Benchmarking Stroke Forecasting with Stroke-Level Badminton Dataset

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Abstract

In recent years, badminton analytics has drawn attention due to the advancement of artificial intelligence and the efficiency of data collection. While there is a line of effective applications to improve and investigate player performance, there are only a few public badminton datasets that can be used by researchers outside the badminton domain. Existing badminton singles datasets focus on specific matchups; however, they cannot provide comprehensive studies on different players and various matchups. In this paper, we provide a badminton singles dataset, ShuttleSet22, which is collected from high-ranking matches in 2022. ShuttleSet22 consists of 30,172 strokes in 2,888 rallies in the training set, 1,400 strokes in 450 rallies in the validation set, and 2,040 strokes in 654 rallies in the testing set, with detailed stroke-level metadata within a rally. To benchmark existing work with ShuttleSet22, we hold a challenge, Track 2: Forecasting Future Turn-Based Strokes in Badminton Rallies, at CoachAI Badminton Challenge @ IJCAI 2023, to encourage researchers to tackle this real-world problem through innovative approaches and to summarize insights between the state-of-the-art baseline and improved techniques, exchanging inspiring ideas. The baseline codes and the dataset are made available at https://github.com/wywyWang/CoachAI-Projects/tree/main/CoachAI-Challenge-IJCAI2023.

1 Introduction

Sports analytics has garnered increasing attention since the advancement of technology, which greatly facilitates data collection and increases data diversity. In recent years, there has been a surge in studies applying advanced artificial intelligence techniques, e.g., computer vision on video frames [Kim *et al.*, 2022], and machine learning models for action valuing [Decroos *et al.*, 2019; Merhej *et al.*, 2021]. Badminton, as one of the major racket sports worldwide in terms of participation, demands high physical and tactical conditions, attracting researchers to introduce novel applications [Wang *et al.*, 2020]. For instance, [Wang *et al.*, 2022a] propose long short-term extractors to quantify the win influence of each shot within a rally, while [Chang *et al.*, 2023] design the movement forecasting task to predict players' movements using graph-based approaches.

	# Players	# Match	# Rally	# Stroke	Year
BadmintonDB [Ban *et al.*, 2022]	2	9	811	9,671	2018-2020
ShuttleSet22 (Ours)	35	58	3,992	33,612	2022

Table 1: Comparison of the previous badminton dataset with our proposed ShuttleSet22.

In this paper, our aim is to introduce, ShuttleSet22, a stroke-level badminton singles dataset collected from real-world high-ranking matches in 2022. ShuttleSet22 extends the original ShuttleSet [Wang *et al.*, 2023], comprising 30,172 strokes (2,888 rallies), 1,400 strokes (450 rallies) in the validation set, and 2,040 strokes (654 rallies) in the testing set. While ShuttleSet22 shares similar stroke-level data formats with ShuttleSet, it consists of matches in 2022 instead of the period between 2018 and 2021. Therefore, ShuttleSet22 can be considered the most recent iteration of the badminton singles dataset, enabling the examination of model effectiveness in recent matches. ShuttleSet22 is sourced from public videos[1] and has been meticulously labeled by domain experts with the shot-by-shot labeling tool [Huang *et al.*, 2022].

To boost researchers' engagements in badminton analytics, we have, for the first time, initiated a challenge within CoachAI Badminton Challenge 2023[2] in conjunction with IJCAI 2023. Specifically, we have organized the forecasting of future turn-based strokes in badminton rallies (Track 2) and provided the state-of-the-art stroke forecasting approach [Wang *et al.*, 2022b] as the official baseline. This track has attracted approximately 100 participants aiming to improve the effectiveness of the stroke forecasting task, with 16 teams submitting their final results on the leaderboard. In addition to the results, we summarize these insights and analyses of this challenge to inspire ideas for bridging the gap between badminton analytics and artificial intelligence communities[3].

[1] http://bwf.tv/
[2] https://sites.google.com/view/coachai-challenge-2023/
[3] The video can be found at https://youtu.be/yhRouMpxb2M.

Shot Type	Not Around Head	Around Head	Forehand	Backhand	Higher than the net	Below than the net	Total Count
Drive	891	41	701	231	497	435	932
Net Shot	5721	4	3110	2615	158	5566	5725
Lob	5205	2	2706	2501	4890	316	5207
Clear	2062	1016	2808	270	2868	210	3078
Drop	2539	643	2863	319	133	3049	3182
Push/Rush	1994	17	992	1019	1277	734	2011
Smash	2402	1280	3641	41	56	3625	3682
Defensive Shot	4079	8	1742	2345	940	3146	4087
Short Service	1620	0	146	1474	21	1599	1620
Long Service	648	0	528	120	644	3	648

Table 2: The statistics of shot types. Short and long services only happen at the first stroke.

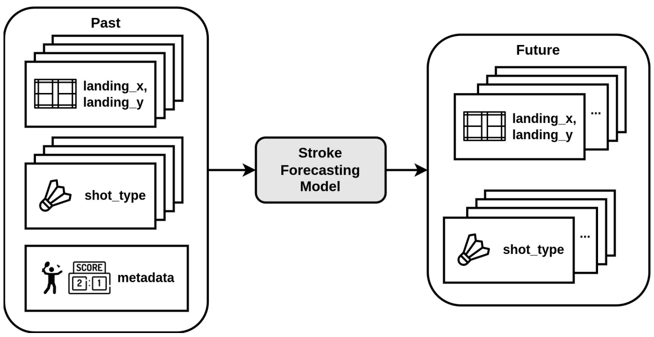

Figure 1: Illustrated system of Track 2: Forecasting Future Turn-Based Strokes in Badminton Rallies.

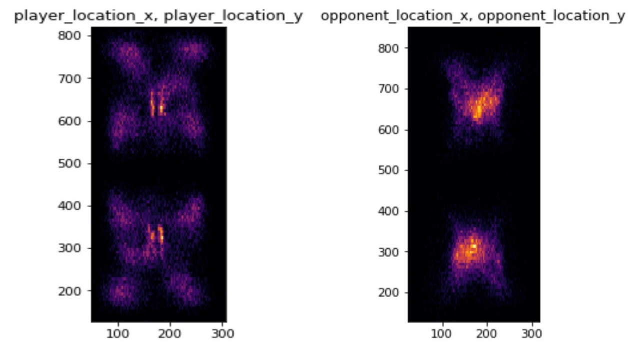

Figure 2: Heatmap of player and opponent locations in ShuttleSet22.

2 Related Work: Public Badminton Datasets

Generally, there are only a few public badminton datasets due to the heavy cost of collecting and labeling fine-grained records by domain experts [Wang, 2022]. Recently, researchers have released badminton datasets to foster the sports community. For instance, the shuttlecock datasets [Cartron, 2022] contains 8K images of shuttlecocks which are resized to 640*640 pixels. This dataset includes the position of shuttlecocks which could train an object detection model. The BadmintonDB [Ban *et al.*, 2022] features rally, strokes, and outcome annotations between two players, which can be used in player-specific match analysis and prediction tasks, which is also the stroke-level dataset. However, BadmintonDB only consists of the same matchup (i.e., Kento Momota and Anthony Sinisuka Ginting) instead of the various matchups. Moreover, BadmintonDB collects matches from 2018 to 2020, while our ShuttleSet22 collects high-ranking matches in 2022 to reflect the state-of-the-art tactic records. We summarize the discrepancies between our ShuttleSet and BadmintonDB in Table 1.

3 The Challenge System

Conventional applications in badminton mainly focus on quantifying stroke performance [Wang *et al.*, 2021] or retrieving information from videos [Chu and Situmeang, 2017], which motivates us to further investigate a more challenging yet critical real-world application. The goal of this shared task is to **forecasting future turn-based strokes in badminton rallies**, which aims to design forecasting models capable of predicting future strokes, including shot types and locations, based on past stroke sequences. Figure 1 illustrates the entire flowchart of our task. As we have built the pipeline from data processing to evaluations, participants only need to modify the stroke forecasting model to swiftly iterate their approaches. The task page is available on Codalab.

3.1 Problem Formulation

Following the definition outlined in [Wang *et al.*, 2022b], for each singles rally, given the observed τ strokes with type-area pairs and two players, the goal is to predict the future strokes, including shot types and area coordinates, for the next n steps. To simplify the problem, τ is set to be 4 in our challenge, and n is various based on the length of the rally, which is given to the participants.

Let $R = \{S_r, P_r\}_{r=1}^{|R|}$ denote historical rallies of badminton matches, where the r-th rally is composed of a stroke sequence with type-area pairs $S_r = (\langle s_1, a_1\rangle, \cdots, \langle s_{|S_r|}, a_{|S_r|}\rangle)$ and a player sequence $P_r = (p_1, \cdots, p_{|S_r|})$. At the i-th stroke, s_i represents the shot type, $a_i = \langle x_i, y_i\rangle \in \mathbb{R}^2$ are the coordinates of the shuttle destinations, and p_i is the player who hits the shuttle. We denote Player A as the served player and Player B as the other for each rally in this paper. For instance, given a singles rally between Player A and Player B, P_r may become $(A, B, \cdots, A, B)$. We formulate the problem of stroke forecasting as follows. For each rally, given the observed τ strokes $(\langle s_i, a_i\rangle)_{i=1}^{\tau}$ with players $(p_i)_{i=1}^{\tau}$, the goal is to predict the future strokes including shot types and area coordinates for the next n steps, i.e., $(\langle s_i, a_i \rangle)_{i=\tau+1}^{\tau+n}$. We note that n is pre-defined as the actual length of the corresponding rally.

3.2 Exploratory Data Analysis

We have released 58 matches, approximately 4,000 rallies with shot-level records following the BLSR format [Wang *et al.*, 2022a] for this task, where parts of the matches from 2018 to 2021 are identical to those in [Wang *et al.*, 2022b], while we have further included new matches collected from 2022.

Figure 2 shows the heatmap of player location and opponent location, indicating that most players position themselves at both the center and the four corners of the courts when preparing to attack. On the contrary, when defending, players intend to stay predominantly in the center of the court to enable quick reactions to any type of shot.

Table 2 presents the numbers of different strike orders by shot types. It is evident that with the exception of the Clear and Smash shots, other shot types do not target around the head area. Furthermore, more than half of the Push/Rush, Defensive Shot, and Short Service shots are executed with the backhand, while other shot types predominantly utilize the forehand. Notably, there is a significant disparity in hitting position based on the service type, with almost all short services directed below the net and almost all long services aimed above the net.

3.3 Evaluation Metrics

The evaluation scenarios will be assessed by cross-entropy for shot type prediction and mean absolute error (MAE) for area coordinates prediction, similar to the original work. Given the stochastic nature of this task, each team will be required to generate 6 predicted sequences for each rally, from which the closest one to the ground truth will be selected for evaluation. It is worth noting that the original work on the stroke forecasting task involved generating 10 sequences, a number we have reduced to 6 for efficiency.

3.4 Official Baseline

Generally, ShuttleNet [Wang *et al.*, 2022b] is a position-aware fusion of rally progress and player styles framework consisting of Transformer-based architectures. ShuttleNet has demonstrated superior performance in predicting the next strokes compared to conventional sequential. This is attributed to its turn-based architecture, which separates the styles of both players in a rally and integrates them with the current rally condition.

4 Participating System

Approximately 95 participants have joined the challenge system, with 16 teams submitting their testing results for the final phase of the CoachAI Badminton Challenge 2023 (Track 2). Most teams modified the official baseline, ShuttleNet, to address the task. The brief descriptions of the submitted methods are summarized in the video due to the page limit.

5 Results and Findings

Table 3 reports the official leaderboard of the participants' methods. It is observed that Team Intro_to_AI_team 8 slightly outperforms the competition Team Badminseok, while Team YHY demonstrates the best performance in terms of area predictions. 11 teams perform better than ShuttleNet; however, we notice that these methods are built on top of ShuttleNet, which highlights the flexibility of ShuttleNet and the potential for improvements in certain aspects, e.g., hyper-parameters and activation functions. In addition, the improvements made by the participating teams primarily focus on the shot type prediction (2.1777 → 1.7892); however, the performance of area coordinates only marginally surpasses ShuttleNet (0.6997 → 0.6797), with most teams being inferior to the baseline. This underscores the challenge of effectively integrating two predictions, which may be a potential future direction for exploration.

Rank	Team	CE	MAE	Total
1	Intro_to_AI_team8	**1.7892**	0.7884	**2.5776**
2	Badminseok	1.8127	0.7703	2.5830
3	NYCU-group4	1.8411	0.7826	2.6237
4	YHY	1.9685	**0.6797**	2.6482
5	20	1.9366	0.7490	2.6856
6	LOL	1.9390	0.7618	2.7008
7	AI Project #15	1.9536	0.7483	2.7019
8	Group27	2.0200	0.7139	2.7339
9	Team_13	1.9681	0.7671	2.7352
10	LinDan	2.0097	0.7743	2.7841
11	Intro_to_AI_group_5	1.9710	0.8726	2.8436
12	14	2.1718	0.7013	2.8731
-	ShuttleNet [Wang *et al.*, 2022b]	2.1777	0.6997	2.8774
13	GD_Wang	2.2479	0.7081	2.9560
14	ShuttleFold	2.1277	1.0107	3.1385
15	Awesome Badminton	2.6579	0.7120	3.3699
16	Badminton is all you need	2.6579	0.7120	3.3699
17	Group_28	4.6615	1.0268	5.6883

Table 3: Performance of the stroke forecasting task in CoachAI Badminton Challenge 2023 (Track 2).

6 Conclusion

In this paper, we propose ShuttleSet22, an extended dataset from ShuttleSet with stroke-level badminton singles records. ShuttleSet22 consists of fine-grained metadata to reinforce researchers to explore various aspects and derive insightful findings. Exploratory data analysis is conducted to elucidate the fundamental compositions of the dataset, aiming to bridge the gap between researchers outside the badminton domain. To foster researchers to incorporate advanced techniques into badminton analytics, we introduce Track 2, a challenge within CoachAI Badminton Challenge 2023, focused on enhancing the effectiveness of stroke forecasting. In addition, we establish the state-of-the-art baseline for the task. We summarize and discuss the methods and insights from participants to provide potential avenues for future research improvement.

References

[Ban *et al.*, 2022] Kar-Weng Ban, John See, Junaidi Abdullah, and Yuen Peng Loh. Badmintondb: A badminton dataset for player-specific match analysis and prediction. In *MMSports@MM*, pages 47–54. ACM, 2022.

[Cartron, 2022] Mathieu Cartron. Shuttlecock dataset. https://universe.roboflow.com/mathieu-cartron/shuttlecock-cqzy3, mar 2022. visited on 2023-05-06.

[Chang *et al.*, 2023] Kai-Shiang Chang, Wei-Yao Wang, and Wen-Chih Peng. Where will players move next? dynamic graphs and hierarchical fusion for movement forecasting in badminton. In *AAAI*, pages 6998–7005. AAAI Press, 2023.

[Chu and Situmeang, 2017] Wei-Ta Chu and Samuel Situmeang. Badminton video analysis based on spatiotemporal and stroke features. In *ICMR*, pages 448–451. ACM, 2017.

[Decroos *et al.*, 2019] Tom Decroos, Lotte Bransen, Jan Van Haaren, and Jesse Davis. Actions speak louder than goals: Valuing player actions in soccer. In *KDD*, pages 1851–1861. ACM, 2019.

[Huang *et al.*, 2022] Yu-Hsien Huang, Yung-Chang Huang, Hao Syuan Lee, Tsì-Uí Ik, and Chih-Chuan Wang. S^2-labeling: Shot-by-shot microscopic badminton singles tactical dataset. In *APNOMS*, pages 1–6. IEEE, 2022.

[Kim *et al.*, 2022] Hyunsung Kim, Bit Kim, Dongwook Chung, Jinsung Yoon, and Sang-Ki Ko. Soccercpd: Formation and role change-point detection in soccer matches using spatiotemporal tracking data. In *KDD*, pages 3146–3156. ACM, 2022.

[Merhej *et al.*, 2021] Charbel Merhej, Ryan J. Beal, Tim Matthews, and Sarvapali D. Ramchurn. What happened next? using deep learning to value defensive actions in football event-data. In *KDD*, pages 3394–3403. ACM, 2021.

[Wang *et al.*, 2020] Wei-Yao Wang, Kai-Shiang Chang, Teng-Fong Chen, Chih-Chuan Wang, Wen-Chih Peng, and Chih-Wei Yi. Badminton coach ai: A badminton match data analysis platform based on deep learning. *Physical Education Journal*, 53(2):201–213, 2020.

[Wang *et al.*, 2021] Wei-Yao Wang, Teng-Fong Chan, Hui-Kuo Yang, Chih-Chuan Wang, Yao-Chung Fan, and Wen-Chih Peng. Exploring the long short-term dependencies to infer shot influence in badminton matches. In *ICDM*, pages 1397–1402. IEEE, 2021.

[Wang *et al.*, 2022a] Wei-Yao Wang, Teng-Fong Chan, Wen-Chih Peng, Hui-Kuo Yang, Chih-Chuan Wang, and Yao-Chung Fan. How is the stroke? inferring shot influence in badminton matches via long short-term dependencies. 14(1), nov 2022.

[Wang *et al.*, 2022b] Wei-Yao Wang, Hong-Han Shuai, Kai-Shiang Chang, and Wen-Chih Peng. Shuttlenet: Position-aware fusion of rally progress and player styles for stroke forecasting in badminton. In *AAAI*, pages 4219–4227. AAAI Press, 2022.

[Wang *et al.*, 2023] Wei-Yao Wang, Yung-Chang Huang, Tsi-Ui Ik, and Wen-Chih Peng. Shuttleset: A human-annotated stroke-level singles dataset for badminton tactical analysis. In *KDD*. ACM, 2023.

[Wang, 2022] Wei-Yao Wang. Modeling turn-based sequences for player tactic applications in badminton matches. In *CIKM*, pages 5128–5131. ACM, 2022.