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Intelligent Decision Making Technique for Handling Game Tactics in Soccer Sports

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Abstract
Understanding the game tactics applied by the opponent team is crucial in shaping the team tactics in soccer sports. Traditionally, various football clubs, organizations, coaches, players, and sports enthusiasts have relied on observations during the match. However, these kinds of subjective measures cannot give detailed insight into the tactics of the opponent side. In this paper, on the contrary, a completely objective technique is proposed, which can provide purely quantitative results. The proposed intelligent decision making technique for game tactics (IDMTGT) presents a novel soccer formation construct n1-n2-n3-nj, which signifies contextual and positional features on the soccer pitch to identify different positions and try to find the relation between diverse player positions. K-means clustering has been applied to partition the player positions with average player position id values 5.42, 19.69, and 14.41 for representing the defensive, attacking, and mid-fielders respectively. Everyone is not privileged to hire a professional soccer coach, manager, or analyst due to financial barriers or geographic factors. Hence, there is a need for such a technique, which can provide decision-making support to coaches, sports enthusiasts, or players for handling game tactics in soccer sports. The proposed technique (IDMTGT) will provide effective decision-making support in terms of automated suggestions for team formation by creating the ball passing pattern network of the opponent team for handling game tactics in soccer sports. The proposed IDMTGT served the purpose by eliminating coach biasness for suggesting the formations. To statistically validate the effectiveness of IDMTGT and to find out the difference between games without change of formation and after the formation changes suggested by the proposed IDMTGT technique based algorithm, Cohen's d effect sizes have been computed. The proposed technique (with own team mean effect size 0.64 and opponent team mean effect size 0.37), evidently indicates the effectiveness and successful validation of the IDMTGT. By analyzing the passing sequences of the other team, significant insights can be obtained, in the form of their attacking or defensive approach, preferred areas of the pitch, and style of play. The study has exploited a total no. of 31 matches, 26314 passes and 875 shots made in UEFA Women's Euro Cup 2022, both group and knock-out stages.

Keywords- Soccer passing pattern network, Intelligent computing, Player positions, Game tactics, Decision making.

1. Introduction

The dynamic and fast-paced world of soccer sports always demand an understanding of the playing patterns and other tactical playing styles of the opponent team for the successful outcome of the soccer matches (Martin, 2012). Over the years, wide varieties of data-driven techniques and highly advanced analytics have transformed soccer sports by supplying important insights into team dynamics, game tactics, strategic planning, and playing behavior (Brooks et al., 2016; Frencken et al., 2013; Madan et al., 2022). Coaches, sports organizations, soccer clubs, and players are always in the race to find innovative approaches for player ranking, enhancing their performance, player evaluation, and gaining viable advantages over their competitors (Pappalardo et al., 2019).

In the past few years, with the introduction of sophisticated tracking technologies for collecting a wealth of soccer tracking data, there are now countless opportunities to improve game tactics and eventually improve the performance of teams and players. As it is possible to have access to extensive player movement, passing, and positioning data, one can pinpoint strengths and weaknesses, analyze complex patterns, and create specialized tactics.

This treasure of knowledge can enable soccer stakeholders to make data-driven decisions, modernizing the sport and raising the bar for performance excellence (Sgrò et al., 2018). Ball passing patterns can serve as a vital tool in effective decision making in soccer sports. Despite having massive assurance, soccer's ball passing patterns are still mostly untapped in contrast to passing patterns in other sports. In this work, the proposed technique employs passing pattern as the main instrument in understanding the team dynamics of the opponent and setting the game tactics for the team accordingly.

These complex designs hold the key to revealing priceless information for effective decision-making and hence offer competitive advantages in the game (Meng et al., 2020). So, it's the ideal time to identify the enormous potential of soccer passing patterns in understanding player dynamics, game tactics, and behavior of the competing teams (Lampis et al., 2023).

The proposed technique based algorithm (IDMTGT) will change the way of playing soccer at both the professional and ground levels by eliminating coach biasness and provide support even at trainee levels, where teams and players were deprived of expert support. The proposed technique (IDMTGT) can dynamically adapt to in-game changes and can provide decision-making support. By doing so, coaches and clubs can revolutionize how teams play, understand the game, and optimize tactics for improved team performance.

An in-depth examination of the players' passing patterns of the opposing team can reveal a plethora of important information about their offensive and defensive strategies. Coaches and players can adapt their tactics to take advantage of opportunities and exploit weaknesses by having a thorough understanding of their preferred passing patterns, identification of key players, and their positions on the pitch and in the transfer market of players (Palazzo et al., 2023). By using this data-driven sports analysis, more competitive and exciting soccer settings can be created, which equips teams with the knowledge they need to make game tactics according to their opponent's weaknesses.

The remaining paper is arranged as follows. Section 2 provides the related work associated with game tactics in different sports, such as football, basketball, handball, and field hockey Section 3 introduces an effective decision-making technique based algorithm for game tactics (IDMTGT) in soccer. Section 4 presents the Experimental validation of the proposed technique for soccer players' passing patterns. Section 5 shows results and analysis, and Section 6 gives insight into the conclusion.

2. Related Work

Over the recent years, a lot of research has been conducted on various aspects of game tactics to improve the performance of soccer teams. Hence, there are already certain related studies accessible in this domain. Some of the distinguished works are as follows:

Ngo et al. (2012) presented the influence of changing defensive rules over exercise intensity in football small-sided games. Man-marking as a defensive tactics rule has been recommended in the study to increase the intensity level. Time motion measures from the global positioning system could be integrated to offer additional performance benefits. Owramipur et al. (2013) employed a dataset of team Barcelona for the 2008-09 season of the Spanish league. The study distinguished an array of features influencing the match scores and final match results of soccer sports. The chosen features are divided into two broad categories i.e. physiological and non-physiological features. Physiological features include the match outcome of the recent five games, home team advantage, the ability of the opposition, and climate conditions. In the same way, non-physiological features include key players' injury list and frequency of the matches. The study employed Bayesian network to find out the factors influencing the match scores and final match results. Puchun (2016) worked on soccer game tactics to enhance the training levels of soccer players as per their role in the team. The work has made use of the manually created dataset. The study employed association rule mining for game tactics, strategic planning, and decision making. Cakmak et al. (2018) proposed a descriptive passing evaluation system to measure the efficacy of passes in football that combines factors like goal chances, risk, and gain. The work is a static flat system that relies on a comparatively smaller set of data points. Chen et al. (2018) presented a technique to produce a defensive approach in the basketball game based on the attacking team's movements. A simulative environment has been provided to coaches and players to understand the behavior of the opponent team by the use of spatio-temporal interactions performed between the players' movements. For this, the offensive team's trajectories have been used as an input to produce the defensive teams' trajectories. A comparison has also been made between the actual and produced defensive play. McLean et al. (2018), used social network visualize (SocNetV) and focused on total passes made by the node to all the other nodes by calculating partial eta squared as a measure of effect size. Korte & Lames (2018) employed a minimum spanning tree to create a visualization of interplay in three different sports i.e. basketball, football, and handball for identifying the roles of various tactical positions in the game. They investigated the network patterns of many teams to identify the player positions and game tactics employed by them. They identified the point guard position in basketball, the defensive midfielder position in football, and the center position in handball as the most central tactical position.

McHale & Relton (2018) presented a system for coaches and managers to identify the key passers on the opponent team and shape their own tactics in line with such key passers of the opponent team. The work could be extended by identifying the key players who can perform in different levels of pressure situations. Aalbers & Haaren (2019) proposed a set of a total of 21 player roles in football. They have proposed a method for identifying a favorable role for every player based on data collected during previous matches. Using supervised learning, firstly, the roles to be played by all the players are distinguished and aimed to derive player positions with the role of players in those positions. Bekkers & Dabadghao (2019) worked on the use of passing behavior in soccer to compare teams from different seasons and to find unique playing styles of both teams based on the motif used. The study elaborates on the relationship between different playing positions. Fernández et al. (2019) have presented a model that provides an expected value of possession in soccer. The model denotes positional, contextual, and motion features to realize the interactions among the players. Framework aims to evaluate players and team performance, analysis of decision-making, and value actions. Matos et al. (2019) used K-means clustering for soccer game training and tactics. The study recommended particular training to enhance the abilities of football players. Not considering the domain-independent information while modeling the players, turned out to be the major drawback of the study. Almulla & Alam (2020) used players' performance metrics to predict the football match outcome in the Qatar Stars League (QSL). Relationship between various variables is identified and these suggested player performance metrics have been used to predict the winner of the match. The main variables exploited for the study were shots on target, distance covered with speed, and successful passes. Rajesh et al. (2020) worked on selecting football players for corresponding positions based on performance, ratings, skills, and wages. They claimed a reduction of risk involved in selecting players for the organization, which can result in financial profit for the management in the case of sports analytics. They aim to make a well-balanced squad by optimizing the selection of players to improve the team outcome.

Geurkink et al. (2021) presented a spectrum of variables for match results in soccer. They tried to find the relationship between variables like shot on target, distance in speed zones, ELO ratings, etc. They worked on 576 matches and their 13 variables. Forcher et al. (2022) conducted a study on soccer to measure own and opposing team performance before and after formation change. The work has employed non-parametric tests to compare the performance of both teams with and without formation change. The study reported that after the formation change suggested by the coach, the own team's performance enhanced moderately and the opponent team's performance dropped slightly. Kolias et al. (2022) investigated the rotation of line-ups in basketball to perform attacking and defensive approaches. Various formations were explored using linear regression. Offensive, net, and defensive ratings were also calculated. Work has collected a wide variety of information to optimize the game tactics in basketball to enhance performance. Lorenzo-Martinez et al. (2020) employed positional type of data to analyze the affirmative effect of defensive and offensive substitutions on tactical behavior in soccer matches. The dataset has been taken from the German Bundesliga season 2016-17. As per the player's roles, the substitutions have been classified as offensive, defensive, or neutral. The tactical behavior of the team has been analyzed using factors like team length, stretch index, space control, team centroid, and inter-team centroid distance. Lord et al. (2023) aimed to analyze the spatial distribution of ball movement in field hockey during international tournaments. An analysis system was built to understand the patterns involving ball movement of international teams and to identify successful game tactics. Rahimian et al. (2023) presented a reinforcement framework for deriving optimal decisions for the actual action-based behavior. Using the destination location of players on the soccer pitch is discovered. The team-specific behavior is compared in terms of shots and short passes. The goal of this paper is to improve the expected goal difference by using optimal strategies.

The comparative analysis of the related literature has been presented in terms of the game tactics approach used and limitations as shown in **Table 1**.

Table 1. Comparative analysis of game tactics approaches in soccer sports.

S. No.	Research study	Game tactics approach	Technique used	Limitations
1.	Ngo et al. (2012)	Man-marking as a defensive tactics rule has been recommended in the study to increase the intensity level	MANOVA Intra-class correlation (ICC) coefficients	Time motion measures from the global positioning system are not included for decision making.
2.	Owramipur et al. (2013)	To test the tactical performance of the soccer team using a probabilistic graphical system.	Bayesian Network	Data of only one playing team Barcelona has been used as a dataset.
3.	Puchun (2016)	An algorithm is proposed for analysis of soccer tactics and to improve the training level of players as per their role in the team formation.	Data Mining Association Rule	Limited dataset for testing purpose.
4.	Cakmak et al. (2018)	Proposes a quantitative passing evaluation system that combines factors like goal chances, risk, and gain.	Genetic optimization Hill-climbing Simulated annealing	The game tactics is a static flat system that relies on a comparatively smaller set of data points.
5.	McHale & Relton (2018)	The study presented a system for coaches and managers to identify the key passers on the opponent team and shape their own tactics in line with such key passers of the opponent team.	Generalized additive mixed model	Identifying the key players who can perform in different levels of pressure situations is missing.

Table 1 Continued…

6.	McLean et al. (2018)	The study focuses on total passes made by the node to all the other nodes by calculating partial eta squared as a measure of effect size.	Social Network Visualizer (SocNetV)	Playing formation of the opponent team is not considered
7.	Aalbers & Haaren (2019)	Proposed the soccer player roles to describe their playing styles and acquire the most relevant position of each player in the team formation.	Stochastic Gradient Descent classifier	Along with primary role of each player, potential optional roles of players in team formation are not included for handling game tactics.
8.	Matos et al. (2019)	System suggests specific tactical decisions and training that can improve soccer players' abilities and performance in respective playing positions.	K-means clustering algorithm	Domain-independent data was not considered in player modeling.
9.	Rajesh et al. (2020)	The study performed on important aspect of game tactics i.e. selecting football players for corresponding positions based on performance, ratings, skills, and wages.	Random Forest Naïve Bayes Decision tree SVC	Spacio-temporal aspects have been ignored. Any technique to classify player positions and dynamic adjustment of game tactics is missing.
10.	Geurkink et al. (2021)	Presented a spectrum of variables for match results in soccer. Study tried to find the relationship between variables like shot on target, distance in speed zones, ELO ratings, etc.	BorutaShap Extreme Gradient Boosting	Some important factors such as playing style have not been considered in the study.
11.	Lorenzo-Martinez et al. (2020)	The study intended to analyze the affirmative effect of defensive and offensive substitutions on tactical behavior in soccer matches.	Linear mixed model	Merely post-priori statistics were applied and the dynamic decision-making of the coaches were not considered.

3. Algorithm based on Intelligent Decision-Making Technique for Game Tactics in Soccer

Soccer formation graphs portray a team's arrangement on the pitch in any soccer match. These arrangements in the form of graph speak about the player's positioning, their interactions with the other players, and player's role in the team, their off-the-ball movement and the general flow of the game. Managers and Coaches precisely choose the player formations based on the strengths and weaknesses of their own squad as well as the challenges put forward by the opponents. Formations aren't merely concerned about player positions; they outline how the players interact with other teammates, and their off-the-ball movement. In this manner, formations revolutionize the whole game into a canvas where game tactics, skill, and strategic planning converge with each other.

Formations reveal the team's core approach to defense, attack, or midfield domination (Xie et al., 2020). In this manner, formations revolutionize the whole game into a canvas where game tactics, skill, and strategic planning converge with each other. Each player's position in soccer demands diverse skills. Various player positions, role, and their names are given in **Table 2**.

There is a need for such a technique, which can provide effective decision-making support to coaches, sports enthusiasts, or players about the team composition and formation in soccer sports. The proposed technique (IDMTGT) provides effective decision-making support by firstly analyzing the ball passing pattern network of the opponent team and suggesting the game tactics for the own team in terms of counter formation, which will assist coaches, sports enthusiasts, and players to a great deal in this cutting-edge competitive world of soccer sport.

The proposed technique suggests a common formation structure (n_1-n_2-n_3-n_j), where n_1 means the number of players at defensive positions, n_2 is the number of players at midfield, n_3 is the number of players at attacking forward positions and n_j is the optional set of players used as hybrid positional arrangement employed in only a few formations (Algorithm 1). In total, there are 11 players in each team, and except the goalkeeper; the remaining 10 players can be arranged in any formation. For example, considering formation involving only n_1-n_2-n_3 set of players, one of the common soccer formation 4-3-3, which generally means there will be 4 players at defensive back positions, 3 players will occupy midfield positions and 3 players will be at attacking forward positions. At times, teams may choose additional layer of players in the form hybrid positional arrangement n_j. The few most common formations of the category are 4-3-2-1 and 4-1-4-1 etc.

Table 2. Soccer positions and abbreviations.

Abbreviation	Position	Role
RB	Right-back	Defender
RCB	Right-centre-back	Defender
CB	Centre-back	Defender
LCB	Left-centre-back	Defender
LB	Left-back	Defender
RWB	Right-wing-back	Defender
LWB	Light-wing-back	Defender
RDM	Right-defensive-midfielder	Midfielder
CDM	Centre-defensive-midfielder	Midfielder
LDM	Left-defensive-midfielder	Midfielder
RM	Right-midfielder	Midfielder
RCM	Right-central-midfielder	Midfielder
CM	Central-midfielder	Midfielder
LCM	Left-central-midfielder	Midfielder
LM	Left-midfielder	Midfielder
RAM	Right-attacking-midfielder	Midfielder
CAM	Central-attacking-midfielder	Midfielder
LAM	Left-attacking-midfielder	Midfielder
LW	Left-winger	Attacking forwards
RCF	Right-centre-forward	Attacking forwards
ST	Striker	Attacking forwards
LCF	Left-centre-forward	Attacking forwards
SS	Secondary-striker	Attacking forwards
RW	Right-winger	Attacking forwards
GK	Goalkeeper	Goalkeeper

K-means clustering has been applied to partition the player positions with average player position id values 5.42, 19.69, and 14.41 for representing the defensive, attacking, and mid-fielders respectively. Silhouette_score function of scikit-learn library has been applied to evaluate the performance of K-means clustering. Results show that with K = 2, 0.56 Silhouette score has been obtained. On the same lines, 0.61 Silhouette_score has been obtained with the value of K = 3. Silhouette_score generally ranges from -1 to 1. Silhouette score +1 signifies that point is well matched to the own cluster and is far-off from others. Score 0 denotes that it is near the decision boundary or on the boundary between clusters. -1 Silhouette_score means point could be in the wrong cluster. As proposed algorithm have three clusters i.e. defensive, midfield and forward positions, the value 0.61 testimony the performance of K-means clustering.

In the graph, soccer players are denoted by nodes, whose area or size is directly proportional to the involvement of the player in the passing network. In the same way, the thickness of the edges is proportional to the number of passes between the players. The frequency of the number of passes between two particular players is indicated by the thickness of the edge between the nodes.

Algorithm 1: Algorithm based on intelligent decision making technique for game tactics (IDMTGT)

1) Input_Team_Passing_Data (Representing the number of passes made by all the players to each other).
2) Create_Passing_Pattern_network
a) Generate an empty directed graph
b) Denote players as nodes in the graph
c) Insert edges from one player to other target players during the pass in the graph.
d) Allocate weight to edges based on the frequency of successfully completed passes between two given players and represent the weights in the form of edge thickness.
3) Identify_Player_Positions
a) Include the abbreviations of player positions for identification of players.
b) Get the number of passes made by each player at various positions
c) Calculate the average position of each player on the pitch
4) Explore_Team_Formation
a) Set team formation based on the average location of each player on the pitch
5) Categorisation_of_Player_Positions
a) Category1 - Left Center Back, Right Center Back, Left Back, Right Back
b) Category2 - Striker, Left Winger, Right Winger
c) Category3 - Left Defensive Midfielder, Right Defensive Midfielder, Center Attacking Midfielder
6) Investigate_Passing_Pattern
a) Examine the passing pattern between a given set of players based on the weightage associated with each edge (frequency of the number of passes made between nodes). Determine the line width of each edge relative to the maximum count of weightage.
b) Calculate the total number of passes, average x, and average y coordinates for all the passes, number of players involved, and average based on their position and categories.
i) Set Total_Number_of_Edges = Sum of edges between the total number of nodes(players)
ii) Set Total_Passes_Made = Sum of successful passes made between set of all players
iii) Set Average_Passes_Made = Total_Passes_Made / Total_Number_of_Edges
iv) Set Total_Passes_Made_Category1 = Sum of successful passes made between category1 positions.
v) Set Total_Passes_Made_Category2 = Sum of successful passes made between category2 positions.
vi) Set Total_Passes_Made_Category3 = Sum of successful passes made between category3 positions.
vii) Set Category1_List_Count = Count of all the player positions in category1
viii) Set Category2_List_Count = Count of all the player positions in category2
ix) Set Category3_List_Count = Count of all the player positions in category3
x) Set Average_Passes_Made_between_Category1 = Total_Passes_Made_Category1/ Category1_List_Count
xi) Set Average_Passes_Made_between_Category2 = Total_Passes_Made_Category2/ Category2_List_Count
xii) Set Average_Passes_Made_between_Category3 = Total_Passes_Made_Category3/ Category3_List_Count
7) Team_Tactics_Decision

If (Average_Passes_Made_between_Category1 > Average_Passes_Made):

Suggested_ Formation _Tactics $\in \{n_1\text{-}n_2\text{-}n_3\text{-}n_j\}$ **where n_1, n_2, n_3 and n_j is $(4 \geq n_1 \geq 3)$, $(4 \geq n_2 \geq 2)$, $(4 \geq n_3 \geq 2)$ and $(2 \geq n_j \geq 0)$ respectively**

Else If (Average_Passes_Made_between_Category2 > Average_Passes_Made):

Suggested_ Formation _Tactics $\in \{n_1\text{-}n_2\text{-}n_3\text{-}n_j\}$ **where n_1, n_2, n_3 and n_j is $(5 \geq n_1 \geq 3)$, $(5 \geq n_2 \geq 2)$, $(2 \geq n_3 \geq 1)$ and $(1 \geq n_j \geq 0)$ respectively**

Else:

Suggested_ Formation _Tactics $\in \{n_1\text{-}n_2\text{-}n_3\text{-}n_j\}$ **where n_1, n_2, n_3 and n_j is $(4 \geq n_1 \geq 3)$, $(5 \geq n_2 \geq 4)$, $(3 \geq n_3 \geq 1)$ and $(1 \geq n_j \geq 0)$ respectively**

4. Experimental Validation of the Proposed Technique based Algorithm

The proposed technique has been validated with the help of an experiment. This study exploited a total of 31 matches, 26314 passes and 875 shots made in the UEFA Women's Euro Cup 2022 both group and knock-out stages. The data used for this study is taken from the Statsbomb dataset (Statsbomb, 2022). A total of 16 teams have participated in this famous tournament. The proposed technique based algorithm (IDMTGT) first identified the opponent's preferred areas of the pitch and especially their style of play. The IDMTGT analyzes the passing pattern network of the opponent team and provides automated suggestions in terms of team formation for handling game tactics for own soccer team. The study has exploited a total of 31 matches and 26314 passes made by these 16 teams and tried to draw every significant pattern that can be exploited by the opponent to get an advantage in the game. Passing sequences of the teams have been analyzed and extract significant insights in the form of their attacking or defensive approach. By understanding the game tactics of the opponent team, the proposed technique generated the tactics for the own team, which is far more effective in tackling the opponent team. To statistically validate the effectiveness of the IDMTGT technique based algorithm and to find out the difference between games without change of formation and after the change of formation suggested by the technique based algorithm IDMTGT, Cohen's d effect sizes have been computed.

It has been seen that teams having more quantitative values in terms of the number of shots, shots on target, corners, and lesser number of fouls usually won the matches in this UEFA Women's Euro 2022 as shown in **Table 3**. But if a team fails to achieve higher values in terms of shots, shots on target, corners, and a lesser number of fouls compared to its opponent, even then the team can succeed by changing their game tactics according to the passing pattern network of the opponent. For instance, passing pattern networks of Spain's women's team have been created for all the matches of the UEFA Women's Euro 2022. Then the passing pattern network of the German women's team versus Spain women's team match has been created. All these passing pattern networks have been created in the Spyder tool where the circle represents players and the edge thickness represents the frequency of successfully completed passes between players.

Table 3. Data from all the matches of the UEFA Women's Euro 2022 show that teams with the higher number of shots, shots on target, corners, and low numbers of faults usually win the matches.

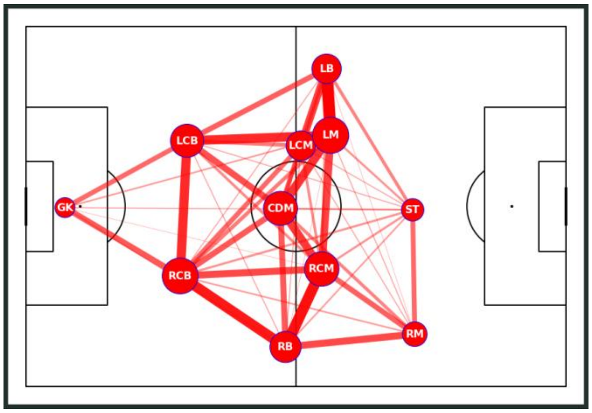
Team	Opposite	Shots	STA	Possession	Passes	Pass accuracy	Fouls	Yellow cards	Red cards	Corners	Result
England	Austria	15	5	60%	525	83%	5	0	0	5	WIN
Austria	England	8	2	40%	347	72%	8	0	0	4	LOSS
Norway	N.Ireland	21	11	66%	521	85%	5	0	0	9	WIN
N.Ireland	Norway	7	2	34%	269	71%	5	1	0	1	LOSS
Spain	Finland	32	13	78%	666	88%	9	1	0	17	WIN
Finland	Spain	4	2	22%	196	58%	8	1	0	0	LOSS
Germany	Denmark	22	9	66%	531	80%	10	3	0	7	WIN
Denmark	Germany	6	2	34%	271	63%	10	1	1	4	LOSS
Portugal	Switzerland	17	6	58%	456	79%	9	0	0	9	DRAW
Switzerland	Portugal	7	2	42%	350	69%	12	3	0	2	DRAW
Netherlands	Sweden	9	3	49%	448	75%	4	0	0	3	DRAW
Sweden	Netherlands	11	4	51%	451	80%	7	0	0	6	DRAW
France	Italy	16	7	59%	489	85%	8	0	0	3	WIN
Italy	France	13	6	41%	337	81%	11	3	0	7	LOSS
Belgium	Iceland	11	8	55%	431	70%	6	2	0	2	DRAW
Iceland	Belgium	23	5	45%	340	65%	5	0	0	10	DRAW
England	Norway	25	15	65%	540	87%	5	0	0	2	WIN
Norway	England	4	1	35%	298	73%	8	3	0	3	LOSS
Austria	N.Ireland	20	8	58%	393	75%	7	0	0	6	WIN
N.Ireland	Austria	4	2	42%	306	69%	7	0	0	3	LOSS
Denmark	Finland	19	5	56%	519	83%	8	1	0	6	WIN
Finland	Denmark	9	2	44%	437	76%	4	0	0	1	LOSS
Germany	Spain	7	2	30%	290	61%	16	2	0	4	WIN
Spain	Germany	12	3	70%	677	82%	9	0	0	6	LOSS
Sweden	Switzerland	15	6	55%	491	75%	12	0	0	3	WIN

Table 3 Continued…

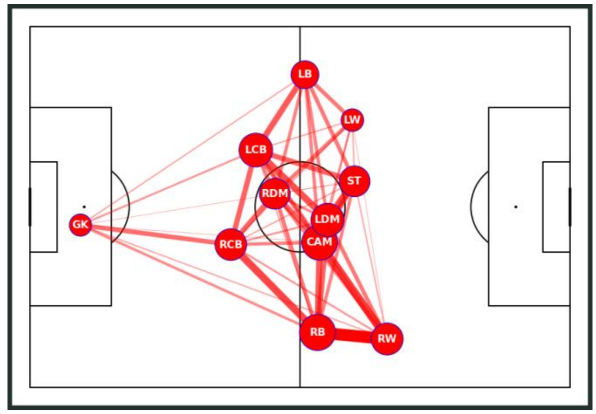
Switzerland	Sweden	5	3	45%	415	67%	14	0	0	2	LOSS
Netherland	Portugal	16	6	62%	474	80%	8	4	0	7	WIN
Portugal	Netherland	10	6	38%	283	70%	11	3	0	4	LOSS
France	Belgium	27	7	60%	561	86%	2	0	0	11	WIN
Belgium	France	2	1	40%	393	76%	8	1	1	1	LOSS
Italy	Iceland	21	8	66%	454	77%	9	1	0	6	DRAW
Iceland	Italy	10	2	34%	245	56%	18	0	0	1	DRAW
England	N.Ireland	27	7	78%	609	88%	6	0	0	9	WIN
N.Ireland	England	3	2	22%	177	53%	5	0	0	0	LOSS
Austria	Norway	18	8	39%	352	67%	6	2	0	6	WIN
Norway	Austria	8	2	61%	546	76%	9	0	0	5	LOSS
Spain	Denmark	17	5	75%	709	86%	2	1	0	9	WIN
Denmark	Spain	10	2	25%	252	58%	7	1	0	2	LOSS
Germany	Finland	33	7	63%	525	83%	10	0	0	13	WIN
Finland	Germany	1	0	37%	323	65%	10	1	0	0	LOSS
Netherlands	Switzerland	18	10	51%	440	82%	11	0	0	2	WIN
Switzerland	Netherlands	14	8	49%	413	79%	4	0	0	6	LOSS
Sweden	Portugal	18	9	53%	310	70%	9	2	0	7	WIN
Portugal	Sweden	7	2	47%	289	72%	11	1	0	2	LOSS
Belgium	Italy	8	2	46%	433	75%	8	0	0	1	WIN
Italy	Belgium	20	6	54%	468	79%	6	1	0	12	LOSS
France	Iceland	18	5	62%	470	80%	9	1	0	4	WIN
Iceland	France	9	2	38%	284	67%	8	2	0	6	LOSS
England	Spain	10	3	42%	470	75%	17	1	0	5	WIN
Spain	England	17	4	58%	645	84%	18	2	0	8	LOSS
Germany	Austria	20	5	62%	460	76%	10	1	0	7	WIN
Austria	Germany	12	2	38%	287	59%	13	3	0	6	LOSS
Sweden	Belgium	33	10	52%	423	76%	3	0	0	13	WIN
Belgium	Sweden	3	0	48%	400	72%	6	2	0	2	LOSS
France	Netherlands	33	13	52%	564	80%	7	0	0	10	WIN
Netherlands	France	9	1	48%	521	80%	15	3	0	5	LOSS
England	Sweden	17	8	58%	453	79%	7	1	0	4	WIN
Sweden	England	12	4	42%	310	72%	13	1	0	6	LOSS
Germany	France	11	4	51%	415	75%	14	2	0	4	WIN
France	Germany	14	2	49%	409	74%	8	2	0	3	LOSS
England	Germany	12	8	48%	460	71%	20	4	0	8	WIN
Germany	England	15	6	52%	493	68%	22	3	0	7	LOSS

Spain women's team passing pattern has been illustrated in **Figure 1**, where the circle represents the average position of the player while making all the passes and edge thickness represents the frequency of all the successfully completed passes between players. Many teams may change formation at different phases of the match like the Spain team did in its matches against England and Denmark women team. Hence, two different passing pattern networks of Spain's women's team have been created in each match played against England and Denmark teams as shown in **Figure 1**. In this tournament, the Spain team usually did more passing between their Left back, right back, left center back, and right center back in almost all the matches as shown in **Figure 1**.

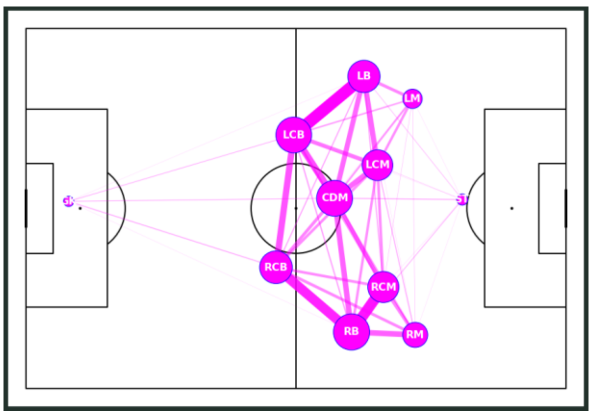
By following the Spain team's passing pattern network as shown in **Figure 2**, the German women's team has transformed their game tactics accordingly. Team Germany made their formation in line with the extra-defensive Spain women's team. This extra defensive passing pattern of Spain's team gave much-needed freedom to team Germany to play more attacking play. Hence, the German women's team made their passing pattern in such a way that their Striker, left winger and right winger came into play much more as compared to other teammates as shown in **Figure 3**.



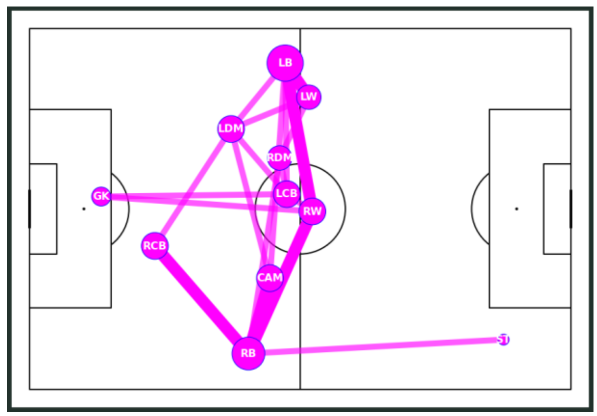
Initial formation of Spain team against England team.



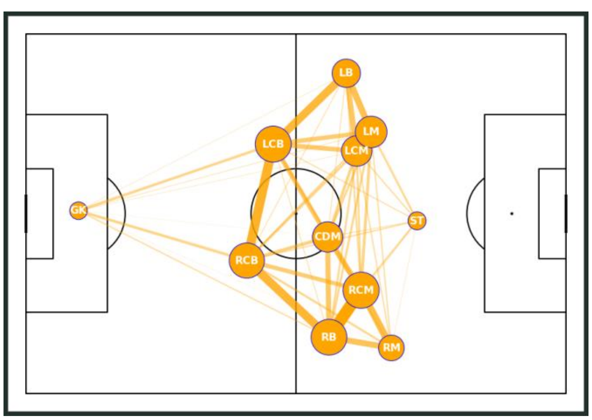
Final formation of Spain team against England team.



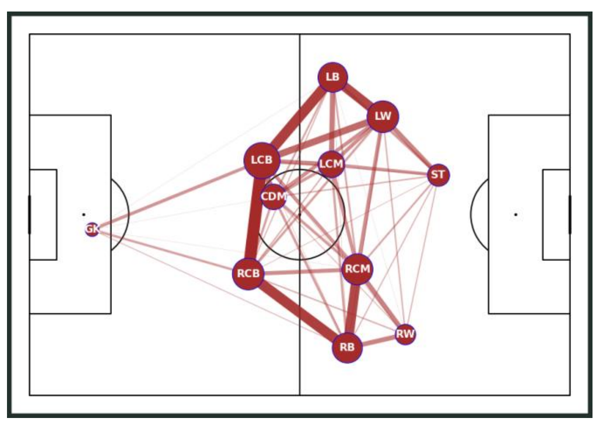
Initial formation of Spain team against Denmark team.



Final formation of Spain team against Denmark team.



Formation of Spain team against Germany team.



Formation of Spain team against Finland team.

Figure 1. Illustration of the passing pattern of the Spain women's team in all the matches of the tournament.

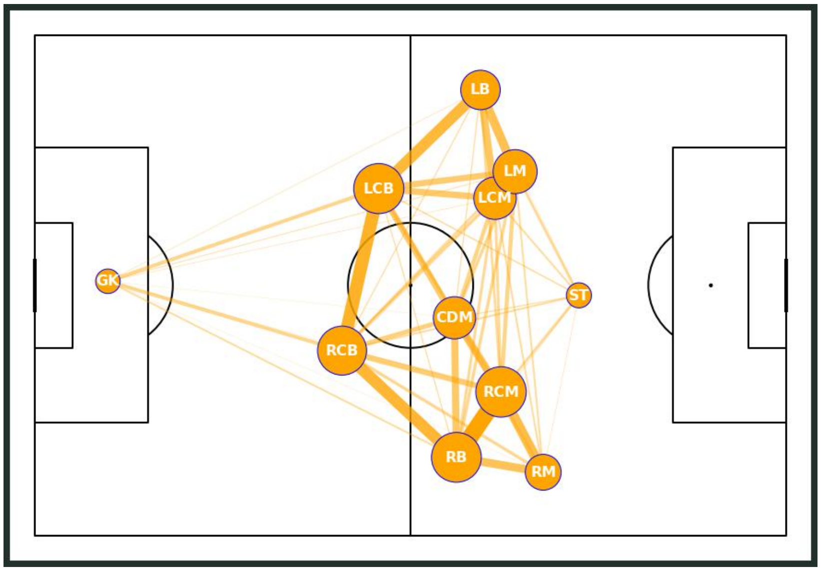


Figure 2. Illustration of passing pattern network of Spain women's team against Germany women's team with pass completion rate 79%.

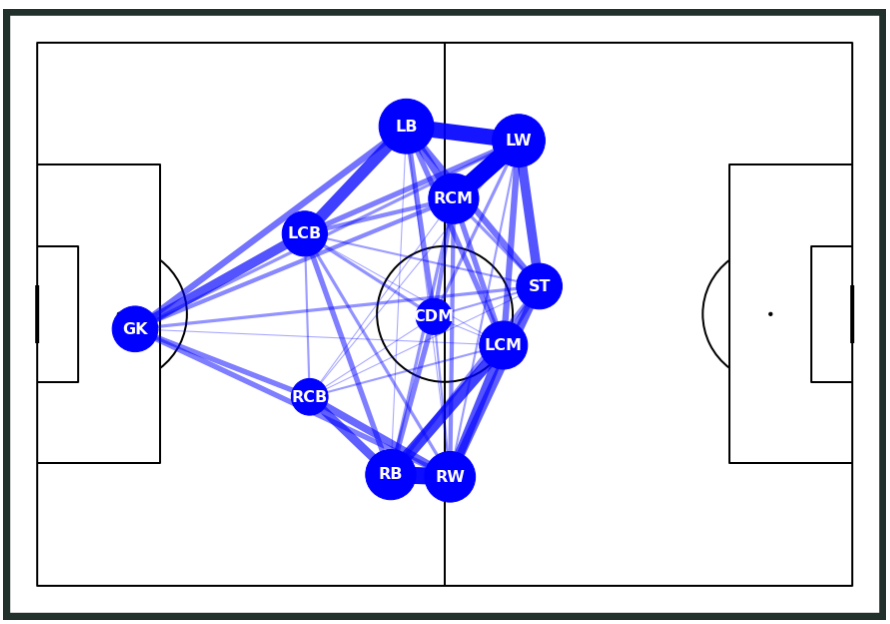


Figure 3. Illustration of passing pattern network of German women's team against Spain women's team with pass completion rate 86%.

Germany's team is blessed with experts and coaching staff to take care of their game tactics. Hence, the proposed technique can fill this gap and able to provide effective decision-making support in terms of automated suggestions for team formation and relationships between the different player positions.

5. Results and Analysis

The proposed technique based algorithm (IDMTGT) gave promising results during experimental validation of the algorithm. As shown in the instance of the German women's team versus Spain women's team match, experimental validation successfully proved the point of identifying the passing pattern of the opponent team and providing effective decision-making to handle game tactics accordingly for enhanced performance. It has been investigated that features like the number of shots, number of shots on target, possession percentage, pass accuracy, number of passes and corners are the deciding factors for the victory in a soccer match. Germany's women's team was lagging in all the departments but still managed to win the match as shown in **Table 4**.

In this competition, most of the Spain women's team matches showcased the trend of maximum passing done between their Left back, right back, left center back, and right center back as shown in **Figure 1**. By anticipating the passing pattern of the Spain team as shown in **Figure 2**, the German team has transformed their game tactics accordingly based on the decision exhibited by the proposed technique. German women's team made their formations in line with the extra defensive Spain women's team as shown in **Figure 3**. It has been seen that the right decision-making played a vital role in this context.

Table 4. The German women's team was lagging in all the departments but still managed to win the match.

Team	Germany women team	Spain women team
Shots	7	12
Shots on target	2	3
Possession	30%	70%
Passes	290	677
Pass accuracy	61%	82%
Fouls	16	9
Yellow cards	2	0
Red cards	0	0
Offside	1	0

The enhancement of team performance was quantified in terms of a total of six variables i.e. shots, shots on target, and corners by the own team as well as the opposing team, three variables each. To statistically validate the effectiveness of IDMTGT and to find out the difference between games without change of formation and after the proposed technique suggested change of formation, Cohen’s d effect sizes have been computed (**Table 5**). Here, three classes have been defined, i.e. small ($0.2 \leq ES \leq 0.5$), medium ($0.5 \leq ES \leq 0.8$), and large ($0.5 \leq ES \leq 0.8$) to decide the magnitude of group difference (Cohen, 2013).

Table 5. Comparison of team performance in terms of effect size before and after formation change suggested by the proposed IDMTGT.

S. No.	Team performance criteria	Before formation change Mean ± SD	After formation change Mean ± SD	Effect size
1.	Own team shots	0.75 ± 0.83	1.77 ± 1.03	1.09
2.	Opposing team Shots	1.12 ± 0.86	0.71 ± 0.81	0.49
3.	Own team STA	0.47 ± 0.68	0.91 ± 0.63	0.67
4.	Opposing team STA	0.78 ± 0.72	0.41 ± 0.69	0.53
5.	Own team corners	0.30 ± 0.33	0.35 ± 0.28	0.16
6.	Opposing team corners	0.40 ± 0.44	0.37 ± 0.23	0.09

The proposed technique with (own team mean effect size 0.64 and opponent team mean effect size 0.37), evidently outperforms one of the rare existing related studies available (Forcher et al., 2022) where the coach's decisions to change the formation results in better own team performance (mean effect size 0.52) and lower opponent team performance (mean effect size 0.35) as shown in **Figure 4**. In this study, formation change had an unpredictable effect on the team performance in all three seasons, as every season is governed by three different coaches. In three seasons, the mean effect size was 0.71, 0.26, and 0.22 respectively.

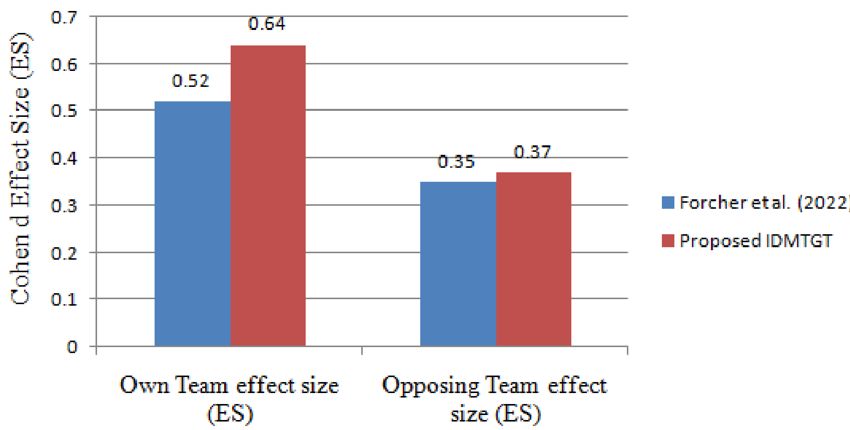


Figure 4. Comparison of the proposed IDMTGT with existing state-of-the-art work in terms of effect of change in team formation.

On the same lines, the proposed technique outshined Mclean et al. (2018), as they worked on total passes made by the node to all the other nodes by calculating partial eta squared as a measure of effect size. Three levels have been defined to classify the effect i.e. small (0.01), moderate (0.06), and large (0.14). There was 0.112 effect size between the forward and 0.097 effect size in case of defensive positions. In contrast, proposed technique has shown significant enhancement and nearly large effect size in both the forward (0.124) and defensive positions (0.116) as shown in **Figure 5**.

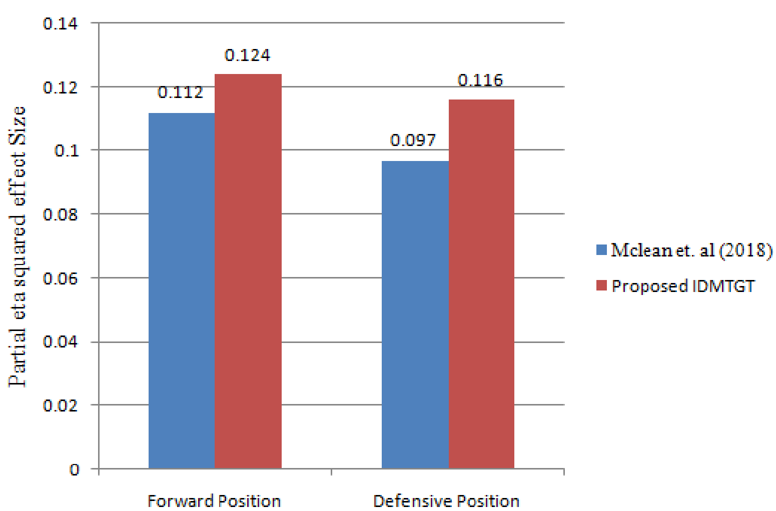


Figure 5. Comparison of the proposed IDMTGT with existing state-of-the-art work in terms of effect of formation change on number of passes made.

Similarly, comparison has been carried out between proposed work and Lorenzo-Martinez et al. (2020). According to Lorenzo-Martinez et al. (2020), Managers and coaches in soccer sports have to perform many changes in form of substitutions and formations to enhance the goal scoring opportunities specifically by greater space control. Difference of performance before and after the changes has been recorded as effect size. Effect size in terms of space control was reported small ES = 0.36. On the contrary, the proposed technique has shown better enhancement in performance by offering moderate effect size i.e. ES=0.54 (**Figure 6**).

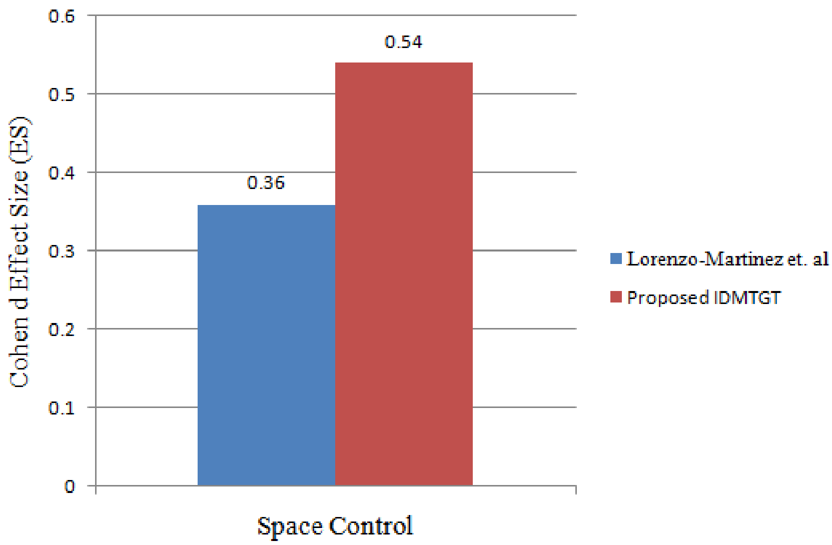


Figure 6. Comparison of the proposed IDMTGT with existing state-of-the-art work in terms of effect of substitutions on team performance.

The proposed technique based algorithm (IDMTGT) has outperformed many state-of-the-art work in terms of many parameters. The worth of change in formation relied heavily on the style of different coaches. However, there is a need for a system, which must be reliable and should not be coach dependent. The proposed technique based algorithm (IDMTGT) served the purpose by eliminating coach biasness by suggesting the formations and facilitates coaches, sports clubs, players, and sports enthusiasts with decision-making support by using the ball passing pattern network of the opponent team for handling game tactics in soccer sports.

6. Conclusion

In today's competitive world, soccer teams contest for supremacy and dominance. The teams try hard to push the boundaries of strategy and game tactics for enhanced performance. Identifying the game tactics of the opponent team and providing decision-making support for adapting and making adjustments correspondingly is the need of the hour. Hence, there is a need for such a technique that can provide effective decision-making support to coaches, sports enthusiasts, or players for game tactics in soccer sports. The proposed technique based algorithm IDMTGT presents a novel soccer formation construct n1-n2-n3-nj, which signifies contextual and positional features on the soccer pitch to identify different positions and try to find out the relation between diverse player positions. K-means clustering has been applied to partition the player positions with average player position id values 5.42, 19.69, and 14.41 for representing the defensive, attacking, and mid-fielders respectively. This study exploited a total of 31 matches, 26314 passes and 875 shots made in the UEFA Women's Euro Cup 2022, both group and knock-out stages. It has been investigated that features like the number of shots, shots on target, possession percentage, number of passes, pass accuracy, and number of corners are the prime deciding factors for victory in a soccer match. To statistically validate the effectiveness of IDMTGT and to find out the difference between games without change of formation and after the formation change suggested by the proposed technique based algorithm, Cohen's d effect sizes have been computed. Experimental validation has shown that a team lagging in all the departments can rise by understanding the game tactics of the opponent and fine-tuning their own game tactics for an unexpected victory. World soccer giants like Team Germany are blessed with experts and coaching staff to take care of their game tactics. Moreover, the worth of change in formation relied heavily on the style of different coaches as noticed in the peer study. The proposed technique based algorithm (IDMTGT) served the purpose by eliminating coach biasness and provide support not only at international level but also at beginner's level, where teams and players were deprived of expert support. Hence, for such underprivileged sections, the proposed intelligent computing-based technique can provide effective decision-making support in terms of automated suggestions for team formation by using the ball passing pattern network of the opponent team for handling game tactics in soccer sports. The proposed technique evidently outperforms the rarely existing related studies available. The proposed technique based algorithm (IDMTGT) will allow soccer teams to control the match flow, form coordinated line-ups corresponding to the opposite teams' style of play, and create varied scoring opportunities.

Conflict of Interest
The authors confirm that there is no conflict of interest to declare for this publication.

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The author(s) declare that no assistance is taken from generative AI to write this article.

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