Play Evaluation Based on Predicting the Outcome of Back-Row Attacks in Volleyball

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Abstract: In volleyball, statistical analysis based on data aggregation at the team or match levels has developed, and its use for player performance evaluation and tactical analysis has expanded. However, there has been limited discussion on the quantitative evaluation of how individual plays affect rally outcomes. To address this issue, a model that predicts rally outcomes under specific conditions using player location data is useful. This study aims to evaluate plays based on a prediction model, focusing on the first transition following a back-row attack. We extracted 103 target scenes from game footage recorded from behind the end line and manually created tracking data for six players per team. Using this dataset, we trained an XGBoost model to predict the future probability of scoring and the probability of blocking by two or more opponents in each game state (receive, toss, attack). To quantify play evaluation, we propose the Valuating Volleyball States by Estimating Probabilities (V2SEP), which expresses play evaluation values in each state based on the prediction model, weighting them according to the percentage of points scored when a player is blocked. To verify the validity of the prediction model used in V2SEP, we assessed F1 scores and SHAP values for each state. The results indicate that the predictions were reasonably accurate and reflected not only the contributions of directly involved players but also those of other players affecting scoring and block induction. Furthermore, the play evaluation metrics demonstrate expected trends whereas some scenes show the limitations, suggesting that V2SEP may be useful for play evaluation in volleyball.

1 INTRODUCTION

Volleyball is a six-player team sport in which players rally the ball across a net while trying to prevent it from touching the ground. The game is played on a rectangular court measuring 18 m $\times$ 9 m. Each team is allowed a maximum of three touches before returning the ball to the opponent's court. The basic sequence of play consists of a receive, a set, and an attack.

According to volleyball rules, back-row players are not allowed to attack near the net. If they attack, they must jump from behind the attack line. An attack executed under this restriction is called a back-row attack (or back-row attack). One advantage of a back-row attack is that involving a back-row player in the offense can create a numerical advantage against the opponent's block. Additionally, combination attacks from both front-row and back-row players increases the variety of offensive plays, such as executing a delayed attack. Furthermore, pressure exerted by the back-row attack can contribute to a higher success rate for front-row attacks. However, because back-row attacks are performed farther from the net, they have a higher likelihood of errors, such as hitting the net or sending the ball out of bounds. Therefore, players must carefully adjust their approach and attack angles. Moreover, not only the attacker but also the positioning and movements of surrounding players play a crucial role in reducing the number of blockers and enhancing the effectiveness of the attack. In this study, we focus on back-row attacks and aim to quantitatively evaluate sequences of play by predicting attack outcomes based on player positions and movements.

In recent years, data analysis in volleyball has advanced, expanding its applications in player performance evaluation and tactical analysis. One example is a study that analyzed the number, duration, and height of tosses in a single men's World Champi-

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onship match (Hashihara et al., 2009). Additionally, by tabulating the tosses and spikes that occur during transitions (switching between offense and defense in response to an opponent's attack), it was revealed that the ability to execute first transitions significantly impacts match results (Yonezawa, 2003). In particular, first transitions in response to combination attacks were found to have a strong influence on match results (Yonezawa, 2004).

Machine learning has also been applied to volleyball analysis. For example, studies have used both rule-based and black-box models (Lalwani et al., 2022), as well as Bayesian networks with hidden Markov processes (Ge and Song, 2024). The former utilizes team-level factors such as win percentage, average points per match, and team ranking, while the latter incorporates intra-match factors such as points scored, successful serves, and successful blocks to predict match results and analyze the influence of these features on predictions. While team-based and match-based data aggregation analyses are progressing, discussions on the quantitative evaluation of each play's impact on rally outcomes remain insufficient. Simple statistical analysis is challenging because rally outcomes depend on numerous factors, including the attacker's position, their approach, the setter's accuracy, coverage by surrounding players, and the opponent's defense. In addition, although player location data on the court coordinates have been publicly released and utilized for analysis in other sports (Fujii, 2025) such as soccer (Somers et al., 2024), basketball (Scott et al., 2024), and badminton (Ding et al., 2024), no such datasets are publicly available for volleyball.

To assess the impact of plays on rally outcomes while considering multiple factors simultaneously, a predictive model based on tracking data is needed. For instance, in soccer, the Valuing Actions by Estimating Probabilities (VAEP) framework quantitatively evaluates the contribution of actions such as passing and dribbling to goal-scoring opportunities (Decroos et al., 2019). Additionally, a method called Valuing Defense by Estimating Probabilities (VDEP), derived from VAEP, has been introduced to assess defensive effectiveness (Toda et al., 2022; Umemoto et al., 2022), contributing to the development of a framework for analyzing both offensive and defensive plays. Although such quantitative evaluation methods for individual plays have been proposed in other sports and have contributed to improving competitive performance, similar research in volleyball remains in its early stages.

In this study, we propose Valuating Volleyball States by Estimating Probabilities (V2SEP), a framework for evaluating plays based on predictive models that utilizes tracking data of six players per team, extracted from match videos (Figure 1). Our analysis focuses specifically on the first transition following a back-row attack. The key contributions of this study are as follows: The main contributions of this study are: (1) We propose a quantitative framework to evaluate the impact of individual volleyball plays on rally outcomes. (2) We present the first publicly available volleyball player location and event dataset for performance analysis. (3) Experimental results indicated that the prediction models were reasonably accurate and capture both direct and indirect player contributions on scoring and block, and demonstrate the overall validity of the proposed method while showing some limitations. The rest of this paper is structured as follows. Section 2 reviews related work. Section 3 introduces our dataset and Section 4 describes our V2SEP method. Section 5 presents experimental results, and Section 6 concludes the paper. Datasets are available at https://github.com/keisuke198619/V2SEP-volleyball.

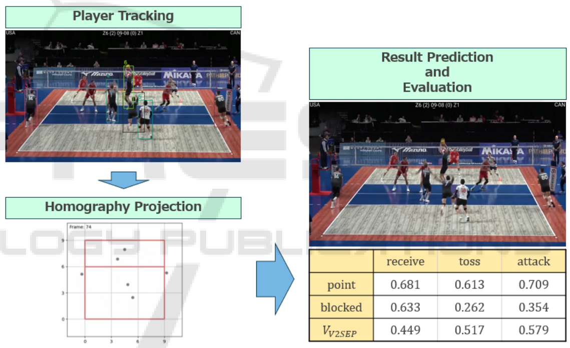

Figure 1: Overview of this study. We tracked the players and obtained their coordinates on the court by using a homography transformation. Then, we used this data to predict the result of the attack and evaluate the play.

2 RELATED WORK

As studies analyzing data on a match-by-match basis, a study has analyzed the relationship between the number of blockers and the type of attack against the opponent's attack during the first transition, as well as the match outcome, reconfirming the significant effect of spiking on match results (Minowa et al., 2016). There is also a study on the defensive side that analyzed factors such as the position before the block, the number of blockers, and block height, and that different factors were weighted in different phases of the game (Matsui et al., 2011). Another study has reported measurements of the time required for blocking at different attack positions, and it showed that reaction time is delayed for attacks from the left and right due to the larger movement steps required (Yamada et al., 2012).

A previous study on back-row attacks found that about 90% of combination attacks included a back-row attack (Yoshida et al., 2018). It was also noted that the occurrence rate and scoring rate of back-row attacks have increased, and that the increase in the scoring rate of back-row attacks has also influenced the scoring rate of other attacks (Yoshida et al., 2016; Nakanishi and Ohkubo, 2021). Additionally, it was reported that the choice of back-row attack position depends on the position of the toss (Adin-Marian and Marilena, 2014).

To analyze the movement of individual players, for example, from a biomechanics perspective, there is a research that analyzes the speed and jump time during a spike, and the angle of the torso and arms at each timing such as during the jump, attack, and landing (Awang Irawan et al., 2023). Another research compared spiking with one foot and both feet, analyzing their respective advantages in terms of center of gravity velocity and horizontal speed (Huang et al., 1999). Furthermore, the study examining the relationship between players' physical characteristics and performance revealed strong correlations, particularly with height, muscle mass, and bone mass (Sanjaykumar et al., 2024). Machine learning has also been applied to analyze individual player contributions. For example, one study used a Bayesian hierarchical logistic model to estimate data from the World Championships (W. Fellingham, 2022).

As described above, previous studies have mainly focused on collecting and analyzing data on a match-by-match basis or examining methods for analyzing individual player performance. However, detailed analysis on a rally-by-rally basis using tracking data, such as player movement and placement, is still unexplored field. This study takes a different approach from previous research by aiming to use tracking data to predict attack outcomes and evaluate play on a rally-by-rally basis.

3 METHODS

3.1 Datasets

In this section, we explain the dataset in this study, preprocessing, and computing variables. We emphasize that our dataset is the first publicly available volleyball player location and event dataset for performance analysis.

3.1.1 Videos

In this study, we selected and analyzed 13 match videos uploaded to the YouTube channel "Volleyball Watchdog". We chose these videos because they were all filmed with a fixed camera positioned behind the end line, providing a relatively clear view of all six players on each team. All videos had a frame rate of 30 fps. The beginning and ending frames of sequences in which a serve, reception, set, and back-row attack occurred were recorded in a spreadsheet. Based on these records, 103 video clips were extracted using the free software Aviutl.

3.1.2 Video Annotation

We performed automatic tracking using basketball-SORT (Hu et al., 2024) on the split videos. Basketball-SORT is an object detection approach specialized for tracking basketball plays, designed to resolve complex occlusion issues involving multiple objects by utilizing players' trajectories and appearance features. The tracking results contained errors such as multiple IDs assigned to a single player, ID swaps between different players, and incorrectly sized bounding boxes (Figure 2). We corrected these issues manually using Labelbox, an online annotation software.

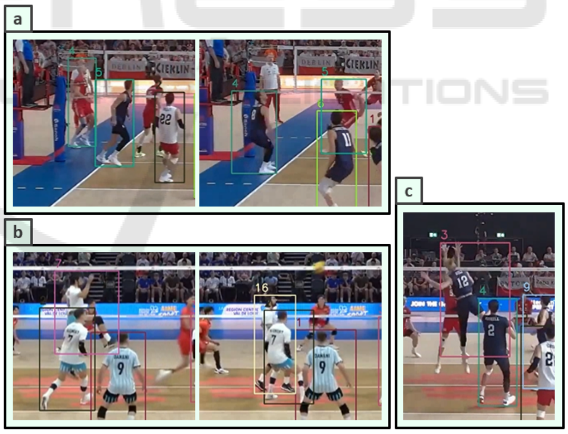

Figure 2: Examples of errors in tracking. (a) is an example of the ID being swapped. (b) is an example of a player with multiple IDs. (c) is an example of an incorrectly sized bounding box.

3.1.3 Acquisition of Player Coordinates

Based on the corrected bounding box data, we applied a homography transformation to obtain player coordinates on a 9 m $\times$ 9 m court. We used the center of the bottom edge of each bounding box as the reference point for player coordinates. Additionally, during the homography transformation, the coordinates of the four corners of the court were manually recorded in advance and used as reference points (Figure 3). The transformed coordinate data had issues such as interruptions in tracking data when players moved off-screen and fluctuations in the y-coordinates due to jumping. To address tracking interruptions, we applied linear interpolation using the last known coordinates before a player exited the screen and the first detected coordinates upon their return. To correct fluctuations in the y-coordinates, We checked frames immediately before takeoff and after landing manually, and performed linear interpolation using the recorded coordinates at these points. After these corrections, we smoothed the coordinate data to mitigate abrupt velocity changes caused by manual annotation adjustments. A moving average with a window width of 5 was applied for smoothing.

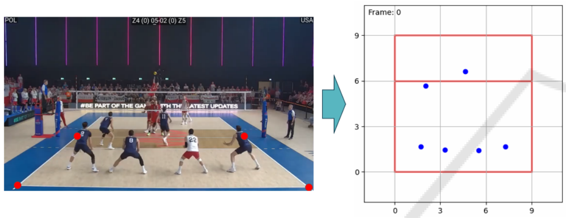

Figure 3: By performing a homography transformation based on the four red points shown on the left, we obtained the coordinates on the coat as shown on the right.

3.1.4 Event Annotation

For each of the videos, we recorded the frame number at which each event occurred, the ID of the player who executed it, the time elapsed between events, the attacker's jump time, and the attack result. The three types of events considered here are receive, toss, and attack. The player ID was assigned based on the created coordinate data.

3.2 Proposed Method: V2SEP

Here we show a quantitative framework to evaluate the impact of individual volleyball plays on rally outcomes.

3.2.1 Preprocessing

In this study, we computed evaluation indices based on the VDEP concept proposed in previous study (Toda et al., 2022). As a preliminary step, we created a dataset for predicting attack outcomes by calculating the movement speed and direction of all players at the moment of an event, using their position data and event information. To compute these values, we first extracted the five frames before and after the event frame. The movement speed was calculated as the average speed over these ten frames, while the movement direction was determined by calculating the direction from the player's coordinates in the first frame to those in the last frame. For the five players other than the one performing the event, we calculated both their distance from the event-performing player and the direction to that player, then sorted them by distance. Finally, for each event, we compiled the event-performing player's coordinates, movement speed, and direction at the time of the event, as well as the other players' coordinates, movement speed, direction, and their distance and direction relative to the event-performing player. We stored the compiled data in a CSV file.

3.2.2 V2SEP

We propose V2SEP to evaluate volleyball play. Specifically, we apply the VDEP methodology to volleyball and modify it to evaluate the process of attack. In this study, we extracted the scenes from the opponent's serve, receive, toss, and attack. Hereafter, the game states in which the attack outcome is predicted are called the receive, toss, and attack states, respectively, and are given by the states $s_i = [s_{receive}, s_{toss}, s_{attack}]$. We define the future probability of scoring $P_{point}(s_i)$ and the probability of an opponent block by two or more players $P_{blocked}(s_i)$ (hereafter called the block probability) in each state. The attacking team is preferred to act so that $P_{point}(s_i)$ is higher or $P_{blocked}(s_i)$ is lower. Therefore, we propose the following formula to calculate the evaluated value of play.

$$V_{V2SEP}(s_i) = P_{point}(s_i) - C * P_{blocked}(s_i) \tag{1}$$

C is a parameter that weights the scoring probability and blocking probability. In the collected data, there were 41 videos where two or more players blocked during an attack, and in 15 of those cases, the attaching team lost the point due to a block. Thus, $\frac{15}{41} \simeq 0.366$, so we set $C = 0.366$.

3.2.3 Probability Prediction Method

For the classifier to predict probabilities, we used eXtreme Gradient Boosting (XGBoost), following previous studies. Gradient boosting methods are known to perform well on a variety of learning problems involving heterogeneous features, noisy data, and complex dependencies. For the features used to predict the probability in a state, we assumed that not only the features in that state but also all the previous features were used. Specifically, the features of the receiving and tossing states were used to predict the probability of the tossing state, and the features of the receiving, tossing, and attacking states were used to predict the probability of the attacking state. For the attack result, we defined *point* and *blocked* as labels to record whether a point was scored as a result of a back-row attack and whether two or more opponents jumped for a block against the attack, respectively. If the attack results in a score, $point = 1$ is assigned, and if the attack fails to score, $point = 0$ is assigned. Similarly, $blocked = 1$ was assigned when two or more opponents jumped for a block. In the data created for this study, out of 103 videos, there were 52 videos with $point = 1$ and 51 videos with $point = 0$. Additionally, 42 videos had $blocked = 1$, and 61 videos had $blocked = 0$.

3.2.4 Validation

Since the method proposed in this study assumes that the predictions made by the classifier are valid, it is necessary to first verify that the classifier is making valid predictions. In addition, by visualizing the degree of influence in the prediction, it will be possible to assess which features have the most influence and to what extent. Therefore, we calculated F1 scores and SHAP values for the score and block predictions in each state, respectively. Next, two verifications are performed to determine whether the calculated evaluation values work as expected. In the first verification, we divided the data into four groups based on the result labels *point* and *blocked*, and calculated the average evaluation value for each group. In the second verification, we compared the calculated evaluation values with the actual footage to qualitatively determine whether the evaluation values are legitimate. Scenes that are prone to receiving unjustified evaluation values are then investigated to identify areas for improvement in the proposed method.

4 EXPERIMENTS

4.1 Validation of the Models

The proposed method (V2SEP) in this study assumes that the attack result predictions are valid. Therefore, we first calculated the F1 score for both the score and block predictions. The results are shown in Table 1. In both predictions, the F1 score gradually increased, which was consistent with our intuition that the attack result becomes more predictable as the game progresses.

Next, feature importance was visualized and qualitatively analyzed by calculating SHAP values. SHAP values quantify how each feature contributes to a paticular prediction, showing how each variable influences the model's output. Figure 4 and Figure 5 shows the top-ranked feature importance in the attack state. For the estimation of scoring probability in the attack state, the features of players who performed back-row attacks tended to have higher absolute SHAP values than those of players who made tosses. On the other hand, for the estimation of block probability, the features of players who made tosses tended to have larger absolute SHAP values. In both predictions for the attack state, 14 or 15 of the top 20 features with the highest absolute importance values belonged to players who were not directly involved in the event, confirming that the movements of such players have a significant impact on the prediction.

Table 1: Evaluation Results for *point* and *blocked*.

	receive	toss	attack
point	0.501	0.531	0.553
blocked	0.493	0.633	0.647

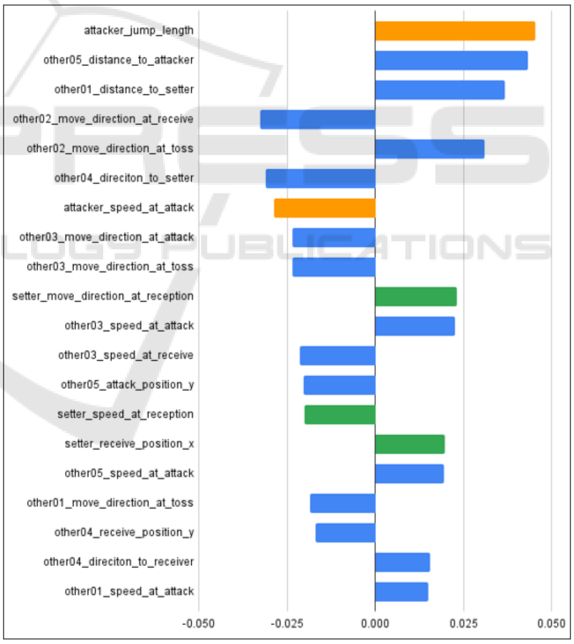

Figure 4: Top 20 absolute SHAP values of features in attack events for score predictions. Orange indicates the feature values for the player who attacked, green for the player who tossed, yellow for the player who received, and blue for the other players.

4.2 Validation of Evaluation Values

We conducted two validations to determine whether the evaluation values calculated based on V2SEP functioned as expected. First, we divided the data

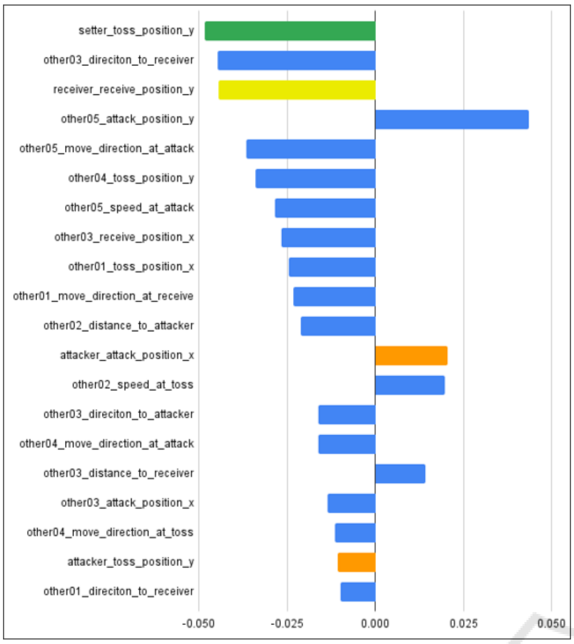

Figure 5: Top 20 absolute SHAP values of features in attack events for block predictions. Orange indicates the feature values for the player who attacked, green for the player who tossed, yellow for the player who received, and blue for the other players.

into four groups based on the attack result labels, *point* and *blocked*, and calculated the average evaluation value for each group. The results are shown in Table 2. When comparing the evaluation values in the receiving state, although the group with $point = 1, blocked = 0$ had a lower value, there was no significant difference between the groups. However, the differences became more pronounced as the game progressed toward the attack state. Furthermore, when comparing the two groups where $point = 1$, the group with $blocked = 0$ had a higher average evaluation value. Similarly, for the two groups where $point = 0$, the group with $blocked = 0$ also had a higher average evaluation value.

Table 2: The average evaluation value for each group.

	receive	toss	attack
$point = 1, blocked = 0$	0.332	0.352	0.362
$point = 1, blocked = 1$	0.357	0.307	0.333
$point = 0, blocked = 0$	0.365	0.317	0.316
$point = 0, blocked = 1$	0.352	0.305	0.281

Next, we visually and qualitatively analyzed whether each video had a valid evaluation value. Specifically, we compared the calculated evaluation values with the actual footage, selected scenes where the evaluation was clearly justified or unjustified, and examined trends in scenes that were particularly prone to unjustified evaluation values. For this analysis, we used the following criteria: whether there was any disruption in movement during receiving or tossing, whether the setter (who tosses the ball directly leading to an attack) was forced to move due to a disrupted receive, and how many players participated in the attack.

First, an example of a scene that received a correctly high evaluation is shown in Figure 6. In this case, the evaluation values were 0.449 for the receiving state, 0.517 for the tossing state, and 0.579 for the attacking state. When checking the frames before and after the tossing state, the movement of the player making the toss appeared relatively smooth, with three front-row players and one back-row player participating in the attack. Furthermore, from the tossing state to the attacking state, the opponent's blockers were drawn toward the two front-row players, leaving the back-row attacker unblocked.

Figure 7 shows an example of a scene that received a correctly low evaluation. In this case, the evaluation values were 0.483 for the receiving state, 0.086 for the tossing state, and -0.025 for the attacking state. While there was no significant disruption in movement during the receiving state, the unsuccessful receive forced the tosser to make a toss while moving backward from the edge of the court. The toss then went to a back-row player, but due to its predictable trajectory and the delay between the toss and the attack, the attacker was blocked by three opponents.

Figure 8 shows an example of a scene with an unjustified evaluation. In this situation, the 6th player was originally supposed to make the toss, but due to a disrupted receive, another player was forced to do so. Additionally, tossing from a position far from the net limits the attack patterns and increases the likelihood of a block, meaning this scene should have received a lower evaluation.

5 DISCUSSIONS

This section discusses the validity of the prediction model and the proposed method (V2SEP) based on the analysis results from the previous section. Table 1 shows that the F1 score tends to improve as the game progresses and the number of features used for prediction increases. In particular, the F1 scores for predictions in the attack state were 0.553 for score prediction and 0.647 for block prediction. Considering the difficulty of predicting outcomes in team sports, these can be regarded as relatively accurate predictions.

The analysis of SHAP values in Figure 4 and

Figure 6: Examples of scenes with correctly high ratings. From left to right: receiving state, tossing state, and attacking state.

Figure 7: Examples of scenes with correctly low ratings. From left to right: receiving state, tossing state, and attacking state.

Figure 8: Examples of scenes with incorrect evaluation values. From left to right: receiving state, tossing state, and attacking state.

Figure 5 suggests that the attacker's movement has a greater influence on whether a point is scored, while the setter's movement has a greater influence on whether the opponent blocks. Furthermore, among the top 20 features ranked by SHAP value, information from players not directly involved in the event also impacted the prediction. This indicates that the proposed method can incorporate the movements of players who are not directly involved in the event into its evaluation. However, the SHAP values for features related to players not directly involved in the event tended to be larger than those for features related to setters and attackers, suggesting that the influence of non-involved players may be overly emphasized.

Table 2 also confirms that as the game progresses, differences emerge in the average evaluation values across groups. This aligns with the analysis of Table 1, which indicated that prediction accuracy improves as the game progresses. In the attack state, when comparing groups with the same *point* value, those with $blocked = 0$ tend to have a higher average evaluation value. Similarly, when comparing groups with the same *blocked* value, those with $point = 1$ tend to have a higher average evaluation value. These findings suggest that the evaluation values follow the expected trend to some extent.

In the qualitative evaluation based on matching with actual video footage, higher evaluation values were often assigned to scenes in which the player successfully guided the opponent's block (Figure 6) and scenes where multiple players were involved in the attack (Figure 7), confirming a certain level of validity. On the other hand, there were cases where evaluation values were not assigned correctly. For example, higher-than-expected evaluation values were given in scenes where the number of players able to participate in the attack decreased due to a loss of balance after receiving (see figure) and in scenes where the setter was unable to make the toss (Figure 8). The former issue is likely due to the fact that changes in player coordinates were small for both stable and unbalanced receptions, making it difficult for the model to distinguish between them. Additionally, since there were only a limited number of scenes where a player lost balance during receiving, the dataset appears insufficient for considering the impact of reception stability on attack outcomes. The latter issue likely arises from the fact that the dataset used in this study does not distinguish players by specific positions, such as front/rear or left/center/right, and does not explicitly identify the setter's movements.

Aside from these issues, this study limited the target scenes and created the dataset by extracting footage from matches of multiple teams, making team-by-team comparisons difficult. To enable such comparisons, it would be necessary to construct a dataset by focusing on specific teams and selecting target scenes accordingly. Furthermore, since this study focused solely on back-row attacks against opponent serves, its general applicability remains undiscussed. To confirm whether the proposed method can be applied to other situations, its validity must be verified by expanding the range of target scenes.

6 CONCLUSIONS

In this study, we evaluated plays in each state based on a prediction model for the outcomes of back-row attacks in volleyball. To assess play performance, we proposed V2SEP, which utilizes the probability of scoring—estimated based on features in each state—as well as block prediction. We then verified the validity of the calculated evaluation values. Given that volleyball is a team sport where outcome prediction is inherently difficult, the prediction model was found to be reasonably accurate. Although some scenes were still not evaluated appropriately, the calculated evaluation values demonstrated a certain degree of validity and generally followed the expected trends.

Future challenges include distinguishing players by specific positions when inputting features for prediction and verifying the general applicability of the proposed method by extending the target scene to cover the period from the opponent's serve until the ball drops. Additionally, to generate prediction data more efficiently, it is necessary to develop a volleyball-specific tracking method or automate the modification of tracking data.

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