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Deep Learning-Driven Decision Tree Ensembles for Table Tennis: Analyzing Serve Strategies and First-Three-Stroke Outcomes

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Abstract. This paper presents a novel artificial intelligence system that integrates deep learning-driven decision tree ensemble algorithms (DLDDTEA) for table tennis match analysis. By analyzing videos of professional matches featuring Lin Yun-Ju and Ma Long, the system extracts key insights into player techniques, hitting positions, and scoring outcomes. DLDDTEA processes the video data and constructs a predictive model to determine optimal serve positions and estimate point win/loss probabilities within the first three exchanges. The results revealed distinct serve strategies and techniques: Lin Yun-Ju favors backhands, whereas Ma Long prefers forehands. Based on these findings, this study offers specific training and strategic recommendations for both players. Thus, the proposed system offers a comprehensive framework for table tennis match analysis, enabling players to gain a deeper understanding of their strengths and weaknesses, ultimately facilitating the development of more effective training and competitive strategies.

Keywords: deep learning, decision tree, video analysis, table tennis match model, notational analysis, convolutional neural networks.

1. Introduction

In table tennis matches, the serve, return of service, and subsequent stroke are collectively known as the “First Three Strokes.” The techniques and tactics employed during the initial three exchanges significantly influence the match outcomes. The first three strokes in table tennis are crucial. The serve, in particular, is critical as it creates opportunities for the subsequent return and is a key tactic for restricting the opponent. Wang [1] analyzed the table tennis matched held at the 2012 London and 2016 Rio Olympics and elucidated the significant importance of serve position and return techniques. Specifically, the serve

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is a preemptive strategy, used either to score directly or to create attacking opportunities. Conversely, the return of service plays a crucial role in the contest of these first three strokes. Yu and Gao [2] analyzed the matches of the 2019 World Table Tennis Championship Men's Singles and found that forehand serves and aggressive returns were the highest-scoring techniques. Yin et al. [3] employed the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method to objectively and accurately analyze the techniques and tactics used in the first three strokes of table tennis matches.

In [4] and [5] identified significant differences in the serve and return techniques between male and female table tennis players. Male players tend to favor positions closer to the net, whereas female players prefer those near the baseline. Regarding return techniques, males use more push strokes near the net, whereas females employ more push strokes near the baseline. Regardless of sex, players require excellent technical skills, physical fitness, tactical variations, and psychological resilience to compete effectively. Through video analysis of table tennis training, Gumilar et al. [6] found that top players enhance the quality of their third stroke after serving to directly increase their scoring chances. [2] and [7] suggested that high-quality returns can transform a defensive situation into an offensive one, increasing scoring opportunities.

Grycan et al. [8] studied the winning actions, techniques, and tactics used by the leading male table tennis players from 1970 to 2021, finding that while the first three strokes remained crucial throughout this period, the importance of serving as a direct scoring stroke decreased. Therefore, this study conducted deep-learning based analysis of match videos to construct a model of the first three strokes used by professional male players Lin Yun-Ju and Ma Long, including the frequency of their techniques and the probabilities of winning or losing points within these exchanges. Using a decision-tree algorithm, this study constructs an artificial intelligence (AI)-based table tennis match model based on the placement strategies of these players. This AI model can be extended to other table tennis players, enabling them to construct their own match models and adjust their training and match strategies.

This paper introduces an AI algorithm that leverages deep learning-driven decision tree ensemble algorithms (DLDDTEA) to analyze table tennis matches. Specifically, convolutional neural networks (CNNs) are used to extract technical information, hitting positions, and scoring outcomes from video footage of matches featuring Lin Yun-Ju and Ma Long. Subsequently, a decision tree ensemble method, based on principles similar to those underlying the C4.5 algorithms, is employed to construct a predictive model. This model is can identify optimal serve positions and estimating the probability of winning or losing points within the first three strokes.

2. Literature Review

This literature review is divided into three subsections: Section 2.1 reviews studies on notational analysis, Section 2.2 analyzes those on the applications of decision trees in sports analysis, and Section 2.3 discusses those employing AI for image analysis.

2.1 Notational Analysis

Several studies have employed notational analysis (also known as tagging analysis) to investigate tactics used in table tennis and other sports. Malagoli et al. [9] used this method to study the matches of 20 top table tennis players, focusing on the playing styles of Asian and European players. Their results indicated that Asian players are more aggressive and have more effective services, providing valuable insights for coaches and athletes regarding both technical and tactical applications. Djokić et al. [10] analyzed 20 matches from the German league and the European TOP 16 semifinals and finals, focusing on serve analysis of top table tennis players. They found that short forehand serves were most prevalent (76.9%), primarily targeting the opponent's backhand area. The direct scoring rate from the serves was 11.6%, whereas the third and fifth strokes featured scoring rates of 22.4 and 10.9%, respectively. Serve errors were primarily observed in the third (25.0%) and fifth strokes (22.4%), with an overall error rate of 1.5%. A correlation between service types and match outcomes was also found. Zhou [11] used notational analysis to examine data from 200 matches of the Chinese table tennis team and found that the scoring rate for attacks within the end line (AIEL) was significantly higher than that for attacks outside the end line (AOEL). Additionally, the timing of attacks significantly influenced the scoring rate, with earlier attacks yielding higher scores. AIEL primarily involved backhand flips, whereas AOEL mainly comprised backhand drives. Pradas de la Fuente [4] applied notational analysis to study the technical and tactical differences between male and female table tennis players. They found that male players use forehand techniques more frequently, whereas female players prefer defensive techniques. Tactically, male players are more aggressive, particularly when using flip techniques, whereas female players tend to be more defensive. Furthermore, male players' movements are faster and more explosive, whereas female players focus more on stability and defense. Guarnieri et al. [12] collected data from 25 Paralympic table tennis matches between 2012 and 2018 and used notational analysis and Kinovea software to analyze players' stroke types, ball-bounce areas, and stroke outcomes. They found that C1 players primarily used backhand and forehand drives, whereas C5 players mainly used backhand and forehand pushes and backhand topspin.

In other sports such as volleyball and football, notational analysis has been used to study technical and tactical indicators, revealing gender-specific preferences in techniques and movements. Huang [13] employed notational analysis to study the techniques of male and female single finalists in the 1990 Grand Slam tennis tournaments held on different court surfaces, revealing significant differences in the players' techniques across various surfaces. Another key finding was that there was no significant difference in the ratio of good-to-bad serves between the first and second serves for either male or female players. However, the overall scoring rate from serves was substantial. Jiang [14] used video notational analysis to study techniques and winning factors in men's single tennis, enhancing the reliability of the study by increasing the observation frequency and ensuring content validity. Gambhir [15] summarized the use of notational analysis at the 16th International Table Tennis Science Congress, highlighting its application for studying the kinematic characteristics, techniques, and health of table tennis players. Malagoli Lanzoni et al. [16] used notational analysis to record and analyze 20 table tennis matches involving 40 male and 40 female players from the top 111 (female) and 120 (male) ITTF world rankings. They found that the most common serve types for both sexes were the forehand topspin and serve. Females preferred backhand blocks and pushes, whereas males preferred forehand topspin counters. Additionally, females often used a single step and preferred not to move their feet while striking, whereas males used crossover and pivot steps. Serves typically targeted areas close to the net and returns were often directed to the opponent's backhand corner. In [17] and [18] used global-positioning-system-based tracking combined with notational analysis to record tactical and physical indicators, and analyzed team possession, passing, and shooting performances. Herold et al. [19] used machine learning with notational analysis to help coaches analyze the attack efficiency and tactics of professional male football players.

2.2 Application of Decision Trees in Sports Analysis

Sigari et al. [20] developed a method for classifying sports videos using four simple classifiers: adjacent nodes, linear discriminant analysis, decision trees, and probabilistic neural networks. The experimental results indicated a correct classification rate of 78.8%. Kostuk and Willoughby [21] used decision-tree-based analysis to examine the choice between scoring and not scoring in the later stages of curling matches. Analysis of world-class curling competitions revealed that North American players often chose not to score in the final moments, whereas European players opted to score, concluding that not scoring in the later stages was a better choice. Pai et al. [22] combined support vector machine and decision tree models to predict basketball game outcomes, and achieved an average accuracy of 85.25%. Mumcu and Mahoney [23] applied decision trees to generate systematic and informed decisions in three sports-marketing scenarios. Çene et al. [24] compared decision trees, Technique for Order Preference by Similarity to Ideal Solution, and Performance Index Rating methods to analyze individual game data of players from the 2017–2018 European Basketball League season and identified the best and worst-ranked players. Yıldız [25] used decision trees to classify top football teams in Spain, Italy, and England with 77% accuracy. Gu and He [26] employed the fuzzy decision tree algorithm to analyze and predict member attrition in the fitness industry, achieving a classification and prediction accuracy of 97.8%. Tsai et al. [27] employed various methods, including logistic regression, support vector machine, decision tree C4.5, classification and regression tree, random forest, and extreme gradient boosting (XGBoost), to analyze the accuracy of stress state detection in table tennis players using electroencephalogram analysis. XGBoost achieved an accuracy of 86.49% for three-level stress classification, outperforming other methods by up to 11.27%. Ghosh et al. [28] used decision trees, learning vector quantization, and support vector machine to predict outcomes from a Grand Slam tennis database and found that decision trees outperformed the other two models. Chiang et al. [29] used decision tree analysis to study the segmented swimming styles of 11–12-year-old Japanese boys and girls in a 200-m individual medley and identified the winning strokes. They found that breaststroke and backstroke were the most successful strokes for boys, whereas breaststroke and butterfly were beneficial for girls. Madinabeitia et al. [30] used decision tree analysis to classify 7,345 individual statistics from 335 games in the 2018/2019 Spanish Men's Basketball League season, identifying low-contribution foreign players (FLC; 23.8% as shooting guards), high-contribution foreign players (FHC; 32.1% as centers), and low-contribution Spanish players (SLC; 32.9% as small forwards), thereby providing coaches with insights into team formation. Zuccolotto et al. [31] used the classification and regression tree algorithm for decision trees to analyze NBA 2020/2021 season data, visually and robustly representing the scoring probabilities of players or teams. Papageorgiou et al. [32] used decision tree analysis on data of 90 NBA players from the 2019–2022 seasons, evaluated the performance of 14 machine-learning models for predicting players' overall performance rankings using 18 advanced basketball statistics and key performance indicators.

2.3 AI-based Image Analysis

Mat Sanusi et al. [33] employed smartphone sensors, Microsoft Kinect, and neural networks to develop the Table Tennis Tutor program, which detects correct and incorrect strokes during table tennis training. Liu and Ding [34] used CNNs and long short-term memory (LSTM) networks to create a table tennis trajectory and spin prediction algorithm, achieving an accuracy rate exceeding 98% and thereby enhancing the performance of table tennis robots. Qiao [35] combined a deep deterministic policy gradient (DDPG), CNN, and LSTM to develop deep-learning techniques for automatically detecting and analyzing technical and tactical indicators from match videos, including stroke type, ball trajectory, spin speed, and landing points. They achieved feature-extraction, target-tracking, and trajectory-prediction accuracies of 89, 93, and 91%, respectively. Song et al. [36] applied k-means clustering to divide player win rates into three stages: service, receive, and rally attacks. They then used a hybrid LSTM–back propagation neural network (LSTM–BPNN) model to predict match outcomes. Finally, they used Shapley additive explanations (SHAP) to analyze the impact of three technical indicators (stroke position, stroke technique, and serve strategy) and three tactical indicators (scoring patterns, return strategies, and the first three stroke analyses) on match outcomes. The results showed that the hybrid LSTM–BPNN model achieved a 92.5% accuracy for predicting match outcomes. Liu et al. [37] used neural networks to analyze the top Taiwanese singles player, Lin Yun-Ju, using a dataset comprising 22 international match videos from 2015 to 2021. Using the 3S (Speed, Spin, Spot) theory for analysis, they found that a slow service speed combined with a long-backhand service spot led to a higher win rate. Conversely, half-long forehand serve spot resulted in a higher loss rate. These findings suggest that Lin could adjust his serving style to improve his win rate.

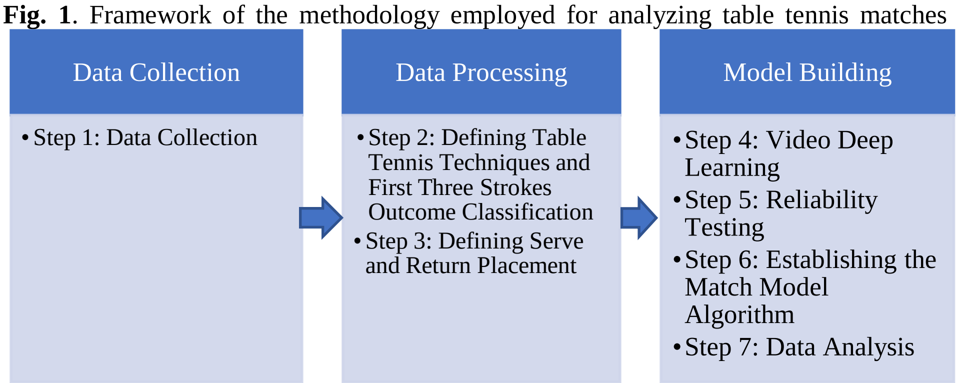
Despite these promising advancements, several challenges have hindered the widespread adoption of AI for table tennis video analysis. First, training robust AI models requires substantial amounts of annotated data, which are time-consuming and labor-intensive to collect and label. Second, their performance can be significantly affected by environmental factors such as lighting and background conditions. Third, the complex nature of deep-learning models makes it difficult to interpret their decision-making processes, limiting their applicability in scenarios requiring transparent explanations, such as refereeing. Finally, the sequential nature of table tennis actions can produce redundant detections when each frame is individually analyzed. Addressing these challenges is crucial for advancing the application of AI in table tennis and unlocking its full potential. In summary, the literature on decision trees reveals their capacity to organize collected data into graphical tree structures, clearly displaying the outcomes at different nodes and thereby identifying the most advantageous options.

3. Research Methodology

Deep-learning techniques, such as CNNs, have revolutionized sports analysis. Recent studies, including that by Li et al. [38], have demonstrated the efficacy of CNNs in automatically extracting technical and tactical features from table tennis videos. This research builds upon earlier work utilizing notational analysis, as exemplified by [9] and [10], which relied on manual coding of matches. Furthermore, machine-learning techniques have been successfully applied for data analysis in other sports, such as curling [21] and basketball [22], to predict outcomes and uncover underlying patterns.

This study employs a multifaceted approach using DLDDTEAs, combining C4.5 decision-tree algorithm, CNNs, and notational analysis to construct a table tennis match analysis model. This model leverages three key variables—techniques, placement, and outcomes—derived from matches featuring Lin Yun-Ju and Ma Long [38-41]. The primary objective was to identify the most effective combinations of these variables that yielded high scoring rates. The research methodology comprised three main stages: data collection, data processing, and model building. These stages were further divided into seven distinct steps, as illustrated in Fig. 1.

Fig. 1. Framework of the methodology employed for analyzing table tennis matches



featuring Lin Yun-Ju and Ma Long

Fig. 2 illustrates the training process of the multifaceted DLDDTEA model, including the image segmentation and video preprocessing techniques. This process involves the following steps: First, the image input parameters are defined. These parameters specify the image segments for nine distinct areas on each side of the table tennis net, primarily to record serve and return positions. Additionally, two grip types are defined: Forehand Backspin and Backhand Backspin. Images for ten common table tennis techniques are also defined, including Backspin, Topspin, Counter Loop, Chiquita, Short Push, Long Push, Flick, Fast Drive, Defense, and Lob. Next, CNNs are employed to convert the video footage into images, which are then classified according to the defined techniques and ball positions. The classification results are categorized as Serve Points, Receiving and Scoring, Third Stroke Attack, Serve Errors, and Continued Rally. Finally, a decision tree algorithm is used to further classify the techniques and ball positions into Serve Points, Receiving and Scoring, Third Stroke Attack, and Serve Errors.

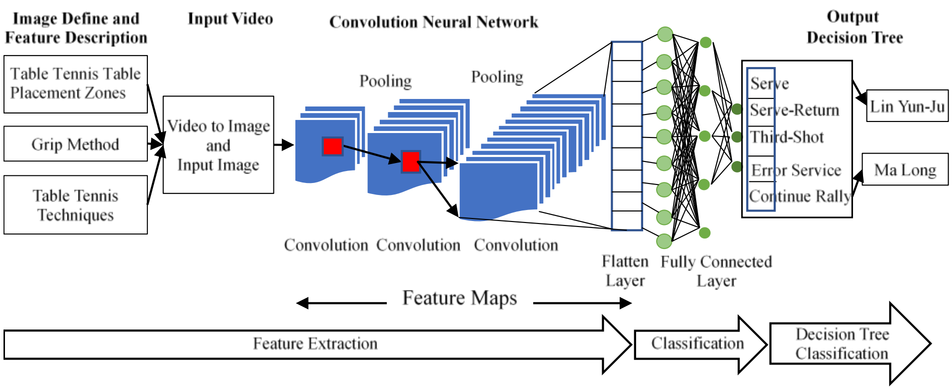


Fig. 2. Flowchart of the proposed multifaceted DLDDTEA approach

Step 1: Data Collection

This study analyzed match videos of professional male table tennis players, Lin Yun-Ju and Ma Long, from 2020, 2022, and 2023, totaling three matches.

Step 2: Defining Table Tennis Techniques and First Three Strokes Outcome Classification

There are ten commonly used table tennis techniques: forehand and backhand backspin, topspin, counter, flick, push, chop, drive, block, and lob [42]. Additionally, the various outcomes of the first three strokes were classified. The algorithm codes for each technique and their outcomes are listed in Table 1.

Table 1. Algorithm codes for table tennis techniques and outcomes

Forehand and Backhand Backspin		Techniques		Results	
Code	Grip	Code	Techniques	Code	Results
1	Forehand Backspin	B	Backspin	S	Serve Points
2	Backhand Backspin	T	Topspin	R	Receiving and Scoring
		CL	Counter Loop	T	Third Ball Attack
		C	Chiquita	S	Serve Error
		SP	Short Push	CR	Continued Rally
		LP	Long Push		
		F	Flick		
		FD	Fast Drive		
		D	Defense		
		L	Lob		

Step 3: Defining Serve and Return Placements

The table tennis table was divided into nine hitting zones, with serve and return placements coded from 1 to 9, as shown in Fig. 3.

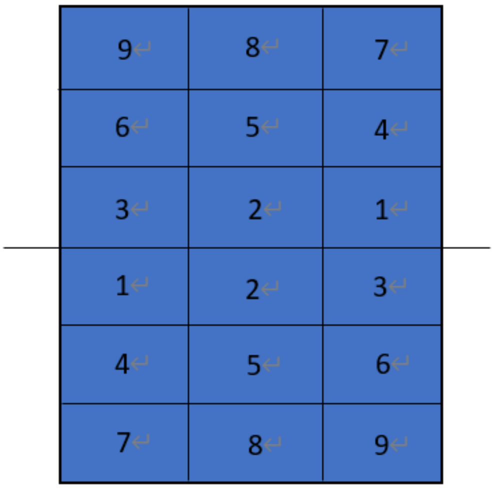


Fig. 3. Serve and return placement zones with their corresponding codes

Step 4: Video-based Deep Learning

CNNs were employed to automatically extract the technical and tactical features of both players during the first three strokes [38]. Through video analysis, the techniques, hitting placements, and point outcomes during the first three strokes were extracted.

Step 5: Reliability Testing

Two table tennis players with more than ten years of experience were invited to watch the videos together. They marked and recorded the match situations of the two players according to the methods described in Steps 2 and 4. Initially, a match was randomly selected and one game was viewed and marked. Thereafter, reliability testing was conducted using Holsti's [43] intercoder agreement and reliability formulas, as shown in Equations (1) and (2). When the reliability exceeded 0.8, the reliability standard is met and comprehensive coding can begin [44].

$$\text{Average inter} - \text{coder agreement} = \frac{2\text{M}}{\text{N1+N2}} \tag{1}$$

$$\text{Reliability} = n \times \frac{\text{Average inter−coder agreement}}{\{1+[(n-1)\times\text{Average inter−coder agreement}]\}} \tag{2}$$

In Equation (1), M represents the number of complete agreements, N1 is the number of agreements by Coder 1, and N2 is the number of agreements by Coder 2. In Equation (2), n is the number of coders involved.

Using these equations, we obtained a reliability measurement of 0.93 > 0.80. The calculation process is as follows:

Average intercoder agreement: ((0.84 + 0.81 + 0.86) / 3 = 0.83)

Reliability: ((3 * 0.83) / [1 + (3 - 1) * 0.83] = 0.93)

This indicated that the consistency among the three coders reached the standard level, allowing for comprehensive coding.

Step 6: Establishing the Match Model Algorithm

The study utilized a notational analysis method to categorize ten types of table tennis techniques and divided the table into nine zones for coding serve and return positions.

This approach aimed to reduce human error and enhance data consistency. Deep-learning techniques using CNN and decision tree models were used to automatically extract technical and tactical features from match videos, rapidly process large datasets, and reduce subjective analyses. The analysis of three match videos from 2020, 2022, and 2023 featuring Lin Yun-Ju and Ma Long involved the following coding and calculation classification processes:

1. All records were treated as a single node.
2. Based on Steps 1–3, the match videos were compared, and for each variable (table tennis techniques, serve and return placements, and first three stroke outcomes), the appropriate split points were identified based on the video analysis.

Reliability testing with experienced players ensured coding consistency, achieving a reliability of 0.93, which was above the standard of 0.8. A decision tree algorithm C4.5 was used to create predictive models to identify the optimal serve positions and win-loss probabilities within the first three shots. The analysis was continued until each ball hit and its outcome satisfied the classification for each node.

4. Results and Discussion

The analysis of the three videos encompassed 238 serves executed by the two players. Table 2 lists the statistics of the techniques used by Lin Yun-Ju and Ma Long, including the top three most frequently used ones

Table 2. Classification of techniques used by Lin Yun-Ju and Ma Long

Table Tennis Techniques	Lin Yun-Ju		Ma Long	
	Times	%	Times	%
Forehand Topspin	3	1.42%	8	3.65%
Backhand Topspin	21	9.95%	11	5.02%
Forehand Backspin	24	11.37%	52	23.74%
Backhand Backspin	16	7.58%	16	7.31%
Forehand Counter	18	8.53%	15	6.85%
Backhand Counter	9	4.27%	13	5.94%
Backhand Flick	63	29.86%	2	0.91%
Forehand Short Push	7	3.32%	33	15.07%
Backhand Short Push	28	13.27%	11	5.02%
Forehand Long Push	5	2.37%	12	5.48%
Backhand Long Push	1	0.47%	0	0%
Forehand Flick	1	0.47%	11	5.02%
Forehand Drive	1	0.47%	1	0.46%
Backhand Drive	4	1.90%	17	7.76%
Forehand Defense	4	1.90%	6	2.74%
Backhand Defense	6	2.84%	11	5.02%
Forehand Lob	0	0%	0	0%
Backhand Lob	0	0%	0	0%
Total	211	100%	219	100.0%

From Table 2, it is evident that neither player used the lob technique in the first three strokes, as it is primarily a defensive technique. This indicates that both players adopted an aggressive approach during the first three strokes.

The most frequently used techniques in the first three strokes were backhand topspin (9.95%), forehand backspin (11.37%), backhand chiquita (29.86%), and backhand short push (13.27%). Backhand topspin and forehand backspin are off-table techniques, whereas backhand chiquita and backhand short push are on-table techniques. This suggests that, when receiving serves and attacking during the third stroke, Lin Yun-Ju primarily used the backhand chiquita for on-table balls, with the backhand short push as a secondary option. For off-table balls, he mainly uses the backhand topspin for topspin balls and forehand backspin for backspin balls.

Ma Long's most frequently used techniques in the first three strokes were the forehand backspin (23.74%) and forehand short push (15.07%). Forehand backspin is an off-table technique, whereas forehand short push is an on-table technique. This indicates that Ma Long primarily used the forehand backspin for off-table balls and the forehand short push for on-table balls. As both are forehand techniques, this suggests that Ma Long prefers using his forehand when receiving serves and during the first three strokes.

There were 37 serve points between the two players (Fig. 4). Lin Yun-Ju scored 23 serve points with the following placement distribution: 1 point for Location 2, 6 points for Location 5, 5 points for Location 6, 5 points for Location 7, 3 points for Location 8, and 3 points for Location 9. In response to Lin Yun-Ju's serves, Ma Long's errors included 12 backspins, 5 topspins, 1 chiquita, 3 short pushes, and 2 flicks. Ma Long scored 14 serve points with the following placements: 1 point for Location 1, 7 points for Location 4, 1 point for Location 6, 1 point for Location 7, 3 points for Location 8, and 1 point for Location 9. In response to Ma Long's serves, Lin Yun-Ju's errors included 2 backspins, 2 topspins, 9 chiquitas, and 1 long push. Therefore, from the serve-point data, it is evident that Lin Yun-Ju scored approximately one-third more than Ma Long, demonstrating a clear advantage in serving. Lin Yun-Ju's points were more dispersed across half-long and long balls, whereas Ma Long's service-return errors were primarily concentrated on the backspin loops. Among Ma Long's 14 serving points, half were concentrated at Location 4, and Lin Yun-Ju's service-return errors were mainly chiquitas. Thus, during training, Lin Yun-Ju should focus on improving his chiquita return technique for balls coming at Location 4.

In terms of receiving and scoring, 62 records were available for the two players (Fig. 5). Among them, Lin Yun-Ju scored 26 points from receiving serves, with 4 forehand and 22 backhand shots. Regarding the techniques used for these points, 4 points were obtained from backspin, five from topspin, 13 from chiquitas, 3 from short pushes, and 1 from long pushes. In terms of placement, 1 point was obtained at Placement 2, 1 at Placement 3, 2 at Placement 4, two at Placement 5, 1 at Placement 6, 9 at Placement 7, 3 at Placement 8, and 7 at Placement 9. Ma Long scored 36 points from receiving serves with 19 forehand and 17 backhand shots. Regarding the techniques used, he scored 23 points from backspin, 3 from topspin, 1 from chiquitas, 6 from short pushes, 2 from long pushes, and 1 from flicks. Regarding placement, 1 point was scored at Placement 2, 3 at Placement 4, 4 ay Placement 5, 5 at Placement 6, 5 at Placement 7, 5 at Placement 8 and 13 points at Placement 9.

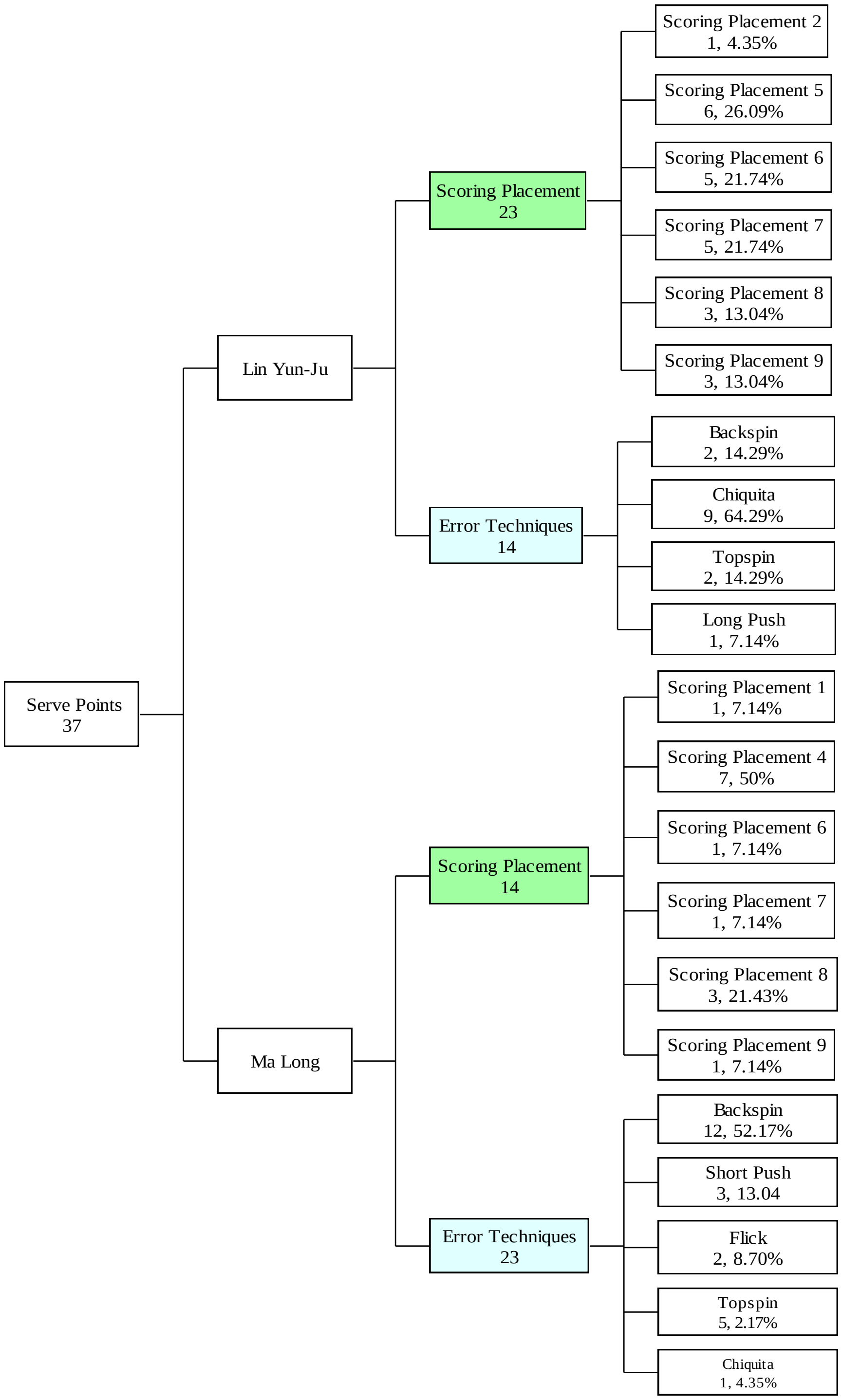


Fig. 4. Serve scoring locations of Lin Yun-Ju and Ma Long

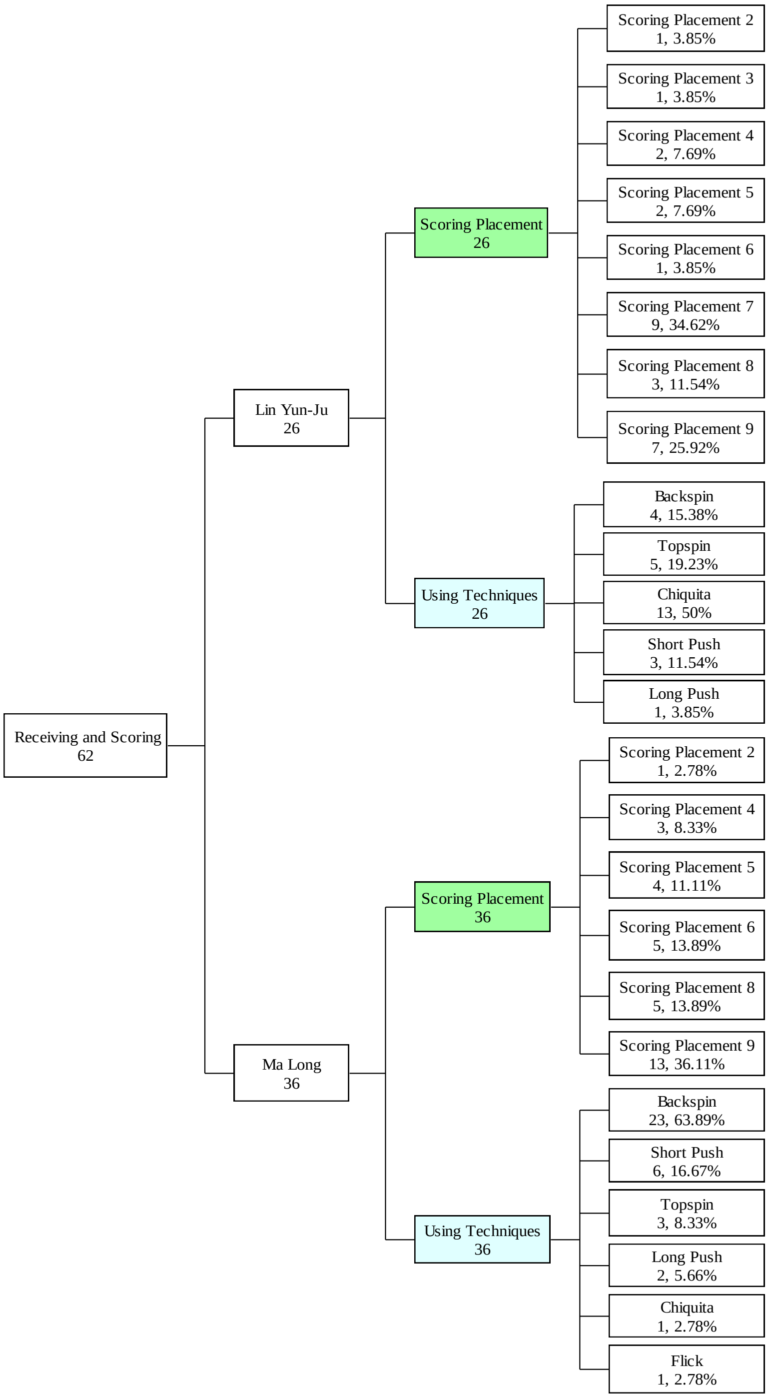


Fig. 5. Relationship between serve-return scoring locations and techniques used by Lin Yun-Ju and Ma Long

From the receiving and scoring data, it is evident that Ma Long scored more points while receiving services than Lin Yun-Ju. However, Lin Yun-Ju's backhand was more prominent when receiving serves, with chiquitas being his primary scoring method. His scoring placements were mainly concentrated at Placements 7 and 9. However, Ma Long's forehand and backhand were relatively balanced when receiving serves, with backspin being his main scoring technique. Additionally, his scoring placements were primarily concentrated in Placement 9. Therefore, if Lin Yun-Ju can use more chiquitas to target Placements 7 and 9 when receiving serves and focus on Ma Long's backspin targeting Placement 9 after serving, it will likely help him score more efficiently. Conversely, if Ma Long can use more backspin to attack Lin Yun-Ju's Placement 9 when receiving serves and defend against Lin Yun-Ju's chiquitas targeting Placements 7 and 9 after serving, it will likely help him score more points.

In terms of third-shot scoring, 49 records were available for both players (see Fig. 6). Lin Yun-Ju scored 25 points, with 16 forehand and 9 backhand shots. Regarding the points scored based on the techniques used, 9 were from backspin, 1 from topspin, 7 from counter, 4 from chiquitas, 1 from flicks, 1 from fast drives, and 2 points from defensive shots. Regarding the placements, 1 point was scored at Placement 4, 15 at Placement 7, 1 at Placement 8, and 8 at Placement 9. Ma Long scored 24 points from the third-shot scoring, with 16 forehand and 8 backhand shots. Regarding the techniques used, 8 points were scored from backspin, 2 from topspin, 7 from counter, 1 from short pushes, 2 from flicks, and 4 from fast drives. Regarding the placement, 1 point was scored at Placement 4, 2 at Placement 5, 2 at Placement 6, 8 at Placement 7, 6 at Placement 8, and 5 at Placement 9.

In terms of third-shot scoring, the two players had relatively balanced scores and primarily used forehand responses. The scoring techniques were predominantly backspin and counter. Lin Yun-Ju's scoring was concentrated at Placements 7 and 9, whereas Ma Long's were distributed across Placements 7, 8, and 9. Therefore, both players should create opportunities for forehand backspin and countering during the third shot after serving. To achieve the most effective scoring strategy, Lin Yun-Ju should focus on attacking Ma Long's Placements 7 and 9, whereas Ma Long should distribute his attacks across Lin Yun-Ju's Placements 7, 8, and 9.

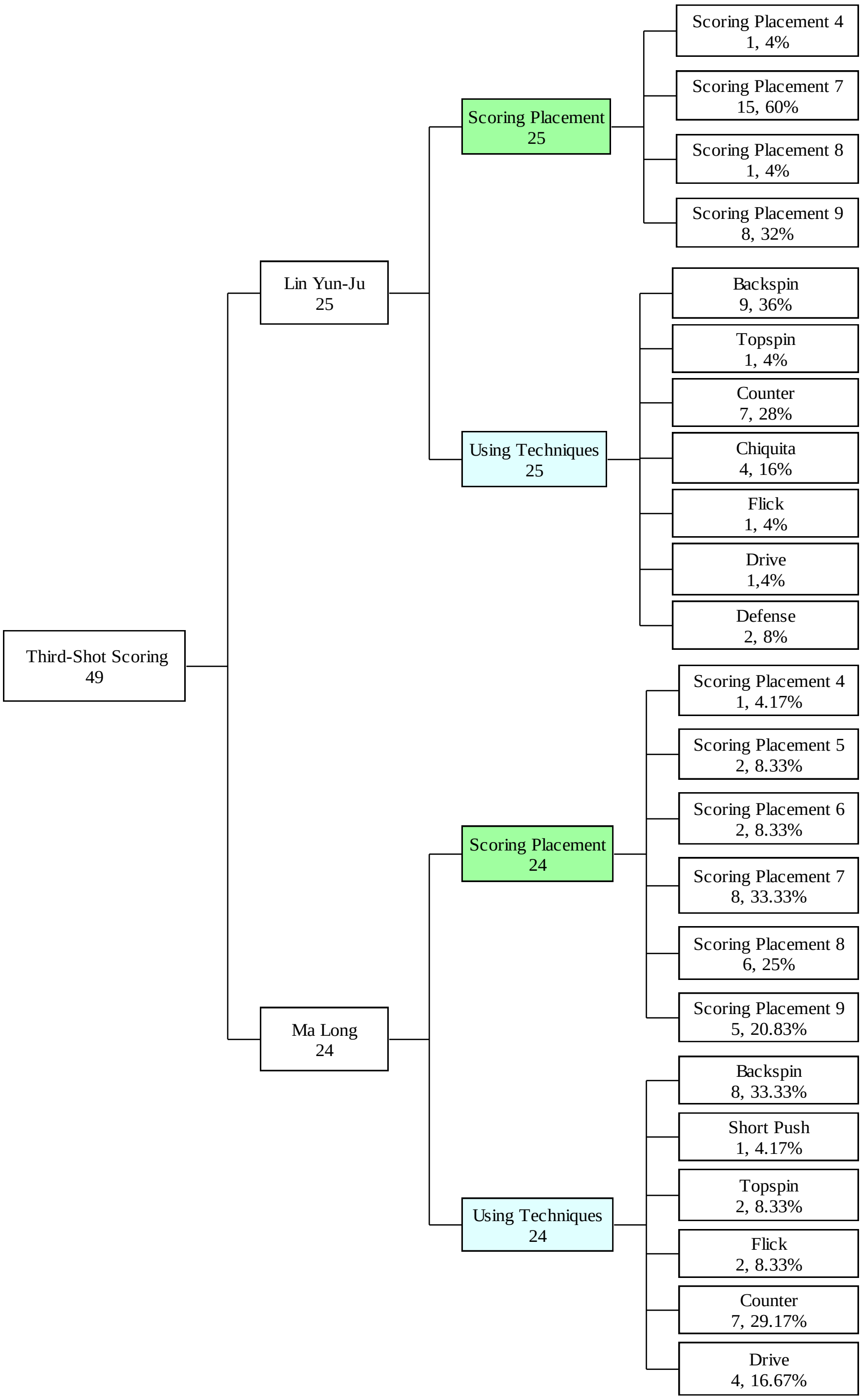


Fig. 6. Relationship between scoring placements and techniques used by Lin Yun-Ju and Ma Long in the third shot

5. Conclusions and Limitations

This study developed an innovative artificial intelligence system for analyzing table tennis matches, integrating notational analysis, deep learning techniques, and decision tree algorithms. By analyzing match videos of Lin Yun-Ju and Ma Long, the system automatically extracted key information, including player techniques, hitting positions, and scoring outcomes. Additionally, a predictive model was constructed to identify optimal serve positions and estimate the probability of scoring within the first three strokes. The main contributions of this study are as follows:

(1) Advancement of Scientific Table Tennis Training: The proposed system not only analyzes the technical characteristics and tactical preferences of two elite players, such as Lin Yun-Ju's preference for backhand strokes and Ma Long's inclination toward forehand strokes, but more importantly, it serves as an objective and quantitative analytical tool. Thus, it can help coaches and players gain a deeper understanding of match dynamics, facilitating the development of evidence-based training plans and more effective competitive strategies.

(2) Facilitation of Personalized Training Regimens: Based on the analytical output of the developed model, coaches can design personalized training regimens tailored to individual players' specific strengths and weaknesses. For example, targeted training can address areas identified for improvement, such as Lin Yun-Ju's receiving skills at Positions 4 and 8, and Ma Long's backhand returns from mid- to long-distance Positions 5, 6, and 7, ultimately enhancing technical proficiency and competitive performance.

(3) Enhancement of Match Outcome Prediction Accuracy: Through deep learning and decision tree algorithms, the system can predict the development trend of a match more accurately, helping players make more informed decisions during matches.

5.1 Future Research Directions

(1) Expanding the research sample: Future research should include more players and match data to improve the generalizability and predictive accuracy of the proposed model.

(2) Analyzing the entire match: In addition to the first three strokes, technical and tactical changes throughout the entire match can be analyzed to gain a more comprehensive understanding of player performance.

(3) Incorporating opponent information: Future research should integrate data on the technical characteristics and tactical strategies of opponents. This inclusion will enable a more accurate assessment of player performance within the context of specific match-ups and facilitate the development of targeted competitive strategies.

(4) Extending the Model to Different Genders and Age Groups: Future studies should aim to extend the model's applicability to encompass players of different genders and age groups. This can facilitate the identification of gender- and age-specific technical and tactical variations, enabling the development of tailored training and competition strategies for diverse player demographics.

The DLDDTEA table tennis match analysis system developed in this study represents a novel approach for table tennis training and performance analysis. By integrating deep learning and decision tree algorithms, it effectively analyzes match data, providing evidence-based insights for coaches and players to enhance to enhance player development and match performance.

5.2 Limitations

Despite the successful development and preliminary validation of the integrated deep-learning and decision tree-based table tennis match analysis system using data from the matches of Lin Yun-Ju and Ma Long, this study had certain limitations:

(1) Limited Sample Size: The analysis was conducted on a limited sample of three matches involving Lin Yun-Ju and Ma Long. This restricted sample size may limit the generalizability of the findings, making it difficult to extend the results to other players or diverse match scenarios.

(2) Restricted Analytical Scope: The study primarily focused on techniques and tactics employed within the first three exchanges of a match, thus not fully capturing the complex dynamics of complete matches. Given the dynamic nature of table tennis, focusing solely on the initial exchanges may not fully represent players' overall performance and strategic adaptability.

(3) Lack of Opponent Information: Although this study offered an in-depth analysis of the techniques and scoring patterns of Lin Yun-Ju and Ma Long, it did not sufficiently account for the influence of their opponents' technical characteristics and tactical approaches. As opponent strategies can significantly influence player performance, the absence of this information may have limited the comprehensiveness of the analysis.

(4) Validation of Model Generalizability: The developed model was trained on data specific to Lin Yun-Ju and Ma Long. Therefore, its generalizability to other players requires further rigorous validation. Its accuracy and reliability may vary when applied to players with different playing styles and skill sets.

These limitations highlight important avenues for future research. Subsequent studies should prioritize increasing the sample size, conducting more comprehensive analyses of full matches, incorporating opponent-specific information, and validating the model across a broader range of players to enhance its generalizability and practical applicability.

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