that take into account different pressure levels associated with varying scores.

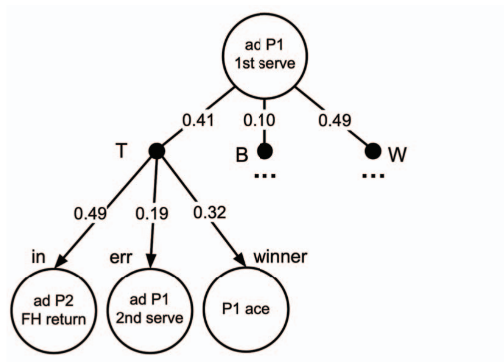

Fig. 3. A partial MDP model demonstrating a serve.

However, in this paper, we opted to present a 6-region model without point-level analytics for ease of player memorization and integration of our data processing methods. In a real tennis match, it is important to avoid overwhelming players with excessive information that could potentially result in hesitation. Fig. 3 shows a partial example of our MDP model, where $P1$ takes the first serve from the ad court with three possible actions (i.e., 41% serve T, 10% serve B, and 49% serve W). Each action contains three possible outcomes (i.e., in, error, winner) with corresponding transition probabilities leading to different next states. Due to space constraints, we do not show the implementation of the MDP model in the PCSP# language. Please refer to the full PCSP# implementation here[3].

C. Strategy recommendations

By utilizing the ability to assess the impact of changes to various actions, we can recommend strategies to improve a player's winning chance based on sensitivity analysis from probabilistic model checking. There are mainly two types of strategies, which we can determine through Algorithm 1.

Pre-match strategy. The first type of strategy concerns detailed tactics about play patterns. Technically, it is related to the *probability distributions* of actions. For example, one can shift 10% T serves to W serves against a particular opponent if

[2] https://github.com/LZYAndy/Insight_Strategy/blob/main/tennis_complex.txt

[3] https://github.com/LZYAndy/Insight_Strategy/blob/main/tennis.txt

Algorithm 1: Computing the optimal strategy.

Data: current state s, policy π, percentage change $\delta\%$, maximum increase in winning chance Δ_{max}

Result: a_{best} (the best action to increase in state s)

$\Delta_{max} \leftarrow -\infty$; $a_{best} \leftarrow None$;
for $a \in \pi(s)$ **do**
  if *pre-match strategy* **then**
    `// pre-match strategy`
    `// add action a's percentage by` $\delta\%$
    $Pr(a|s) \leftarrow Pr(a|s) + \delta\%$;
    for $a' \in \pi(s) \setminus [a]$ **do**
      $Pr(a'|s) \leftarrow Pr(a'|s) - \frac{\delta\%}{|\pi(s)|}$;
  else
    `// training strategy`
    `// reduce action a's error by` $\delta\%$
    $Pr(in|s, a) \leftarrow Pr(in|s, a) + \delta\%$;
    $Pr(err|s, a) \leftarrow Pr(err|s, a) - \delta\%$;
  `// compute increase in winning chance`
  $\Delta p_{win} \leftarrow$ increase in winning chance;
  `// update the best action to increase`
  if $\Delta p_{win} > \Delta_{max}$ **then**
    $\Delta_{max} = \Delta p_{win}$; $a_{best} = a$;

the historical data shows the opponent is weaker in returning W serves. As coaching is prohibited during a tennis match, we name the first type of strategy "pre-match strategy" as it can be directly applied by a player before the match begins without changing the reliability (i.e., success rate) of his/her sub-skills. The strategy is shown in Algorithm 1, where we can find the best action to increase in each state (e.g., $P1$ should play more forehand cross-court in the deuce court against $P2$).

Training strategy. The second type of strategy is to increase the *success rates* for certain types of shots via targeted training. Therefore, we name it "training strategy". This type of strategy may not be applicable immediately before a match as a player cannot suddenly be good at a skill. For example, before playing against Nadal who is known for his powerful forehand, Federer may focus on training his backhand down-the-line shots at the ad court so that he can reduce the error by 2%. Such a strategy not only increases Federer's backhand success rate but also reduces Nadal's forehand threat because the down-the-line shot leads to Nadal's backhand.

V. Evaluation

We used the PAT model checker to implement our model and carried out evaluations on actual professional tennis matches to assess the performance of our strategy analytics approach. Our experiments are designed around the following three sections:

A. How accurate is the model in predicting players' winning chances when playing against different opponents?

To predict one's winning probability against a particular player, our framework provides flexibility to extract data from interested matches *before the date of a target match*. For instance, consider predicting a match between players $P1$ and $P2$, with Elo rankings [15] $e1$ and $e2$, respectively. To gather data for $P1$, we collect information from matches between $P1$ and opponents *similar to* $P2$ over the past two years . We define "similar" as the opponents should have (1) the same handedness as $P2$, and (2) Elo rankings fall within the range of $[e2 - \delta_{elo}, e2 + \delta_{elo}]$, where $\delta_{elo} \in \mathbb{N}$. We follow the same approach to gather data for P2. Once we have selected the related historical matches, we can construct the MDP model and predict the match outcome. The processing time for a match is usually about 1 second.

TABLE I
Betting results over the past 10 years.

δ_{elo} ($\pm$)	Num of bets	Profits	ROI	Annualized ROI
50	461	\$10,592	105.92%	7.49%
100	1,388	\$30,385	**303.85%**	**14.98%**
150	2,177	-\$8,194	-81.94%	-15.73%
200	2,871	-\$8,471	-84.71%	-17.12%

1) Betting simulation: We adopt the bookmakers' odds[4] as our baseline as it currently represents the state-of-the-art approach in the field. In our experiment, we apply a well-established betting strategy – Kelly criterion [16]. To evaluate the profitability, we calculate the return on investment (ROI) and the annualized ROI. The initial bankroll is \$10,000. We explore various constraints on the range of Elo ranking differences $\delta_{elo} \in [50, 200]$ when selecting related historical matches. When the value of δ_{elo} is small, the selected matches are of higher quality but the quantity may be limited. Conversely, as δ_{elo} increases, a greater number of matches are included, although they may be less directly related to the target matches.

Our betting strategy focuses on matches that have a minimum of 4 relevant historical matches for each player to ensure prediction accuracy. The outcomes of the betting simulations are presented in Table I. Analysis of the table reveals that the models with $\delta_{elo} = 50$ and 100 make long-term profits. However, a further increase in δ_{elo} results in negative profitability. The reason is that the selected historical matches exhibit lower relevance to the targeted players. This experiment demonstrates that our model has an excellent performance in predicting the winning *probability* of tennis matches.

2) Comparison with existing works: A reliable winning probability prediction model should provide well-calibrated estimations that align with real-world outcomes. Traditional measures like accuracy and log-loss do not adequately reflect the actual winning probabilities. To address this, we evaluate the models' predictions using the expected calibration error (ECE) [17], which measures the disparity between predicted probabilities and observed outcomes.

We assess the performance of our model with $\delta_{elo} = 100$ against other well-established match outcome prediction models as mentioned in Section II-B, including a point-based method [18], a paired comparison method [15], and the bookmakers. As shown in Table II, our model has the best performance with the lowest ECE of 0.0099.

[4] http://www.tennis-data.co.uk/

TABLE II
ECE SCORES FOR DIFFERENT METHODS.

Method	ECE (5 bins)
Point-based [18]	0.0973
Paired comparison [15]	0.0317
Bookmakers	0.0207
Our method	**0.0099**

B. Does our model provide effective pre-match and training strategies to increase players' winning chances?

Our system enables users to assess the impact of various pre-match or training strategies on their performance, aiding players in identifying the most effective means of improvement. However, gauging the real-world effectiveness is a challenge, as we can hardly request professional players to apply our strategies. Thus, we evaluate based on observations from historical data.

Consider the 16 recorded matches between Roger Federer and Rafael Nadal from 2011 to 2022. Before 2017, Federer only won 2 out of 10 matches, but after 2017, he won 5 out of 6 matches. Upon analyzing Federer's actions and sub-skill reliability, a notable difference is observed before and after 2017. To determine if this improvement is due to changes in strategy, we created two MDP models based on historical data before and after 2017, respectively. Using PMC, we then calculated Federer's winning rate, and the results were 35.7% and 53.2% respectively, which match the actual results.

Furthermore, we want to see whether our system can help players to identify pre-match and training strategies to achieve optimized improvements in the future. Our idea is to test the following:

- For pre-match strategy, identify the best action to increase in each state by modifying **probability distributions**.
- For training strategy, identify the best action to improve/train on in each state by modifying **success rates**.
- Check whether the player has indeed increased/improved on the identified actions later on.

We applied the above idea to all 11 states for both pre-match and training strategies. The results showed that: (1) for pre-match strategy, 9 out of 11 best actions identified by our method match Federer's actual adjustments; and (2) for training strategy, 8 out of 11 recommended improvement actions align with Federer's actual improvements in terms of increasing action success rates.

To further validate our approach, we collected additional examples similar to Federer against Nadal and used the same validation method. These examples should follow the pattern where a player has a significant increase in win rate against a specific player after a certain time point. We use the data before that point to generate recommendations and use the data after that point to validate our recommendations. Table III summarizes the empirical results, demonstrating that a majority of our recommendations align with players' actual strategy adjustments and improvements. Hence, we can conclude that our strategy analytics are reasonable and effective.

C. What new insights a player/coach can get from our strategy recommendations?

One may argue that our recommendations largely overlap with what pro athletes already do. However, these valuable insights may not be easily accessible to players without the same level of coaching staff and resources. Our goal is to make high-quality strategy analysis accessible to the broader tennis community. In this section, we will delve deeper into the insights generated by our system and show how players and coaches can benefit from them.

Our system can generate opponent-specific strategy recommendations for different player matchups. Table IV presents examples of our pre-match and training strategy suggestions. It is important to note that we only present the most effective strategy in each state, which corresponds to the action that yields the highest gains when increasing the probability distributions or success rates by 2%. Our strategy recommendations exhibit remarkable diversity across different matchups. For instance, we suggest distinct pre-match strategies for Zverev against different opponents, such as employing more forehand cross-court (FH_CC) against Nadal and forehand down the line (FH_DL) against Federer in the De_Stroke state. Moreover, when different players face the same opponent, our system recommends Wawrinka to increase his forehand inside-out (FH_IO) and Cilic to increase his backhand down the line (BH_DL) at Ad_Stroke when playing against Djokovic.

Sometimes our method can generate "unusual" (novel) strategy suggestions that players/coaches may not be aware of. For instance, by analyzing matches between Roger Federer and Andy Murray before 2014, our system suggests that Federer's most effective pre-match strategy was to play more backhand down the line to Murray's forehand, despite the common belief that attacking the opponent's backhand side is better. But in fact, after 2014, Federer did not lose any match against Murray and indeed increased backhand down the line by 4.8%.

In addition, even if players/coaches are aware of the sub-skills they need to work on, they may not know the precise adjustments/improvements needed to effectively maximize their winning chances. Our system can calculate precise numbers for these improvements. One potential application is to assist players in customizing their training in a more effective manner.

VI. CONCLUSION

In this paper, we have presented a novel MDP framework for tennis to conduct strategy analytics using probabilistic model checking. Our methodology is adaptable to other sports[5] such as badminton, table tennis, and soccer.

Compared to existing methods, our MDP-based model connects match outcomes with the reliability and probability distribution of individual sub-skills for both players, using

[5]https://github.com/LZYAndy/Insight_Strategy

TABLE III

SYSTEM SUGGESTED ACTIONS FOR IMPROVEMENT COMPARED WITH PLAYERS' ACTUAL STRATEGY ADJUSTMENTS. "WIN%" DENOTES THE WINNING CHANCE. "ALIGN_I" DENOTES THE FRACTION OF OUR PRE-MATCH SUGGESTIONS THAT ALIGN WITH PLAYERS' ACTUAL STRATEGY ADJUSTMENTS. "ALIGN_T" DENOTES THE FRACTION OF OUR TRAINING SUGGESTIONS THAT ALIGN WITH PLAYERS' ACTUAL SUB-SKILL IMPROVEMENTS.

Player	Opponent	Turning-point year	Win% before year	Win% after year	Align_I	Align_T
Federer R.	Nadal R.	2017	20.0%	83.3%	9/11	8/11
Nadal R.	Djokovic N.	2017	26.1%	60.0%	7/11	8/11
Murray A.	Nadal R.	2015	14.3%	50.0%	10/11	8/11
Zverev A.	Tsitsipas S.	2021	20.0%	50.0%	8/11	7/11
Djokovic N.	Tsitsipas S.	2020	50.0%	100.0%	9/11	8/11
Djokovic N.	Medvedev D.	2021	50.0%	100.0%	9/11	7/11
Zverev A.	Federer R.	2018	33.3%	66.7%	8/11	9/11
Thiem D.	Federer R.	2019	50.0%	100.0%	7/11	10/11
Cilic M.	Djokovic N.	2016	0.0%	33.3%	8/11	8/11

TABLE IV

DIFFERENT PRE-MATCH AND TRAINING STRATEGIES AT EACH STATE.

Player	Opponent	De_Serve	De_Serve_2nd	Ad_Serve	Ad_Serve_2nd	De_FHR	Ad_FHR	De_BHR	Ad_BHR	De_Stroke	Mid_Stroke	Ad_Stroke
Pre-match Strategy												
Zverev A.	Nadal R.	T	T	W	W	DL	IO	CC	CC	FH_CC	FH_IO	FH_DM
Zverev A.	Federer R.	T	T	T	T	CC	DM	II	DM	FH_DL	FH_CC	BH_DL
Wawrinka S.	Djokovic N.	W	B	T	W	CC	II	IO	DL	BH_II	BH_IO	FH_IO
Cilic M.	Djokovic N.	T	T	B	W	DL	CC	DM	DL	FH_CC	FH_IO	BH_DL
Training Strategy												
Thiem D.	Djokovic N.	T	T	W	W	CC	CC	IO	DL	FH_CC	FH_CC	BH_DL
Thiem D.	Federer R.	W	T	T	W	DL	II	DM	CC	FH_DL	FH_IO	BH_CC

video analytics techniques to obtain shot-by-shot data from past matches. We strike a balance between accuracy and explainability so players and coaches can easily understand and apply our recommendations. We have evaluated the effectiveness of our strategies from multiple angles, such as comparing match prediction results with bookmakers' predictions and players' actual strategy adjustments. We also demonstrate the insightfulness of our proposed strategies through real-world examples and potential applications.

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