# Stroke Analysis in Wheelchair Tennis Based on Wheelchair Recognition and Skeleton Estimation

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Abstract: Objective performance analysis in para-sports is essential for evidence-based training, yet sensor-based approaches in wheelchair tennis face practical limitations and cannot fully capture the complex interactions among the wheelchair, player, and ball. This study proposes a comprehensive, non-contact stroke analysis framework based on single-view match video. First, a novel three-dimensional wheelchair localization method is introduced to estimate precise court coordinates. Wheel regions are detected using RF-DETR, and perspective correction is applied to project the wheelchair position into the court plane, overcoming inaccuracies associated with conventional two-dimensional bounding box–based methods. Second, 97 quantitative features are extracted by integrating multimodal information from the video. These features include wheelchair kinematics derived from the estimated 3D positions, upper-body skeletal motion obtained via RTMPose, and ball trajectory parameters tracked using TrackNetV3. This representation captures the interdependent dynamics of wheelchair operation, player movement, and ball behavior. Third, a machine learning–based model is constructed to classify stroke effectiveness into three categories: "Win," "Continue," and "Lose." Validation using match data from the Japan Open 2025 shows that, among the classifiers evaluated (including Random Forest and LightGBM), the Random Forest model achieves an accuracy of 78.18%. Feature importance analysis indicates that ball return speed is the feature most strongly associated with stroke effectiveness. The proposed framework enables practical, video-based performance evaluation without wearable sensors.

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## 1 INTRODUCTION

Wheelchair tennis is a major event at the four Grand Slam tournaments and the Paralympic Games, and is a popular sport with growing professionalization. Although the emergence of young talent has increased the number of players in recent years, many beginners struggle to acquire the necessary skills because of physical constraints.

Consequently, the demand for scientific analysis is high, and there is a strong need for methods that capture match situations and analyze the strokes that directly lead to points. In the scientific analysis of wheelchair tennis, conventional wearable sensors (Ju et al., 2021; van der Slikke et al., 2020) suffer from limitations in the data they can acquire and from restrictions on their use in official matches, which makes the establishment of video-based analysis methods indispensable. Recent advances in image analysis technology (Ferlinghetti et al., 2024) have enabled comprehensive, non-contact evaluation that integrates the player, the wheelchair, and the ball. In particular, stroke analysis that takes into account the high-intensity nature of the sport (Croft et al., 2010) and whole-body coordination (Papageorgiou, 2021) is strongly desired because it directly contributes to improving practical match performance.

The decisive difference between able-bodied tennis and wheelchair tennis is that the wheelchair functions as a part of the player's body. Whereas able-bodied players exploit lower-limb drive and trunk rotation, in wheelchair tennis the simultaneous control of the wheelchair's position, orientation, and direction of movement determines the power and accuracy of a shot.

When analyzing the characteristics of strokes that directly lead to points, what matters is not merely whether the swing succeeds, but how efficiently the momentum of the wheelchair is transferred to the ball at the moment of impact. In other words, the ability to operate the wheelchair as an integrated part of the body, achieving both optimal positioning and an effective hitting motion, is considered a key characteristic of strokes that contribute to winning points.

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In this study, we propose a new method that evaluates strokes by integrally analyzing information on the player's upper-body skeleton, the wheelchair, and the ball obtained from wheelchair tennis match videos.

Specifically, the wheelchair position, the ball trajectory, and the player's upper-body skeleton are simultaneously extracted from single-view match video. For the wheelchair, we propose a method that estimates its position and direction of movement in three-dimensional space from the appearance of the wheels in the two-dimensional image, namely their size and position on the screen.

Furthermore, stroke evaluation features are computed by integrating this information, and a stroke effectiveness evaluation model is constructed by machine learning that automatically classifies each stroke into three categories: strokes that directly contribute to winning a point, strokes that continue the rally, and strokes that lead to losing a point through the player's own error. Through this framework, we aim to clarify the qualities of strokes that contribute to scoring.

# 2 RELATED WORK

## 2.1 Current State of Para-Sports

In recent years, the use of artificial intelligence (AI) and image analysis technology has advanced rapidly in sports science, enabling motion analysis of athletes, strategy planning, and quantification of training effects (Reis et al., 2024; Naik et al., 2022). In basketball, for example, studies have evaluated player performance to quantify each player's contribution to the team (Gutiérrez, 2024), and methods have been developed that recognize two-point and three-point shots to classify player abilities (Huang and Chen, 2023). In soccer, techniques for detecting, classifying, and tracking the ball, players, and referees in match videos have also been developed (Naidoo and Tapamo, 2006; Liu et al., 2009).

This wave of technological innovation has also reached para-sports. Para-sports originated as part of rehabilitation after World War II and have since developed into full-fledged competitive sports (DePauw and Gavron, 2005). Today they attract growing attention not only in Japan but also internationally (Brittain et al., 2023). Against this background, there is a strong demand for scientific evidence that enables athletes with disabilities to perform at a high level and to compete fairly (Paulson and Goosey-Tolfrey, 2017; Laferrier et al., 2012). Para-sports have special rules and techniques that reflect the influence of physical impairments on competition, and it is therefore difficult to simply apply motion analysis methods developed for able-bodied athletes. Establishing objective motion analysis methods tailored to the characteristics of each event is thus essential for the further development of para-sports (Seron et al., 2019; Sánchez-Pay and Sanz-Rivas, 2021).

## 2.2 Differences between Wheelchair Tennis and Able-Bodied Tennis Strokes and the Assessment of Stroke Quality

The strokes of wheelchair tennis and able-bodied tennis differ fundamentally because of the rules, the equipment used, and the constraints on body movement (Sánchez-Pay and Sanz-Rivas, 2021).

First, the rules differ. In wheelchair tennis, the ball remains in play after bouncing twice, and the player may return it at any time before a third bounce occurs (Sánchez-Pay et al., 2020). This rule gives players considerably more time to return the ball. At the same time, however, this extra time increases the complexity of timing decisions, making the tactical ability to read the opponent's intention and choose the optimal moment to hit even more important.

Second, the wheelchair functions as a part of the player's body. When executing a stroke, the player must simultaneously control the wheelchair's position, orientation, and direction of movement. Whereas able-bodied players stabilize their trunk through footwork, wheelchair tennis players fix their trunk by operating the wheelchair brakes or gripping the hand rim, thereby building a stable base for the stroke (Ju et al., 2021; Rietveld et al., 2023).

Third, there are technical constraints on the backhand stroke. Because most players operate the wheelchair with one hand, the two-handed backhand is difficult to execute; as a result, one-handed slice shots that prioritize control and accuracy over power are frequently used (Sánchez-Pay et al., 2017).

Given these differences, assessing the effectiveness of a wheelchair tennis stroke requires the integrated evaluation of multiple indicators. The first indicator is the choice of hitting timing: with two bounces allowed, the decision of at what distance relationship to the ball the stroke should be executed becomes important (Sánchez-Pay et al., 2020). The second indicator is the distance and relative position between the ball's landing point and the player; the player must predict the ball trajectory, instantly determine the hitting point that can be reached most effi-

ciently, and execute the stroke at the optimal location. The third indicator is the most direct criterion: the contribution to winning or losing a point (Sánchez-Pay et al., 2015). Combining these indicators makes it possible to assess stroke quality objectively.

### 2.3 Research on Able-Bodied Tennis

Human keypoint detection has evolved from early handcrafted-feature and regression-based approaches to CNN-based heatmap estimation (Wei et al., 2016), and more recently to end-to-end methods using vector-field representations and Transformers (Vaswani et al., 2017; Chen et al., 2023). These techniques have been widely applied in sports, not only for motion analysis and match recording but also for performance evaluation, injury prevention and rehabilitation support, refereeing assistance, and training optimization (Roggio et al., 2024). For tennis, reported studies include a method that predicts a player's movement trajectory from pose sequences using a Transformer (Vaswani et al., 2017; AlShami et al., 2023), tennis action recognition based on 3D video (Ning and Na, 2021), and a real-time system that classifies swings using a racket-mounted sensor (Ma, 2021). In addition, a deep generative model that forecasts the next shot location from time-series player motion data (Fernando et al., 2020), and a study (Mora and Knottenbelt, 2017) that classified fine-grained tennis actions with high accuracy using a three-layer LSTM network (Hochreiter and Schmidhuber, 1997) fed with image features extracted by Inception (Szegedy et al., 2015), have also been reported.

### 2.4 Research on Wheelchair Tennis

Wheelchair tennis shares its basic rules and tactical structure with able-bodied tennis, so the studies above provide important references. However, the movement modality of swinging a racket while operating a wheelchair differs substantially, which changes both how techniques are used and how loads are distributed over the body. Wheelchair tennis therefore needs to be treated as a distinct subject when designing motion analysis and recognition methods.

In wheelchair sports, the application of sensor technology to compute performance indicators during matches has been reported (Shepherd et al., 2018; Weizman et al., 2024). In particular, inertial measurement units (IMUs) attached to the wheelchair frame have been used to evaluate mobility performance during matches (Rietveld et al., 2024; Rietveld et al., 2023), and attempts have been made to measure mobility performance in wheelchair court sports (van der Slikke et al., 2020). IMUs attached to players have also been used to quantify trunk and shoulder motion and upper-limb vibration during strokes, aiming to assess upper-limb load and injury risk (Ju et al., 2021).

Meanwhile, an increasing number of studies use image analysis to extract match and player information from video. Examples include a method that reconstructs the three-dimensional court space from multi-view video to learn and support wheelchair tennis players' navigation (Wu et al., 2025), and a method that estimates the direction of hand contact with a marker-less vision system to analyze wheelchair propulsion (Ferlinghetti et al., 2024). Furthermore, recent progress in monocular 2D and 3D pose estimation (Liu et al., 2022) can serve as a foundation for automatically estimating keypoints of the wheelchair and the player, enabling detailed motion information to be extracted from match videos.

## 3 PROPOSED METHOD

### 3.1 Three-Dimensional Wheelchair Localization

When tracking a player's movement from tennis court video, the center of the bounding box produced by an object detector is commonly used. In wheelchair tennis, however, the shape of the bounding box changes dynamically with the player's posture and the wheelchair's orientation, so the computed center deviates non-negligibly from the actual ground-contact center of the wheelchair.

To address this problem, the proposed method detects the wheels of the wheelchair individually. By analyzing the shape and size of the wheels, the spatial relationship based on perspective is identified, and the true center of the wheelchair is inferred in three dimensions. This enables accurate reconstruction of the player's spatial trajectory on the court plane.

### 3.2 Stroke Evaluation Features

Next, features that determine stroke quality are extracted through image analysis. The analysis unit is a time series of 21 frames, consisting of the 10 frames before and after the moment of impact between the racket and the ball. All extracted coordinates (ball, wheelchair, and player skeleton) are first transformed from image coordinates to real-world coordinates by homography, and features concerning the wheelchair motion, the ball behavior, the wheelchair-ball rela-

tionship, and the player's upper-body skeleton are defined on the basis of physical Euclidean distances. Details of the features are described in Section 6.

### 3.3 Stroke Effectiveness Evaluation Model

Using the collected dataset, each stroke outcome is classified into three classes: Win (a stroke that directly contributes to winning a point), Continue (a stroke that keeps the rally going), and Lose (a stroke that leads to losing a point through the player's own error). Multiple machine learning algorithms are applied and compared in terms of prediction accuracy to optimize the model. By analyzing the predictions of the constructed model in detail, we identify which features contribute most to stroke quality.

## 4 INFORMATION EXTRACTION FROM VIDEO

To collect and organize the necessary data efficiently, the following video analysis pipeline is prepared.

First, the court region is identified by line detection using the Hough transform. The major lines of the tennis court are accurately extracted (Figure 1), providing the correspondence points required for the homography transformation.



Figure 1: Major line extraction of tennis court.

Next, RF-DETR (Robinson et al., 2026) is adopted for high-accuracy wheel detection. The model is trained on a dedicated wheel dataset built from wheelchair tennis videos to improve detection accuracy.

The player's upper-body skeleton is defined by 10 keypoints, namely the head, neck, and waist, the left and right shoulders, elbows, and wrists, and the racket, as shown in Figure 2. The CSPNeXt-L model of RTMPose (Jiang et al., 2023) is selected and fine-tuned from weights pre-trained on the AIC (Wu et al., 2017) and COCO (Lin et al., 2014) datasets. As a result, the pose estimation accuracy reached 99.38% (Figure 3), enabling accurate extraction of the upper-body posture from match videos (Figure 4).

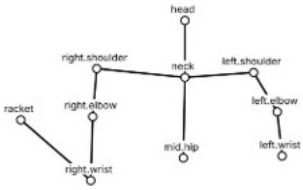



Figure 2: Upper-body skeleton structure.

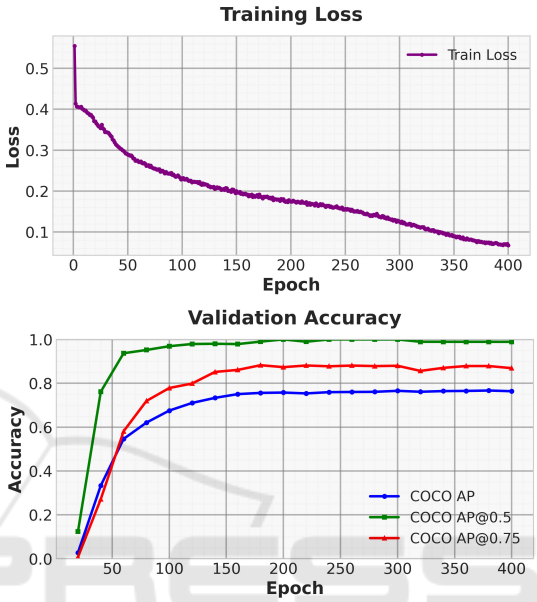



Figure 3: Changes in loss and accuracy during RTMPose training.



Figure 4: Extraction of upper body posture.

For ball detection and tracking, TrackNetV3 (Chen and Wang, 2023) is adopted and trained on the existing WASB (Tarashima et al., 2023) tennis ball dataset. As shown in Figure 5, the accuracy on the validation data reached 95.13%, allowing the trajectory of the fast-moving ball to be acquired stably and accurately.

By integrating these tools and trained models, we establish an analysis platform that consistently extracts court coordinates, wheelchair positions, upper-body skeletons, and ball trajectories from wheelchair tennis videos with high accuracy.

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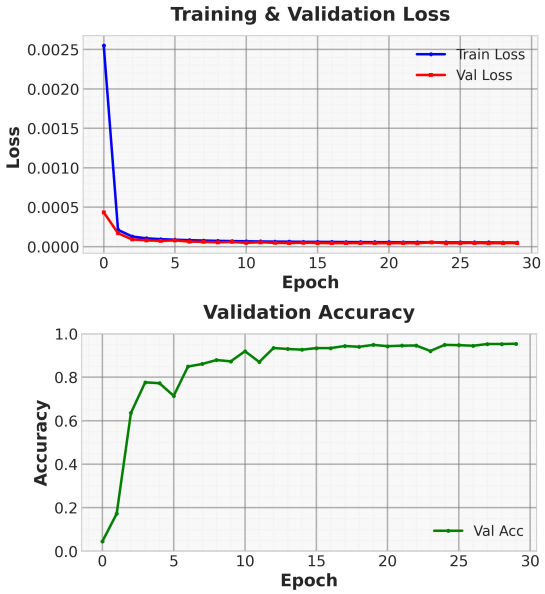



Figure 5: Changes in loss and accuracy during TrackNetV3 training.

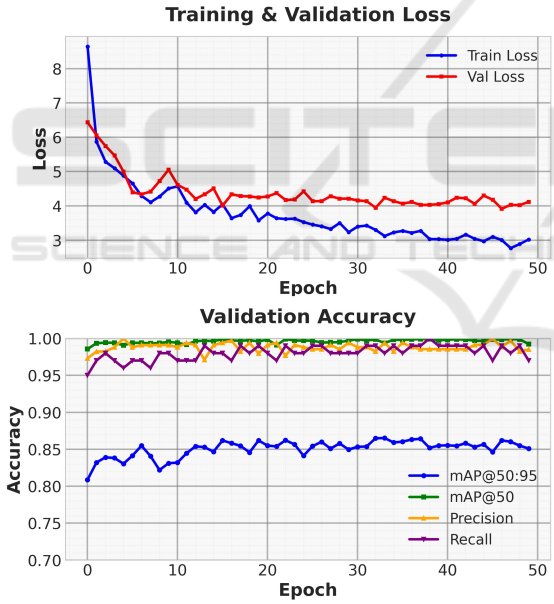



Figure 6: Changes in loss and accuracy during RF-DETR training.

## 5 IMPLEMENTATION OF THREE-DIMENSIONAL WHEELCHAIR LOCALIZATION

For the wheel detection model, RF-DETR (Robinson et al., 2026), which excels at real-time object detection, was adopted. Specifically, RF-DETR-m, a model with 33.7M parameters, was selected and fine-tuned for wheelchair wheel detection. As shown in Figure 6, the trained model achieved 0.8510 in mAP@50:95, 0.9924 in mAP@50, and 0.9850 in precision, demonstrating high detection capability.

To estimate the three-dimensional position of the wheelchair, the points where the detected left and right wheels touch the ground are used as reference positions. Taking perspective into account, the geometric center of the wheelchair is then computed using the side-length ratio of the bounding boxes (Figure 7).

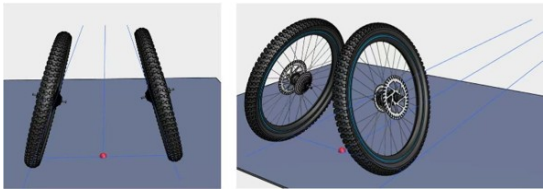


Figure 7: Observation of wheel shapes from multiple perspectives.

Figure 8 compares the center point computed with the proposed perspective correction (red dot) with the bottom center of the bounding box obtained by simply detecting the whole wheelchair.

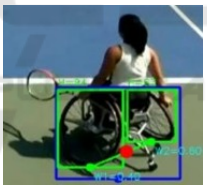


Figure 8: Estimated geometric center of wheelchair.

## 6 COMPUTATION OF STROKE EVALUATION FEATURES

To construct the dataset, the 10 frames before and after the moment of impact, i.e., 21 frames in total (about 0.7 sec), are grouped into one analysis unit.

The three-dimensional wheelchair positions described above, the ball coordinates, and the coordinates of the 10 upper-body skeleton keypoints are transformed from the image coordinate system to the real-world coordinate system by homography. As a normalization step, the Euclidean distances from the origin (maximum and mean) are computed. The features are extracted as follows.

Wheelchair features (12 dimensions): in addition to the maximum speed, mean speed, and standard de-

viation of speed, the frame-to-frame movement direction, the total travel distance, and the straight-line distance (displacement) between the start and end positions together with its angle are computed.

Ball features (16 dimensions): focusing on the behavior before and after impact, the mean speed, maximum speed, and direction are extracted for the incoming and the returned ball, respectively. In addition, the changes in speed and direction caused by the impact and the total flight distance are used.

Wheelchair-ball relationship (3 dimensions): to capture their interaction, the angular difference (absolute value) between the movement directions of the wheelchair and the ball, and their relative distance, are added as features.

Upper-body skeleton features (66 dimensions): for each of the 10 keypoints, the confidence values (maximum and mean), the travel distance, the Euclidean distance from the origin, and the standard deviation of the x- and y-coordinates are computed, yielding 60 dimensions. In addition, six dimensions describing physical movement characteristics are added: the extension of the upper limbs (shoulder-elbow-wrist), the racket-arm distance, the ball-racket distance, and the inclination of the body.

In total, a 97-dimensional feature vector integrating the above is constructed and used as the input to the models.

# 7 EXPERIMENTS ON STROKE EFFECTIVENESS EVALUATION

In this study, 30-fps match videos from the Japan Open 2025—a Super Series event on the ITF UNIQLO Wheelchair Tennis Tour and thus contested by top-ranked professional players—were used, and 273 strokes were extracted from eight matches involving eight players and labeled as Win, Continue, or Lose (Table 1). For each stroke, the stroke evaluation features described above were computed for use as input to the machine learning models. To reduce the influence of outliers in the features on training, outlier removal based on the interquartile range (IQR) was performed. Specifically, with Q1 and Q3 denoting the first quartile (25th percentile) and the third quartile (75th percentile), the IQR was computed as Q3 - Q1, and data outside the range [Q1 - 1.5×IQR, Q3 + 1.5×IQR] were removed as outliers. After outlier removal, the features were normalized, and the data were randomly split at the stroke level into 80% training and 20% test data; these preprocessing statistics were computed over the full dataset (see Limitations). Multiple machine learning models were trained on the training data and compared in terms of classification accuracy on the test data. We evaluated several classifiers, including Random Forest (Breiman, 2001) and LightGBM (Ke et al., 2017). In this paper we report the Random Forest model, which achieved a prediction accuracy of 78.18%. To evaluate the classification performance of Random Forest quantitatively, the confusion matrix on the test data is shown in Table 2.

Table 1: Strokes in the dataset.

| Class | Number |
|---|---|
| Win | 68 |
| Continue | 113 |
| Lose | 92 |
| Total | 273 |

Table 2: The confusion matrix of strokes on test data in percentage. Rows in true labels, columns in estimated labels.

| | Win | Continue | Lose |
|---|---|---|---|
| Win | 64.29 | 28.57 | 7.14 |
| Continue | 8.70 | 86.96 | 4.35 |
| Lose | 5.56 | 16.67 | 77.78 |

The feature importances computed by Random Forest, sorted in descending order, are shown in Figure 9. The results confirm that the return speed of the ball is the most important feature.

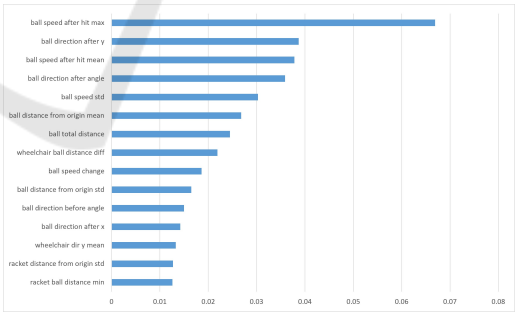



Figure 9: Feature importances by Random Forest.

# 8 DISCUSSION

## 8.1 Interpretation of Feature Importance

The feature importance analysis identified the return speed of the ball as the feature most strongly associated with the effectiveness class of a stroke. This

association should, however, be interpreted with care. A high return speed is not necessarily a direct cause of winning a point: it may co-vary with factors that were not explicitly controlled in this study, such as the speed of the incoming ball, the tactical context of the rally, the relative skill levels of the two players, and the behavior of the opponent. The importance scores therefore indicate which features are informative for the classifier, rather than establishing a causal relationship between any single feature and stroke outcome.

### 8.2 Practical Implications for Coaching

Despite this caveat, the framework offers several concrete possibilities for data-driven coaching. Because the model operates on interpretable, physically grounded features, its outputs can be traced back to specific aspects of a stroke. Coaches could use the estimated wheelchair trajectories to identify positioning problems and inefficient wheelchair movement, such as excessive travel distance or poor alignment between the wheelchair and the ball at impact; use the impact frame relative to the ball trajectory to detect suboptimal stroke timing; and combine the wheelchair–ball relationship features with the upper-body posture to characterize the ball-contact situations that tend to accompany successful and unsuccessful strokes. Because the analysis is fully video-based and non-contact, such feedback can in principle be produced from ordinary match footage without instrumenting the athlete.

### 8.3 Limitations

Several limitations should be noted. First, the dataset is small: it comprises 273 strokes from eight matches involving eight players, whereas the classifier uses a 97-dimensional feature vector. This imbalance between sample size and feature dimensionality entails a risk of overfitting, and the reported accuracy should be read in that light. Second, the 80/20 train–test division was a random split at the stroke level, so strokes from the same player or match may appear in both the training and the test sets; the reported accuracy therefore reflects within-distribution performance and may overestimate generalization to unseen players or matches. Third, the preprocessing statistics (IQR-based outlier removal and normalization) were computed over the whole dataset before the split rather than being fitted on the training partition alone, which may introduce a mild optimistic bias. Fourth, the stroke labels were assigned by a single annotator using the Win/Continue/Lose criteria defined above, and inter-rater agreement was not assessed. Fifth, the proposed three-dimensional wheelchair localization was evaluated only qualitatively; its accuracy was not validated against an independent ground truth in metric units. Finally, all data were drawn from a single tournament captured from a single viewpoint, and no external validation on independent data was performed. Addressing these points—through larger and more diverse datasets, player- and match-independent evaluation, an ablation study isolating the contribution of the wheelchair and body-movement features, and metric validation of the localization—remains important future work.

## 9 CONCLUSION

In this study, aiming to evaluate stroke quality in wheelchair tennis quantitatively and objectively, we proposed a method that integrally analyzes information on the wheelchair, the player, and the ball using only match video.

We developed a three-dimensional wheelchair localization method based on wheel detection and perspective-based correction. This enables the acquisition of more accurate wheelchair trajectories that do not depend on appearance changes in the video.

We defined 97-dimensional stroke evaluation features derived from the player's upper-body skeleton, the wheelchair motion, and the ball trajectory, and constructed a dataset using match data from the Japan Open 2025.

Finally, we constructed a model that classifies stroke outcomes into the three classes Win, Continue, and Lose. Among the classifiers evaluated, including Random Forest and LightGBM, the Random Forest model achieved a classification accuracy of 78.18%. In particular, the feature importance analysis revealed that the return speed of the ball is the feature most strongly associated with stroke effectiveness. This finding suggests that, in wheelchair tennis, maintaining a high ball speed rather than merely returning the ball may be an important characteristic of point-winning strokes; as discussed in Section 8, however, this is an association rather than a demonstrated causal effect, and it points to the potential of the framework for data-driven coaching.

The results of this study provide scientific evidence for optimizing training and developing tactics for wheelchair tennis players, and contribute to establishing a practical analysis system that supports performance improvement. A distinctive feature of this study is that it realizes detailed motion analysis and performance evaluation using only non-contact video

analysis, without requiring body-worn sensors. By capturing the interaction between wheelchair operation and hitting motion as integrated features, rather than treating them separately, the proposed approach enables an evaluation that reflects the characteristics specific to para-sports.

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