Moving towards Automating Badminton Player Feedback from Publicly-Available Match Videos

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May 1, 2022

1 Abstract

Badminton's relatively young age compared to other Olympic racket sports and high threshold for technical ability at the elite level hinders its global diversity. Often, countries new to the sport have to offer large monetary incentives to foreign coaches as a means of transferring knowledge, thus creating large inequalities between nations. The use of deep learning for video analysis have opened the possibility to derive insightful metrics from a large, publicly-available data set: full-length match videos. By building upon prior models and conducting a sensitivity analysis for predicting rally-by-rally winners as well as rally lengths, this paper outlines a framework for a semi-automated video match analysis pipeline to track player positions and poses and shuttlecock trajectories. As a case study, I highlight the differences within two badminton matches between Kento Momota and Viktor Axelsen before and after the COVID-19 pandemic to understand key differences in how their game play has evolved.

2 Introduction

2.1 Motivation

Despite being the world's fastest racket sport and hugely popular in many Asian countries, badminton's relatively young age compared to other Olympic racket sports and high threshold for technical ability at the elite level hinders its global diversity (Fig. 1). Performing at the elite level in badminton requires a diverse range of technical training ranging from racket skills to strategic game plans. However, the knowledge of successful training regimes is often kept as national secrets in the form of experienced coaches. This inequity of coaching expertise is further exaggerated by a major positive feedback loop in most sports: as top players from a few nations continue to improve by seeding in elite tournaments, lower-ranked players are stuck playing in less intensive tournaments and consequently, struggle to climb up the world rankings. Thus, some form of intervention at a national scale is necessary to break this feedback loop and enable badminton to diversify its global reach. The most common intervention is for nations that are new to badminton to incentivize experienced coaches to switch nations; however, such actions are highly inequitable towards developing countries that lack infrastructure in their national sports teams. A notable recent intervention to break this positive feedback cycle was taken by reigning Olympic champion Viktor Axelsen in inviting four players from several nations relatively new to badminton to join his training camp. His efforts resulted in Singapore's first badminton world champion in 2021 and two other players rapidly rising 14 places in the world ranking. This result further demonstrates the importance of making badminton match analyses into a publicly available asset for all players.

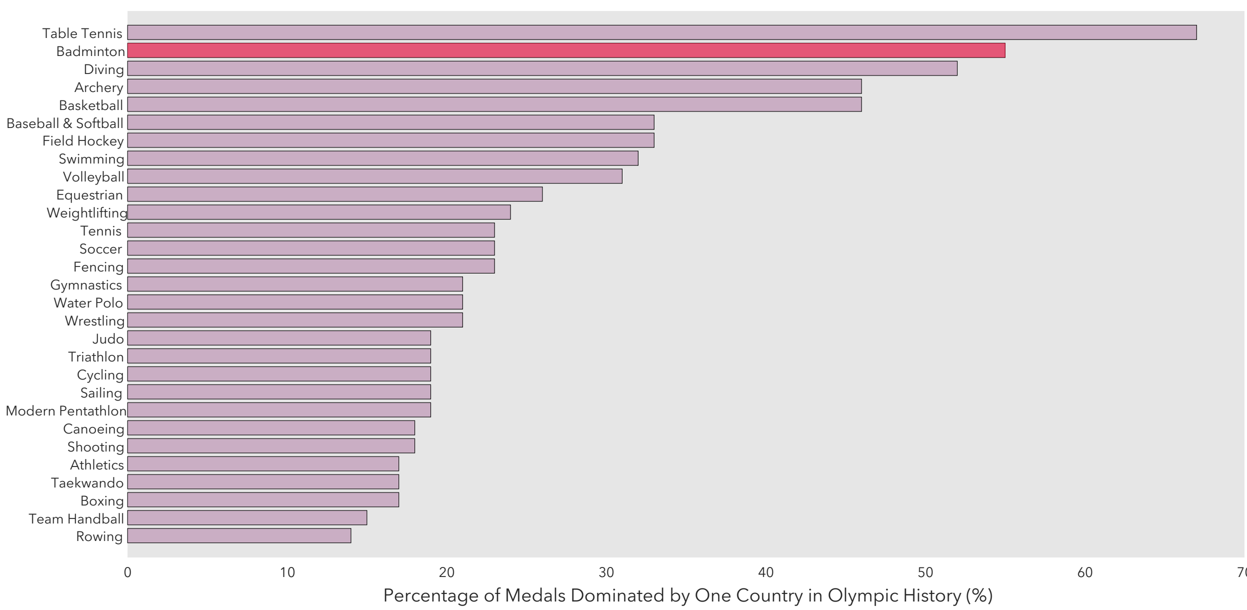

Figure 1: **Sport diversity leading up to the 2016 Rio Olympics (Gehrz, 2016)**. Note how over 50% of badminton medals have been won by a single nation, China, making it the second least diverse sport after table tennis.

Current statistics presented in matches are primarily limited to smash placement, speed, and rally length (BWF, 2021). However, the first two metrics solely describe the last shot played in a rally and lack contextual awareness of the shots preceding. At the elite level, rally length has a relatively small impact on rally outcomes due to players' stamina being significantly higher than amateur players. Thus, the currently available statistics in live match videos are quite limited in terms of providing useful information that would guide players' strategies and training.

2.2 Objectives

Having motivated the idea of increasing the accessibility of strategies and techniques in badminton, it is natural to turn to the recent rise of data science in sports to accomplish this task. Thus, I form the guiding research question of this paper as:

How can we leverage machine learning to build a pipeline that enables the generation of insightful analytics from publicly available badminton match videos?

To meet this need, I propose a scalable framework capable of generating automated analyses of large match datasets of single-view badminton matches to generate helpful analytics. While the output of this pipeline can be fed into an infinite number of models to generate numerous analytics, I narrow this work into predicting two specific quantities:

1. The winning player at the end of each rally (classification)
2. The length of a rally (regression)

A significant number of works discussed in Section 3 attempt predicting the outcome of matches given data on head-to-head encounters, player rankings, tournament locations, etc. However, these match prediction models cannot help guide a player's training regime since they do not carry any information of the process through which a player wins. Instead, predicting individual rally outcomes emphasizes the motions and shots that lead to a player winning, thus justifying the first response variable in the aforementioned list.

Every player's goal is to win a tournament, not an individual match. Given that players have a limited amount of energy and can only recover so much after every match, players must conserve their energy while winning the first few matches in a tournament to ensure sufficient resources to play the next match. Thus, determining the key metrics associated with predicting the length of a rally is crucial to informing players certain strategies to pursue.

2.3 Case Study: Kento Momota & Viktor Axelsen

The proposed pipeline in Section 4 is designed to be scalable to analyzing hundreds of videos by leveraging GPU performances. In this work, I specify the dataset as the encounters between two specific players: Kento Momota (JPN) and Viktor Axelsen (DEN) in 2020 and 2022.

The COVID-19 pandemic has impacted players worldwide in different ways. For some, the break from constant travel may be a well-timed opportunity to practice on improving skills and for others, the break may be detrimental to keeping up form. For approximately two years prior to the pandemic, Momota was dominant on the World Tour, setting a world record with 11 titles in 2019.

However, at the start of the tournament, Momota was involved in a tragic car crash, underwent two critical surgeries, and then caught COVID. Axelsen has always been a top player, but had a 1:13 win-loss record against Momota and also caught COVID during the pandemic. In the 2020 Olympics, the reigning world-champion Momota unexpectedly lost in the group stage and Viktor Axelsen became the new Olympic champion. As the Badminton World Federation began its return back to normally scheduled tournaments, Momota has struggled to recover back to his form from 2019, while Viktor Axelsen has been nearly undefeated since the pandemic began. These results qualitatively highlight how the COVID-19 pandemic and tragic events to Momota have impacted either of their abilities as players, but there lacks a quantitative analysis for their developments over the last two years. Thus, I use the proposed pipeline to analyze two of their matches before and after the COVID-19 pandemic: 2020 Malaysia Masters Final (won by Momota) and 2022 Denmark Open Final (won by Axelsen). Then, I conduct a sensitivity study on which metrics best predict rally-by-rally winners and rally length and discuss how the importance of these metrics differs between the two matches.

3 Literature Review

As discussed in the following literature review section, efforts have been made to leverage the advances in computer vision models and GPU hardware to extract more information from publicly available match videos. Forty of the top papers in Google Scholar given the key words [“badminton” AND [“strategy” OR “tracking” OR “analytics” OR “computer vision” OR “machine learning”]] were read and classified according to relevance to the project into the previously mentioned tasks of the proposed pipeline. Key points of each paper are provided in the appendix. While some papers have developed techniques to extract the shuttlecock (Chu Situmeang, 2017; Bingqi Zhiqiang, 2007) and others have detected the pose of players in a match (Hsu et al., 2019; Su Liu, 2018), there lacks a synthesis of these techniques into one generalized pipeline to process large batches of video data to extract insightful analytics from. If each paper is given a score based on the number of tasks it fulfills out of the following: scene detection, shuttlecock tracking, player detection, pose estimation, shot classification, and tactical insights, it is notable that there is a clear lack of an existing data pipeline into a predictive model incorporating all aspects of the game (Fig. 2).

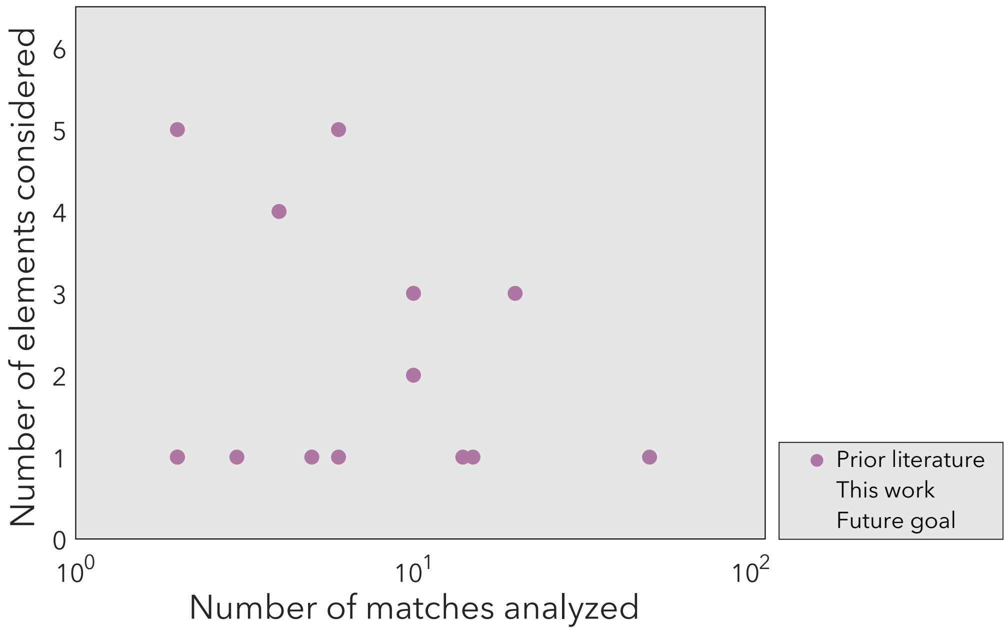

Figure 2: **Quantitative summary of prior literature relevant to analyzing badminton match data.** The six elements are: scene detection, shuttlecock tracking, player detection, pose estimation, shot classification, and tactical insights. Note the apparent trade-off between analysis complexity and the size of the dataset analyzed. This work aims to push the complexity of analysis done on a small dataset to the fullest to derive useful player analytics. I design all models with scaling in mind by reducing time and memory complexity wherever possible.

4 Methods

4.1 Datasets

The sole datasets into the pipeline are the following two match videos:

1. 2020 Malaysia Masters Final: https://www.youtube.com/watch?v=boQC4J4E1ZQ
2. 2022 Denmark Open Final: https://www.youtube.com/watch?v=W_Oi9TemBW0&feature=youtu.be

4.2 Video Processing Pipeline

The video processing pipeline takes as an input a match video and outputs player and shuttle positions as a time series vector for every rally. The players' positions not only encode data on their movement, but also shot placement and shot speed as their movement is dictated by having to return the shuttle before it touches the ground. The shuttle positions encodes data on the rally length and shot choice by each player. While, it is ideal to decode the data into individual shots, I simplify the pipeline into outputting processed time series of entire rallies. These are then converted into useful metrics in Section 5.1 via contextual feature selection. Thus, I specify the following modular tasks within the proposed pipeline:

1. **Scene detection:** A match video consists of overhead camera angles, slow-motion replays, audience reactions, player close-ups, etc. This module classifies the scenes corresponding to the overhead camera and then divides the rally up into individual rallies (Section 4.2.1).
2. **Background estimation:** Pose detection algorithms applied on the whole image identify players, line judges, umpires, and even audience members. Given the video of an individual rally, this module estimates the background image without players present to enable difference mapping to heigten contrast between players and the relatively static background.
3. **Pose & player detection:** This module detects the poses of every person, puts bounding boxes on every person, and then identifies the relevant players within a rally.
4. **Shuttle tracking:** This module tracks the shuttle during a rally. In future works, the shuttle position in image coordinates should be converted to 3D world coordinates; however, for this analysis, shuttle detection is used to detect the start and end of rallies.
5. **Camera calibration:** All measurements taken of player pose and position are in image coordinates. Given the constraint that their feet are approximately on the court floor, this module converts their position in image coordinates to world coordinates to reconstruct the rally.

4.2.1 Scene Detection

Given a full-length match video and the total number of rallies, I build a model capable of automatically classifying the scene as rally (1) or not-rally (0). While there exists methods to do so using CNN-based networks, I implement a simpler, less computationally expensive decision tree model that uses solely aggregate statistics of a frame and still achieves a very high accuracy of approximately 98%. As seen in Figure 3a, the algorithm first loops through every frame of the video and calculates the average R,G,B values across the entire image. I design the decision tree to classify the frame as part of a rally if all three R,G,B values lie within a certain threshold z-score of the mode of the R,G,B values in the entire match video. The algorithm automatically determines the threshold value by incrementally increasing it from 0 until the correct number of rallies is detected. Having segmented every frame, the algorithm applies morphological opening to remove short timescale false positive results (Fig. 3b). The final result is then passed to a GUI for the user to confirm whether or not the segmentation is correct. The process involving the user takes approximately 10 minutes per match video.

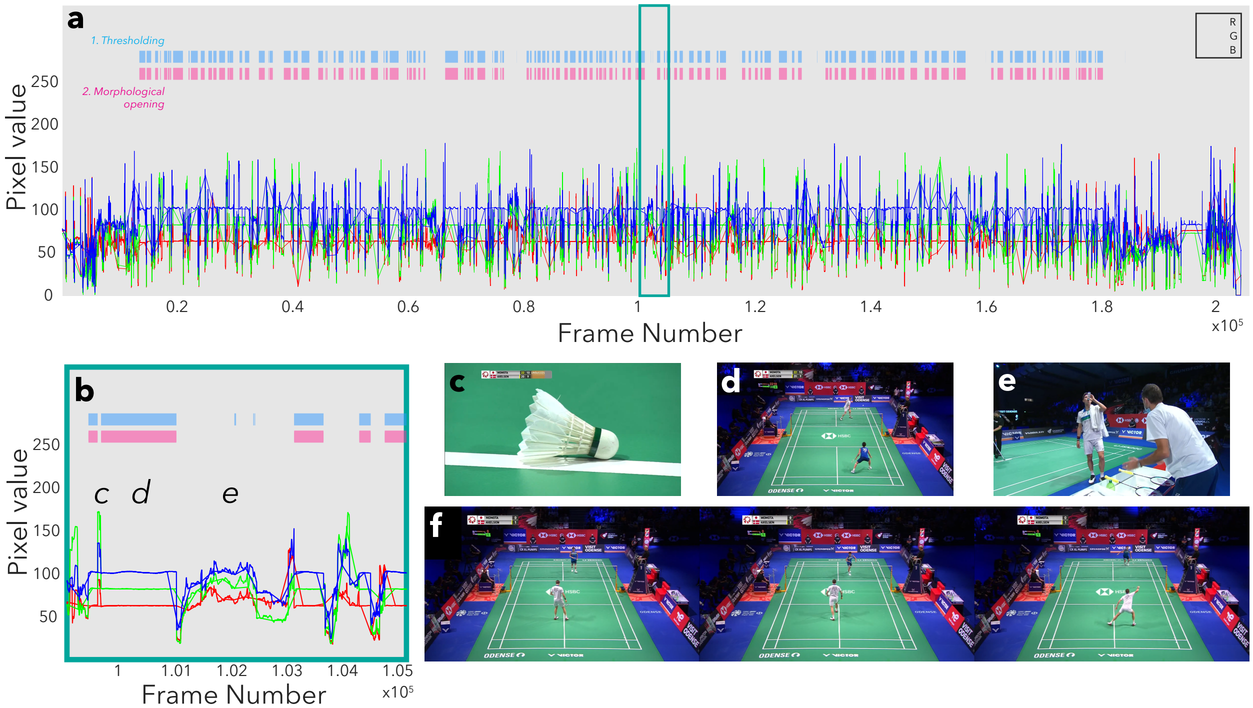

Figure 3: **Semi-automatic decision tree for scene detection.** (a) First, the model calculates the average R,G,B values for every frame in the video. If the average pixel intensities in a given frame lie within a range of the mean values, then the decision tree flags the frame as potentially in a rally (blue rectangles). Many short-timescale outliers are removed through morphological opening (pink rectangles). (b) Zoomed in plot of (a). (c)-(e) Three different cases for scenes: 'slow-motion replay', 'desired rally play', and 'other'. (f) The rallies that remain are passed to the user for confirmation that they are rallies by showing three evenly spaced frames of the rally. The accuracy prior to user confirmation is **98%**.

4.2.2 Background Estimation

The background estimation module is responsible for recreating an image that represents the background image of the rally video without the players present. Such an image is required to correctly identify which poses detected correspond to the players and which correspond to background entities or noise in the pose detection module (Section 5).

I build a mode-based background estimation model that, in the context of the relevant badminton rally videos, outperforms some popular ML-based methods in literature. The method is illustrated in Figure 4. It loops through every pixel in the 1920x1080 and treats each R,G,B value as a time series throughout the video. Then, the algorithm identifies the mode intensity and identifies that as the background intensity. This method works extremely well in cases that the players are moving around the court, which is almost always given in badminton matches. As seen in Figure 4, the proposed algorithm's background estimate does not suffer from the same artifacts as ML-based solutions (Stauffer, C, 2022) in Figure 4c.

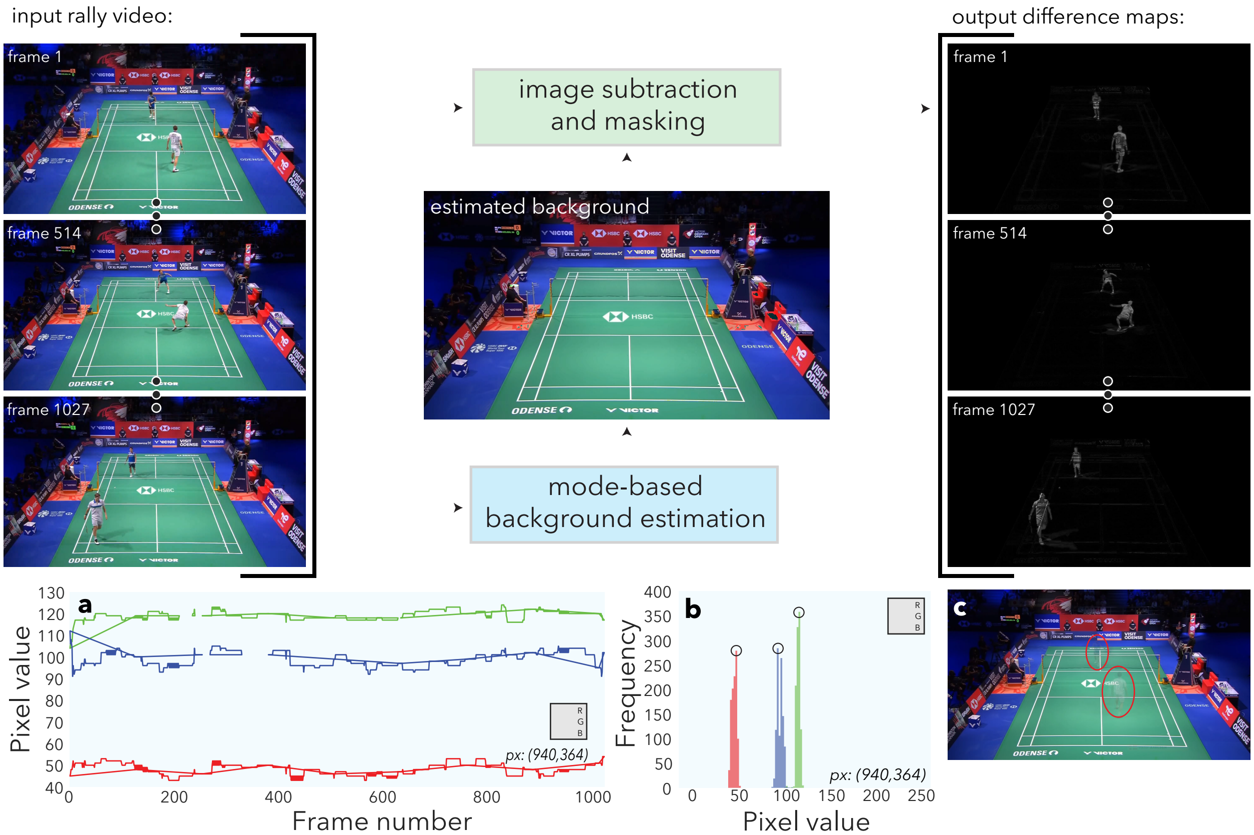

Figure 4: **Mode-based background estimation module.** The model treats every pixel in the 1920x1080 video as a time-series vector of R,G,B intensity values. (a)-(b) The background intensity is identified as the mode of the time-series vectors. The estimated background contains no players. (c) A popular ML-based solution shows clear artifacts of the players in the estimated background.

4.2.3 Pose Estimation

To detect individual players in a rally, I use the popular module, OpenPose, which identifies 18 body parts within players and then makes affinity heatmaps to connect body parts together to form person detections (Z. Cao, 2018). While the model outputs person detections, the data is (1) not limited to the players and (2) sometimes not detecting the players (i.e. not temporally continuous). Thus, I use the difference mapping from the background estimation module (Section 4.2.2) to assign scores to all output bounding boxes from OpenPose corresponding to the mean difference in pixel intensity values between the current frame and the background. The two bounding boxes with the highest scores are then assumed to correspond to the two players. While this fixes the first problem, it still does not solve the lack of temporal continuity in the player detections. Thus, if both players are detected, I assign them to their corresponding player by predicting where the player is expected to be based on the previous two frames. If any player is not detected, their respective position data is the linear extrapolation of the last two detected positions. This method is illustrated in Figure 5.

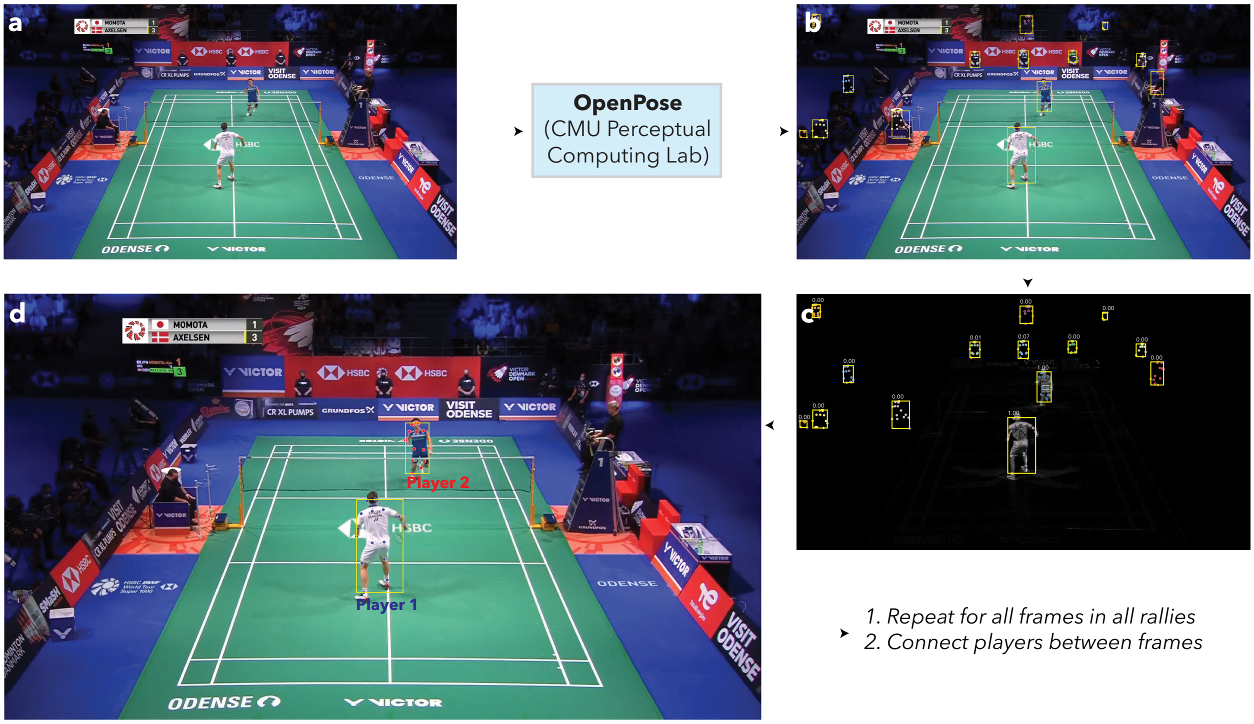

Figure 5: **Pose estimation module.** (a) A sample frame from the rally video. (b) OpenPose person detections with bounding boxes and each detected body part plotted as a point. (c) Each bounding box is assigned a score based on the average value of the underlying difference map from the background estimation module. (d) The bounding boxes with the highest two scores are assumed to be the two players.

4.2.4 Shuttlecock Tracking

Tracking the shuttlecock is a crucial aspect of (1) detecting when the rally is in progress and (2) classifying shots and shot speeds. In this paper, I limit the scope to solely measuring the length of rallies since the shot selection is indirectly encoded in the player movement data. To detect the shuttlecock, I employ TrackNet (Huang et al., 2019), a pre-trained CNN-based neural network that takes as input three consecutive frames of a video and outputs a heatmap of where the shuttlecock is. Then, I build a data processing algorithm to deal with missed detections and false positives. The algorithm first morphologically opens short-timescale detections and then combines detections together to measure the rally length (Figure 6).

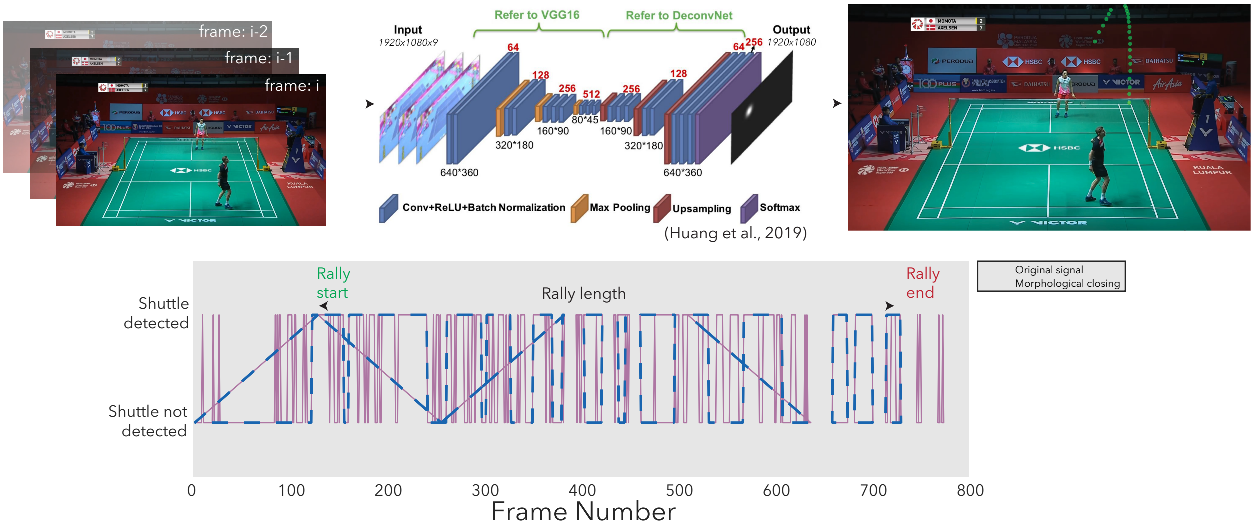

Figure 6: **Shuttle tracking module.** The pre-trained TrackNet module identifies the shuttlecock from three consecutive frame inputs from the video. The green dots in the rightmost image show the tracked shuttle trajectory. Morphological operations are used to eliminate false positives and measure the length of individual rallies.

4.2.5 Camera Calibration

The pose and player estimation module measures the positions of the players in the image plane; however, this information is only useful after converting it into world coordinates. Thus, I build a camera calibration model to convert the image coordinates to world coordinates on the court (Figure 7). Let the image and world coordinates be (x_i, y_i) and (x_w, y_w, z_w), respectively. For a full 3D reconstruction, a stereo-camera setup would be required; however, by assuming that the player's feet remain approximately on the floor of the court (i.e. $z_w = 0$), the world coordinates of the players can be estimated. Given the known standard badminton court dimensions (Figure 7b) and the detected corresponding image points (Figure 7a), I fit two multivariate cubic distortion models: $x_w = f(x_i, y_i)$ and $y_w = g(x_i, y_i)$. The average reprojection error using this model is less than 1.5 cm.

5 Results & Discussion

5.1 Feature Construction

Based on intuition for which features may be important when predicting who wins a rally or how long a rally is, I propose the following aggregate statistics to calculate from the measured time series data in each rally: Winning player (0 or 1); Rally length (in seconds); Game number (1, 2, or 3); Average x and y positions (in meters) of each player on court (4 variables); Variances

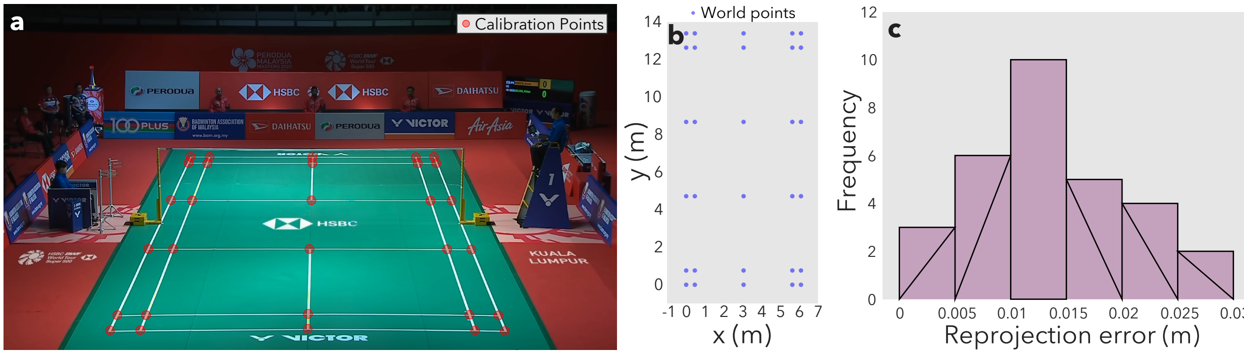

Figure 7: **Camera calibration module.** (a) The detected corners of the badminton court using Hough line transforms. (b) The world coordinates of the corners. (c) Reprojection errors of a cubic model for converting image coordinates to world coordinates are on average about 1.5 cm.

of x and y positions (in meters) of each player on court (4 variables); Average difference in x and y (in meters) between the players (2 variables); Average angle made by the two players with the long axis of the court (1 variable). Pairwise correlation plots of each variable are provided in the Appendix (Figures 12 and 13). Due to the low number of training samples (77 for Malaysia Masters match and 109 for Denmark Open), I repeatedly split the set into training (65%), validation (15%), and test (10%) and take the average as the test score. The validation set is used for tuning any regularization parameters.

5.2 Predicting Rally Outcomes

I first test several different classification models with all features to determine which model to optimize. As seen in Figure 8, the 20-split tree performs best for the 2022 Denmark Open and the KNN nearest neighbour performs best for the 2020 Malaysia Masters dataset. Both of these optimized models are very non-linear. This result agrees within the interpretation of outcomes of a badminton rally being highly sensitive to small decisions. Thus, a model such as a KNN with 1 neighbour attempts to find the rally closest to the one that is being predicted similar to how a coach would train a player by showing relevant clips of rallies of an opponent.

Using the optimized models determined earlier, I remove one variable at a time to determine which variable contributed the most marginal improvement to the accuracy as a means of ranking feature importances (Figure **??**).

As seen in Figure 10, I find that Kento Momota's variance of movement in the y-direction (i.e. forward and back) is the most important feature in both datasets. This cannot be an artifact of any noise in the video pipeline's measurements because the players switch sides multiple times during the match. In 2022, Kento Momota's movement was more crucial in predicting rally outcome

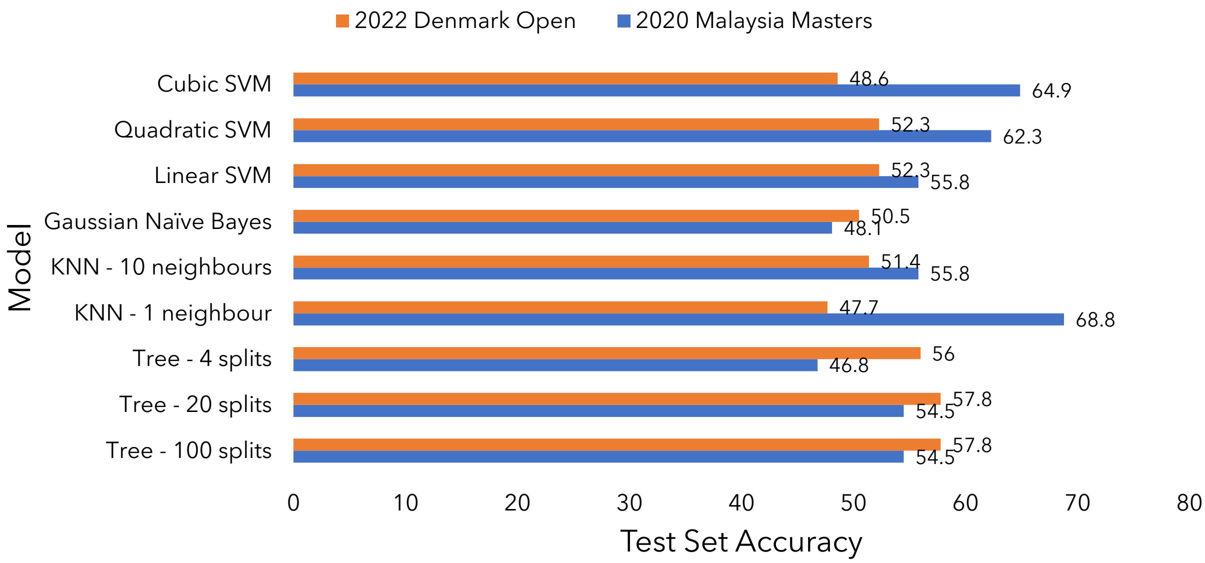

Figure 8: **Classification results of rally-by-rally winners for both datasets using all features as predictors.**

2020 Malaysia Masters

Model used	Feature removed	Accuracy (%)
KNN - 1 neighbour	rally_length	68.8
KNN - 1 neighbour	game #	68.8
KNN - 1 neighbour	avg_x1	67.5
KNN - 1 neighbour	avg_y1	66.2
KNN - 1 neighbour	avg_x2	66.2
KNN - 1 neighbour	avg_y2	67.5
KNN - 1 neighbour	var_x1	68.8
KNN - 1 neighbour	var_y1	63.6
KNN - 1 neighbour	var_x2	68.8
KNN - 1 neighbour	var_y2	71.4
KNN - 1 neighbour	diff_x	66.2
KNN - 1 neighbour	diff_y	66.2
KNN - 1 neighbour	angles	68.8

2022 Denmark Open

Model used	Feature removed	Accuracy (%)
Tree - 20 splits	rally_length	56.0
Tree - 20 splits	game #	57.8
Tree - 20 splits	avg_x1	55.0
Tree - 20 splits	avg_y1	56.0
Tree - 20 splits	avg_x2	57.8
Tree - 20 splits	avg_y2	54.1
Tree - 20 splits	var_x1	56.9
Tree - 20 splits	var_y1	45.9
Tree - 20 splits	var_x2	60.6
Tree - 20 splits	var_y2	57.8
Tree - 20 splits	diff_x	58.7
Tree - 20 splits	diff_y	60.6
Tree - 20 splits	angles	53.2

Figure 9: **Classification results of rally-by-rally winners for both datasets using all except one feature with optimized model from Figure ??.** The best model for the 2020 Malaysia Masters has: accuracy = 71.4%, TPR = 68.9%, TNR = 75.0%. The best model for the 2022 Denmark Open has: accuracy = 60.6%, TPR = 53.1%, TNR = 66.7%.

than in 2020. A higher variance is a result of more movement around the court. As several critics have noted, Kento Momota's level of attack has significantly decreased since the beginning of the pandemic (BWF, 2022), and thus, he is forced to be more patient and wait for opportunities rather than attack in rallies right away. Thus, he wins most of his points through long, patient rallies. Another notable change is the importance of using angles in his shots in 2022 rather than in 2020. Since his attack power has decreased significantly, Momota is winning more points through sharp angled shots rather than powerful smashes straight toward his opponent's court. Thus, these simple

Feature	Marginal improvement in accuracy	
	2020 Malaysia Masters	*2022 Denmark Open*
rally_length	0	1.8
game #	0	0
avg_x1	1.3	2.8
avg_y1	2.6	1.8
avg_x2	2.6	0
avg_y2	1.3	3.7
var_x1	0	0.9
var_y1	5.2	11.9
var_x2	0	-2.8
var_y2	-2.6	0
diff_x	2.6	-0.9
diff_y	2.6	-2.8
angles	0	4.6

Figure 10: **Marginal improvements in accuracy as a metric for ranking feature importances.** The most important features are consistently Kento Momota's variance in movement in the y-direction in both 2020 and 2022.

models show how the proposed match pipeline is advantageous for drawing higher-level statistical information than previously described in literature.

5.3 Predicting Rally Lengths

While predicting the winner of a rally and then determining the most important parameters leading to that result are a priority, determining what strategies lead to shorter rallies are also important for players to come up with efficient strategies to win matches with. Rather than predicting the rally length, I aim to predict the magnitude of the rally length by taking its log because the precise rally length is highly sensitive to small variations in either players shot and to ensure that the model is not penalized greatly for the occasional very short or very long rally. In other words, I prioritize predicting whether a rally will be 10 seconds or a minute over predicting 10 seconds vs. 20 seconds. I first develop a baseline RMSE score using linear models (Figure 11a,c) for both datasets. Then, I train several other models and find that a Gaussian SVR model captures the data well as seen by the large reduction in test set RMSE in Figure 11b,d. Since a Gaussian SVR model prioritizes boundary decisions close to nearby datum and only penalizes deviations from the prediction when it is over a certain threshold, it models the non-linearity in the datasets well and handles the noise from external factors in rally lengths. A similar sensitivity study to Section 5.2 reveals that in 2020, the most important feature is forward and backward movement of Viktor Axelsen, while in 2022, the most important feature is the variance in Momota's movement in the x-direction. To derive useful analytics from these findings for rally length requires a deeper analysis into their physical intuition, and thus, will be excluded from this report due to time constraints. In all, relatively simple models are able to predict the length of a rally within approximately a factor of $10^{0.2356} = 1.72$ of the true rally length in seconds.

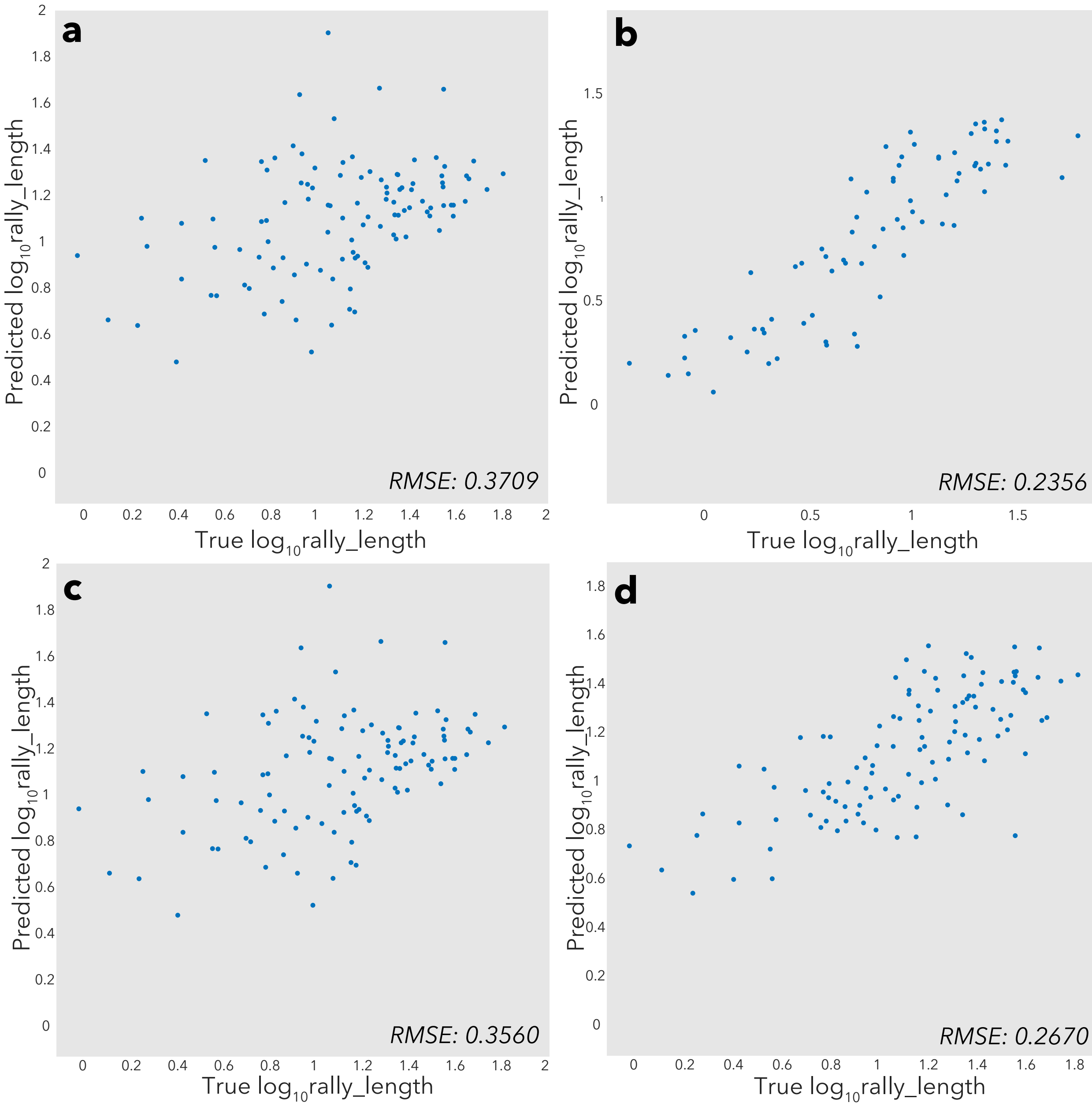

Figure 11: **Regression results for rally length.** (a) Linear regression result with all features for 2020 dataset. (b) Best Gaussian SVR model for 2020 dataset. (c) Linear regression result with all features for 2022 dataset. (d) Best Gaussian SVR model for 2022 dataset.

6 Conclusion

With the rise in deep learning networks for pose detection and video processing, data science has opened the door to derive insightful analytics from public match videos. In particular, this paper presents a pipeline that fully automatically detects scene, estimates background, detects players, calibrates cameras, and tracks the shuttlecock to give processed and continuous time-series data of player movement in every rally. In the case study of Kento Momota and Viktor Axelsen, I show how Momota is relying more on angled shots and patient play over his previous aggressive style which may be the reason for his recent losses. I also show the potential to model rally lengths using relatively simple models to extract energy-efficient strategies for badminton players. Future work lies in scaling the pipeline to many matches and make the output data more accessible to a public audience.

7 Acknowledgements

Thank you to Professor Hanke and Sulin for useful feedback throughout the process and a wonderful class! Thank you to Joshua from Olympiads School in Canada for lending my multiple GPU clusters. Thank you to my mom for her support throughout the research experience.

8 Appendix

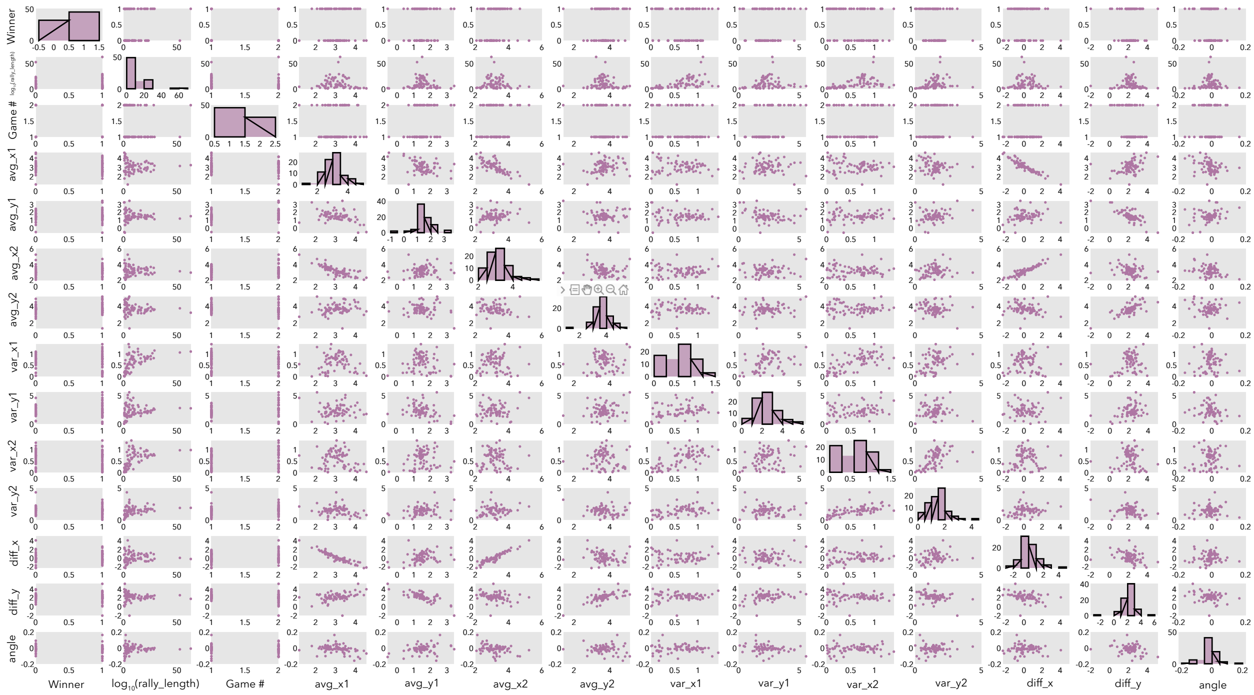

Figure 12: Pairwise plots for all features in the 2020 Malaysia Masters Final match.

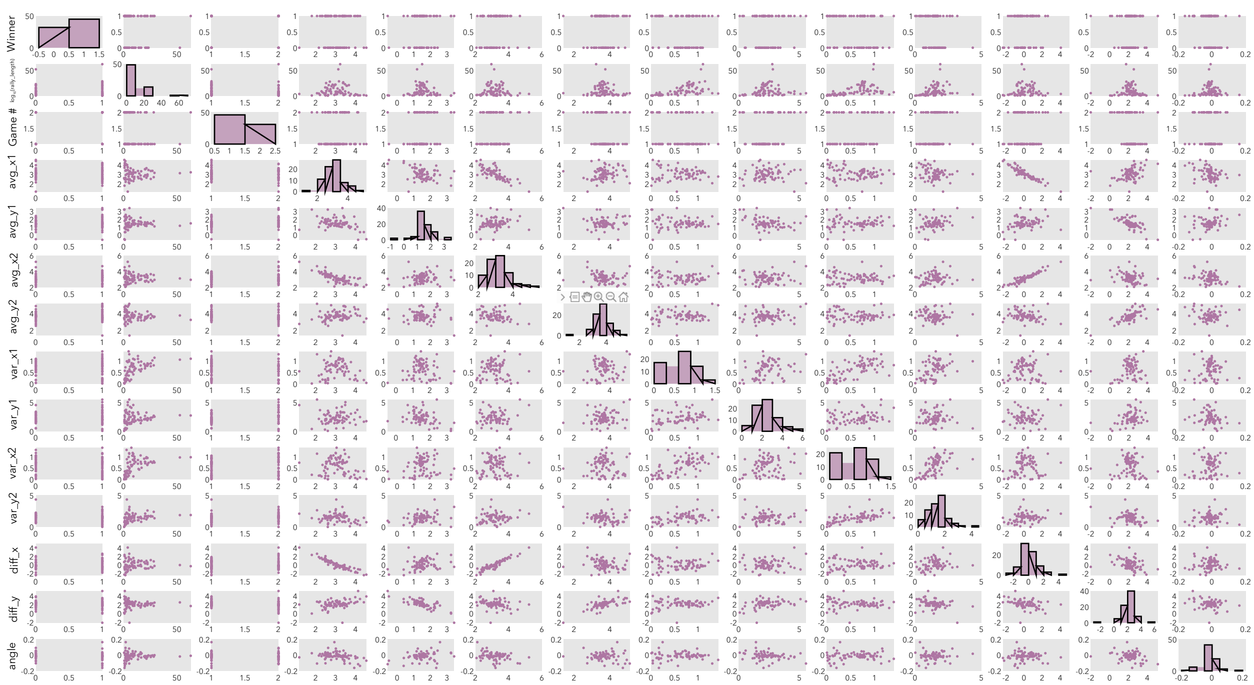

Figure 13: Pairwise plots for all features in the 2022 Denmark Open Final match.

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