applied sciences

MDPI

Systematic Review

Applications of Machine Learning to Optimize Tennis Performance: A Systematic Review

Tatiana Sampaio [1,2,3,*], João P. Oliveira [1,2,3], Daniel A. Marinho [1,2], Henrique P. Neiva [1,2] and Jorge E. Morais [3,4]

[1] Department of Sports Sciences, University of Beira Interior, 6201-001 Covilhã, Portugal; jpco-2001@live.com.pt (J.P.O.); marinho.d@gmail.com (D.A.M.); hpn@ubi.pt (H.P.N.)
[2] Research Centre in Sports, Health and Human Development (CIDESD), 6201-001 Covilhã, Portugal
[3] Research Centre for Active Living and Wellbeing (LiveWell), Instituto Politécnico de Bragança, 5301-856 Bragança, Portugal; morais.jorgestrela@ipb.pt
[4] Department of Sports Sciences, Instituto Politécnico de Bragança, 5301-856 Bragança, Portugal
* Correspondence: tatiana_sampaio30@hotmail.com

Abstract: (1) Background: Tennis has changed toward power-driven gameplay, demanding a nuanced understanding of performance factors. This review explores the role of machine learning in enhancing tennis performance. (2) Methods: A systematic search identified articles utilizing machine learning in tennis performance analysis. (3) Results: Machine learning applications show promise in psychological state monitoring, talent identification, match outcome prediction, spatial and tactical analysis, and injury prevention. Coaches can leverage wearable technologies for personalized psychological state monitoring, data-driven talent identification, and tactical insights for informed decision-making. (4) Conclusions: Machine learning offers coaches insights to refine coaching methodologies and optimize player performance in tennis. By integrating these insights, coaches can adapt to the demands of the sport by improving the players' outcomes. As technology progresses, continued exploration of machine learning's potential in tennis is warranted for further advancements in performance optimization.

Keywords: machine learning; performance; tennis; artificial intelligence (AI)

check for updates

Citation: Sampaio, T.; Oliveira, J.P.; Marinho, D.A.; Neiva, H.P.; Morais, J.E. Applications of Machine Learning to Optimize Tennis Performance: A Systematic Review. *Appl. Sci.* **2024**, *14*, 5517. https://doi.org/10.3390/app14135517

Academic Editor: Arkady Voloshin

Received: 28 May 2024
Revised: 20 June 2024
Accepted: 21 June 2024
Published: 25 June 2024

Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

Tennis has undergone a transformation in recent decades [1]. Once a sport dominated by finesse and technical skill [2], it has become a lightning-fast, power-driven game where players regularly perform serves exceeding 210 km per hour [2]. Success hinges not on a single dominant physical attribute but rather on a complex interplay of various physical components [1]. To compete at the highest level, athletes now require a holistic combination of speed, agility, and power, coupled with moderate to high aerobic capacity [1]. Supporting these physical demands are critical cognitive and psychological processes [3,4]. Players must exhibit exceptional reactive abilities, anticipation skills, and decision-making skills while maintaining mental fortitude to cope with fatigue, the pressure of high-stakes points, and the draw of significant extrinsic rewards, such as ranking and lucrative endorsements [5–7]. The stop-and-start nature of tennis competition further adds to the complexity [2].

Matches are characterized by intermittent periods of high-intensity activity lasting 4–10 s, combined with brief recovery periods of 10–20 s and longer rest intervals of 60–90 s [2,8,9]. Essential tennis skills, including technique, coordination, focus, and tactics, may not be used in long-lasting matches if the athlete is not in excellent condition due to rapid exhaustion, which can affect nearly all tennis-specific skills [3,10,11]. Therefore, factors that may influence tennis players' performance have been heavily studied [12–14]. Optimizing these aspects of performance presents a significant challenge for players,

coaches, and trainers. Artificial intelligence (AI) emerges as a potential tool to address this challenge, offering new techniques for analyzing and optimizing performance in tennis. Tennis generates large volumes of data that capture nuanced aspects of performance. These characteristics make tennis particularly suitable for machine learning applications, as AI algorithms can efficiently process these complex datasets to extract meaningful insights.

In recent years, computational intelligence has emerged as a powerful tool for optimizing athletic performance across various sports [15], and research interest concerning AI and its subcategories is growing exponentially, with considerable potential for further growth in the coming years [16]. In this dynamic and data-rich environment, machine learning emerges as a powerful tool for applied scientists [14,17]. Machine learning, a subfield of artificial intelligence, investigates the realm of knowledge discovery within data [18]. Additionally, neural networks are used in deep learning, an additional branch of machine learning, to accomplish the same purpose. Once the data have been collected, a considerable amount of time is usually spent formatting and preparing the data for analysis [18]. This includes standardizing the data for analysis, removing or interpreting variables with an excessive number of missing values, and performing common statistical tests to evaluate relationships, such as collinearity [18].

Machine learning has been applied in several fields of investigation for talent identification in tennis [19], as well as in sports injury prevention in soccer [20,21], skiing [22], baseball pitchers [23], basketball [24], and volleyball [25]. Additionally, machine learning has also been applied to predict match results [26–28]. These advancements across diverse sports suggest the potential of machine learning to change performance optimization in tennis as well.

Although machine learning has changed various aspects of sports science, including talent identification, injury prevention, match outcome prediction, and training optimization, its application in optimizing tennis performance remains an under-explored topic. While several systematic reviews have explored various applications of machine learning in tennis [29–31], a comprehensive understanding of how machine learning can be applied across various aspects of tennis performance is lacking in the literature. Therefore, the aims of this study are: (i) to comprehensively analyze machine learning applications in tennis performance, focusing on psychological and affective states, talent identification, match outcome prediction, spatial and tactical analysis, and injury prevention and training effects, and (ii) to provide practical insights for coaches, trainers, and athletes on how machine learning can be used to optimize training and enhance performance.

2. Materials and Methods

2.1. Literature Search and Article Selection

This systematic review adhered to the guidelines delineated in the Preferred Reporting Items for Systematic Reviews and Meta-Analysis Statement (PRISMA) [32]. To ensure thoroughness, articles published up to 2024 (until April) were considered, and the search commenced on 1 May. PubMed Medline, Web of Science (Web of Science SM; Current Contents Connect), and Scopus were utilized. The search strategy aimed to identify articles that used artificial intelligence, mainly machine learning, in tennis.

Utilizing a systematic approach, the search strategy entailed combining the term "tennis" with various AI-related terminologies using the Boolean operator "AND/OR" [33]. These terminologies encompassed "artificial intelligence", "machine learning", "deep learning", "neural network", "support vector machine", "nearest neighbor", "random forest", "Bayesian logistic regression", and "predictive modeling". This search strategy aimed to capture all relevant studies investigating the application of AI and its subfields, including machine learning, within the domain of tennis performance.

Hence, two evaluators independently analyzed the titles and abstracts of identified articles. In instances of ambiguity regarding eligibility, the full text was procured for further assessment. Subsequently, two independent reviewers assessed the articles for eligibility based on predetermined criteria. Each article underwent a two-tier evaluation process:

initially predicated on title and abstract, followed by a thorough examination of the full text. Any discordance concerning eligibility was resolved through collegial discourse and, if requisite, settled with the involvement of a third author.

2.2. Inclusion and Exclusion Criteria

The eligibility criteria were structured using the PICOS framework (P: population, I: intervention or independent variable, C: comparators, O: outcomes, and S: study design), as presented in Table 1. Exclusion criteria encompassed studies employing other statistical methods for analyzing data, articles lacking full-text availability, grey literature, and studies published in languages other than English.

Table 1. PICOS search strategy.

Item	Inclusion Criteria	Exclusion Criteria
Population	Studies involving tennis players	Studies involving players from other team sports (i.e., table tennis, basketball, rugby, football, futsal, etc.)
Intervention	Data analyzed using machine learning algorithms	Data not processed or not processed using machine learning methods (i.e., traditional statistical methods)
Comparator	NA	NA
Outcome	Predictions about any performance-related variable	Non-related performance variables (i.e., financial status, etc.)
Study Design	Experimental studies, longitudinal, cross-sectional, and randomized control trials	Conference abstracts

Note. NA, not applicable.

2.3. Data Extraction

Following the data extraction template developed by the Cochrane Consumers and Communication Review Group, an extraction of data was created in Microsoft Excel (v. 2016, Microsoft Corporation, Readmon, WA, USA) [34]. The Excel sheet was used to evaluate the conditions for inclusion and then verified for every study that was selected. The two authors (TS and JO) carried out the process independently. Any disagreement over study eligibility was settled through conversation. Reasons for excluding any full-text articles were noted. Every document, including both included and excluded studies, was recorded and maintained in the datasheet for reference and transparency.

The following data were compiled from the included articles: (i) participants (sample number and level) or data used, (ii) variables or features, (iii) study aim, (iv) machine learning metrics (algorithms and prediction percentage), and (v) results and practical implications.

2.4. Methodological Assessment

The STROBE assessment criteria for cross-sectional studies were modified, and the two authors (TS and JO) conducted a methodological quality assessment process in search of research that met the inclusion requirements [35]. The STROBE assessment criteria consisted of 10 items and corresponded to the following components: provide an adequate and informative summary of what was carried out and the results in the abstract (Item 1); describe your objectives, including any predefined hypotheses (Item 2); describe the requirements for eligibility as well as the sources and techniques used to choose the participants (Item 3); provide information about the methods of assessment (measurement) and data sources for each variable of interest. If there are multiple groups, describe how the assessment techniques can be compared (Item 4); clarify the methods used in the analyses to handle quantitative variables. If relevant, explain the classifications that were selected and the rationale behind them (Item 5). Describe the study's participant characteristics (Item 6); highlight the main findings in accordance with the objectives of the study (Item 7); address the study's limitations while considering potential bias or inaccuracy sources.

Discuss about the potential bias's direction and strength (Item 8); provide a careful, broad interpretation of the findings, taking into account the objectives, constraints, variety of analyses, findings from related studies, and other pertinent evidence (Item 9). Identify the funding source and the role of the funders for the current study as well as, if relevant, for the original study that served as the basis for the current article (Item 10) [35].

Each disagreement was discussed and resolved by agreement. Numerical characterization was used to evaluate each component (1 being completed and 0 being incomplete). Each study's rating was qualitatively interpreted as follows: studies with a punctuation value of less than seven points are deemed to be low quality or with a risk of bias, whereas studies with a higher punctuation value are deemed to be good quality or with little risk of bias [36].

3. Results and Discussion

3.1. Study Identification and Selection

Through the search in the PubMed/Medline, Web of Science, and Scopus databases, 1720 articles were found. We removed 757 duplicates and excluded 324 after evaluating the title and abstract.

Subsequently, we organized these studies into distinct categories: articles involving robots, studies not employing any ML technique, and those with outcomes that did not align with our criteria. Thus, we assessed the 639 remaining studies by reading the relevant sections. We excluded 616 studies that did not meet the inclusion criteria, grouping them into studies that did not use machine learning (n = 455) and studies involving other sports (n = 161). Finally, 23 studies that met the criteria and aims of this systematic review were included, as shown in Figure 1.

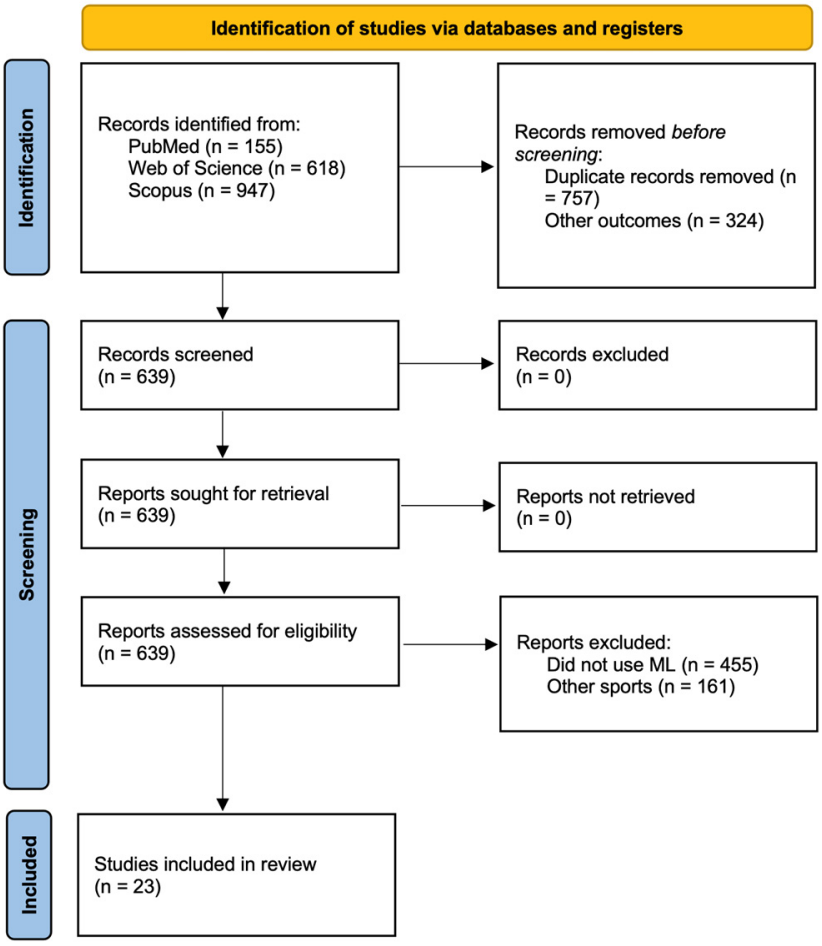


Figure 1. Flowchart of the systematic literature review.

3.2. Methodological Assessment

The methodological quality of the included studies is presented in Table 2. The following studies were considered to have high-quality (low risk of bias) [37–52]. Studies [53–59] were considered to have low quality (high risk of bias).

Table 2. Methodological assessment of the included studies.

Author (Year)	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6	Item 7	Item 8	Item 9	Item 10	Score	Quality
Almarashi et al. (2024) [37]	1	1	0	0	1	1	1	1	1	1	8/10	High
Bozděch and Zháněl (2023) [38]	1	1	1	1	1	1	1	1	1	1	10/10	High
Filipcic et al. (2014) [53]	1	1	0	0	1	1	1	1	1	0	7/10	Low
Gaoa and Kowalczykc (2021) [39]	1	1	0	0	1	1	1	1	1	1	8/10	High
Ghosh et al. (2014) [54]	1	1	0	1	0	1	1	1	1	0	7/10	Low
Giles et al. (2020) [40]	1	1	1	1	1	1	1	1	1	1	10/10	High
Giles et al. (2023) [41]	1	1	1	1	1	1	1	1	1	1	10/10	High
Hao and Hong (2017) [42]	1	1	0	1	0	1	1	1	1	1	8/10	High
Havlucu et al. (2022) [55]	1	1	0	0	0	1	1	1	1	0	6/10	Low
Jekauc et al. (2024) [43]	1	1	1	1	1	1	1	1	1	1	10/10	High
Khder and Fujo (2022) [56]	1	1	0	1	0	1	1	1	1	0	7/10	Low
Kovalchik et al. (2017) [44]	1	1	0	1	1	1	1	1	1	1	9/10	High
Li et al. (2023) [57]	1	1	0	0	0	1	1	1	1	0	6/10	Low
Makino et al. (2020) [58]	1	1	0	0	0	1	1	1	1	0	6/10	Low
Panjan et al. (2010) [45]	1	1	1	1	1	1	1	1	1	0	9/10	High
Rosker and Rosker (2021) [46]	1	1	1	1	1	1	1	1	1	0	9/10	High
Schulc et al. (2023) [47]	1	1	0	1	1	1	1	1	1	1	9/10	High
Siener et al. (2021) [48]	1	1	0	1	1	1	1	1	1	1	9/10	High
Vives et al. (2023) [49]	1	1	0	1	1	1	1	1	1	1	9/10	High
Whiteside and Reid (2017) [51]	1	1	0	1	1	1	1	1	1	1	9/10	High
Whiteside et al. (2017) [50]	1	1	0	1	1	1	1	1	1	1	9/10	High
Zhang (2024) [59]	1	1	0	0	0	1	1	1	1	1	7/10	Low
Zhou and Liu (2024) [52]	1	1	1	1	1	1	1	1	1	1	10/10	High

3.3. Studies' Characteristics

Studies' characteristics were extracted and grouped into five subsections: (i) psychological and affective states, (ii) talent identification, (iii) match outcome prediction, (iv) spatial and tactical analysis, and (v) injuries and training effects.

In the presented tables, the columns detail the author (year), participants/data, attributes/features, aim of prediction, type of algorithm used, the % of the sample used to train the algorithm, and the prediction accuracy metrics. The "prediction accuracy metrics" column measures how accurately machine learning models predict outcomes. Accuracy refers to the proportion of correct predictions out of all predictions made. However, it is important to note that accuracy alone may not fully capture model performance, especially in scenarios with imbalanced data or differing error costs. Cells marked "NA" (not available) indicate where specific accuracy metrics were not reported, possibly due to researchers opting for other suitable evaluation metrics aligned with their study goals. These metrics could include precision, recall, F1 score, ROC-AUC, RMSE, MAE, R-squared, confusion matrices, and cross-validation scores.

3.3.1. Psychological and Affective States

Regarding the psychological and affective states, two studies [43,55] employed different methodologies to investigate players' psychological state during competition. Havlucu et al. [55] employed a sensor-based approach, leveraging data from inertial measurement units (IMUs) worn by a small group of elite coaches (n = 2) and professional players (n = 4). In contrast, Jekauc et al. [43] used video analysis, examining five players in their study. Both studies implemented distinct algorithms and metrics to evaluate the efficacy of their machine learning models. Havlucu et al. [55] utilized a long short-term memory recurrent neural network model, achieving a prediction accuracy of 85%. Jekauc et al. [43] employed a neural network, achieving a prediction accuracy range of 63.9% to 68.9%. Additional information regarding the included studies' characteristics (No. of participants or data, attributes/features, aim of prediction, algorithm, % of the sample used to train the algorithm, and prediction accuracy metrics) for the psychological and affective states are presented in Table 3.

Table 3. Study characteristics of the psychological and affective states.

	Author (Year)	Participants/Data	Attributes/Features	Aim of Prediction
Psychological and affective states	Havlucu et al. (2022) [55]	2 elite coaches and 4 professional players	IMU data and elite coaches' labels on players' performances	To explore a novel approach for detecting psychological states using off-the-shelf wearable technology, ML algorithms, and expert labels.
	Jekauc et al. (2024) [43]	5 players	Video	To develop of an AI system specifically designed for recognizing affective states in real-life situations, as opposed to relying on data from acted or posed situations.
	Author (Year)	**Algorithm**	**Training Algorithm**	**Prediction Accuracy Metrics**
	Havlucu et al. (2022) [55]	Long short-term memory recurrent neural network model	50%	AC = 85%
	Jekauc et al. (2024) [43]	Neural network	80%	AC = 63.9% to 68.9%

Note. IMU: inertial measurement unit; ML: machine learning; AC: accuracy; AI: artificial intelligence.

Havlucu et al. [55] investigated the feasibility of AI for predicting a player's state of optimal performance, termed "the zone", using wearable sensor data and coach labels. Jekauc et al. [43] focused on recognizing broader affective states (e.g., frustration and joy) through video analysis of real-world tennis matches. Both studies demonstrated the potential of ML in this field. Havlucu et al. [55] achieved high accuracy (above 85%) in predicting "the zone" utilizing a personalized modeling approach. Their approach relied on machine learning algorithms, likely leveraging techniques such as support vector machines (SVMs) or random forests, to identify patterns in the wearable sensor data associated with coach-labeled instances of "the zone" [55]. This approach offers an opportunity for real-time feedback on mental state, potentially allowing for targeted interventions to maintain focus and optimize performance during competition.

Moreover, Jekauc et al. [43] highlighted the advantage of training models on real-world data, achieving an accuracy of 68.9% for affective state recognition from video footage. They employed a convolutional neural network (CNN) architecture, a deep learning technique for recognizing patterns in visual data. Nonetheless, limitations require further consideration [43]. Havlucu et al. [55] acknowledged the subjectivity inherent in coach assessments, a potential source of bias in their model. Jekauc et al. [43] highlighted the relatively small sample size employed in their study, requiring further data collection for robust model generalizability. However, similar studies published demonstrated successful applications with relatively small participant samples. Khan et al. [60] explored activity recognition in cricket using only six participants, mostly amateurs, highlighting the feasibility of such systems even with limited data. Hölzemann and Van Laerhoven [61] achieved promising results in recognizing basketball activities with IMUs using only three participants. These examples suggest that even with small sample sizes, valuable insights can be gathered when the research design is carefully constructed and focuses on specific tasks or outcomes.

3.3.2. Talent Identification

Regarding talent identification, four studies [38,45,48,53] focused on the application of ML in talent identification. Notably, the studies employed a wide range of participant numbers, with Panjan et al. [45] analyzing the largest group of 1002 players, while Siener et al. [48] focused on a smaller group of 174 young players.

The data used for analysis also vary. Panjan et al. [45] and Siener et al. [48] leveraged physical characteristics and motor skills assessments, while Filipcic et al. [53] analyzed player rankings, match details, and tournament specifics. Bozděch and Zháněl [38] took a unique approach, utilizing individual player statistics alongside official tournament

documents. Moreover, the logistic regression model stood out, with the highest reported accuracy (90.4%) in the study of Siener et al. [48].

Table 4 presents the study characteristics of No. of participants or data, attributes/features, aim of prediction, algorithm, % of the sample used to train the algorithm (training algorithm), and prediction accuracy metrics of the studies that used ML algorithms for talent identification.

Table 4. Study characteristics of the talent identification studies.

	Author (Year)	Participants/Data	Attributes/Features	Aim of Prediction
Talent Identification	Panjan et al. (2010) [48]	1002 players	20 m sprint, fan, body height, hand tapping, and body weight	To examine the predictability of the competitive performance of Slovene tennis players by using the most promising morphological measures and motor tests selected by automatic computer methods and by experienced tennis coaches.
	Filipcic et al. (2014) [53]	300 players	Ranking data, match variables, and tournament variables	To define different quality groups of tennis players based on their position on the ATP ranking list.
	Siener et al. (2021) [48]	174 players	Five physical fitness tests and four motor competence tests	To compare the prognostic validity of common statistical prediction methods regarding the future performance success of young tennis players based on their juvenile performance profiles.
	Bozděch and Zháněl (2023) [38]	WJTF participants from 2012 to 2016	Individual player stats and Official WJTF documents	To employ AI techniques alongside baseline (non-game) variables to forecast the outcomes of a junior elite tennis tournament. To investigate the potential influence of participation and performance in an elite junior tournament on subsequent sports careers.
	Author (Year)	**Algorithm**	**Training Algorithm**	**Prediction Accuracy Metrics**
	Panjan et al. (2010) [45]	The naive Bayes classification method, decision tree, the C4.5 algorithm, the k-nearest neighbor, SVM, and logistic regression	70%	AC = 59% to 77%
	Filipcic et al. (2014) [53]	K-means with a Euclidean metric, k-means with a Manhattan metric, Xmeans	NA	NA
	Siener et al. (2021) [48]	Linear recommendation score, a logistic regression, a discriminant analysis, and a neural network	80%	AC tennis recommendation score = 72.4% AC logistic regression = 90.4% AC discriminant analysis = 79.5% AC neural network analysis = 72.9%
	Bozděch and Zháněl (2023) [38]	SVM and Ensemble	70%	AC = 87.5%

Note. AC: accuracy; AI: artificial intelligence; WJTF: World Junior Tennis Final; SVM: support vector machine; ATP: Association of Tennis Professionals; NA: not available.

Several studies converged on the potential for ML talent prediction in tennis. Panjan [45] achieved promising results using machine learning to analyze motor skills and physical measurements of young players. Their approach, particularly effective for female athletes, proved superior to coach selections based on experience alone. Similarly, Siener [48] compared various ML prediction algorithms, finding all four (including a neural network) to exhibit moderate to high accuracy in identifying future high performers among eight-year-old players. These findings suggest that ML can analyze objective data to identify promising young athletes, potentially complementing traditional scouting methods.

However, limitations remain. Both Panjan [45] and Siener [48] emphasized the importance of incorporating factors beyond just physical capabilities or early performance. Future research should delve deeper into the role of psychological aspects and mental development, potentially exploring psychometric testing or physiological measures in conjunction with motor skills' analysis. Additionally, Siener [48] highlighted the limitations of relying solely on sensitivity or specificity metrics for evaluating prediction models. The F1 score and ROC value offer a more nuanced perspective by considering both true positives (correctly identified future stars) and true negatives (players predicted to not succeed) [48].

Moreover, ML can also be used for player classification based on performance. Filipic [53] demonstrated the use of machine learning algorithms to classify professional tennis players into different quality groups based on their ATP ranking. This approach could be valuable for coaches and athletes to identify variables where players need improvement. However, Filipic's study [53] also highlighted the influence of external factors on such classifications. Changes in ranking systems can impact classification accuracy, requiring the development of models that account for the evolving nature of the sport [53].

The limitations of game statistics for long-term career prediction were explored by Bozděch and Zháněl [38]. While they achieved good accuracy (AC = 87.5%) in predicting tournament outcomes based on game statistics from junior tournaments, they were unable to reliably predict a player's professional ranking using only percentage-based data [38]. This finding suggests that factors beyond in-game performance, such as mental fortitude, training strategies, and psychological resilience, play a significant role in determining a player's long-term success [38]. Therefore, research should expand its scope to incorporate a wider range of variables.

3.3.3. Match Outcome Prediction

Six studies [37,39,44,54,56,58] used ML techniques to predict match outcomes. Sample sizes and data varied across the studies. Almarashi et al. [37] focused on just three players. In contrast, Gaoa and Kowalczykc [39] utilized a broader range of variables encompassing physical, psychological, and match-related factors.

Predicting match outcomes is a studied topic, as seen in the studies of Gaoa and Kowalczykc [39], Ghosh et al. [54], and Khder and Fujo [56]. Additionally, Makino et al. [58] predicted point winners in ATP singles matches and identify shot patterns influenced by court conditions and players. Almarashi et al. [37] used a unique approach, focusing on predicting player performance over time. The variety of ML algorithms employed further underscores the versatility of this approach. Logistic regression features in the studies of Ghosh et al. [54], Kovalchik et al. [44], and Makino et al. [58] achieved high accuracy for predicting match outcomes in both men's and women's tennis (up to 98.96% in Ghosh et al.'s study [54]).

Table 5 presents the study characteristics of No. of participants or data, attributes/features, aim of prediction, algorithm, % of the sample used to train the algorithm (training algorithm), and prediction accuracy metrics of the studies that used ML algorithms for match outcome prediction.

Each data point in supervised learning contains an input (xi) and an output (yi) that specifically describe the data, known as labeled data [62]. Ghosh et al. [54] exemplified this effectively. Their study found decision trees to be proficient at classifying winners of grand slam singles matches based on historical data, achieving upwards of 80% accuracy. This suggests decision trees excel at extracting subtle patterns within past performance that can inform future win–loss predictions. Similarity, Khder and Fujo [37] reinforced the value of supervised learning by employing both linear regression and decision trees. The study achieved an accuracy of 99.8%.

Table 5. Study characteristics of the match outcome prediction studies.

	Author (Year)	Participants/Data	Attributes/Features	Aim of Prediction
Match Outcome Prediction	Ghosh et al. (2014) [54]	Tennis Match Statistics dataset	NA	To predict the result of tennis singles matches using eight UCI databases of grand slam tennis tournaments and evaluate the classification performance
	Kovalchik et al. (2017) [44]	86 ATP and 82 WTA matches from the 2016 Australian Open	Contextual and physical factors	To predict the likelihood of a challenge and predict the success of a challenge
	Makino et al. (2020) [58]	Match Charting Project men's professional singles	Serve, receive, receive against serve, shot type, net play, turn back, and swing around	To predict point winners in ATP singles matches and identify shot patterns influenced by court conditions and players
	Gao and Kowalczykc (2021) [39]	ATP World Tour datasets from 2000 to 2016	Physical, psychological, court-related, and match-related variables	To achieve accurate prediction of match outcomes and identify key components contributing to those predictions
	Khder and Fujo (2022) [56]	Players since 1968 until 2020	Rankings data, match variables, and tournament variables	To implement supervised machine learning models on a tennis match dataset
	Almarashi et al. (2024) [37]	3 players	Probability of winning, number of aces, game dominance, and double faults per year	To predict player performance, this study employs a dynamic technique that analyzes the structure of performance using both linear and non-linear time series models
	Author (Year)	**Algorithm**	**Training Algorithm**	**Prediction Accuracy Metrics**
	Ghosh et al. (2014) [54]	Decision tree, learning vector quantization, and SVM	70%	AC men's = 92.07% to 98.96% AC women's = 91.93% to 98.57%
	Kovalchik et al. (2017) [44]	Univariate and multivariate logistic regression	NA	AC women's = 74.5% AC men's = 79.2%
	Makino et al. (2020) [58]	Logistic regression	NA	AC = 66.5%
	Gao and Kowalczykc (2021) [39]	SVM with a radial basis function kernel, random forest classification, and logistic regression	80%	AC $\geq$ 80%
	Khder and Fujo (2022) [56]	Linear regression and decision tree	80%	AC = 99.8%
	Almarashi et al. (2024) [37]	Non-linear neural network auto-regressive	NA	RMSE = 0.0461 to 145.9614 MAE = 0.0398 to 110.6277 MAPE = 4.9312 to 75.8978

Note. RMSE: root mean squared error; MAE: mean absolute error; MAPE: mean absolute percentage error; AC: accuracy; SVM: support vector machine; WTA: Women's Tennis Association; ATP: Association of Tennis Professionals; NA: not available.

Machine learning extends beyond predicting winners, offering insights into specific in-game situations. Kovalchik et al. [44] explored this by analyzing data from challenged and unchallenged serves. Their machine learning models achieved an accuracy of 79.2% in identifying factors such as ball location and shot speed that influence the success of a challenge. This allows players with data-driven insights to optimize their challenge decisions. Although these studies present valuable insights, accuracy limitations exist. Goa and Kolvalchik et al. [44] highlighted the focus on relatively simple models, suggesting that more advanced techniques, such as deep learning, might yield even higher accuracy. Additionally, the accuracy of these models can vary depending on factors such as the quality and completeness of the training data, as well as the specific task at hand (predicting a winner versus a successful challenge) [44]. Therefore, future research should address these limitations by exploring algorithms such as deep learning to potentially improve prediction accuracy. Additionally, investigating the generalizability of models across different surfaces, playing styles, and player levels is crucial. Incorporating additional data sources, such as player psychology or weather conditions, could create more comprehensive models.

Moreover, Almarashi et al. [37] explored a different application of machine learning, focusing on predicting player performance throughout a season. Their study utilized a non-linear neural network auto-regressive (NNAR) model, demonstrating its advantage over conventional models in terms of accuracy metrics, such as root mean squared error (RMSE) [37]. This suggests that incorporating time series analysis can lead to more precise predictions of a player's performance trajectory.

Therefore, machine learning algorithms proved to be a valuable tool for analyzing tennis data and predicting outcomes. While accuracy can vary depending on the specific task and model complexity, supervised learning algorithms have shown promise in classifying match winners (upwards of 80% accuracy) and identifying factors that influence in-game events, such as challenges and serves. As research continues to refine existing models and explore new algorithms, such as deep learning and NNAR models, machine learning holds potential for enhancing our understanding of the complex dynamics at play on the court. In contrast, traditional statistical methods, such as t-tests, have been employed to compare winners and losers based on specific match indicators, analyzing game elements among male players in Roland Garros and Wimbledon across various match indicators, such as service success rates, aces, unforced errors, and service speeds [63].

3.3.4. Spatial and Tactical Analysis

Eight studies [40,41,46,49,51,52,57,59] used ML techniques to analyze spatial and tactical factors. The studies encompassed a wide range of participant numbers. Zhang [59] analyzed 120 matches to evaluate tactical performance, while Li et al. [57] focused on a smaller group of just 6 players to study the impacts of batting strength. The data used for analysis were equally varied. Zhang [59] delved into match data, analyzing details such as serve type, shot selection, and player positioning. In contrast, Li et al. [57] focused on kinematic variables, and Rosker and Rosker [46] examined player movement patterns during serves and returns.

The variety of ML algorithms employed further underscores the versatility of this approach. Backpropagation neural networks [59] and convolutional neural networks [57] were used for tasks such as evaluating tactical performance and classifying groundstroke stances. Random forests [41,46] were utilized for tasks such as movement pattern classification and point-winning prediction. Interestingly, clustering techniques were also employed by Whiteside and Reid [51] and Giles et al. [41] for ball trajectory analysis and exploring individual nuance in movement, respectively.

The varying accuracy metrics across the studies reflect the different goals and data used. Notably, Vives et al. [49] achieved a high accuracy (94%) in uncovering the variables associated with a greater serve effectiveness, while Rosker and Rosker's [46] study on visual search strategies during serves yielded a wider range of accuracy values (21% to 78%).

Table 6 presents the study characteristics of No. of participants or data, attributes/features, aim of prediction, algorithm, % of the sample used to train the algorithm (training algorithm), and prediction accuracy metrics of the studies that used ML algorithms for special and tactical analysis.

Spatial and tactical analysis is fundamental in tennis, as it provides crucial insights into player strategies, decision-making, and court positioning dynamics during matches [64]. Additionally, machine learning offers innovative tools to enhance spatial and tactical analyses by leveraging complex data patterns derived from player movements, shot placements, and court coverage.

Each study utilized ML models to forecast various in-game aspects, encompassing serve outcomes [51], change-of-direction movements [40], returning player and performance categories [46], and forehand/backhand stances [52]. This data-driven approach hinges on the collection of diverse data, including match footage [46,57], player tracking data [40], and notation systems [52]. These data allow training and evaluation of the ML models, aiming to provide valuable insights that empower players and coaches to elevate performance. This translates into optimizing training drills [46,52] and comprehending

opponent trends [46]. Similarly, Vives et al. [49] delved into the serve in professional doubles tennis. Their study utilized machine learning algorithms to pinpoint key factors that maximize serve effectiveness, such as serve angle and lateral bounce distance.

Table 6. Study characteristics of the spatial and tactical studies.

	Author (Year)	Participants/Data	Attributes/Features	Aim of Prediction
Spatial and tactics analysis	Whiteside and Reid (2017) [51]	151 male tennis players	Spatiotemporal (impact location, speed, projection angles, landing location, and relative player locations) and contextual (score).	To quantify ball trajectories and player locations in first serves, with a view to differentiating aces from serves that were returned into play
	Giles et al. (2020) [40]	19 professional players	Total Euclidean distance travelled, the lateral distance travelled, degree of change, minimum and maximum speed, minimum and maximum acceleration, and the average depth of the player's position.	To develop an automated method for identifying and classifying COD movements in professional tennis using tracking data
	Rosker and Rosker (2021) [46]	17 male tennis players	Tossing hand movement area, ball upwards movement, lower body, area surrounding server, racket, hips, ball release, upper body, ball contact area, and back leg.	To analyze whether visual search strategies can be attributed to the individual server and the returning player during the tennis serve return or return performance
	Li et al. (2023) [57]	6 national first-class and second-class experienced tennis players	15 Kinematic variables	To study the impacts of batting strength and angle of tennis players on batting results based on DL image processing technology
	Vives et al. (2023) [49]	14,146 serves were analyzed from 97 full men's doubles matches played during the Davis Cup	Speed, dL, serve angle, loss of speed, net clearance, vertical projection angle, position, and direction	To uncover the variables associated with a greater serve effectiveness in men's professional doubles matches using a large dataset from Davis Cup doubles matches and machine learning techniques
	Giles et al. (2023) [41]	139 players	150,000 direction changes	To employ these new analysis techniques to objectively explore individual nuance and style factors in the execution of COD movements in professional tennis
	Zhang (2024) [59]	120 men's tennis hard-court singles match	Serving linking, receiving and serving linking, serving and catching linking, receiving and catching linking, stalemate I linking, and stalemate II linking	To evaluate the tactical performance of exceptional male Chinese tennis players
	Zhou and Liu (2024) [52]	36 players	4 influencing variables (landing zone of the ball, positioning of the player, returning direction of the ball, and landing zone of the returning ball) and 1 target variable (groundstroke stance)	To examine the probability of the four stances used for forehand and 2BH in different court situations, with the goal of distinguishing the use pattern of each stance

Author (Year)	Algorithm	Training Algorithm	Prediction Accuracy Metrics
Whiteside and Reid (2017) [51]	Classification tree and K-means clustering	69%	AC = 87.02%
Giles et al. (2020) [40]	Random forest	70%	AC = 77.1% to 80.6%
Rosker and Rosker (2021) [46]	Random forest machine learning models	80%	AC = 21% to 78%
Li et al. (2023) [57]	Convolution neural network	NA	PRE = 87.49% RE = 78.58% F1 = 82.8%
Vives et al. (2023) [49]	Deep neural network	70%	AC = 94%
Giles et al. (2023) [41]	Clustering was based on an agglomerative hierarchical clustering technique	NA	NA
Zhang (2024) [59]	Back propagation neural network	80%	MSE validation set = 0.00037146 MSE training set = 0.0104
Zhou and Liu (2024) [52]	Bayesian network	80%	NA

Note. MSE: mean square error; AC: accuracy; DL: deltoid ligament; COD: change of direction; NA: not available.

An analysis of the implemented ML algorithms revealed a diverse methodological landscape. Most of the articles used supervised learning algorithms. Zhang et al. [59] utilized decision trees to construct a diagnostic model for player performance evaluation, exploiting a common classification technique.

Additionally, unsupervised learning was also employed. Whiteside and Reid [51] utilized a k-means clustering to pinpoint optimal landing locations for aces. This clustering algorithm groups data points into a predefined number of clusters based on similarities. Additionally, Li et al. [57] implemented a convolutional neural network to analyze batting strength and angles based on video footage. CNNs excel at image recognition tasks, making them well suited for this application. Finally, Zhou and Liu [52] leveraged a Bayesian network to predict the probability of different stances based on court situations.

However, while the studies achieved high accuracy levels (e.g., Whiteside and Reid's model, with 87% accuracy for serve outcome prediction), further exploration of advanced algorithms, such as deep learning architectures, could potentially yield even higher levels of precision. Furthermore, generalizability across different surfaces, playing styles, and player levels remains a crucial consideration. Investigating how models trained on one dataset perform when applied to a different context is essential for ensuring their robustness and practical applicability.

3.3.5. Injuries and Training Effects

Three studies [42,47,50] used ML techniques to analyze injuries and training effects. The studies involved a diverse range of participants. Whiteside et al. [50] analyzed data from 19 players, while Schulc et al. [47] worked with a larger dataset of video recordings from 129 athletes.

The data used for analysis also differed considerably. Whiteside et al. [50] and Schulc et al. [47] both focused on biomechanical data. Whiteside et al. [50] utilized data from inertial measurement units, while Schulc et al. [47] analyzed video recordings to assess body movements and identify potential injury risks. In contrast, Hao and Hong [42] incorporated a broader range of internal and external factors, including physical attributes, weather conditions, and training performance metrics, to predict how effective a tennis training program would be for a particular athlete.

Table 7 presents the study characteristics of No. of participants or data, attributes/features, aim of prediction, algorithm, % of the sample used to train the algorithm (training algorithm), and prediction accuracy metrics of the studies that used ML algorithms for injuries and training effects.

The studies by Schulc et al. [47] and Whiteside et al. [50] showcased the versatility of video analysis in ML applications in tennis. Schulc et al. [47] focused on identifying biomechanical patterns indicative of ACL injury risk. Their approach involved training a long short-term memory (LSTM) network on data extracted from video footage. They obtained a 75% to 81% accuracy in identifying athletes at risk, highlighting the potential of this method for early ACL injury detection. Whiteside et al. [50] employed video analysis for a different purpose, to label data from wearable inertial measurement units (IMUs) worn by players during training [50]. Their system can automatically classify and quantify different strokes performed, aiding in training load quantification. They achieved a high accuracy of 97.5% using a combination of algorithms, such as support vector machines (SVMs) and random forest, demonstrating the effectiveness of this approach for training load measurements [50]. Furthermore, existing research underlines the importance of identifying knee valgus loading—a movement pattern where the knee collapses inwards—as a risk factor for ACL injuries. Previous research focused on the applications of ML to different sports regarding injury prevention. Studies by Della Villa et al. [65] and Lucarno et al. [66] on professional soccer players of both sexes reported a high prevalence of knee valgus loading in ACL injuries. Similarly, Krosshaug et al. [67] observed knee valgus in basketball players across various skill levels, although they also found a higher frequency in females compared to males. It is important to note that these studies focused

on analyzing injury mechanisms in athletes with existing ACL injuries, not necessarily diagnosing ACL ruptures from other conditions using video analysis alone.

Additionally, Hao and Hong [42] used a distinct approach, utilizing a radial basis function neural network to predict the effectiveness of a tennis training program. They focused on a dataset of performance metrics, such as VO_{2max} and % body fat, demonstrating the versatility of ML beyond video analysis. The selection of algorithms in these studies reflects the evolving nature of the field, with each approach demonstrating success using different metrics.

Table 7. Study characteristics of the injuries and training effects.

	Author (Year)	Participants/Data	Attributes/Features	Aim of Prediction
Injuries and Training Effect	Whiteside et al. (2017) [50]	19 players	Inertial measurement unit data	To develop a non-invasive, portable, and automated solution for quantifying hitting load and to develop an automated video analysis system that uses AI to identify biomechanical patterns associated with ACL injury
	Hao and Hong (2017) [42]	58 military students	External factors (weather, temperature, humidity, and wind) and internal factors (VO_{2max}, quantitative load heart rate, 2000 m running, % body fat, vital capacity index, squats, push-ups, basic heart rate, sit-ups, 400 m running, BMI, and 100 m)	To propose a prediction method for athletes' tennis training effects
	Schulc et al. (2023) [47]	210 video parts from 129 individual athletes	Angle-based measures between body segments (knee flexion, knee abduction, foot rotation, hip abduction, hip rotation, and torso flexion)	To develop an automated video analysis system that uses AI to identify biomechanical patterns associated with ACL injury
	Author (Year)	**Algorithm**	**Training Algorithm**	**Prediction Accuracy Metrics**
	Whiteside et al. (2017) [50]	SVM, discriminant analysis, random forest, k-nearest neighbor, classification tree, and neural network	NA	AC = 97.5%
	Hao and Hong (2017) [42]	Boundary value constraints and radial basis function neural network	86%	RE = 0.009% to 2.931%
	Schuluc et al. (2023) [47]	Fully connected neural network and long short-term memory network	90%	AC = 75% to 81%

Note. VO_{2max}: maximal oxygen uptake; AI: artificial intelligence; NA: not available; BMI: body mass index; ACL: anterior cruciate ligament.

4. Practical Implications

The practical implications outlined in this review were derived from a rigorous evaluation of study quality, as detailed in Table 2. Methodological rigor influenced the reliability and applicability of the findings. The majority of studies included in this analysis were selected for their high methodological quality, characterized by robust study designs and comprehensive data analyses.

This selection ensured that the practical insights presented are grounded in robust evidence, facilitating their integration into coaching strategies aimed at optimizing tennis performance.

4.1. Psychological and Affective States

The integration of machine learning and wearable technologies into tennis offers several advanced methodologies for enhancing player performance through the monitoring of psychological states. Based on the studies by Havluc et al. [55] and Jekauc et al. [43], several practical implications for coaches emerged.

Firstly, the use of wearable technologies, such as PsychWear, which leverage inertial measurement unit (IMU) data, can predict a player's psychological state, specifically 'the zone', with an accuracy exceeding 85%. This requires initial training sessions where coaches provide subjective labels for each player, resulting in highly personalized models. These personalized assessments underscore the importance of the coach's role, as the system is designed to complement, rather than replace, their expertise. The subjective nature of labeling 'the zone' is not a limitation but a strength, considering the highly individual nature of this state. Each player must be labeled by their own coach, who understands their unique behaviors and cues. Consistency in labeling practices is essential, as the coach's expert insights are crucial for accurate model training. This personalized approach ensures that assessments are context-specific and tailored to individual needs.

The principles of using wearable technology for psychological state monitoring in tennis can also be applied to other sports and physical activities where mental state significantly impacts performance. Moreover, utilizing video footage from real tennis matches allows for the training of machine learning models in naturalistic environments. This approach enhances the ecological validity of the models and their applicability to real-world scenarios. Advanced convolutional neural networks (CNNs) used in these models analyze players' bodily expressions to recognize affective states with up to 68.9% accuracy, providing coaches with valuable insights into players' emotional states during competition. As the field of wearable technology and machine learning evolves, coaches should stay informed about new developments and integrate the latest research findings into their training practices.

4.2. Talent Identification

The studies focused on talent identification in tennis revealed several practical implications for improving the process of identifying promising young athletes [38,45,48,53]. The use of automated methods, particularly machine learning, has demonstrated higher accuracy of competitive performance in players younger than 16 years. These automated methods outperform coach-based evaluations, especially for female players when linear regression is applied. This suggests that coaches and talent scouts should integrate automated methods alongside their evaluations to enhance the accuracy of predicting young players' performance, thereby adopting a more data-driven approach.

In identifying significant variables, both morphological and motor characteristics, such as body height (M-1) and acceleration (S-1), have been recognized as crucial by both coaches and automated methods. The advantage of body height in tennis is evident in its contribution to reaching higher contact points and performing various strokes, while acceleration significantly explains the variance in competitive performance. Thus, talent identification programs should prioritize the assessment and development of these key characteristics to ensure competitive readiness [45].

Siener et al. [48] emphasized that combining different statistical prediction methods, including non-linear methods, such as neural networks, with linear methods, yielded the highest prognostic validity. Despite this, some high-performance players may still elude prediction by any method. Therefore, talent identification programs should utilize a combination of linear and non-linear methods to improve prediction accuracy, offering a more comprehensive assessment of a player's potential.

Participation in elite junior tournaments has been identified as crucial for future career development, with a significant proportion of participants achieving professional rankings [38]. Coaches should, therefore, encourage and facilitate participation in these tournaments, as they are pivotal for long-term development and success. Additionally,

continuous data collection and model refinement are essential for improving predictive accuracy. Expanding the research scope to include more variables and a larger number of junior tournaments can enhance the predictive models. This approach will help identify the most critical variables for career prediction, ensuring models remain relevant and accurate over time [38].

4.3. Match Outcome

The research conducted on predictive modeling of tennis match outcomes provides several key practical implications for the field [37,39,44,54,56,58].

Ghosh's et al. [54] study underscored the advantage of decision tree classifiers over other models, such as learning vector quantization (LVQ) and support vector machine (SVM). These findings suggest that decision tree classifiers should be prioritized in predictive models to enhance the reliability of match outcome predictions. Coaches and analysts can leverage these models to make more informed decisions based on historical match data, thereby improving training and match preparation strategies.

The identification of serve strength as a critical predictor of match outcomes emphasizes the need for focused technical training. Players and coaches should prioritize training regimes that enhance serve effectiveness, including aspects such as serve angle, speed, and placement. The detailed analysis of factors influencing serve strength, such as trunk rotation and shoulder angle, provides actionable insights for optimizing training protocols to improve match performance.

Kovalchik's et al. [44] research on the use of the challenge system in tennis revealed important insights into decision-making processes and system vulnerabilities. The identification of factors influencing the likelihood and success of challenges, such as shot speed and point importance, suggests that players can improve their challenge success rates by better understanding these variables. Additionally, Vives et al.'s study [49] on serve characteristics in doubles matches indicated that variables such as serve angle and placement are crucial for success. These findings can be extended to develop predictive models for doubles matches, providing coaches with specific tactical insights. Furthermore, the methodological approach used in this study, involving tracking data and ML techniques, can be applied to other sports and contexts. This broader application can enhance predictive modeling across various sports, leading to more tailored and effective training and strategy development.

Furthermore, Almarashi's et al. [37] research emphasized the significance of incorporating time as a factor in performance prediction models. The superior performance of the neural network auto-regressive (NNAR) model over the other models suggests that time-series analysis should be integrated into predictive models. This approach allows for more accurate forecasts of player performance over time, aiding in long-term planning and performance improvement. Coaches and sports analysts can utilize these models to track and predict performance trends, making data-driven decisions for future matches.

4.4. Spatial and Tactics Analysis

Collectively, recent studies in tennis provide coaches with invaluable insights into various facets of player performance and development [40,41,46,49,51,52,57,59]. Integrating deep learning techniques into tactical analysis, as demonstrated by Zhang [59], allows coaches to offer real-time feedback to players based on comprehensive diagnostic indicators, optimizing on-court performance. Furthermore, biomechanical analyses, such as those conducted by Li et al. [57], offer coaches a deeper understanding of players' technique and tactical considerations, enabling them to tailor training regimens to enhance players' overall proficiency.

Moreover, spatiotemporal analyses, as exemplified by Whiteside and Reid [51], provide coaches with actionable data to refine players' serving techniques and increase their effectiveness on the court. Understanding players' agility and responsiveness, as investigated by Giles et al. [40], allows coaches to design training programs aimed at improving players' movement capabilities, thus enhancing their competitive edge.

Additionally, insights into visual search strategies, as explored by Rosker and Rosker [46], empower coaches to develop tailored training programs focused on improving players' decision-making skills during matches. Finally, understanding the optimal stance selection for different court situations, as highlighted by Zhou and Liu [52], enables coaches to optimize players' groundstroke performance and elevate their competitive performance.

4.5. Injuries and Training Effects

The studies by Whiteside et al. [50], Schulc et al. [47], and Hao and Hong [42] each offer significant advancements with practical implications for coaches in tennis.

Whiteside et al. [50] introduced an approach to quantify hitting load using an automated stroke classification system. By leveraging inertial measurement unit (IMU) technology and machine learning algorithms, coaches can now accurately monitor players' hitting load, crucial for injury prevention and training optimization. This system enables coaches to tailor training programs, prescribe adequate rest periods, and mitigate the risk of overuse injuries, particularly in areas prone to strain, such as the lower back and shoulders.

Schuluc et al. [47] analyzed the challenge of diagnosing ACL injuries during gameplay by developing an AI-based video analysis system. By extracting biomechanical features from video footage and training neural network algorithms, the study demonstrated promising results in automatically detecting ACL injuries. This technology empowers coaches and medical staff to identify potentially serious injuries promptly, facilitating timely treatment and reducing the risk of further complications. Integration of this system into injury prevention protocols allows coaches to proactively safeguard players' long-term health and performance.

Hao and Hong [42] proposed a predictive method for assessing athletes' training effectiveness using neural network algorithms. By analyzing various physiological and performance-related factors, such as heart rate and body composition, the study developed a model capable of accurately predicting training outcomes. This approach equips coaches with the tools to optimize training regimens tailored to individual athletes' needs, maximizing performance gains while minimizing the risk of overtraining or undertraining. Leveraging predictive analytics empowers coaches to make informed decisions that enhance players' development and performance potential on the court.

Collectively, these studies offer coaches in tennis valuable insights and technological innovations to revolutionize injury prevention strategies and training optimization. With access to advanced tools and methodologies, coaches can safeguard players' well-being, optimize performance outcomes, and elevate their overall success in the sport.

5. Limitation and Future Research

This study presented several limitations related to the inclusion of studies with varying quality assessments and potential biases. Notably, some studies included in this review were classified as having low quality and high risk of bias. Despite these limitations, they were retained due to their relevance to the research questions and the scarcity of alternative studies addressing similar aspects of machine learning applications in tennis.

Looking forward, the integration of machine learning and wearable technologies in tennis offers promising insights for future research and application. Therefore, longitudinal investigations are crucial to evaluate the sustained efficacy of predictive models in real-world tennis environments. Standardizing protocols for deploying wearable technologies and machine learning algorithms across diverse player cohorts and competitive levels will enhance comparability and generalizability. Additionally, future studies should also explore the scalability of these technologies beyond elite athletes, encompassing broader demographics and non-competitive settings. By addressing these gaps and fostering interdisciplinary collaborations, future research can advance methodologies that optimize training strategies, improve performance outcomes, and mitigate injury risks in tennis.

6. Conclusions

In conclusion, this systematic review highlighted the significant contributions of machine learning technologies to tennis coaching practices. Across various domains, including psychological state monitoring, talent identification, match outcome prediction, and injury prevention, machine learning algorithms have demonstrated their effectiveness in enhancing player performance, optimizing training strategies, and reducing the risk of injuries.

Specifically, the integration of wearable devices and machine learning algorithms enables real-time monitoring of psychological states, providing coaches with personalized insights into player readiness and performance levels. Moreover, automated methods for talent identification offer a more data-driven approach, improving the accuracy of predicting young players' performance potential. In match outcome prediction, machine learning models provide coaches with valuable insights into tactical strategies and player performance, enabling more informed decision-making during training and competitions. Decision tree classifiers in match outcome prediction improve the reliability of strategic decisions based on match data, highlighting the tactical advantages of data-driven coaching methodologies.

As technology continues to advance, coaches can exploit these insights to refine their coaching methodologies and enhance their players' performance.

Author Contributions: Conceptualization, T.S. and J.E.M.; methodology, J.P.O. and T.S.; data curation, J.P.O. and T.S.; funding, D.A.M.; writing—original draft preparation, T.S.; writing—review and editing, J.P.O., T.S., D.A.M., H.P.N. and J.E.M. All authors have read and agreed to the published version of the manuscript.

Funding: This work is supported by national funds (FCT—Portuguese Foundation for Science and Technology) under the project UIDB/DTP/04045/2020.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Fernandez-Fernandez, J.; Sanz-Rivas, D.; Mendez-Villanueva, A. A Review of the Activity Profile and Physiological Demands of Tennis Match Play. *Strength Cond. J.* **2009**, *31*, 15. [CrossRef]
2. Kovacs, M.S. Tennis Physiology: Training the Competitive Athlete. *Sports Med.* **2007**, *37*, 189–198. [CrossRef]
3. Hornery, D.J.; Farrow, D.; Mujika, I.; Young, W. Fatigue in Tennis. *Sports Med.* **2007**, *37*, 199–212. [CrossRef] [PubMed]
4. Elferink-Gemser, M.; Visscher, C.; Lemmink, K.; Mulder, T. Relation between Multidimensional Performance Characteristics and Level of Performance in Talented Youth Field Hockey Players. *J. Sports Sci.* **2004**, *22*, 1053–1063. [CrossRef] [PubMed]
5. Gould, D.; Medbery, R.; Damarjian, N.; Lauer, L. A Survey of Mental Skills Training Knowledge, Opinions, and Practices of Junior Tennis Coaches. *J. Appl. Sport Psychol.* **1999**, *11*, 28–50. [CrossRef]
6. Houwer, R.; Kramer, T.; Hartigh, R.D.; Kolman, N.; Elferink-Gemser, M.; Huijgen, B. Mental Toughness in Talented Youth Tennis Players: A Comparison Between on-Court Observations and a Self-Reported Measure. *J. Hum. Kinet.* **2017**, *55*, 139–148. [CrossRef]
7. Fernandez-Fernandez, J.; Zimek, R.; Wiewelhove, T.; Ferrauti, A. High-Intensity Interval Training vs. Repeated-Sprint Training in Tennis. *J. Strength Cond. Res.* **2012**, *26*, 53. [CrossRef] [PubMed]
8. Fernandez, J.; Mendez-Villanueva, A.; Pluim, B.M. Intensity of Tennis Match Play. *Br. J. Sports Med.* **2006**, *40*, 387–391. [CrossRef] [PubMed]
9. Morais, J.E.; Bragada, J.A.; Silva, R.; Nevill, A.M.; Nakamura, F.Y.; Marinho, D.A. Analysis of the Physiological Response in Junior Tennis Players during Short-Term Recovery: Understanding the Magnitude of Recovery until and after the 25 Seconds Rule. *Int. J. Sports Sci. Coach.* **2022**, *18*, 1208–1216. [CrossRef]
10. Girard, O.; Millet, G.P. Neuromuscular Fatigue in Racquet Sports. *Neurol. Clin.* **2008**, *26*, 181–194. [CrossRef]
11. Mendez-Villanueva, A.; Fernandez-Fernandez, J.; Bishop, D. Exercise-Induced Homeostatic Perturbations Provoked by Singles Tennis Match Play with Reference to Development of Fatigue. *Br. J. Sports Med.* **2007**, *41*, 717–722; discussion 722. [CrossRef]

12. Mainer-Pardos, E.; Álvarez, V.E.V.; Moreno-Apellaniz, N.; Gutiérrez-Logroño, A.; Calero-Morales, S. Effects of a Neuromuscular Training Program on the Performance and Inter-Limb Asymmetries in Highly Trained Junior Male Tennis Players. *Heliyon* **2024**, *10*, e27081. [CrossRef] [PubMed]
13. Colomar, J.; Corbi, F.; Baiget, E. Improving Tennis Serve Velocity: Review of Training Methods and Recommendations. *Strength Cond. J.* **2023**, *45*, 385–394. [CrossRef]
14. Deng, N.; Soh, K.G.; Abdullah, B.; Huang, D.; Sun, H.; Xiao, W. Effects of Physical Training Programs on Female Tennis Players' Performance: A Systematic Review and Meta-Analysis. *Front. Physiol.* **2023**, *14*, 1234114. [CrossRef]
15. Hammes, F.; Hagg, A.; Asteroth, A.; Link, D. Artificial Intelligence in Elite Sports—A Narrative Review of Success Stories and Challenges. *Front. Sports Act. Living* **2022**, *4*, 861466. [CrossRef]
16. Dindorf, C.; Bartaguiz, E.; Gassmann, F.; Fröhlich, M. Conceptual Structure and Current Trends in Artificial Intelligence, Machine Learning, and Deep Learning Research in Sports: A Bibliometric Review. *Int. J. Environ. Res. Public Health* **2022**, *20*, 173. [CrossRef] [PubMed]
17. Musa, R.M.; Abdul Majeed, A.P.P.; Suhaimi, M.Z.; Abdullah, M.R.; Mohd Razman, M.A.; Abdelhakim, D.; Abu Osman, N.A. Identification of High-Performance Volleyball Players from Anthropometric Variables and Psychological Readiness: A Machine-Learning Approach. *Proc. Inst. Mech. Eng. Part P J. Sports Eng. Technol.* **2023**, *237*, 317–324. [CrossRef]
18. Martin, R.K.; Pareek, A.; Krych, A.J.; Maradit Kremers, H.; Engebretsen, L. Machine Learning in Sports Medicine: Need for Improvement. *J. ISAKOS* **2021**, *6*, 1–2. [CrossRef]
19. Nijenhuis, S.B.; Koopmann, T.; Mulder, J.; Elferink-Gemser, M.T.; Faber, I.R. Multidimensional and Longitudinal Approaches in Talent Identification and Development in Racket Sports: A Systematic Review. *Sports Med.-Open* **2024**, *10*, 4. [CrossRef] [PubMed]
20. Robles-Palazón, F.J.; Puerta-Callejón, J.M.; Gámez, J.A.; De Ste Croix, M.; Cejudo, A.; Santonja, F.; Sainz de Baranda, P.; Ayala, F. Predicting Injury Risk Using Machine Learning in Male Youth Soccer Players. *Chaos Solitons Fractals* **2023**, *167*, 113079. [CrossRef]
21. Rossi, A.; Pappalardo, L.; Cintia, P. A Narrative Review for a Machine Learning Application in Sports: An Example Based on Injury Forecasting in Soccer. *Sports* **2021**, *10*, 5. [CrossRef]
22. Radovanović, S.; Petrović, A.; Delibašić, B.; Suknović, M. *Ski Injury Predictions with Explanations*; Springer: Berlin/Heidelberg, Germany, 2019; pp. 148–160.
23. Piergiovanni, A.J.; Ryoo, M.S. Early Detection of Injuries in MLB Pitchers from Video. In Proceedings of the 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), Long Beach, CA, USA, 16–17 June 2019; pp. 2431–2438.
24. Taborri, J.; Molinaro, L.; Santospagnuolo, A.; Vetrano, M.; Vulpiani, M.C.; Rossi, S. A Machine-Learning Approach to Measure the Anterior Cruciate Ligament Injury Risk in Female Basketball Players. *Sensors* **2021**, *21*, 3141. [CrossRef] [PubMed]
25. de Leeuw, A.-W.; van der Zwaard, S.; van Baar, R.; Knobbe, A. Personalized Machine Learning Approach to Injury Monitoring in Elite Volleyball Players. *Eur. J. Sport Sci.* **2022**, *22*, 511–520. [CrossRef]
26. Sukumaran, C.; Selvam, D.; Sankar, M.; Parthiban, V.; Sugumar, C. Application of Artificial Intelligence and Machine Learning to Predict Basketball Match Outcomes: A Systematic Review. *Comput. Integr. Manuf. Syst.* **2022**, *28*, 998–1009.
27. Huang, M.-L.; Li, Y.-Z. Use of Machine Learning and Deep Learning to Predict the Outcomes of Major League Baseball Matches. *Appl. Sci.* **2021**, *11*, 4499. [CrossRef]
28. Joseph, A.; Fenton, N.E.; Neil, M. Predicting Football Results Using Bayesian Nets and Other Machine Learning Techniques. *Knowl.-Based Syst.* **2006**, *19*, 544–553. [CrossRef]
29. Sigurdson, H.; Chan, J. Machine Learning Applications to Sports Injury: A Review. In Proceedings of the 9th International Conference on Sport Sciences Research and Technology Support, Online Streaming, 28–29 October 2021; SCITEPRESS-Science and Technology Publications: Setúbal, Portugal, 2021; pp. 157–168.
30. Šarčević, A.; Vranić, M.; Pintar, D.; Krajna, A. *Predictive Modeling of Tennis Matches: A Review*; IEEE: Piscataway, NJ, USA, 2022; pp. 1099–1104.
31. Reyaz, N.; Ahamad, G.; Khan, N.J.; Naseem, M. *Machine Learning in Sports Talent Identification: A Systematic Review*; IEEE: Piscataway, NJ, USA, 2022; pp. 1–6.
32. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 Statement: An Updated Guideline for Reporting Systematic Reviews. *Syst. Rev.* **2021**, *10*, 89. [CrossRef]
33. Waffenschmidt, S.; Janzen, T.; Hausner, E.; Kaiser, T. Simple Search Techniques in PubMed Are Potentially Suitable for Evaluating the Completeness of Systematic Reviews. *J. Clin. Epidemiol.* **2013**, *66*, 660–665. [CrossRef]
34. Cochrane Consumers & Communication Review Group. Data Extraction Template for Included Studies. 2016. Available online: https://cccrg.cochrane.org/ (accessed on 20 June 2024).
35. Cuschieri, S. The STROBE Guidelines. *Saudi J. Anaesth.* **2019**, *13*, S31–S34. [CrossRef]
36. O'Reilly, M.; Caulfield, B.; Ward, T.; Johnston, W.; Doherty, C. Wearable Inertial Sensor Systems for Lower Limb Exercise Detection and Evaluation: A Systematic Review. *Sports Med.* **2018**, *48*, 1221–1246. [CrossRef]
37. Almarashi, A.M.; Daniyal, M.; Jamal, F. A Novel Comparative Study of NNAR Approach with Linear Stochastic Time Series Models in Predicting Tennis Player's Performance. *Bmc Sports Sci. Med. Rehabil.* **2024**, *16*, 28. [CrossRef] [PubMed]

38. Bozděch, M.; Zháněl, J. Analyzing Game Statistics and Career Trajectories of Female Elite Junior Tennis Players: A Machine Learning Approach. *PLoS ONE* **2023**, *18*, e0295075. [CrossRef] [PubMed]
39. Gao, Z.; Kowalczyk, A. Random Forest Model Identifies Serve Strength as a Key Predictor of Tennis Match Outcome. *J. Sports Anal.* **2021**, *7*, 255–262. [CrossRef]
40. Giles, B.; Kovalchik, S.; Reid, M. A Machine Learning Approach for Automatic Detection and Classification of Changes of Direction from Player Tracking Data in Professional Tennis. *J. Sports Sci.* **2020**, *38*, 106–113. [CrossRef] [PubMed]
41. Giles, B.; Peeling, P.; Kovalchik, S.; Reid, M. Differentiating Movement Styles in Professional Tennis: A Machine Learning and Hierarchical Clustering Approach. *Eur. J. Sport Sci.* **2023**, *23*, 44–53. [CrossRef] [PubMed]
42. Hao, W.; Hong, Y. Training Project Arrangement for Tennis Athletes Based on BP Neural Network Model. *Int. J. Reason.-Based Intell. Syst.* **2017**, *9*, 144–148. [CrossRef]
43. Jekauc, D.; Burkart, D.; Fritsch, J.; Hesenius, M.; Meyer, O.; Sarfraz, S.; Stiefelhagen, R. Recognizing Affective States from the Expressive Behavior of Tennis Players Using Convolutional Neural Networks. *Knowl.-Based Syst.* **2024**, *295*, 111856. [CrossRef]
44. Kovalchik, S.A.; Sackmann, J.; Reid, M. Player, Official or Machine? Uses of the Challenge System in Professional Tennis. *Int. J. Perform. Anal. Sport* **2017**, *17*, 961–969. [CrossRef]
45. Panjan, A.; Šarabon, N.; Filipčič, A. Prediction of the Successfulness of Tennis Players with Machine Learning Methods. *Kinesiology* **2010**, *42*, 98–106.
46. Rosker, J.; Majcen Rosker, Z. Skill Level in Tennis Serve Return Is Related to Adaptability in Visual Search Behavior. *Front. Psychol.* **2021**, *12*, 689378. [CrossRef]
47. Schulc, A.; Leite, C.B.G.; Csákvári, M.; Lattermann, L.; Zgoda, M.F.; Farina, E.M.; Lattermann, C.; Tősér, Z.; Merkely, G. Identifying Anterior Cruciate Ligament Injuries through Automated Video Analysis of In-Game Motion Patterns. *Orthop. J. Sports Med.* **2024**, *12*, 23259671231221579. [CrossRef] [PubMed]
48. Siener, M.; Faber, I.; Hohmann, A. Prognostic Validity of Statistical Prediction Methods Used for Talent Identification in Youth Tennis Players Based on Motor Abilities. *Appl. Sci.* **2021**, *11*, 7051. [CrossRef]
49. Vives, F.; Lazaro, J.; Guzman, J.F.; Martinez-Gallego, R.; Crespo, M. Optimizing Sporting Actions Effectiveness: A Machine Learning Approach to Uncover Key Variables in the Men's Professional Doubles Tennis Serve. *Appl. Sci.* **2023**, *13*, 13213. [CrossRef]
50. Whiteside, D.; Cant, O.; Connolly, M.; Reid, M. Monitoring Hitting Load in Tennis Using Inertial Sensors and Machine Learning. *Int. J. Sports Physiol. Perform.* **2017**, *12*, 1212–1217. [CrossRef] [PubMed]
51. Whiteside, D.; Reid, M. Spatial Characteristics of Professional Tennis Serves with Implications for Serving Aces: A Machine Learning Approach. *J. Sports Sci.* **2017**, *35*, 648–654. [CrossRef] [PubMed]
52. Zhou, J.Q.; Liu, Y. Probability Prediction of Groundstroke Stances among Male Professional Tennis Players Using a Tree-Augmented Bayesian Network. *Int. J. Perform. Anal. Sport* **2024**, *1*, 13. [CrossRef]
53. Filipcic, A.; Panjan, A.; Sarabon, N. Classification of Top Male Tennis Players. *Int. J. Comput. Sci. Sport* **2014**, *13*, 36–42.
54. Ghosh, S.; Sadhu, S.; Biswas, S.; Sarkar, D.; Sarkar, P.P. A Comparison between Different Classifiers for Tennis Match Result Prediction. *Malays. J. Comput. Sci.* **2019**, *32*, 97–111. [CrossRef]
55. Havlucu, H.; Akgun, B.; Eskenazi, T.; Coskun, A.; Ozcan, O. Toward Detecting the Zone of Elite Tennis Players Through Wearable Technology. *Front. Sports Act. Living* **2022**, *4*, 939641. [CrossRef]
56. Khder, M.A.; Fujo, S.W. Applying Machine Learning-Supervised Learning Techniques for Tennis Players Dataset Analysis. *Int. J. Adv. Soft Comput. Its Appl.* **2022**, *14*, 189–214. [CrossRef]
57. Li, J.; Zhang, X.; Yang, G. The Biomechanical Analysis on the Tennis Batting Angle Selection Under Deep Learning. *IEEE Access* **2023**, *11*, 97758–97768. [CrossRef]
58. Makino, M.; Odaka, T.; Kuroiwa, J.; Suwa, I.; Shirai, H. Feature Selection to Win the Point of ATP Tennis Players Using Rally Information. *Int. J. Comput. Sci. Sport* **2020**, *19*, 37–50. [CrossRef]
59. Zhang, Y. The Optimization of College Tennis Training and Teaching under Deep Learning. *Heliyon* **2024**, *10*, e25954. [CrossRef] [PubMed]
60. Khan, A.; Nicholson, J.; Plötz, T. Activity Recognition for Quality Assessment of Batting Shots in Cricket Using a Hierarchical Representation. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* **2017**, *1*, 1–31. [CrossRef]
61. Hölzemann, A.; Van Laerhoven, K. Using Wrist-Worn Activity Recognition for Basketball Game Analysis. In Proceedings of the iWOAR'18: 5th International Workshop on Sensor-based Activity Recognition and Interaction, Berlin, Germany, 20–21 September 2018; pp. 1–6.
62. Lindholm, A.; Wahlström, N.; Lindsten, F.; Schön, T.B. *Supervised Machine Learning*; Department of Information Technology, Uppsala University: Uppsala, Sweden, 2019; p. 112.
63. Katić, R.; Milat, S.; Zagorac, N.; Durović, N. Impact of Game Elements on Tennis Match Outcome in Wimbledon and Roland Garros 2009. *Coll. Antropol.* **2011**, *35*, 341–346. [PubMed]
64. Hizan, H.; Whipp, P.; Reid, M. Gender Differences in the Spatial Distributions of the Tennis Serve. *Int. J. Sports Sci. Coach.* **2015**, *10*, 87–96. [CrossRef]
65. Della Villa, F.; Buckthorpe, M.; Grassi, A.; Nabiuzzi, A.; Tosarelli, F.; Zaffagnini, S.; Della Villa, S. Systematic Video Analysis of ACL Injuries in Professional Male Football (Soccer): Injury Mechanisms, Situational Patterns and Biomechanics Study on 134 Consecutive Cases. *Br. J. Sports Med.* **2020**, *54*, 1423–1432. [CrossRef] [PubMed]

66. Lucarno, S.; Zago, M.; Buckthorpe, M.; Grassi, A.; Tosarelli, F.; Smith, R.; Della Villa, F. Systematic Video Analysis of Anterior Cruciate Ligament Injuries in Professional Female Soccer Players. *Am. J. Sports Med.* **2021**, *49*, 1794–1802. [CrossRef]
67. Krosshaug, T.; Nakamae, A.; Boden, B.P.; Engebretsen, L.; Smith, G.; Slauterbeck, J.R.; Hewett, T.E.; Bahr, R. Mechanisms of Anterior Cruciate Ligament Injury in Basketball: Video Analysis of 39 Cases. *Am. J. Sports Med.* **2007**, *35*, 359–367. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.