Enhancing Tennis Serve Scoring Efficiency: An AI Deep Learning Approach

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Abstract

The playing field of a tennis competition is a dynamic and complex formative environment given the following preliminary knowledge: (a) the basic technical, tactical, situational, and special types of shots used by the opponent; (b) the hitting area of the tennis player; (c) the place of service; (d) the ball drop position; and (d) batting efficiency and other related information that may improve the chances of victory. In this study, we propose an AI classification model for tennis serve scores. Using a deep learning algorithm, the model automatically tracks and classifies the serve scores of professional tennis players from video data. We first defined the players' techniques, volleys, and placements of strokes and serves. Subsequently, we defined the referee's tennis terms and the voice in deciding on a serve score. Finally, we developed a deep learning model to automatically classify the serving position, landing position, and use of tennis techniques. The methodology was applied in the context of 10 matches played by Roger Federer and Rafael Nadal. The proposed deep learning algorithm achieved a 98.27% accuracy in the automatic classification of serve scores, revealing that Nadal outscored Federer by 2.1% in terms of serve-scoring efficiency. These results are expected to facilitate the automatic comparison and classification of shots in future studies, enabling coaches to adjust tactics in a timely manner and thereby improve the chances of winning.

Keywords

Deep Learning, IoT, Markerless Motion Capture, Notational Analysis, Tennis Techniques And Tactics, Video Analysis.

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I. Introduction

There are four major tennis Grand Slam tournaments played around the world: US Open, Australian Open, French Open, and Wimbledon. It is the ultimate dream of professional tennis players to win any of these championships, attaining the highest level of glory in the sport [1]. Unsurprisingly, many videos are generated during these tournaments. Whitson and Horne [2] compared the results of large-scale sports events in Canada and Japan, finding that the analysis of footage showing various sports competitions is associated with commercial interests, diverse entertainment effects, and a large audience base [3]. With developments in software and hardware for image analysis, Nhamo et al. and Keshkar et al. [4]–[5] considered the attendance restrictions for various sports competitions during the COVID-19 pandemic, and employed information technology to share footage analyzed in real time, allowing the audience to interact through the Metaverse technology. Today, athletes increasingly look toward the assistance of multimedia systems to obtain analyses of relevant factors such as athlete habits, movements, sports performance, basic and advanced data, and tactics [6]–[9]. To address the audience's perspective, sports video analyses tend to focus on scene classification or the capture of exciting moments. To achieve this, these analyses provide footage from multiple camera angles, allowing users to quickly receive the desired multimedia data and emotionally invest themselves in live matches [10]–[11]. During competitions, video assistant referees, players, coaches, and referees can request the use of computer technology to ensure a fair decision-making process when addressing disputed situations [12]–[14]. The aforementioned image analysis techniques primarily focus on the real-time transmission and analysis of individual matches, aiming to increase interaction with the audience. Rangasamy et al. [15] compiled deep learning methods and AI-based image analyses, many of which combine computer vision technologies such as human-computer interfaces, handwriting recognition, and speech recognition with big data to analyze an athlete's performance in single and multiple matches.

The analysis of video footage has a direct and profound impact on the outcomes of games, as the player's grip, technical movements, physical strength, and overall hitting style determine their performance on the court. Following an analysis, the player's posture and grip on the racket helps improve control, and the proficiency of technical movements directly relates to the accuracy and speed of hitting the ball [8]. In addition, the athlete's endurance and psyche are also key factors. Good endurance ensures sustained high-level performance in

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the game, while a strong mindset allows players to stay calm under pressure and adapt to changes in opponents. The quality of playing habits directly determines the outcome of a game and is crucial to the player's success on the court. The combat models of tennis players have been widely studied and classified at the academic level, with technical characteristics covering different tactical styles [7]. First, baseline golfers primarily stand at the baseline position and demonstrate superb baseline skills, including steady hitting and excellent endurance, to suppress their opponents. Second, net players focus on approaching the net area to win with fast and precise offensive tactics, demonstrating excellent reaction speed and volleying skills. Finally, all-court players combine the advantages of the baseline and net types by flexibly using the entire court and continuously adjusting tactics. This technical classification provides a theoretical basis for tennis matches that helps players tailor their strategies to combat their opponents.

In this study, we designed a two-dimensional virtual Internet-of-Things (IoT) tracking model by defining action images for commonly used tennis techniques [16]–[17]. The tennis court, represented virtually in two dimensions, is divided into 48 areas. We employed deep learning to analyze 10 matches played by Roger Federer and Rafael Nadal from 2007 to 2019. Each shot played by Federer and Nadal was recorded and classified automatically, enabling the analysis of tennis techniques and player positions. This allowed us to compile the playing styles and habits of both players.

The rest of the paper is structured as follows. In Section 2, we present a literature review of shot classification applied to motion analysis and applications of deep learning in sports. In Section 3, we describe the materials and algorithm used in this study. Our experimental results are presented and discussed in Section 4. Finally, Section 5 concludes the paper.

II. Literature Review

A. Shot Classification Applied to Motion Analysis

Currently, sensors and videos are used for the analysis of movements in tennis. Duan et al. [18] proposed a unified classification framework for sports video shots by extracting 5-10 shots from sports movies and defining semantic shot categories. Using supervised learning, they achieved accuracy rates of 85–95% in the classification of tennis, basketball, volleyball, and football events, videos, and catalogs. Dang et al. [19] proposed a court-line pixel detection method, using the RANSAC linear parameter estimation method to determine the sideline range and subsequently deploying an image tracking system to automatically identify video footage of the four major tennis tournaments, achieving accuracy rates of 96–99%. Connaghan et al. [20] examined the accuracy of sensor recognition and classification in tennis strokes, with seven players trained on the three actions of serves, backhands, and forehands. They achieved recognition rates of 82.5%, 86%, 88%, and 90% for configurations corresponding, respectively, to the accelerometer and gyroscope; accelerometer and magnetometer; gyroscope and magnetometer; and accelerometer, gyroscope, and magnetometer. Raymond et al. [21] employed wearable sensors to identify strike types and rotations. In their study, 17 college-age athletes completed 10 exercises for each action with 5–10 shots for each shot over six games. The statistical results show that the average error of shots and spins was 32.0%. Other studies have also employed sensors to collect data for the purpose of action recognition in tennis [22]–[26].

B. Deep Learning in Sports

Batting techniques in tennis can be classified into four primary categories: serve, draw, slice, and volley [27]. In addition to good technical, physical, tactical, psychological combat plans and strategies, players must have an excellent ability to control the ball in a variety of game scenarios. Furthermore, good playing strategies must rely on continuous simulation, training, and accumulated experience. To date, scholars have primarily integrated video features and design-related algorithms to achieve the content understanding, indexing, annotation, and retrieval of sports videos for the development of automatic referees, as well as technical and tactical analyses.

Voeikov et al. [28] proposed the TTNet neural network model, which employs a high-speed camera to provide online real-time automatic refereeing of table tennis matches, achieving an accuracy of 97.5%. Xu et al. [29] deployed a K-nearest neighbor algorithm to achieve human motion and gesture recognition in table tennis videos. The deep learning process was divided into two stages: semi-supervised video image feature learning, and the supervised optimization of video sequence features. The resulting image recognition method achieved a 1.9% improvement in accuracy over the conventional image capture method. Qiao [30] employed a long short-term memory model to instantly track images of table tennis games for action feature recognition, achieving a maximum recognition accuracy of 89% and a target tracking effect and trajectory prediction accuracy of 90%. Compared with a traditional convolutional neural network (CNN), the model proposed by Qiao achieved a 23.17% improvement in accuracy.

Deep learning has also been used for tennis image recognition. Reno [31] deployed a CNN to learn video data of tennis matches after filtering the background of the game environment to track the ball's landing, achieving an accuracy rate of 98.77%. Ganser et al. [32] developed an automatic classifier for tennis shots. Specifically, they equipped tennis players with wearable sensors, and subsequently analyzed and classified the collected signals using a CNN. Of the 5682 shots collected, 91% were successfully detected and classified. Bastanfard and Amirkhani [33] used a CNN to classify tennis videos with 92% accuracy. Huang [34] proposed the HyperNet CNN model to extract and analyze tennis videos through a loss function, achieving an orientation accuracy of 96.32% and a size accuracy of 91.05%. Sports video analyses are typically conducted with 2D images for identification. Ning and Na [35] employed a dynamic time normalization barycenter averaging algorithm, as well as a K-means clustering algorithm, to analyze 3D dynamic tennis videos with the objective of identifying batting actions, achieving an accuracy of 94.5%. Li et al. [36] proposed a 3D CNN architecture and constructed a 3D video analysis algorithm for tennis videos, reaching an identification accuracy of 94.8%.

Successful tennis techniques must combine power and speed as key factors to win the game. Accordingly, individual skill must be complemented by smart tactics to gain advantage. Therefore, we conducted video and annotation analyses, using deep learning to examine the tactics and habits of two professional players, including their positions, techniques, and shooting points. Our results can be used by players to optimize their strategies during matches and training sessions.

III. Proposed Framework

This research used a recurrent neural network (RNN) to develop a two-stage analysis model, analyze the tactics used by Roger Federer and Rafael Nadal from 2007 to 2019, construct a battle model, and adjust autonomous training and match strategies. To accurately identify the two players' positions, techniques, and scores from video data, we designed a two-stage deep learning algorithm. Prior to the analysis, we preprocessed the data by eliminating extraneous images from the footage. Subsequently, we deployed the RNN algorithm for classification. Through image recognition and deep learning with RNN, the algorithm identifies the ball placement when Nadal and Federer win points, their respective positions on the court, and the tennis techniques they employ. The research process is illustrated in Fig. 1, and the analysis procedures are detailed below.

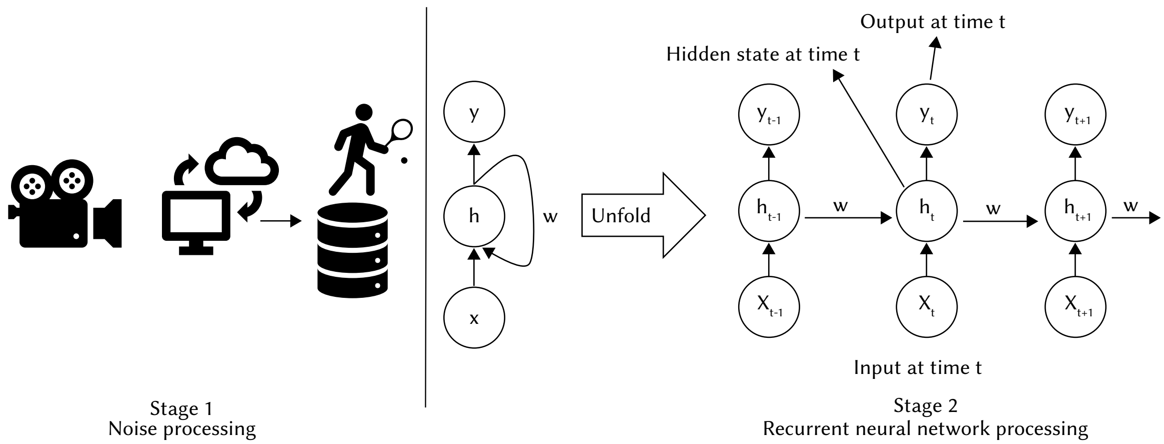

Fig. 1. The research process.

IV. Stage 1: Denoising

Step 1: Defining Noise

Certain scenes in the video data—such as audience reactions, ball retrieval breaks, court maintenance, shots with stationary balls, advertisements, reporter broadcasts, and graphic analyses—were considered noise, as they did not represent actual play. We eliminated these scenes prior to training the RNN to improve analytical accuracy. Noise was defined according to the following criteria: (1) scenes not focused on the tennis court, (2) scenes where the ball was out of bounds, and (3) scenes where neither player was engaged in receiving or serving actions. As shown in Fig. 2, we modeled the tennis court with 48 relative positions for both players during a match. The encoding of these positions corresponds to the players' on-court locations. Fig. 3 depicts the ball's landing positions. Table 1 lists common receiving and serving techniques in tennis [37]-[38]. Any scene that failed to meet the criteria defined in Fig. 2 was considered noise.

8	16	24	32	40	48	41	33	25	17	9	1
7	15	23	31	39	47	42	34	26	18	10	2
6	14	22	30	38	48	43	35	27	19	11	3
5	13	21	29	37	45	44	36	28	20	12	4
4	12	20	28	36	44	45	37	29	21	13	5
3	11	19	27	35	43	46	38	30	22	14	6
2	10	18	26	34	42	47	39	31	23	15	7
1	9	17	25	33	41	48	40	32	24	16	8

center mark baseline

Baseline in tennis court center mark ↓

Fig. 2. Players' position on the tennis court.

	I	N	
	J	M	
	K	L	
	L	K	
	M	J	
	N	I	

Fig. 3. Returner's impact location of player.

Step 2: Filtering Noise

The selected video footage was processed to eliminate noise as defined in Step 1.

Step 3: Marking Noise Timestamps

The timestamps of identified noise shots were marked for later verification and analysis.

V. Stage 2: Recurrent Neural Network Algorithm

We deployed the RNN algorithm according to the following steps:

Step 1: Defining Image Features for Analysis

Based on the definitions provided in Fig. 2, Fig. 3, and Table I, the positions of the players, the ball's landing locations, and the tennis techniques are defined and recognized in the images.

Step 2: Initialize

We define the dimensions of various parameters—including U, V, W, b, and c—to implement the basic RNN unit.

Input: At each time step t, the input $x(t)$ is fed into the network.

Hidden State: $h(t)$ represents the hidden state at time step t, serving as the "memory" of the network. $h(t)$ is computed based on the current input and hidden state from the previous time step, and $h(t)$ is defined as (1). This function is considered a non-linear transformation, such as tanh or *ReLU*.

$$h(\mathrm{t}) = f(Ux(\mathrm{t}) + W\mathrm{h}(\mathrm{t}-1)) \tag{1}$$

Weights: The RNN has input-hidden connections parameterized by the weight matrix U, recurrent hidden-hidden connections parameterized by the weight matrix W, and hidden-output connections parameterized by the weight matrix V. All the weights are shared across time.

Output: $o(t)$ represents the output of the network. This output is often subject to non-linear transformations, especially when the network contains more layers downstream.

Step 3: Forward pass

Based on our equations for each timestamp t, we compute the hidden state $h(t)$ and apply the softmax function to obtain the output $o(t)$, which represents the probability of the next character.

Calculating softmax and numerical stability:

The softmax function takes an N-dimensional real-valued vector and transforms it into a real-valued vector within the range of (0, 1), with the elements summing to 1. We performed this transformation using the formula as (2):

TABLE I. Tennis Techniques and Corresponding Algorithm Codes

Techniques	Code	Definition
Forehand	FH	A stroke in which the inner side of the palm of the dominant hand that is holding the racket faces forward. Essentially, the tennis forehand is made by swinging the racket across one's body in the direction one wants to land the ball.
Backhand	H	A shot in which one swings the racket around one's body with the back of the hand preceding the palm. In a backhand volley, the term backhand refers to a groundstroke.
Forehand Volley	FHV	A fairly simple movement, in which the player uses one arm to hit the ball by their dominant side without letting the ball touch the ground. The player usually hits volleys when standing close to the net and inside the service box. This move requires firm hands and fast reflexes.
Backhand Volley	BHV	The player's hitting arm is bent, and their elbow is centered between their shoulders. The backhand volley begins with a hip and shoulder turn. This volley can be shot while standing close to the back fence to test the size of one's backswing.
Forehand Half-volley	FH	A shot in which the player hits the ball just after it bounces off the ground and before it reaches the height of a normal volley: 1.Move quickly to get into position for the shot. The ideal position is slightly behind the baseline, but not too far back. 2.Keep your knees slightly bent and your weight on the balls of your feet to maintain balance, and be ready to move in any direction. 3.As the ball approaches, take a small step forward and to the side to get into the right position. 4.Keep your racket head up and swing forward with a smooth and controlled motion. Try to contact the ball just after it bounces off the ground. 5.Follow through with your swing and always keep your eye on the ball. 6.Recover quickly and be ready for the next shot.
Backhand Half-volley	BH	A shot where the player hits the ball just after it bounces off the ground and before it reaches the height of a normal volley, using their backhand stroke: 1.Move quickly to get into position for the shot. The ideal position is slightly behind the baseline, but not too far back. 2.Keep your knees slightly bent and your weight on the balls of your feet to maintain balance and be ready to move in any direction. 3.As the ball approaches, take a small step forward and to the side to get into the right position. 4.Keep your racket head up and swing forward with a smooth and controlled motion using your backhand stroke. Try to contact the ball just after it bounces off the ground. 5.Follow through with your swing, and always keep your eye on the ball. 6.Recover quickly and be ready for the next shot.
Forehand Spin	FHS	The ability of a player to apply spin to the ball while executing a forehand stroke. Forehand spin is achieved through a combination of racquet and stroke techniques. Topspin involves brushing the racquet from above the ball's center towards the bottom, generating a downward spin on the ball. This causes the ball to descend in an arched trajectory as its rotational speed increases.
Backhand Spin	BHS	The ability of a player to impart spin to the ball when hitting the backhand. Backhand spin is achieved through a combination of racket and stroke techniques. This can produce topspin or backspin depending on how the player uses the racket and body when hitting the ball. Spin is generated mainly from the angle, speed, and position of the hitting point of the racket.
First Serve	FS	The first serve a player makes at the beginning of a serving game. This serve is usually the strongest and fastest serve a player can deliver, and is intended to achieve a direct score or take advantage of the opponent's return.
Second Serve	SS	The player's second serve in the service game, occurring after the player misses the first serve or the receiver successfully returns the ball.
Smash	S	Usually occurs when the player is in front of the net. When the ball is in the air, the player quickly jumps and hits the ball down hard, so that the ball falls to the opponent's court with great speed and force.
Unsuccessful Shots	US	A shot that fails to achieve the intended goal or produce the desired effect. These shots may occur in a variety of situations. Examples of unsuccessful shots include the following: Errors: These include unforced and forced errors. An unforced error is the failure to complete a successful stroke without apparent stress, such as hitting the ball out of bounds or netting. A forced error may occur when the opponent applies pressure or creates difficulty, e.g., by making a hard return that leaves the other player unable to hit back. Hitting the ball too deep: When the player hits the ball beyond the bottom line, leading the ball to fall behind the backcourt, the shot is considered unsuccessful. This can result in missed scoring opportunities and give the opponent the opportunity to counterattack. Too-short shot: A shot is judged unsuccessful when it does not have enough power or height to keep the ball from clearing the net and landing in its own court. This usually gives the opponent the opportunity to attack, forcing the player to react. Net shot: A shot is deemed unsuccessful when the player does not hit the ball high enough for it to go over the net. This results in a lost scoring opportunity, allowing the opponent to score or restart the round. Unstable shot: A shot is considered unsuccessful when it lacks stability, i.e., when the player cannot accurately control the direction, height, or spin of the ball. This may cause the ball to go out of bounds or give the opponent a chance to score. Unsuccessful shots commonly occur in games, and present opportunities for players to improve and adjust their shot techniques and tactics. Through reflection and training, players can improve the stability and accuracy of their shots, thereby increasing their chances of success.
Others	O	Not defined above; all count as other tennis skills.

$$p_i = \frac{e^{a_i}}{\sum_{k=1}^{N} e_k^{a}} \tag{2}$$

Step 4: Compute Loss

In a text generation model, the next character can be any unique character from the given vocabulary. Accordingly, we implemented a cross-entropy loss. In multi-class classification, the logarithmic loss values are summed for each predicted class in the observation. The compute loss is also defined as (3).

$$\mathrm{CE} = -\sum_{c=1}^{M} y_{o,c} \log\left(p_{o,c}\right) \tag{3}$$

Step 5: Backpropagation

The gradients must propagate from the last cell to the first cell. The product of these gradients may become zero or grow exponentially. The latter case corresponds to the gradient explosion problem, where a significant increase in the gradient norm accumulates during the training process. The former case corresponds to the gradient vanishing problem, wherein long-term components reach a norm of zero, rendering the model unable to learn correlations between events that are far apart in time.

Step 6: Update Weights

The gradients for each model parameter are calculated and updated accordingly.

Step 7: Repeat Steps 2-6

To train the model and generate text from the data, it is necessary to train the model for a certain period of time and evaluate the loss following each iteration. If the loss exhibits an overall decrease, the model's learning is progressing as expected.

VI. Results and Discussions

Our analysis was conducted on 10 videos of matches played by Roger Federer and Rafael Nadal from 2007 to 2019. We recorded the techniques, player positions, shot landing points, and serve landing points for each ball until every ball was analyzed.

Our deep learning analysis yielded a total of 122 valid shots between the two players. Table II lists statistics pertaining to the techniques used by Federer and Nadal individually, and Fig. 4 and Fig. 5 depict the corresponding graphic representations. The five most used techniques by both players, in order, were: forehand groundstroke, backhand groundstroke, first serve, backhand slice, and second serve.

TABLE II. Analyzed Player Statistics

Tennis Techniques	Federer		Nadal	
Code	times	accuracy	times	accuracy
FH	2232	35.94%	2506	41.48%
H	1948	31.37%	1809	29.95%
FHV	770	12.40%	871	14.42%
BHV	477	7.68%	364	6.03%
FH	414	6.67%	341	5.64%
BH	118	1.90%	31	0.51%
FHS	87	1.40%	24	0.40%
BHS	88	1.42%	51	0.84%
FS	35	0.56%	19	0.31%
SS	23	0.37%	20	0.33%
S	11	0.18%	2	0.03%
US	7	0.11%	1	0.02%
O	0	0.00%	2	0.03%
Summary	6210	100%	6041	100.0%

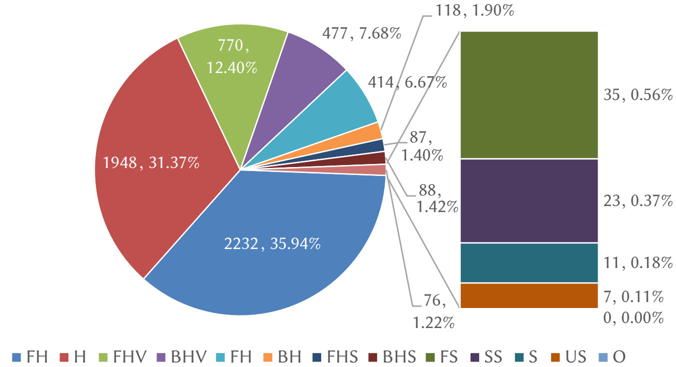

Fig. 4. Statistics of tennis techniques used by Federer.

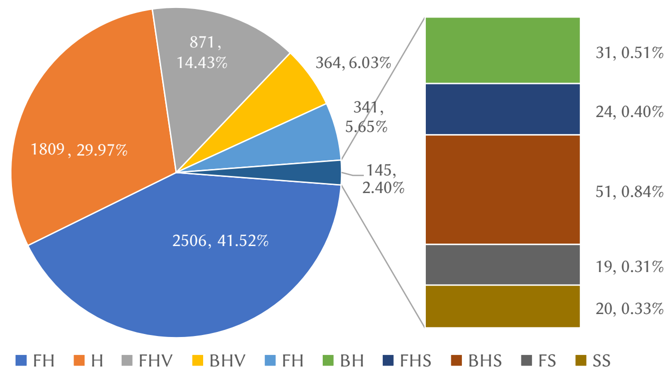

Fig. 5. Statistics of tennis techniques used by Nadal.

To illustrate the analytical results, we consider the first serves and winning shots used by Federer and Nadal. Federer hit a total of 770 first serves, of which 275 resulted in points and 495 led to second shots. Nadal hit a total of 871 first serves, with 243 yielding points and 628 leading to a second shot. Looking at the first serve points, Federer's scoring efficiency is 53.1%, whereas Nadal's is 46.9%. An analysis of player positions, techniques, and landing points corresponding to first serve scores is presented in Table III.

In Federer's case, 60.36% of the successful first serves were shot from position 12, with the remaining 39.64% shot from position 13.

In Nadal's case, 51.03% of the successful first serves were shot from position 12, with the remaining 48.97% shot from position 13.

Because Federer scored 275 points with his first serve, whereas Nadal scored 243 points, Federer has a lead of 32 points over Nadal. Both players were more successful when serving for position 12. For this position, Federer leads Nadal by 42 points.

When Federer served from position 12, most of the balls landed in position I, corresponding to 32.36% of his points. When Nadal served from position 12, most of the balls also landed in position I, corresponding to 23.46% of his points. We can observe that both players scored higher when they served from position 12, as well as when the ball landed in position I. However, these results indicate that Federer had an advantage over Nadal when serving.

In a comparative analysis, we employed existing models to examine the two players' first-serve performance. For Federer, Qiu's method [16] achieved a classification accuracy of 96.73%, the C5.0 algorithm by Chang and Qiu [17] achieved a classification accuracy of 98.36%, and our proposed method achieved a classification accuracy of 98.96%. For Nadal, Qiu's method achieved a classification accuracy of 98.36%, the C5.0 algorithm achieved a classification accuracy of 99.10%, and our proposed method achieved a classification accuracy of 99.37%. Thus, the proposed deep learning method outperformed the two existing methods for both players.

TABLE III. Analysis of First Serves

Plays \ Score Analysis	Batting Position	Ball Drop				
		Location	Times	Sum	Total	%
Federer	12	I	89	166	275	32.36%
		J	8			2.91%
		K	69			25.09%
	13	L	61	109		22.18%
		M	5			1.82%
		N	43			15.64%
Nadal	12	I	57	124	243	23.46%
		J	38			15.64%
		K	29			11.93%
	13	L	56	119		23.05%
		M	29			24.37%
		N	34			28.57%

Because tennis is an open-ended sport, players must not only exercise their own abilities, but also adjust their playstyle in response to their opponents. In this study, we defined and classified the variables of shot placement, technique usage, and landing point using a deep learning algorithm to analyze video footage. Our model was successfully used to interpret the playstyles, strengths, and weaknesses of two professional tennis players.

VII. Conclusions

In this study, we employed the techniques of annotation analysis and decision tree algorithms to categorize the scoring techniques of two prominent tennis champions. Accordingly, we constructed an adversarial model to identify the habitual scoring positions, stroke techniques, and shot placements of players during matches. The matchup model can be applied to analyze the strengths and weaknesses of any tennis player by simultaneously analyzing their opponent. Through this approach, we attained an understanding of the pivotal factors contributing to the victories of the two tennis champions.

The following observations were confirmed by our analysis:

(1) The results in Table 3 indicate that both Federer and Nadal aim for the inside corner K when serving from position 12, whereas they target the outside corner I when serving from position 13. This corresponds to the results shown in Figures 2 and 3, indicating that Federer's serves primarily attack Nadal's forehand, whereas Nadal focuses on targeting Federer's backhand.

(2) Although Nadal's serves predominantly target Federer's backhand, the probabilities of the six target areas are relatively even, and Nadal scores fewer points with his serves than Federer. In contrast, Federer's serves concentrate on the inside and outside corners irrespective of serving position, with lower probabilities in the middle. This tactical approach of aiming for the edges and creating wide angles not only increases the likelihood of scoring, but also forces the opponent to create openings, which explains why Federer scores more points.

(3) To prevent the opponent from scoring, data analyses can be conducted in advance to understand the opponent's preferred shot techniques and playstyle. In this study, we utilized the labeled analysis method to mark the landing points of shots, and integrated the serving positions, techniques, and landing points of both players using decision tree algorithms to develop a matchup model. This model can provide guidance to players during pre-match training and preparation, helping them overcome their limits, address weaknesses, enhance strengths, and maximize winning potential.

A limitation of this study is that we only considered 10 matches played by Federer and Nadal between 2007 and 2019. We did not account for variations in match venues, such as tennis court surfaces. In future studies, new deep learning methods can be developed to enhance classification performance.

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