SN Computer Science (2025) 6:302
https://doi.org/10.1007/s42979-025-03815-7

ORIGINAL RESEARCH

# Time-Series Analysis of Ball Carrier Open-Space (BCOS) in Association Football

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Received: 15 October 2024 / Accepted: 20 February 2025


**Abstract**

Assessing team performance in association football (commonly known as football or soccer) is challenging due to the sport's low-scoring nature and inherent unpredictability. While evaluating strategies based on space control and the creation of open spaces has been explored in the literature, the temporal aspect of space availability for the ball carrier remains under-explored. This work introduces a novel time-series performance evaluation metric, Ball Carrier Open Space (***BCOS***), which focuses on the temporal dynamics of space available to the ball carrier to assess team performance. Additionally, it presents a novel approach to quantify open space for the ball carrier using player data extracted from television footage. This work discuss on ***BCOS*** in defensive third, central third and attacking third and a machine learning model is developed to evaluate their significance and temporal patterns. Trained model achieved 80.7% accuracy in classifying match-winning performances, underscoring the significance of ***BCOS***. Correlation analysis between temporal features and match outcomes further reveals that ***BCOS*** in central third and attacking third are more important for match winning outcomes, while first-half performance plays a more critical role in determining match results than second-half performance. Based on the results of the correlation analysis, this study proposes a weighted ball carrier open space (***wBCOS***) metric to assess team performance, assigning weights to ***BCOS*** in attacking third, central third and defensive third based on their contributions to positive match outcomes. A machine learning model trained using ***wBCOS*** achieved an 82.5% accuracy in classifying match-winning performances, surpassing the performance of any previously published match-winner classification model.

**Keywords** Football · Soccer · Performance evaluation · Open space · Time-series · Machine learning

## Introduction

Globally recognized as the most popular sport [1], association football captures unparalleled attention and fan engagement around the world. This is evidenced by the FIFA World Cup 2022, which drew an astonishing 5.7 billion television viewers worldwide, solidifying its position as the most-watched sporting event in history [2]. Such widespread appeal highlights the sport's global significance and influence. The sport's immense popularity also drives significant economic value across

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Published online: 19 March 2025

football and related industries. With ongoing advancements in technology, football teams and stakeholders are investing in computational intelligence to gain a competitive advantage. These technological innovations hold the potential to not only improve team performance but also to reduce dependence on costly star players and prioritizing tactical and strategic improvements.

Classified as an invasion sport [3, 4], association football involves teams attempting to attack the opposition's territory while simultaneously defending against opposing advances. The nature of the game often leads to low-scoring outcomes and is widely regarded as being significantly influenced by chance or luck [5–7]. Consequently, assessing team or individual performance and predicting match outcomes presents considerable challenges. Recent literature has increasingly explored the application of computational intelligence for tactical analysis and match outcome prediction.

In association football, creating open spaces is a key tactic that helps generate goal-scoring opportunities by disrupting the defensive setup. Former Barcelona player and current manager Xavier Hernandez once remarked, "I understand football as a time-space, and it is the use of space" [8]. When a player receives the ball in open space, they have more time to analyze the situation and make impactful attacking decisions with less pressure and greater creativity. To create these open spaces for the ball carrier, a combination of actions is required-either the ball carrier's actions (such as forward passes, through balls, or dribbling) or off-ball runs to open areas. This movement can pull defenders out of position, destabilizing their structure. Pep Guardiola, current Manchester City manager and the only manager to win the continental treble twice, once stated, "It's not about passing for the sake of it. The key is to pass with the clear intention of drawing defenders to one side and creating space on the other. Then, move the ball into that created space to attack." [9]. Despite its importance, the creation of open spaces for the ball carrier and its time-series analysis for evaluating team and individual player performance remains relatively underexplored in existing research.

This work addresses the absence of investigation into the open space available to the ball carrier, as well as the lack of temporal analysis or time-series performance evaluation metrics in this context. It evaluates the temporal nature of team performances, and introduces a novel time-series performance evaluation metric based on the open spaces available for the ball carrier using information retrieved from televised video data.

## Related Work

Association football is a highly unpredictable sport, heavily influenced by chance [5–7], largely due to its low-scoring nature. Scoring in association football relies solely on successfully shooting the ball into the opposition's goal. However, on average, only 0.1% of shots result in a goal [10]. Consequently, performance evaluation based solely on actual scores can be misleading. To address this, prior research has focused on estimating the probability of scoring using expected goals (xG) models based on shot events [11–13] and the sequences of events leading up to shot events [14]. Additionally, studies have explored the likelihood of scoring from specific event locations through non-shot expected goals models [15]. However, these xG models are limited in that they overlook the value of opportunities created and the contributions of players who make key passes or movements, as their focus is solely on shot-related events. To overcome this shortcoming, Karun Singh introduced the Expected Threat (xT) model, which has gained popularity for assessing individual and team performance [16].

The xT model focuses on evaluating individual or team actions that advance the ball into high expected goals (xG) areas and threatening positions, regardless of the possession's final outcome [16]. To implement this, the pitch is divided into 192 equally-sized regions (arranged into 12 rows and 16 columns), where the probabilities of passing and shooting are calculated for each region. Movements are assigned values based on movement probability using a transition matrix, which captures the likelihood of moving to each specific region. Shots are assessed using shot probabilities and their associated xG values. However, these xT models do not directly consider defender positions and overlook the significance of open space created for the ball carrier.

Fernandez and Bornn proposed a method to quantify spatial value in open-play situations, focusing on space occupation and generation [17]. Space occupation refers to creating open space for oneself, while space generation involves creating opportunities for teammates in open areas and disrupting opponents' positioning. Their study develops a pitch control model that incorporates player movement data, the ball's location, and player positions. By analyzing the pitch control areas of all players on the field, they present a potential pitch control map for any moment in the game. Additionally, they introduced a model using feed-forward neural networks to assign a relative value to any position on the field based on the ball's location. Martens et al. expanded this approach by introducing a data-driven movement model to quantify space and control [18]. However, these studies do not address the time-series nature of open space generation for the ball carrier and its link to match-winning performances.

Performance evaluation metrics such as possession and territory are widely used to assess team performance. However, the existing literature provides mixed evidence regarding the link between these metrics and match-winning outcomes. Some studies suggest that teams with higher possession rates are more likely to win [19, 20], while others find no significant relationship between possession and winning [21, 22]. As football tactics continue to evolve, teams adopt diverse strategies, with some emphasizing possession-based play to maintain control and create scoring opportunities, while others focus on defensive tactics and counter-attacking. Consequently, prior research has explored the analysis of team tactics [23–25]. Notably, Wang et al. proposed the Team Tactic Topic Model (T3M), an unsupervised method for uncovering tactical patterns in association football by analyzing historical match logs, capturing both player locations and passing dynamics [25]. Jose Mourinho, one of football's most successful managers, once noted, "Many people believe that the team with more possession is the team that is more dominant. But that depends on the way you look at it; a team without the ball can still be in control of the game" [26]. Similarly, teams using defensive and counter-attacking strategies can exert control without high possession percentages. Research by Tenga et al. shows that counterattacks have a higher success rate of scoring (13.4%) compared to general attempts (8.8%) [10]. In counterattacks, teams often recover possession in the defensive third and quickly advance to the attacking third, leading to more open spaces in attacking areas. Thus, analyzing the creation of open spaces for the ball carrier could provide valuable insights into the effectiveness of these tactics which often differ significantly from one another.

## Methodology

Ethics approval for this study was granted by the Coventry University Ethics Approval Committee (Approval Number: P174511). All procedures conducted in this study adhered to the ethical standards set by Coventry University, UK.

This work performs a temporal analysis of the significance of open space available for the ball carrier. It presents a novel approach for quantifying open space available for the ball carrier relative to the opposition, player locations, and viewable area from data obtained from televised videos of the game. The significance of extracted temporal features on match-winning performances was evaluated by developing a match-winning performance classification machine learning model. Having identified the importance of the proposed time-series performance evaluation metric, this work further evaluates the importance of open space available for the ball carrier in attacking third, central third and defensive third (As defined in existing literature [27, 28].). Later these quantified importance are used to develop a weighted approach for a match winner prediction model. Figure 1 shows the summary of the proposed approach.

Within this research, the term "event" denotes a specific game-related occurrence involving a player's action or the subsequent outcomes, which are capable of being documented. "Ball carrier open space" ("Open space available for the ball carrier") refers to an unoccupied area of the field surrounding the player in possession of the ball, providing ample room for him/her to maneuver without any interference from opposition. For this, immediate surrounding open space available to the ball carrier upon receiving the ball following another event and all possible movements of surrounding opposition players towards immediate open space are considered. This preceding event could be executed by the same ball carrier or by a different player. For instance, when a pass is made, the preceding event is executed by a different player, whereas when the ball carrier dribbles past an opponent and shoots at the goal, the preceding event (dribbling past the opposition player while carrying the ball) is executed by the same player.

### Data

For this work, "Statsbomb 360" data from the "Statsbomb open-data" dataset [29] was used. This dataset contains event-log data in top-tier international and club competitions in Europe along with player coordinates of players from both teams retrieved from televised video. Additionally dataset coordinates of the area of the field covered by the televised angle of a particular event. Further, considering tactical and physical differences identified between Men's and Women's games [30], the dataset was segmented under gender. However, due to a lack of data, this analysis was conducted on the men's dataset only. Men's dataset consisted of data from televised games from FIFA World Cup 2022, EUFA Euro Cup 2020, EUFA Euro Cup 2024, Spanish La Liga 2020/2021, Bundesliga 2023/2024, Ligue 1 2021/2022 and Ligue 1 2022/2023.

Two teams in each game were represented by a home team (referred to as "Team A") and an away team (referred to as "Team B") for identification purposes in the original dataset. The event locations, viewing angles, and player locations within the games were mapped using coordinates on a grid measuring $120 \times 80$, with the direction of attack progressing from left to right across the grid. Additionally, each event contains additional information on events such as event type (e.g. pass, carry), and player information (e.g. player name).

For the purpose of temporal analysis and training the match winner prediction model, games that ended within regular time and those with a match winner were considered. This choice was made as the main focus was to evaluate the correlation between the proposed metric and match-winning performances, and including games that proceeded to extra time could significantly alter the game duration, thus affecting the consistency of the dataset. The final pre-processed dataset considered for model development consisted of 130

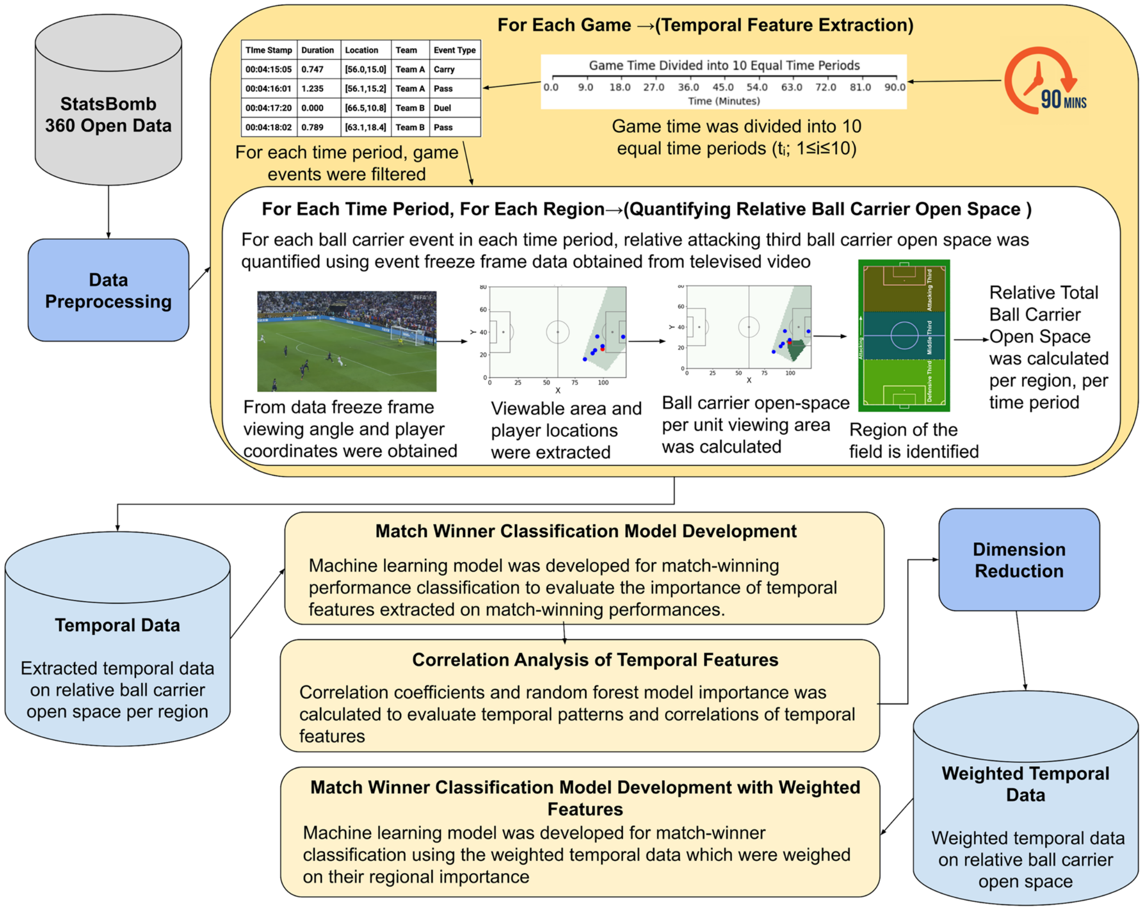


**Fig. 1** Summary of the proposed approach which includes temporal feature extraction, machine learning model development and evaluation

games. In the pre-processed dataset, 70 games have been won by Team A (54%) and 60 games (46%) have been won by Team B.

## Ball Carrier Open-Space Calculation

Existing literature has separated football field into three regions based on the direction of the attack; Defensive third (first third), Central Third (second third), and attacking third (final third) [27, 28] (Fig. 2). This work proposes extracting the *BCOS* in these three regions separately as temporal features to evaluate team performance. This work defines,

1. *D3BCOS*: Defensive Third Ball Carrier Open Space
2. *C3BCOS*: Central Third Ball Carrier Open Space
3. *A3BCOS*: Attacking Third Ball Carrier Open Space

In televised football games, the camera typically focuses on the ball carrier and their immediate surroundings. As a result, the visible portion of the pitch changes over time. The "Statsbomb 360" data provides coordinates of this visible area and the players within it, including the ball carrier,

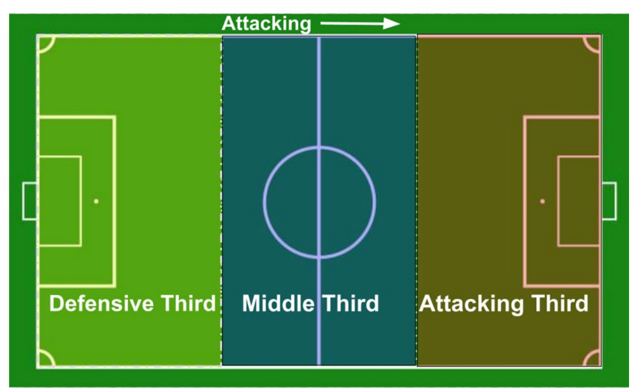


**Fig. 2** Defensive, Middle (Central) and Attacking third on a football field

depicted on a $120 \times 80$ grid. This study proposes determining the extent of the visible area as a relative measure by the number of grid cells (grid pixels) it covers within the $120 \times 80$ grid, providing a standardized relative measure for analysis across different events. Similarly, the open space accessible to the ball carrier was determined relative to the number of grid cells it occupies within the $120 \times 80$ grid. To generate this measure, the coordinates of the ball carrier and opposition players within the visible area and their all possible movements were taken into account. For this calculation, it was assumed that all the players could move at an equal velocity in any direction. This analysis did not consider the actual velocities of players due to data constraints. The velocities of individual players cannot be tracked from the data as all the players are not visible within the visible area for every event. Figure 3 illustrates the steps of ball carrier open space calculation from retrieving freeze frame coordinates to open space and visible area calculation and the pseudo-code presented in Algorithm 1 outlines the process of calculating the relative visible area, the relative open space area for the ball carrier, and highlights the open space for the ball carrier on a $120 \times 80$ grid.

However, visible area ($VA$; $VA > 0$) in televised video for a particular event varies with time. Therefore, in order to normalize and compare with other events, the open space available for the ball carrier in a particular event ($BCOS$) was divided by the visible area for that particular event. This results in an $BCOS$ per unit area measure.

$$BCOS_{\text{per unit area}} = \frac{BCOS}{VA} \tag{1}$$

## Temporal Feature Extraction

To conduct a time-series analysis on open space available for the ball carrier, features were extracted in a temporal manner. Each football game was segmented into ten equal time intervals ($t$; $1 \leq t \leq 10$), and the total open space area

**Algorithm 1** Pseudo code for ball carrier open space calculation

```
Input: ball_carrier_location, opposition_player_locations,
    max_velocity, visible_area
Output: open_space_grid, open_space_cells, visible_area_cells

Initialize a 2D array open_space_grid with all elements set to 0
Set open_space_cells = 0, visible_area_cells = 0

For each cell (i, j) in the grid:
    If cell (i, j) is within visible_area:
        Increment visible_area_cells by 1
        distance_to_ball_carrier = Euclidean distance from (i, j) to
            ball_carrier_location

        For each opposition_player_location in
            opposition_player_locations:
            distance_to_opposition_player = Euclidean distance from (i,
                j) to opposition_player_location

            If distance_to_opposition_player < distance_to_ball_carrier
                :
                Exit the loop

        If the loop was not exited:
            Set open_space_grid[i, j] = 1
            Increment open_space_cells by 1

Return open_space_grid, open_space_cells, visible_area_cells
```

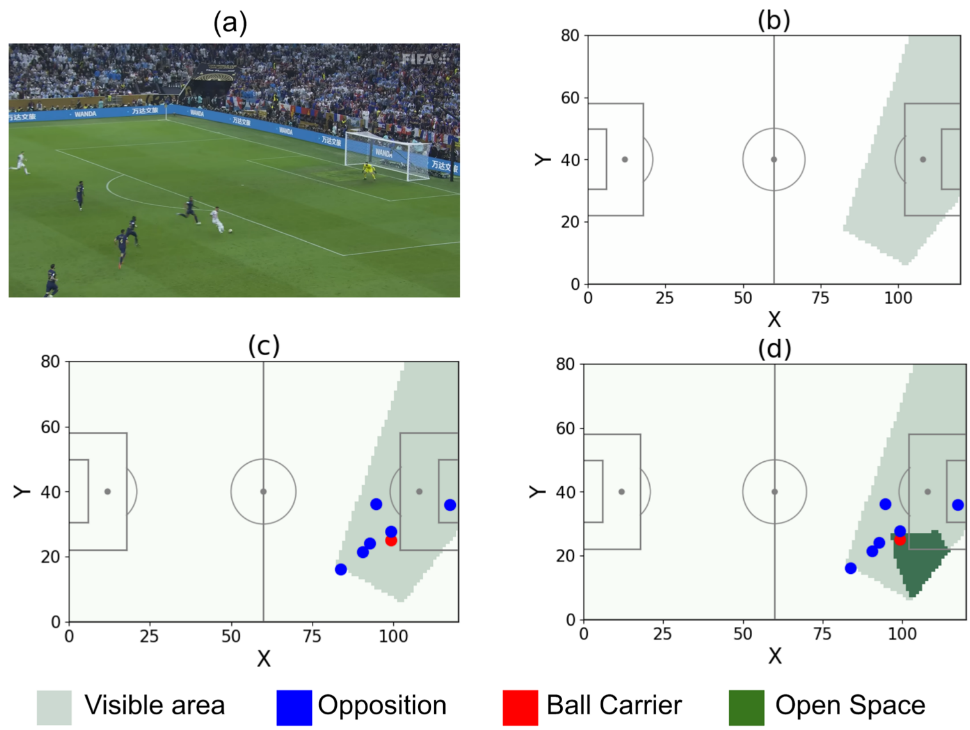


**Fig. 3** Attacking third ball carrier open space calculation steps: **a** freeze frame, **b** visibile area identification on a $120 \times 80$ grid, **c** ball carrier and opposition locations identification on the $120 \times 80$ grid, **d** ball carrier open space identification on the $120 \times 80$ grid

available for the ball carrier by each team per each region of the field during these intervals was computed under three regions of the field separately (defensive third $D3BCOS$, central third $C3BCOS$, attacking third $A3BCOS$). Only actions directly involving the ball carrier, such as passing, attempting a shot on goal, and carrying (running or dribbling while retaining control and possession of the ball), were taken into account when calculating the total open space area available for the ball carrier. Open space available during off-the-ball events was not considered, as the focus was on the space created around the ball carrier. Assuming $n$ ball carrier events occurred with team $A$ is in possession during time period $t_i$ $(1 \leq i \leq 10)$ within a particular named region (e.g., Attacking third),

$$\text{Total } BCOS^{A}_{\text{per unit area}}(t_i) = \sum_{j=1}^{n} \frac{BCOS_j}{VA_j} \tag{2}$$

for $\forall j \in \{1, 2, \ldots, n\}, \quad VA_j > 0.$

where, $BCOS_j$ is the BCOS created in the event $j$.

Nevertheless, with injury time in games, regular playing time of games may vary from one game to another. Therefore, to compare the temporal measures across games, ball carrier open space area per unit area per unit time in a particular region of the field ($Total\ BCOS^{A}_{\text{per unit area/time}}(t_i)$) was calculated for each time period by dividing the ball carrier open space per unit area in each region of the field (defensive third, central third, attacking third) by the duration of the time period. Assuming the duration of time period $t_i$ is $\Delta t$ $(\Delta t > 0)$, ball carrier open space area per unit area per unit time for Team A in a given region of the field (e.g., attacking third) during time period $t_i$ ($Total\ BCOS^{A}_{\text{per unit area/time}}(t_i)$) is:

$$Total\ BCOS^{A}_{\text{per unit area/time}}(t_i) = \frac{Total\ BCOS^{A}_{\text{per unit area}}(t_i)}{\Delta t} \tag{3}$$

For simplicity, term $Total\ BCOS^{A}(t_i)$, is used in this paper as a shorthand for $Total\ BCOS^{A}_{\text{per unit area/time}}(t_i)$.

The $Total\ BCOS^{A}(t_i)$ for the defensive third, central third, and attacking third of a region is referred to as $Total\ D3BCOS^{A}(t_i)$, $Total\ C3BCOS^{A}(t_i)$, and $Total\ A3BCOS^{A}(t_i)$ respectively.

This results in ten temporal features for each region of the field for each team on total ball carrier open-space per unit area per unit time (considering 10 time periods). When all three regions are considered, it totals to 30 temporal features for a game for each team (60 temporal features for both teams).

## Ball Carrier Open-Space Temporal Analysis

To visualize and explore potential relationships between ball carrier open space area per unit area per unit time in three regions of the field (attacking thid, central third and defensive third) temporally, four FIFA World Cup 2022s-round games were analyzed. Specifically, these games were selected based on their close competitiveness, either ending in draws or with the winning team prevailing by just one goal. Figure 4 illustrates the temporal features (total BCOS

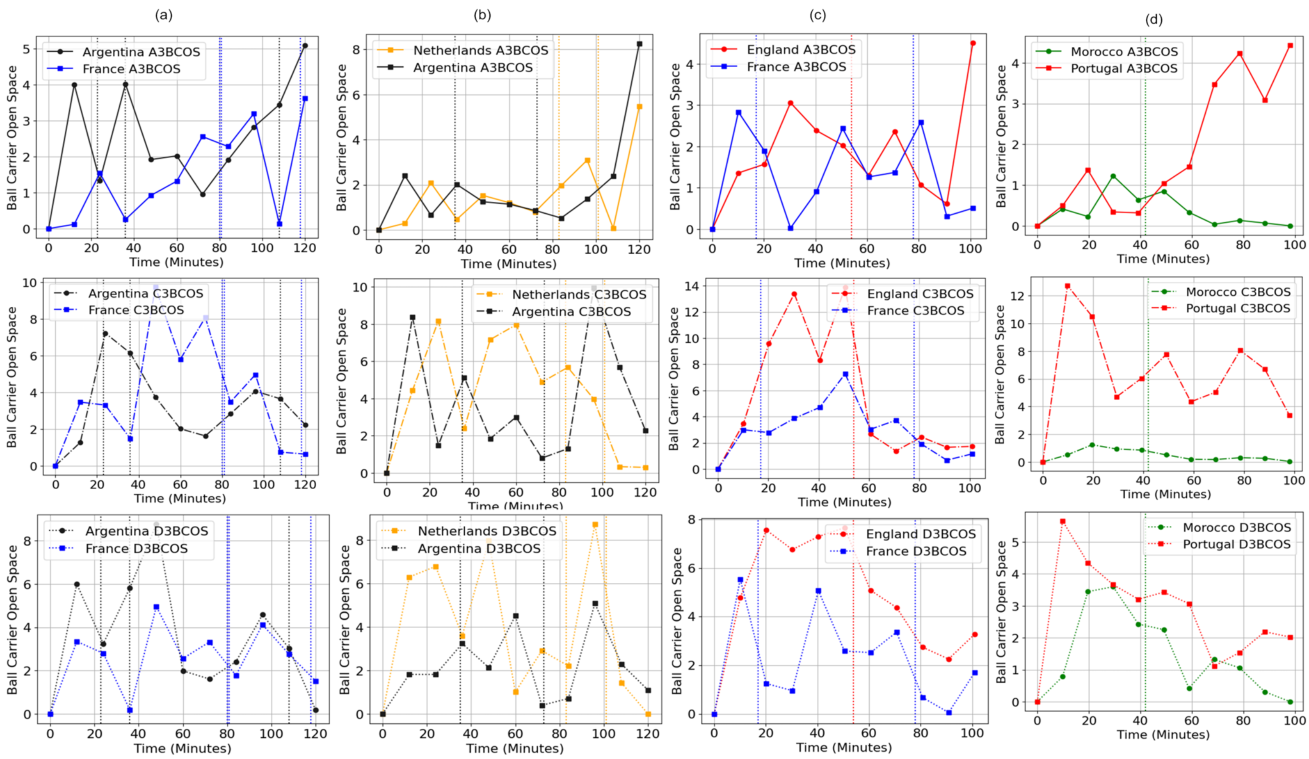


**Fig. 4** Initial temporal feature analysis of FIFA world cup 2022 games; **a** Argentina (3) vs France (3) (final), **b** Netherlands (2) vs Argentina (2) (Quarter-Final), **c** England (1) vs France (2) (Quarter-Final), **d** Morocco (1) vs Portugal (0) (Quarter-Final). Dotted vertical lines represent instances of goal scoring, with the color of each dotted line corresponding to the respective team

by each team during time period $t_i$ ) plotted against time (in minutes) and region on the field for the chosen FIFA World Cup 2022 games.

In Fig. 4 games (a) and (b) end up with equal scores before deciding the game-winner with penalty shootouts. Games (c) and (d) were won by France and Morocco with a single-goal advantage. In all these four games, it was observed with the majority of the goals that the goal-scoring teams have maintained higher total attacking third ball carrier open space (*A3BCOS*) than the opponent prior to the goal scoring. However, it was also observed that leading teams (Fig. 4c, d) were not maintaining higher *A3BCOS* towards the end of the game compared to the opponent. This can be due to defensive approaches followed by leading teams towards the end of the game by employing tactics like parking the bus [31]. Nevertheless, in equal score games (Fig. 4a, b) both teams have maintained similar *A3BCOS* toward the end of the game. It can also be observed that in general, teams who has maintained more central third ball carrier open space (*C3BCOS*) have tend to achieve more attacking third ball carrier open space (*A3BCOS*) during those time periods. However, no strong correlation can be observed between total defensive third ball carrier open space (*D3BCOS*) and open space in other two regions of the field.

Teams in games (a),(b) and (C) were equally ranked and were among the top 10 ranked teams prior to the FIFA World Cup 2022 (Argentina ranked 3, France ranked 4, England ranked 5, Netherlands ranked 8). Therefore, games (a),(b) and (C) can be considered as games between equal strengths. In these three games, it can be observed that teams who has created more total central third ball carrier open space (*TC3BCOS*) has managed to create more attacking third ball carrier open space (*A3BCOS*) during those time periods. In general, similar pattern can be observed with Portugal's (ranked 9 prior to the FIFA World Cup 2022) performance as well. However, this pattern is not observed with Morocco's (which was ranked 22 prior to the FIFA World Cup 2022) performance against Portugal. This can be due to use of different tactics employed by team Morocco when competing with stronger teams where they have considered more on defense and counterattacking. Existing literature [31] has revealed that weaker teams tend to use more defensive approaches against stronger teams.

## Relative Ball Carrier Open-Space Calculation

To reduce the number of temporal features for machine learning model development, the difference between *BCOS* per unit time of two teams in each region of the field at a specific time period ($t_i$) was considered as a relative measure of the *BCOS* ($\Delta BCOS(t_i)$). This involved subtracting Team B's total BCOS created per unit area per unit time (Total $BCOS^B(t_i)$) in a particular region of the field from Team A's total BCOS area per unit area per unit time (Total $BCOS^A(t_i)$) in the same region of the field for each time period.

Here, when the considered region of the field is,

1. Defensive third:

$$\Delta D3BCOS(t_i) = \text{Total}\, D3BCOS^A(t_i) - \text{Total}\, D3BCOS^B(t_i) \tag{4}$$

where, $\Delta D3BCOS(t_i)$ represent the relative *BCOS* between two teams in defensive third during the time period $i$, $D3BCOS^A(t_i)$ and $D3BCOS^B(t_i)$ represent the defensive third *BCOS* of team A and B respectively during the time period $i$

2. Central third:

$$\Delta C3BCOS(t_i) = \text{Total}\, C3BCOS^A(t_i) - \text{Total}\, C3BCOS^B(t_i) \tag{5}$$

where, $\Delta C3BCOS(t_i)$ represent the relative *BCOS* between two teams in central third during the time period $i$, $C3BCOS^A(t_i)$ and $C3BCOS^B(t_i)$ represent the central third *BCOS* of team A and B respectively during the time period $i$

3. Attacking third:

$$\Delta A3BCOS(t_i) = \text{Total}\, A3BCOS^A(t_i) - \text{Total}\, A3BCOS^B(t_i) \tag{6}$$

where, $\Delta A3BCOS(t_i)$ represent the relative *BCOS* between two teams in attacking third during the time period $i$, $A3BCOS^A(t_i)$ and $A3BCOS^B(t_i)$ represent the attacking third *BCOS* of team A and B respectively during the time period $i$

Three temporal features were extracted for each time period, representing the relative *BCOS* per unit of time between two teams, based on the above equations. This resulted in thirty temporal features per game, as the game was divided into 10 equal time periods for the extraction of temporal features (3 regions × 10 features).

## Machine Learning Model Development

To assess the relationship between the extracted temporal features on *BCOS* and match-winning performances, a match-winner prediction model was developed. The model utilized thirty extracted temporal features as input, with the target being a binary variable indicating whether the match was won by Team A (1) or Team B (0). Figure 5 illustrates the composition of the 30 temporal features and the target variable used for initial machine learning model development.

The relationship between temporal features, derived from the relative *BCOS* per unit of time, and the performance of match-winning performances was evaluated using a Random Forest (RF) classification model. RF is a popular ensemble learning algorithm for both classification and regression tasks. In general, ensemble models improve overall performance by combining the predictions of multiple models. A random forest consists of an ensemble of decision trees, where each tree is trained on a random subset of the data and features. This structure allows Random Forrest models to handle non-normally distributed data effectively. Random Forests are favored in machine learning due to their ability to handle a large number of input features, deal with missing data, ease of use, and computational efficiency. In this case, the input consisted of 30 features, making Random Forest a suitable choice for model development.

For naming purposes, this model is named as "30 feature RF model" in this work. This "30 feature RF model" was developed only with extracted temporal features on relative *BCOS* between two teams for the defined ten time periods. The objective of this model is to assess the importance of extracted temporal features on match winning performance

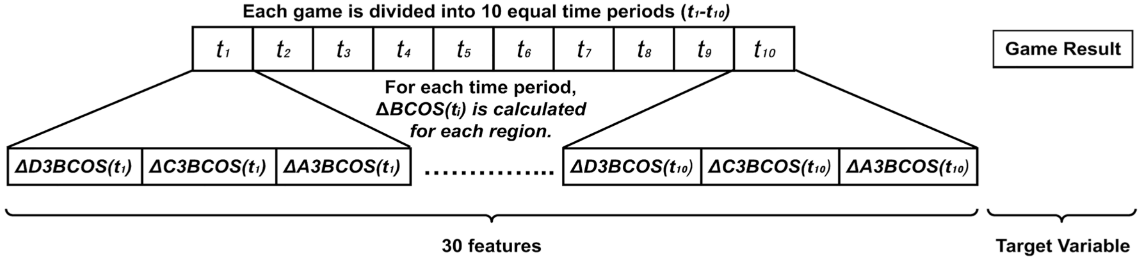


**Fig. 5** Composition of 30 features and target variable for initial machine learning model development

in order to identify the team performance evaluation aspect of *BCOS*. Use of only single metric (*BCOS*) allows to identify the importance of *BCOS* and to evaluate team performance of a team as a time-series team performance evaluation metric.

To thoroughly assess the performance of this "30 feature RF model", a five-fold cross-validation approach was used. This evaluation process involved performing fifty iterations of five-fold cross-validation, resulting in a total of 250 evaluations. From these evaluations, key metrics such as average classification accuracy, Matthews Correlation Coefficient (MCC), Area Under the Receiver Operating Characteristic Curve (ROC-AUC), F1-score, precision, and recall were computed.

## Temporal Feature Correlation Analysis

After developing the "30-feature RF model," the relationship between temporal features and favorable match outcomes was analyzed to identify temporal patterns and assess the contribution of relative *BCOS* in each third of the field to match-winning performances. To evaluate the correlation between the temporal features of relative *BCOS* (*BCOS* difference between two teams for each region of the field in a given time period $t_i$) and match-winning outcomes, both RF model feature importance and correlation coefficients were considered. The correlation coefficients were computed using both Pearson and Spearman correlation methods.

## Weighted Machine Learning Model Development

The initial "30-feature RF model" was built using 30 features. To enhance its performance, dimension reduction was explored, taking into account the size of the training dataset. A weighted arithmetic mean approach was used for this purpose, where the *BCOS* value differences between two teams for each third of a specific time period ($\Delta BCOS(t_i)$) were weighted by their respective correlation coefficients. The weighted arithmetic mean relative *BCOS* value for time period $t_i$ ($wBCOS(t_i)$ ) was computed for each time period $t_i$ by considering the weighted sum of the attacking third *BCOS* difference between two teams ($\Delta A3BCOS$), central third *BCOS* difference between tow teams ($\Delta C3BCOS$), and defensive third *BCOS* difference between two teams ($\Delta D3BCOS$) during a specific time period $t_i$.

$$wBCOS(t_i) = \frac{CCD3(t_i) \times \Delta D3BCOS(t_i) + CCC3(t_i) \times \Delta C3BCOS(t_i) + CCA3(t_i) \times \Delta A3BCOS(t_i)}{CCD3(t_i) + CCC3(t_i) + CCA3(t_i)} \tag{7}$$

where,

$wBCOS(t_i)$ is the weighted arithmetic mean of relative *BCOS* for time period $t_i$ ($1 \le i \le 10$),

$CCD3(t_i)$ is the correlation coefficient of $D3BCOS$ difference between two teams for the time period $t_i$ ($\Delta D3BCOS(t_i)$),

$CCC3(t_i)$ is the correlation coefficient of $C3BCOS$ difference between two teams for for the time period $t_i$ ($\Delta C3BCOS(t_i)$)

$CCA3(t_i)$ is the correlation coefficient of $A3BCOS$ difference between two teams for the time period $t_i$ ($\Delta A3BCOS(t_i)$)

This approach resulted in 10 weighted features per game representing weighted arithmetic mean *BCOS* during ten time periods considered. These 10 features were considered for machine learning model development with match result as the target variable. Figure 6 illustrates the composition of 10 weighted features and target variable for the machine learning model development using weighted arithmetic mean *BCOS* data.

The Ramsey Regression Equation Specification Error Test (RESET) was performed to assess the linearity of the distributions, and the results indicated that the distributions were linear. However, both the Shapiro-Wilk and Anderson-Darling tests, conducted to examine the

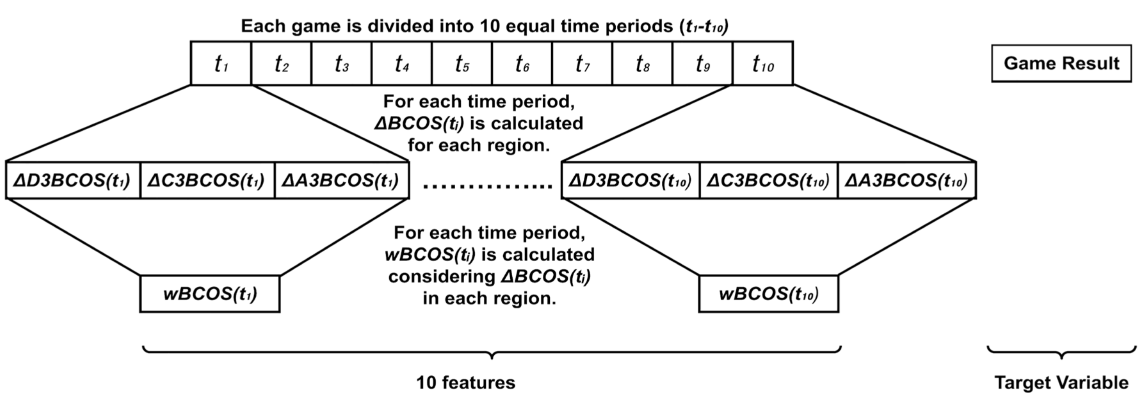


**Fig. 6** Composition of 10 weighted features and target variable for weighted machine learning model development

**Table 1** Results with match winning performance classification

| Evaluation metric | Average performance |
|---|---|
| Accuracy | 0.80738 |
| F1-Score | 0.82020 |
| Precision | 0.82198 |
| Recall | 0.83199 |
| ROC-AUC | 0.80870 |
| MCC | 0.61970 |

normality of the distributions, suggested that the distributions were not normally distributed. Typically, Pearson correlation coefficients are more appropriate for normally distributed data with linear relationships. Nevertheless, in this case, both correlation coefficients were utilized in the development of two machine learning models to determine which coefficient yielded the best performance.

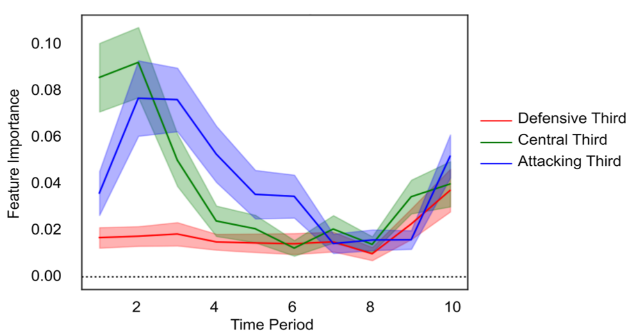


**Fig. 7** RF feature importance of relative *BCOS* in each third, analyzed across 10 time periods. Solid lines indicate the mean importance values while shaded areas indicate the standard deviations

A total of 50 rounds of five-fold cross-validation (resulting in 250 evaluations) were conducted for a thorough assessment of model performance. To prevent data leakage from correlation coefficients, these coefficients ($CCD3(t_i)$,$CCC3(t_i)$,$CCA3(t_i)$) were calculated for each evaluation using only the training fold data. The evaluation metrics computed included average classification accuracy, Matthews Correlation Coefficient (MCC), Area Under the Receiver Operating Characteristic Curve (ROC-AUC), F1-score, precision, and recall.

## Results

### Match Winning Performance Classification Model Results

The proposed match-winning performance classification model "30 feature RF model", trained using temporal features extracted from relative *BCOS* in each third of the football field, achieved an average accuracy of 80.74% in predicting match-winners, based on 50 rounds of five-fold cross-validation. Table 1 provides a summary of the results, including the model performance with other evaluation metrics considered for this study.

### Feature Importance and Correlation Analysis

The feature importance of the Random Forest (RF) model were analyzed to uncover temporal patterns and the contribution of relative *BCOS* in each region of the field to match-winning performances. Figure 7 illustrates the RF model's feature importance values for relative *BCOS* in each third, evaluated across 10 time periods.

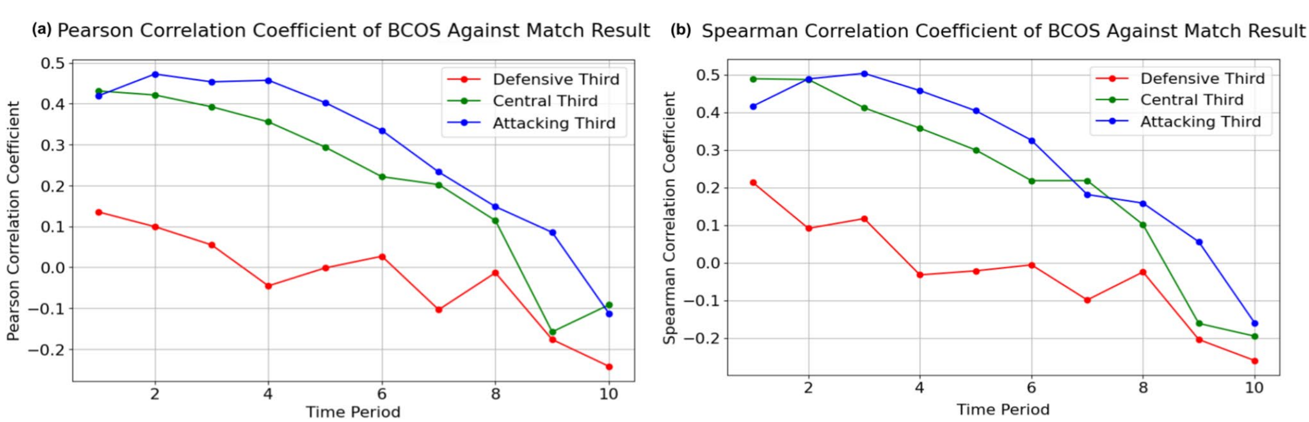


**Fig. 8** Correlation coefficients of BCOS against match result (Whether it's a win or a loss); **a** Pearson correlation coefficients, **b** Spearman correlation coefficients

The Random Forest model's feature importance reveals that the model has assigned greater importance to relative *BCOS* in the attacking and central thirds, with the attacking third receiving the highest overall importance. In contrast, relative *BCOS* in the defensive third is deemed far less significant. Additionally, relative *BCOS* in the attacking and central thirds during the early phases of the game holds more importance compared to later stages. However, there is a noticeable increase in feature importance across all three thirds in the final time period. These findings suggest that first-half performance plays a more significant role in favorable match outcomes. Further, attacking third relative *BCOS*, followed by central third relative *BCOS*, influence most for match-winning performances.

Next, the correlation coefficients between individual temporal features across ten time periods and match-winning performances were analyzed to uncover further hidden insights related to the temporal features. Correlation coefficients for each third of the field, across each time period, were calculated against the match result (win or loss) using both Pearson (Fig. 8a) and Spearman correlation (Fig. 8b).

The correlation coefficients reveal that relative *BCOS* in the attacking and central thirds shows a stronger relationship with match winning performances compared to the defensive third. Attacking third relative *BCOS* consistently displays the highest Pearson correlation across all time periods, except for time period 1 ($t_1$), where central third relative *BCOS* exhibits a stronger correlation in both Pearson and Spearman coefficients. These findings suggest that attacking third relative *BCOS* is the most critical factor for match-winning performances, followed by central third relative *BCOS*. In contrast, defensive third relative *BCOS* shows significantly lower correlation, indicating its relatively minor role in match-winning outcomes.

The correlation coefficients revealed a stronger positive relationship between favorable match outcomes and relative *BCOS* in the attacking and central thirds during the first four time periods (approximately 0–40 min). This suggests that first-half performance is more influential than second-half performance. After the fourth time period, the magnitude of correlation coefficients for relative *BCOS* in both the attacking and central thirds declines, with a significant drop toward the end of the game. Notably, all three thirds show negative correlation coefficients in the final time period, likely due to defensive strategies, such as "parking the bus", employed by leading teams to protect their advantage [31]. These tactics involve allowing the opposition to attack while defending deep and minimizing risk to secure the lead.

Correlation coefficients between defensive third relative *BCOS* and central third relative *BCOS*, defensive third relative *BCOS* and attacking third relative *BCOS*, as well as central third relative *BCOS* and attacking third relative *BCOS* were further analyzed to determine if there are temporal relationships between them, or if relative *BCOS* in one region influences the others. Figure 9a shows the Pearson correlation coefficients comparisons between the regions of the field, while Fig. 9b shows the Spearman correlation coefficient comparisons between the regions of the field.

As shown in Fig. 9, the correlation coefficients between central third relative *BCOS* and attacking third relative *BCOS* are notably higher than those for other comparisons. This suggests that relative *BCOS* in the attacking third is likely influenced by relative *BCOS* in the central third. In contrast, the correlation between defensive third relative *BCOS* and attacking third relative *BCOS* is much lower, indicating that relative *BCOS* in the defensive third has a relatively minor impact on the open space in the attacking third.

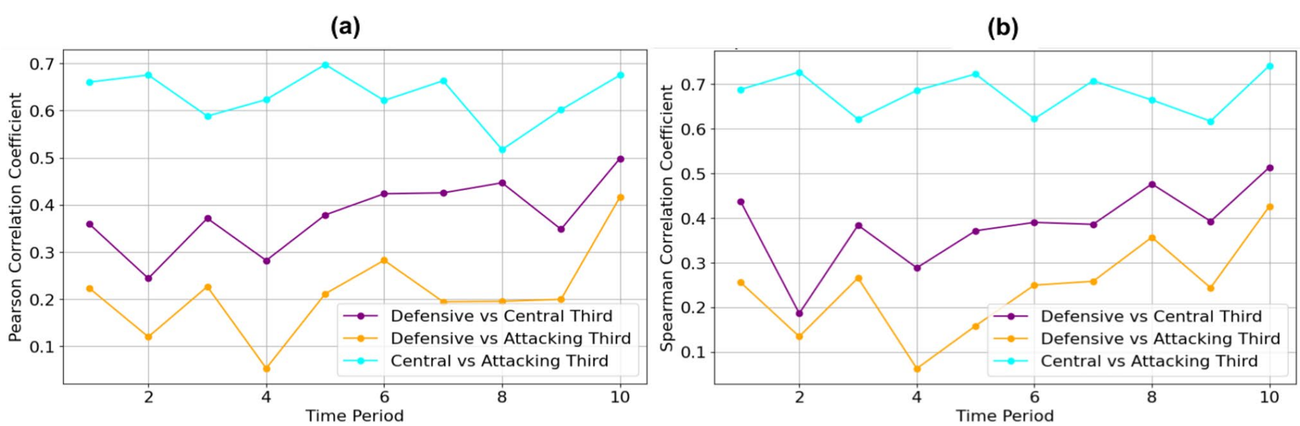


**Fig. 9** Correlation coefficients between BCOS in different regions of the field **a** Pearson correlation coefficients, **b** Spearman correlation coefficients

## wBCOS Model Results

The RF classification models trained with *wBCOS* data (10 features), achieved higher performance than “30 feature RF model”. Both models trained with *wBCOS* calculated for each time period using (a) Pearson Correlation Coefficients, and (b) Spearman Correlation Coefficients as weights achieved average accuracies over 82% based on results from 50 rounds of five-fold cross-validation. The *wBCOS* model, trained on *wBCOS* data generated using Spearman correlation coefficients as weights, achieved the highest accuracy of 82.5%, based on results from 50 rounds of five-fold cross-validation. Table 2 provides a summary of these results of models trained with *wBCOS* data (10 features).

**Table 2** Performance of the *wBCOS* models where weights were computed using (a) pearson correlation and (b) spearman correlation

| | Model Development Approach | |
|---|---|---|
| Evaluation Metric | Weights calculated using Pearson Correlation | Weights calculated using Spearman Correlation |
| Accuracy | 0.82061 | **0.82461** |
| F1-Score | 0.82964 | **0.83267** |
| Precision | **0.85114** | 0.84716 |
| Recall | 0.82274 | **0.83277** |
| ROC-AUC | 0.82506 | **0.82869** |
| MCC | 0.64676 | **0.65470** |

Higher performances are highlighted in bold font

## Comparison with Existing Literature

In this study, a novel team performance evaluation metric was introduced. Additionally, the temporal features extracted using the proposed time-series team performance evaluation metric (*BCOS*) have been used to develop machine learning models for match winning performance classification. To the best of the author’s knowledge, there has been no previous research examining team performance using similar temporal features or incorporating them into match-winner prediction models. However, this study presents a match-winner prediction model developed solely on the proposed temporal feature data extracted using in-game data and no historical game related features have been considered. The aim was to assess the importance of these temporal features on match-winning performances, uncovering potential insights. Due to differences in datasets, direct comparison between this model and those in existing literature is not appropriate. Nevertheless, the developed “*wBCOS* RF model” has achieved better performance in match winning performance classification than any other published work while, “30-feature RF model” has achieved similar performance to the previously highest achieved classification model. This offers a preliminary understanding of the significance of the temporal features considered for determining match-winning performances. Table 3 provides a comparison between match-winner prediction models from recent literature and the approach presented in this study.

While Al Mulla et al. employed a temporal feature extraction method from game data, they utilized 22 player evaluation metrics, resulting in 396 data points for prediction [33]. Their primary focus was on developing an accurate match-winner prediction model using a computationally intensive deep learning technique known as Gated Recurrent Unit (GRU). However, due to GRU’s black-box nature, it lacks the ability to provide insights into temporal features. In contrast, this study and author’s previous work [34] emphasizes the development of a time-series performance evaluation metrics aimed at capturing and assessing team performance. Furthermore, a trained match-winner prediction model, using only the proposed time-series metric data, achieved a higher model performance using a computationally inexpensive, simpler RF model. This work, author’s previous work [34] and the work by Al Mulla et al. [33] involve the extraction of temporal features, allowing for the development of match-winner prediction models capable of predicting winners at different timestamps. This could be explored in future work.

The RF model, trained with *wBCOS* data has demonstrated the highest accuracy and f1-score better than the published match winner prediction models in the literature. This underscores the significance of open space available for the ball carrier as a determining factor in achieving victories in Association Football. Thus, both *wBCOS* and *BCOS* in each region ($A3BCOS$,$C3BCOS$,$D3BCOS$) can be used as time-series team performance evaluation metrics which provides valuable information about a particular team’s performance during or after the game conclusion.

# Discussion

This study assessed the significance of the open space available to the ball carrier for match-winning team performances, introducing it as a novel time-series team performance evaluation metric (*BCOS*) in Association Football. A machine learning model developed using temporal features derived from *BCOS* in three areas of the field-the attacking third, central third, and defensive third-achieved 80.74% accuracy in classifying match-winning performances. Additionally, the study proposed a weighted arithmetic mean (*wBCOS*) approach to simplify the feature set and build a match-winner classification model. A random forest (RF) model trained with *wBCOS* data outperformed all previously published models for classifying match winners (82.46%

**Table 3** Comparison with other match winner prediction models

| Literature | Approach | Features | Model | Acc | F1-Score | Perf. Eval. Aspect |
|---|---|---|---|---|---|---|
| Danisik et al. [32] | Player attributes and results from the last five games have been analyzed using data from top-tier club leagues in Europe | 139 features | LSTM | 70.21% | – | Evaluating optimal player combinations within the squad |
| Al Mulla et al. [33] | Player performance have been assessed temporally in the Qatar Stars League | 396 features | GRU | 80.77% | 80.93% | N/A |
| Bandara et. al. [34] | Event distribution randomness have been analyzed to evaluate offensive team performance in top-tier club and international competitions | 10 temporal features (single metric is used *EDRan*) | GLM | 80.00% | 81.89% | Temporal analysis of team performance |
| This work (2024) ("30 feature RF model") | The proposed metric *BCOS* is computed over 10 time periods across 3 regions of the field, using data from top-tier men's international and club leagues | 30 temporal features (single metric is used) | RF | 80.74% | 82.02% | Temporal analysis of team performance |
| This work (2024) ("*wBCOS* RF model") | The proposed metric *wBCOS* is evaluated temporally across 10 time periods using data from top-tier men's international and club leagues | 10 temporal features (single metric is used) | RF | **82.46%** | **83.26%** | Temporal analysis of team performance |

Highest performance is highlighted in bold font accuracy). These findings underscore the importance of ball carrier open space in contributing to positive game results. Furthermore, temporal analysis of the *BCOS* data revealed that open space in the attacking and central thirds plays a more significant role for match-winning performances.

This study further contributes by proposing a computationally inexpensive simpler approach for extracting temporal features on open space created for the ball carrier in association football. The developed approach uses player location information retrieved from television videos making it a simpler and computationally inexpensive approach that could be beneficial for television broadcasters and performance evaluators. The proposed approach requires no technologically advanced equipment to capture the player's performances.

However, a relatively small dataset has been used in this work due to data availability and dataset limitations. Future work could explore a larger dataset with complex deep learning models that capture the temporal relationships (e.g., Long Short Term Memory network). Also, this work does not consider player velocities due to dataset deficiencies in capturing them. It can be expected that player velocities could add more value to the proposed work. Furthermore, this work values all the space created within a region equally. However, in reality, space created closer to the goal could be more valuable than the space created far away from the goal. This could be explored in future work. This study utilizes player coordinates extracted from televised video footage of real association football games. As a direction for future research, the use of video game data could be explored to assess its potential as synthetic data for similar analyses.

In addition to the team performance evaluation, individual player performance could be evaluated with the proposed performance evaluation metric *BCOS*. As discussed in [35], individual performance could be evaluated with *BCOS* under two aspects,

1. Active Ball Carrier Open Space Creation: Actions by ball carriers to create open space for him/herself or teammates in immediate subsequent events. Actions include passes, through balls, carries with dribbles.
2. Passive Ball Carrier Open Space Creation: Actions by players to create open space when receiving the ball from preceding event. Actions include off ball runs, placements.

This individual player performance evaluation could be further explored in a future work.

## Conclusion

In conclusion, this study introduced a novel time-series team performance evaluation metric (*BCOS*), which measures the open space available to the ball carrier, alongside a simpler method for calculating the metric using data extracted from televised videos. A simple computationally inexpensive machine learning model trained solely on features derived from the proposed *BCOS* metric in three regions of the field achieved accuracy comparable to the best results in the literature, while the model based on the proposed *wBCOS* metric outperformed all previous work for similar classification tasks. These findings emphasize the significance of *BCOS* and *wBCOS* in determining match-winning performances and establish its reliability as a performance evaluation metric in association football.

Moreover, temporal analysis of *BCOS* data revealed that open space in the attacking third (*A3BCOS*) and central third (*C3BCOS*) plays a greater role in driving match-winning outcomes, whereas open space in the defensive third (*D3BCOS*) has a minimal impact. Additionally, *C3BCOS* was found to influence positive *A3BCOS*. Therefore, it is reasonable to conclude that generating open spaces for ball carriers, through both on- and off-ball movements, is a key factor in successful team performances. Teams should prioritize creating open space for the ball carrier in the central and attacking thirds to improve match-winning chances.

**Acknowledgements** The authors acknowledge Statsbomb for providing a publicly available association football data set from real match data. The authors would also like to acknowledge the Coventry University Ethics Committee for their approval and support in conducting this study.

**Author Contributions** Ishara Bandara was responsible for conceptualization, data curation, investigation, methodology, software development, visualization, and writing of the original draft. Ishara also contributed to the review and editing of the manuscript. Sergiy Shelyag, Sutharshan Rajasegarar, Dan Dwyer, Eun-jin Kim, and Maia Angelova contributed to formal analysis, funding acquisition, investigation, project administration, provision of resources, supervision, and validation of the research. They all participated in the review and editing of the manuscript.

**Funding** Open Access funding enabled and organized by CAUL and its Member Institutions. This research was funded by the Deakin-Coventry Cotutelle Scholarship program. The authors gratefully acknowledge the financial assistance provided by this scholarship, which enabled the successful completion of this project.

**Data Availability** The dataset used for this study is publicly available and can be accessed from statsbomb open-data Github repository at https://github.com/statsbomb/open-data.

## Declarations

**Conflict of interest** The authors declare that they have no conflict of interest.

**Ethics Approval** Ethics approval for this study was granted by the Coventry University Ethics Approval Committee (Approval Number: P174511). All procedures conducted in this study adhered to the ethical standards set by Coventry University, UK.

**Informed Consent** Not applicable.



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