Passing to Win: Using Characteristics of Passing Information for Match Winner Prediction

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Abstract: Predictingthe football match results has received great attention both in sports industry and academic fields. Many researchers have studied on predicting the match outcome using the simple features such as the number of shots and passes. However, little attention has been paid to using pass interaction features, which can represent how players in a match interact to each other. To this end, we propose a win-lose prediction model that predicts a match result using the pass interaction and other features, achieving high accuracy of 79.5%. By conducting an ablation study, we find that the proposed interaction features play an important role in accurately predicting match results. We believe our work can provide important insights both for industry and academic researchers who want to understand the characteristics of winning teams.

1 INTRODUCTION

Recent advances in computing technology have driven researchers to analyze diverse information of football matches. Researchers can access not only general match statistics such as match winner, number of shoots in a match, or total number of passes in a match, but also in-game statistics of individual players (e.g., total running distances) and even interactions among the players such as passing data between two players (Linke et al., 2020; Pons et al., 2019). Such comprehensive information can enable conducting an in-depth analysis on winning matches or individual playing performance (Johansen et al., 2013; Bastida Castillo et al., 2018).

The abundant and comprehensive match data has spurred researchers in industry and academia to investigate match winners (Harrop and Nevill, 2014; Clemente et al., 2015) or winning strategies (Georgievski et al., 2019), which has provided valuable insights into understanding the key factors to win a match. Harrop *et. al* revealed that increasing success rates of passes and shots and decreasing the number of passes and dribbles are important to win a match (Harrop and Nevill, 2014). Clemente *et. al* built a players' network and showed that the networks of winning teams tend to be dense (Clemente et al., 2015). Georgievski *et. al* suggested that the current rank of the team in a league need to consider the degree of offensiveness/defensiveness of teams (Georgievski et al., 2019).

In recent years, there have been much efforts on predicting the match results or match winners, using simple statistical information of matches. For example, Razali *et. al* proposed a machine learning model based on Bayesian Networks, which uses match statistics like number of shots (Razali et al., 2017). Pettersson *et. al* used a Long Short-term Memory (LSTM) model with the history of the match results of two teams to predict the match winner (Pettersson and Nyquist, 2017). Hassan *et. al* proposed an Artificial Neural Network (ANN) to predict the match results using the data collected from TRACAB that utilizes a beam-forming sensor & receiver equipments (Hassan et al., 2020). However, although these studies have provided valuable insights into understanding statistical features in predicting match winners, little research has paid attention to model and analyze how interactions among players through passing in a match can be used to predict match winners.

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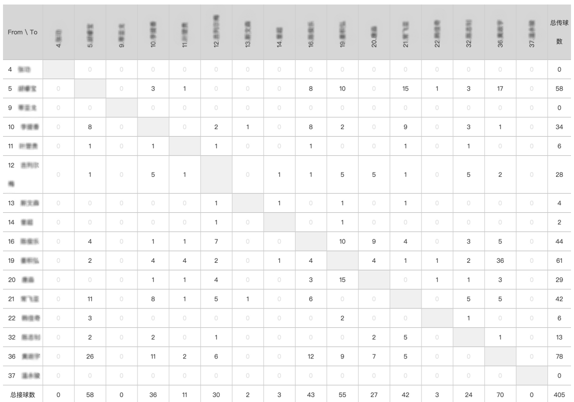
In this paper, we propose a machine learning-based prediction model for match winners, which adopts both statistical match traits as well as interaction patterns of two teams in a match. To this end, we collected the match results and their associated data including team statistics (e.g., possession rate), players' individual statistics (e.g., number of ball steals), and the pass matrices whose element is the passing counts between two players, from CHAMPION DAtA[1] that logs all the football matches in Chinese Super League and A League. Using the collected dataset, we model the passing interaction as a directed graph, called *a pass map*. Based on both the characteristics of the pass maps (e.g., betweenness centrality in a graph) and the statistical information of two teams in a match, the proposed model can predict the match winner with 79.5% accuracy.

2 METHODS

We describe our methodology for developing a machine learning-based model to predict match winners. In particular, we first describe the data collection method, e.g., crawling the match results with comprehensive in-game statistics and passing information. After modeling the passing patterns of each team in a match as a pass map, we extract two feature sets: (i) statistical features including in-game traits, and (ii) interaction features with the characteristics of the passing patterns. We then describe the proposed machine learning-based model that can predict the match result using the extracted features.

2.1 Data Collection



From \ To	4	5	9	10	11	12	13	14	16	19	20	21	22	32	36	37	总传球数
4		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0		0	3	1	0	0	0	8	10	0	15	1	3	17	0	58
9	0	0		0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	8	0		0	2	1	0	8	2	0	9	0	3	1	0	34
11	0	1	0	1		1	0	0	1	0	0	1	0	1	0	0	6
12	0	1	0	5	1		0	1	1	5	5	1	0	5	2	0	28
13	0	0	0	0	0	1		1	0	1	0	1	0	0	0	0	4
14	0	0	0	0	0	1	0		0	1	0	0	0	0	0	0	2
16	0	4	0	1	1	7	0	0		10	9	4	0	3	5	0	44
19	0	2	0	4	4	2	0	1	4		4	1	1	2	36	0	61
20	0	0	0	1	1	4	0	0	3	15		0	1	1	3	0	29
21	0	11	0	8	1	5	1	0	6	0	0		0	5	5	0	42
22	0	3	0	0	0	0	0	0	0	2	0	0		1	0	0	6
32	0	2	0	2	0	1	0	0	0	0	2	5	0		1	0	13
36	0	26	0	11	2	6	0	0	12	9	7	5	0	0		0	78
37	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0
总接球数	0	58	0	36	11	30	2	3	43	55	27	42	3	24	70	0	405

Figure 1: A screenshot of a pass matrix available on CHAMPION DATA. Note that we anonymized the players' names.

[1] http://data.champdas.com/

We build the dataset to detect which team will win the match by collecting the match information from CHAMPION DATA, which provides the results of the football matches in Chinese Super League and A League with diverse match-relevant information including statistical in-game traits both form the perspectives of teams and players, and the pass matrices that represent how frequent players pass to each other. An example of a pass matrix is illustrated in Figure 1. That is, each row and column in a pass matrix M represents a player, and the element of the matrix at i-th row and j-th column (i.e,, M_{ij}) indicates the number of passes from player i to player j. Note that two pass matrices for each team are provided for a match. To collect the match-related information from CHAMPION DATA, we developed a web crawler that fetches the web pages including the match results with detailed in-game information. Using the crawler, we collected 2,682 match data from 75 teams. After filtering the tie match data, we finally gathered the 1,999 match results, 3,998 pass matrices, and statistical information of individual players and teams. Among them, we use 80% as the training set of our model ans use the remaining 20% for testing. Table 1 summarizes in-game statistical information of individual players and teams, respectively.

2.2 Pass Map Construction

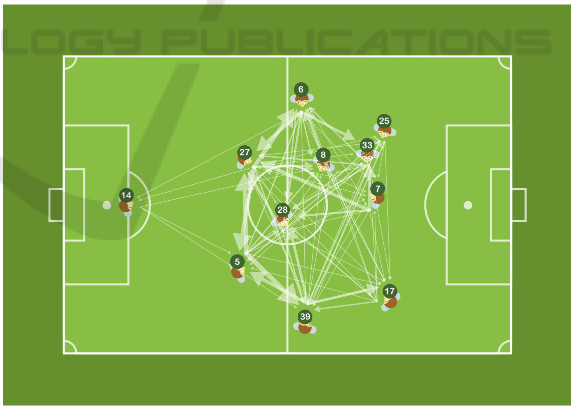


Figure 2: An illustration of an example of a pass map of a team in a match.

The passing information among team players has been considered as an important factor to infer team's characteristics or even success in a match. Inspired by this, we construct a pass map by using NetworkX [2] to characterize the passing patterns among the team players in a match. That is, a pass map is defined as a directed graph $G = (V, E, W)$, where V and E are the

[2] https://networkx.org/

Table 1: The collected in-game statistical information of individual players and teams.

Team Stats.	Player Stats.
# of shots, # of shots on target, # of penalty kicks, # of free kicks, # of front court free kicks, # of corner kicks Possession rate, # of total passes, Pass success rate, Dominance rate	# of key passes, # of cross passes, # of break through, # of fouls obtained, # of steals, # of intercepts, # of catches, # of offside violations, # of clearance kicks, # of pass blocks, # of shoot blocks, # of yellow cards, # of red cards, # of short passes, # of long passes, Short pass rate (%), Long pass rate (%), Direct pass rate (%), Cross pass rate (%), Diagonal pass rate (%), Back pass rate (%)

sets of players (of a team) and passes among the players, respectively. Note that an edge e_{ij} from node i and node j exists when player i passes the ball to player j. The weight of e_{ij} is computed as the number of passes from node i to node j. An example of a pass map of a team in a match is illustrated in Figure 2.

2.3 Feature Extraction

From the collected dataset and the constructed pass maps, we extract the features that are used to detect which team wins the match. In particular, for a given team, we compute two feature sets of the features, statistical and interaction features, described as follows:

- **Statistical Features:** We use 10 team and 21 player features, described in Table 1, as the statistical features in a match. To compute the features of a team from the players' statistics, we calculate the average values of the individual statistics of 11 players in the starting lineup.
- **Interaction Features:** We use the characteristics of the pass maps of two teams in a match as the interaction features. We use the NetworkX to compute the following node features: in-degree, out-degree, degree centrality (Tang et al., 2013), closeness centrality (Bavelas, 1950), and betweeness centrality (Freeman, 1977), each of which is summarized in Table 2. Since the features are computed from individual player's perspective, we simply compute average values and standard deviations of each feature to generate a interaction feature set of a team.

To compute the features of a match, we simply concatenate two feature sets of each team (home and away), which finally results in 92 statistical and 20 interaction features for each match. See Table 3 in Appendix for all the listed features. The whole process of feature extraction is illustrated in Figure 3.

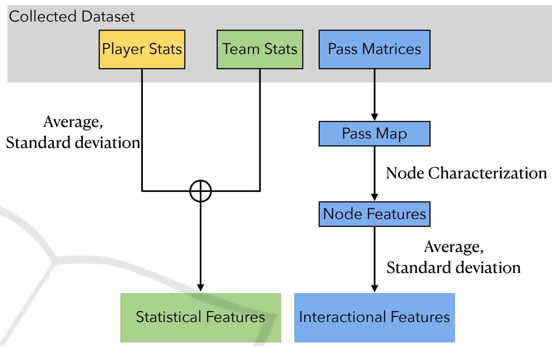


Figure 3: An illustration of feature extraction process.

2.4 Match Winner Prediction Model

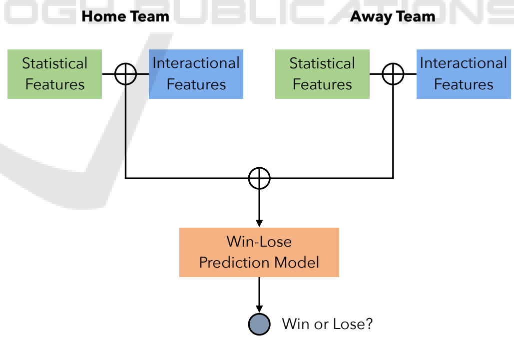


Figure 4: Overall architecture of the match winner prediction model.

We define the prediction task that predicts which team will win the match as a binary classification problem. That is, we first divide the given the constructed dataset $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{n} (x_i \in \mathbb{R}^m, y_i \in \{1 \dots c\})$ with n matches, m match features (i.e., statistical and interaction features), and c match result classes (i.e., positive when home team wins the match, negative otherwise) into two datasets $\mathcal{D}_{tr}$ and $\mathcal{D}_{test}$, which represent the datasets for training and testing, respectively. We then train our model using $\mathcal{D}_{tr}$ and finally predict

Table 2: Five interaction features with their definitions and descriptions. g is the number of nodes and i is the index of the nodes. x_{ij} represents the total number of direct connections between N_i and other $g-1$ nodes, $dis(i,j)$ indicates the distance from node i to node j, and $sd(j,i,k)$ means the shortest path from j to k passes through i.

Characteristics	Definition	Description
In-degree	–	How many players pass the ball to the given player
Out-degree	–	How many passes are concentrated to the player
Degree centrality	$C_D(N_i) = \frac{\sum_{j=1}^{g} x_{ij}(i \neq j)}{g-1}$	How a given node plays a central role in connecting other nodes
Closeness centrality	$C_C(N_i) = \frac{g-1}{\sum_{j=1}^{g} dis(i,j)}$	How many a given player receives direct passes from other players
Betweenness centrality	$C_B(N_i) = \frac{\sum_{j,k=1}^{g} sd(j,i,k)}{\sum_{j,k=1}^{g} (j,k)}, (j \neq k)$	How essential a given player is to connect small groups of the players

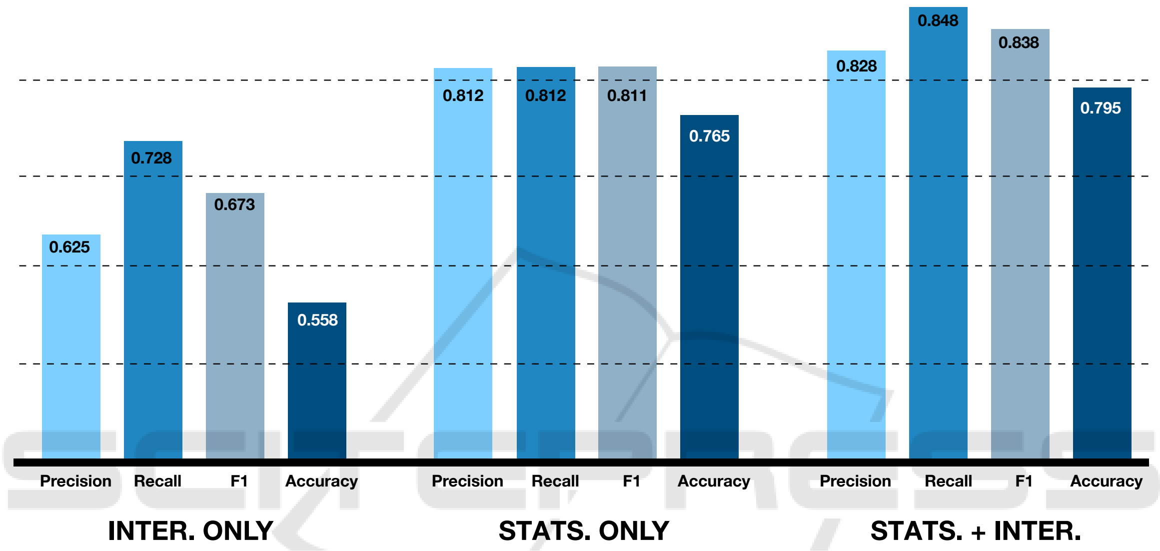


Figure 5: Performance results of the match result prediction model. INTER. ONLY, STATS. ONLY, and STATS. + INTER. denote interaction features only, statistical features only, and statistical + interaction features, respectively.

the match result class c based on the features (i.e., $x_i \in \mathbb{R}^m$) in $\mathcal{D}_{test}$.

To solve the classification problem, we first investigated popular machine-learning-based classifiers including Support Vector Machines (Gunn et al., 1998), Random Forest (Breiman, 2001), and eXtreme Gradient Boosting (XGBoost) (Chen and Guestrin, 2016). After performance comparison, we select XGBoost as the prediction model as it outperforms others. In the experiment, we use the scikit-learn[3] and the XGBoost python library[4] to conduct training and testing. The formal definition of XGBoost is defined as follows:

$$\hat{y}_i = \phi(x_i) = \sum_{k=1}^{K} f_k(x_i) \quad (1)$$

where $\hat{y}_i$, f_k, K, and $f_k(x_i)$ are the predicted class for the i-th match, k-th independent tree, the number of trees, and the prediction score given by the k-th independent tree on the match features extracted from the i-th match, respectively. The objective function of the model, $\mathcal{L}(\phi)$, can be calculated as follows:

$$\mathcal{L}(\phi) = \sum_i l(y_i, \hat{y}_i) + \sum_k \Omega(f_k) \quad (2)$$

where l and $\sum_k \Omega(f_k)$ are the loss function between the predicted class $\hat{y}_i$ and the target class y_i and the regularization term that penalizes the complexity of the model, respectively. Here, we use squared error as the loss function. As a regularized term, we use $\Omega(f) = \gamma T + \frac{1}{2}\lambda||w||^2$, where λ and γ controls the penalty for the number of leaves T and magnitude of the leaf weights w, respectively.

3 RESULTS

In this section, we report the performance results of the prediction model for match winners. We then explore what features play important roles in the prediction.

[3] https://scikit-learn.org/

[4] https://xgboost.readthedocs.io/

3.1 Model Performance

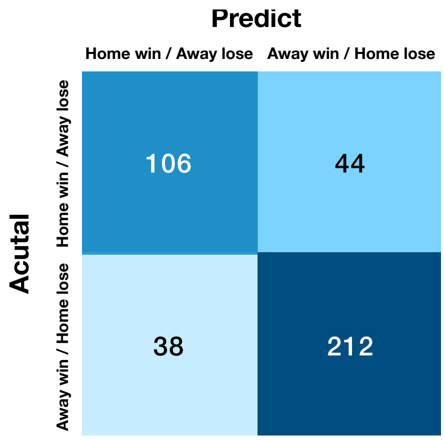


Figure 6: Confusion matrix of the model trained with both team and interaction features.

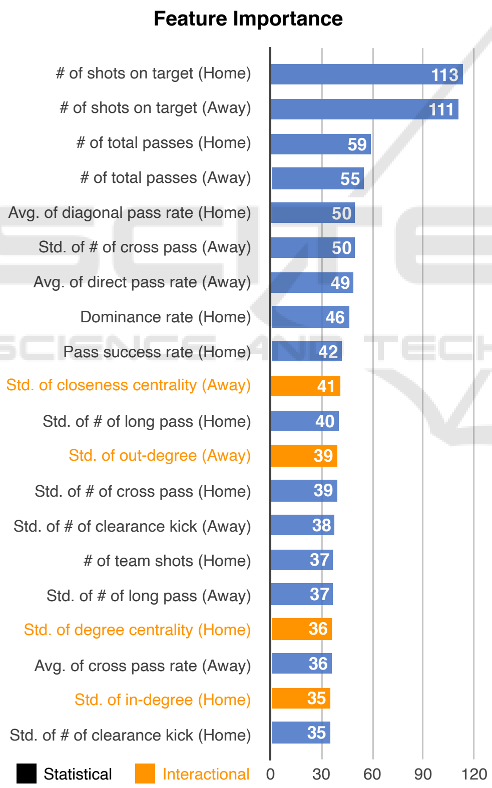


Figure 7: Top 20 Important Features.

Figures 5 and 6 show the prediction result of the proposed model. Here, we report four performance metrics: (i) Precision ($\frac{TP}{TP+FP}$), (ii) Recall ($\frac{TP}{TP+FN}$), (iii) F1 score ($2 \times \frac{precision \times recall}{precision+recall}$), and (iv) Accuracy ($\frac{TP+TN}{TP+TN+FP+FN}$) where TP, FP, FN, and TN represent the true positive, false positive, false negative, and true negative, respectively. In addition, we evaluate the proposed model with three different feature sets: (i) interaction, (ii) statistical, and (iii) both (i.e., interaction + statistical). Overall, the model using both feature sets outperforms all the other models. The accuracy of the model is 79.5% while the ones of the models solely using interaction or statistical features are 55.8% and 76.5%, respectively. When we look at the confusion matrix in Figure 6 that indicates the number of the classified instances, the total number of the instances correctly classified (upper-left and lower-right) is 318 while the one at the other locations is 82, meaning that the proposed model can predict the match winners with high accuracy. Furthermore, the performance of the model using both interaction and statistical features is higher than other models using a single feature set (i.e., either interaction or statistical), implying that interaction and statistical features are complementary to each other.

3.2 Feature Importance

We further investigate what features play significant roles in predicting match winners by observing the top 20 features in terms of the importance scores for prediction calculated by the average gain across all splits the feature is used in, as shown in Figure 7. In general, the statistical features like the number of shots, the number of total passes, and average diagonal pass rates or total passes are located at higher position, showing that statistical features are important indicators in predicting match winners. Interestingly, the standard deviations of closeness centrality, out-degrees, degree centrality, and in-degrees are listed in the top 20 features, which implies that whether all the players in a match pass to each other with a similar degree can be important predictors for match winners. In other words, the passing interaction behavior in a match is important for predicting match winners.

4 CONCLUDING DISCUSSION

In this paper, we proposed a machine learning model that predicts the football match winners based on the statistical and interaction features. We collected the match results with their associated information for 2,682 matches of Chinese Super League and A League (2014-2020). By conducting an ablation study, we revealed that the extracted interaction features are complementary to statistical features.

There are a few limitations in our work. First, we conducted experiments only on the football matches in Chinese League, thus generalizing the methods and the results in this paper to other leagues such as English Premier League (EPL), Bundesliga, or LaLiga should be cautiously considered. As a future work, we plan to evaluate our proposed model to these leagues. Second, we only considered eleven players in the starting lineup, which has the rooms for improvement. Despite the limitations, we believe our experimental design and results can provide important insights for both football industry and academic researchers who want to lighten important characteristics of winning teams.

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REFERENCES

Bastida Castillo, A., Gómez Carmona, C. D., De la Cruz Sánchez, E., and Pino Ortega, J. (2018). Accuracy, intra-and inter-unit reliability, and comparison between gps and uwb-based position-tracking systems used for time–motion analyses in soccer. *European journal of sport science*, 18(4):450–457.

Bavelas, A. (1950). Communication patterns in task-oriented groups. *The journal of the acoustical society of America*, 22(6):725–730.

Breiman, L. (2001). Random forests. *Machine learning*, 45(1):5–32.

Chen, T. and Guestrin, C. (2016). Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining*, pages 785–794.

Clemente, F. M., Martins, F. M. L., Kalamaras, D., Wong, P. D., and Mendes, R. S. (2015). General network analysis of national soccer teams in fifa world cup 2014. *International Journal of Performance Analysis in Sport*, 15(1):80–96.

Freeman, L. C. (1977). A set of measures of centrality based on betweenness. *Sociometry*, pages 35–41.

Georgievski, B., Labadze, L., and Aboelsoud, M. E. (2019). Comparative advantage as a success factor in football clubs: Evidence from the english premier league (epl). *Journal of Human Sport and Exercise*.

Gunn, S. R. et al. (1998). Support vector machines for classification and regression. *ISIS technical report*, 14(1):5–16.

Harrop, K. and Nevill, A. (2014). Performance indicators that predict success in an english professional league one soccer team. *International Journal of Performance Analysis in Sport*, 14(3):907–920.

Hassan, A., Akl, A.-R., Hassan, I., and Sunderland, C. (2020). Predicting wins, losses and attributes' sensitivities in the soccer world cup 2018 using neural network analysis. *Sensors*, 20(11):3213.

Johansen, H. D., Pettersen, S. A., Halvorsen, P., and Johansen, D. (2013). Combining video and player telemetry for evidence-based decisions in soccer. In *icSPORTS*, pages 197–205.

Linke, D., Link, D., and Lames, M. (2020). Football-specific validity of tracab's optical video tracking systems. *PloS one*, 15(3):e0230179.

Pettersson, D. and Nyquist, R. (2017). Football match prediction using deep learning. *Psychology of Sport and Exercise*, 15(5):538–547.

Pons, E., García-Calvo, T., Resta, R., Blanco, H., López del Campo, R., Díaz García, J., and Pulido, J. J. (2019). A comparison of a gps device and a multi-camera video technology during official soccer matches: Agreement between systems. *PloS one*, 14(8):e0220729.

Razali, N., Mustapha, A., Yatim, F. A., and Ab Aziz, R. (2017). Predicting football matches results using bayesian networks for english premier league (epl). In *Iop conference series: Materials science and engineering*, volume 226, page 012099. IOP Publishing.

Tang, X., Wang, J., Zhong, J., and Pan, Y. (2013). Predicting essential proteins based on weighted degree centrality. *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, 11(2):407–418.

APPENDIX

Table 3: A list of match features used for training the match winner prediction model.

index	feature	index	feature
1	# of total penalty (Home)	57	Avg. of in-degree (Home)
2	# of total shots (Home)	58	Std. of in-degree (Home)
3	# of total shots on target (Home)	59	Avg. of out-degree (Home)
4	Possession rate (Home)	60	Std. of out-degree (Home)
5	# of total passes (Home)	61	Avg. of degree centrality (Home)
6	Pass success rate (Home)	62	Std. of degree centrality (Home)
7	Dominance rate (Home)	63	Avg. of closeness centrality (Home)
8	# of total free kick (Home)	64	Std. of closeness centrality (Home)
9	# of total frontcourt free kick (Home)	65	Avg. of betweenness centrality (Home)
10	# of total corner kick (Home)	66	Std. of betweenness centrality (Home)
11	# of total penalty (Away)	67	Avg. of # of catches (Away)
12	# of total shots (Away)	68	Avg. of # of key pass (Away)
13	# of total shots on target (Away)	69	Avg. of # of cross pass (Away)
14	Possession rate (Away)	70	Avg. of # of break through (Away)
15	# of total passes (Away)	71	Avg. of # of be fouled (Away)
16	Pass success rate (Away)	72	Avg. of # of offside (Away)
17	Dominance rate (Away)	73	Avg. of # of steal (Away)
18	# of total free kick (Away)	74	Avg. of # of intercept (Away)
19	# of total frontcourt free kick (Away)	75	Avg. of # of clearance kick (Away)
20	# of total corner kick (Away)	76	Avg. of # of block pass (Away)
21	Avg. of # of catches (Home)	77	Avg. of # of block shot (Away)
22	Avg. of # of key pass (Home)	78	Avg. of # of yellow card (Away)
23	Avg. of # of cross pass (Home)	79	Avg. of # of red card (Away)
24	Avg. of # of break through (Home)	80	Avg. of # of short pass (Away)
25	Avg. of # of be fouled (Home)	81	Avg. of # of long pass (Away)
26	Avg. of # of offside (Home)	82	Std. of # of catches (Away)
27	Avg. of # of steal (Home)	83	Std. of # of key pass (Away)
28	Avg. of # of intercept (Home)	84	Std. of # of cross pass (Away)
29	Avg. of # of clearance kick (Home)	85	Std. of # of break through (Away)
30	Avg. of # of block pass (Home)	86	Std. of # of be fouled (Away)
31	Avg. of # of block shot (Home)	87	Std. of # of offside (Away)
32	Avg. of # of yellow (Home)	88	Std. of # of steal (Away)
33	Avg. of # of red (Home)	89	Std. of # of intercept (Away)
34	Avg. of # of short pass (Home)	90	Std. of # of clearance kick (Away)
35	Avg. of # of long pass (Home)	91	Std. of # of block pass (Away)
36	Std. of # of catches (Home)	92	Std. of # of block shot (Away)
37	Std. of # of key pass (Home)	93	Std. of # of yellow (Away)
38	Std. of # of cross pass (Home)	94	Std. of # of red (Away)
39	Std. of # of break through (Home)	95	Std. of # of short pass (Away)
40	Std. of # of be fouled (Home)	96	Std. of # of long pass (Away)
41	Std. of # of offside (Home)	97	Avg. of short_pass_rate (Away)
42	Std. of # of steal (Home)	98	Avg. of long_pass_rate (Away)
43	Std. of # of intercept (Home)	99	Avg. of direct_pass_rate (Away)
44	Std. of # of clearance kick (Home)	100	Avg. of cross_pass_rate (Away)
45	Std. of # of block pass (Home)	101	Avg. of diagonal_pass_rate (Away)
46	Std. of # of block shot (Home)	102	Avg. of back_pass_rate (Away)
47	Std. of # of yellow (Home)	103	Avg. of in-degree (Away)
48	Std. of # of red (Home)	104	Std. of in-degree (Away)
49	Std. of # of short pass (Home)	105	Avg. of out-degree (Away)
50	Std. of # of long pass (Home)	106	Std. of out-degree (Away)
51	Avg. of short pass rate (Home)	107	Avg. of degree centrality (Away)
52	Avg. of long pass rate (Home)	108	Std. of degree centrality (Away)
53	Avg. of direct pass rate (Home)	109	Avg. of closeness centrality (Away)
54	Avg. of cross pass rate (Home)	110	Std. of closeness centrality (Away)
55	Avg. of diagonal pass rate (Home)	111	Avg. of betweenness centrality (Away)
56	Avg. of back pass rate (Home)	112	Std. of betweenness centrality (Away)