International Journal of Sports, Health and Physical Education 2024; 6(2): 160-167

ISSN Print: 2664-7559
ISSN Online: 2664-7567
IJSHPE 2024; 6(2): 160-167
www.physicaleducationjournal.in
Received: 05-07-2024
Accepted: 04-08-2024

Dr. Khalid Oudah Gashyyish
Assistant Professor, Ministry of Higher Education and Scientific Research, College of Physical Education and Sports Sciences, Al-Muthanna University, Iraq

Corresponding Author:
Dr. Khalid Oudah Gashyyish
Assistant Professor, Ministry of Higher Education and Scientific Research, College of Physical Education and Sports Sciences, Al-Muthanna University, Iraq

Predicting classification according to playing lines using artificial neural networks in light of the skill capabilities of football players

Dr. Khalid Oudah Gashyyish

DOI: https://doi.org/10.33545/26647559.2024.v6.i2c.158

Abstract
The current research aims to build an artificial neural network model to help football coaches classify players according to playing lines (defense, midfield, attack) based on their skill capabilities. To achieve this goal, the researchers used the descriptive approach, specifically the design of cross-sectional survey studies, and data from a sample of football players in secondary schools in the center of Diwaniyah Governorate, consisting of (80) players, were used to train a model based on a multi-layer neural network to predict the classification of players according to playing lines. The model predicted the classification of players correctly by (96.4%) for the training sample and by (91.7%) for the test sample.

Keywords: Artificial neural networks, skill abilities, classification, football, high schools

Introduction

Determining selection models or what is known as the best player models is one of the prominent and important issues in the field of selecting and classifying talented people in the sports field in general and the game of football in particular. Determining the specifications of distinguished players in the stage of sports excellence, and choosing the appropriate individual for the type of sports activity practiced is the first step and directing him towards the line or playing center is the second step towards reaching the championship level, so specialists in various sports activities have moved towards determining the necessary and specific specifications for each activity and each playing line separately, and this helps in selecting the young athlete according to specific scientific foundations with the aim of reaching high sports levels. Although football is a team game, there are divisions that include distributing players within playing lines, and it may happen that there are common characteristics between these lines that make their performance similar, which gives justification to coaches to allocate the player to a playing line without considering the characteristics required by that line, which may not be compatible with the characteristics of that player. The coach and the player may discover after a period of training and preparation for that player that his characteristics do not match the characteristics and requirements of that line, which means wasting a lot of effort and time, and more importantly, wasting material that may have been good if he had been directed correctly from the beginning. In order to reach the ideal formula for classifying players, we must adopt a precise scientific method in which we take into account the individual differences between them. Taking into account the differences and variations that exist between them gives a greater opportunity to direct them towards the appropriate playing line for them, as each playing line has special requirements that distinguish it from other playing lines, and these requirements are usually reflected in the specifications that must be available in the players within each line, and then comes the process of choosing the best of them within each line. At present, the application of artificial intelligence has developed in all areas of life, including the sports field. Researchers use many methods to obtain and analyze primary data and extract high-level information about player behavior. To build models capable of classifying and predicting players' abilities, research indicates that some variables are more efficient predictors than others, in terms of predicting the classification of players according to the type of game and according to playing lines and positions. Skill abilities are one of the factors that affect the classification of players. In the current research, six variables (predictions) were used as inputs to build an artificial neural network (ANN) model capable of predicting the classification of football players according to playing lines. The theoretical importance of the research appears through establishing a cognitive framework for football coaches on classifying players according to playing lines using artificial neural networks, as it represents a scientific approach and a new addition that provides a tool for classifying players according to playing lines. As for the practical importance, it appears through its results and recommendations, which may help answer some questions about the feasibility of classification using such methods (Artificial neural networks).

Research problem

While classification has remained within the circle of personal efforts and subjective judgments, where chance, randomness and casual observation have the largest share in this process when classifying football players according to playing lines, it still depends mostly on the player's desire, the coach's skill and the amount of his experience. And in the belief of the researchers in the importance of using modern technologies to reach solutions and answer questions revolving around the processes of prediction, classification, guidance and placement, the researchers hope through their study to answer the following question, which may help in reaching objective and accurate results in classification, which may contribute to improving the performance of football players: (Is it possible to use artificial neural network technology to build a model through which football players can be classified according to the playing lines that suit them in light of the skill capabilities specific to each playing line?).

Research objectives

The current research aims to develop an artificial neural network model to predict the optimal classification of players of the Diwaniyah Education team in football according to the playing lines (Defense, midfield, attack) based on their skill capabilities.

Research areas

- **First - Human field:** Football players in high school teams in the center of Diwaniyah Governorate, for the academic year (2022 – 2023)
- **Second-Temporal field:** The period from (1/1/2023) to (1/6/2024)
- **Third - Spatial field:** Tests were conducted on the research sample at the local administrative stadium in Diwaniyah Governorate.

Research methodology

The main purpose of the current research is to classify football players according to the playing lines appropriate for each player in light of his skill capabilities, so the researchers will focus on describing the skill capabilities of the players as they are of interest to obtain basic information describing those capabilities. Accordingly, the current study will be descriptive using a survey design, specifically a cross-sectional survey design.

Research community and its samples

The statistical community of the current research includes football players in the boys' middle school teams in the center of Diwaniyah Governorate, for the academic year (2022-2023). Except for goalkeepers. Since one of the priorities when determining the research tools is to choose the sample on which the research will be conducted. Since each stage of the research has a specific goal, different samples were chosen in a manner that is consistent with the purpose of each stage. The samples are:

The main sample

- The exploratory experiment sample
- The sample for standardizing measurement tools (Tests)

First - The main sample

This sample was selected using the random phase method using the equal method, according to the following steps:

1. Schools were randomly selected from among the schools that have school teams, which were prepared to participate in the official tournaments held by the sports activity for the Diwaniyah Governorate Education.
2. The players of each school team selected in (1) were divided into (3) groups according to the playing lines.
3. players were randomly selected from each team as follows:
4. Players were randomly selected from each team from the defense line.
5. Players were randomly selected from each team from the midfield.
6. Players were randomly selected from each team from the attack line.

Thus, the size of the sample that was selected became (80) players, with (10) players for each team. Table (1) shows this.

Table 1: The main experiment sample distributed according to schools and playing lines

No	School Name	Number of players according to playing lines			Total
		Defense	Midfield	Attack	
1	Central Preparatory School	3	4	3	10
2	Qutaiba First Preparatory School	3	4	3	10
3	Qutaiba Second Preparatory School	3	4	3	10
4	Al-Jawahiri Preparatory School	3	4	3	10
5	Al-Sadrain Preparatory School	3	4	3	10
6	Al-Mutamayizin Preparatory School	3	4	3	10
7	Al-Karamah Preparatory School	3	4	3	10
8	Abi Turab Preparatory School	3	4	3	10
Total		24	32	24	80

Second - The exploratory study sample

At this stage, a sample of (24) players was drawn from the main research sample, with (3) players for each team, and at a rate of (one player) for each line of play to represent the exploratory study sample. This sample was drawn using the random stratified method and the equal method. As in Table (2).

Table 2: The exploratory experiment sample distributed according to schools and playing lines

No	School Name	Number of players according to playing lines			Total
		Defense	Midfield	Attack	
1	Central Preparatory School	1	1	1	3
2	Qutaiba First Preparatory School	1	1	1	3
3	Qutaiba Second Preparatory School	1	1	1	3
4	Al-Jawahiri Preparatory School	1	1	1	3
5	Al-Sadrain Preparatory School	1	1	1	3
6	Al-Mutamayizin Preparatory School	1	1	1	3
7	Al-Karamah Preparatory School	1	1	1	3
8	Abi Turab Preparatory School	1	1	1	3
Total		8	8	8	24

Third - Standardization of Tests Sample

At this stage, a sample of (24) players was drawn from the main research sample, with (3) players for each team, and at a rate of (one player) for each line of play. This sample was added to the exploratory experiment sample, so the total becomes (48) players representing the standardization sample of the skill tests concerned with the current research. The standardization sample was drawn using the random stratified method and the equal method. As in Table (3).

Table 3: The standardization sample distributed according to schools and lines of play

No	School Name	Number of players according to playing lines			Total
		Defense	Midfield	Attack	
1	Central Preparatory School	2	2	2	6
2	Qutaiba First Preparatory School	2	2	2	6
3	Qutaiba Second Preparatory School	2	2	2	6
4	Al-Jawahiri Preparatory School	2	2	2	6
5	Al-Sadrain Preparatory School	2	2	2	6
6	Al-Mutamayizin Preparatory School	2	2	2	6
7	Al-Karamah Preparatory School	2	2	2	6
8	Abi Turab Preparatory School	2	2	2	6
Total		16	16	16	48

Data collection methods

The researchers used data on some measurement tools (tests that measure the skill capabilities of football players) as a basic means of data collection, which are

- **First test:** Extinguishing the ball with all parts of the body except the arms inside a square with dimensions of (2 x 2) meters.
- **Second test:** Rebounding to a target drawn on a wall.
- **Third test:** Shooting with the foot at overlapping rectangles.
- **Fourth test:** Rolling the ball for a distance of (15) meters.
- **Fifth test:** Hitting the ball with the head into circles drawn on the ground.
- **Sixth test:** Passing the ball between the signs (dribbling) for a distance of (15) metez.

Exploratory experiment

A survey study was conducted on (24) players representing the sample of the exploratory experiment. Several objectives were achieved through this experiment, including:

1. Verifying the validity of the methods used when applying the tests.
2. Producing and arranging the application of tests based on their motor requirements and level of difficulty.
3. Organizing rest periods between one test and another, to ensure that players return to their normal state at the beginning of each test.
4. Understanding the contexts of conducting tests by players and the work team.
5. The extent of the appropriateness of the specified time period for implementing a single test and the tests as a whole.
6. Availability of the required capabilities in terms of the suitability of the designated places for conducting the tests, as well as the availability of appropriate devices and tools for the measurement process.
7. The adequacy of assistants and their good training.
8. The extent of motivation and good response of players when applying the tests.

Verifying the scientific characteristics of measurement tools

Standardizing measurement tools requires certain conditions that play a major role in confirming the integrity and scientific nature of that standardization, and the validity, stability and objectivity of the measurement tool are among the most important of these conditions. The most important conditions that must be met in the measurement tool in order to be good and suitable for the purpose for which it was created will be addressed.

First - Validity of the results of the measurement tools

The validity associated with the criterion (experimental-concurrent validity) was used to verify the validity of the test results in the current research.

To achieve this type of validity, the correlation between the players' scores in the tests and their scores on the criterion (arbitrators' estimates) was estimated, and the results came as in Table (4).

Table 4: Values of the correlation coefficients between the test scores and the criterion scores

Test	Correlation coefficient value	F-test		
		Calculated F	Degree of Freedom	Statistical Significance
Stopping the ball with all parts of the body except the arms inside a square of dimensions (2 x 2) meters	0.659	4.860	47	0.001
Rebound handling to a target drawn on a wall	0.640	4.779	47	0.001
Shooting with the foot at overlapping rectangles	0.691	5.836	47	0.001
Rolling the ball for a distance of (15) meters	0.730	5.930	47	0.001
Heading the ball into circles drawn on the ground	0.639	4.860	47	0.001
Passing the ball between the markers (dribbling) for a distance of (15) meters	0.489	2.885	47	0.001

Table (4) shows that there is a correlation between the scores of the standardization sample of skill tests and their scores on the test (judges' estimates) because all the values of the significance level (F) accompanying the values of the correlation coefficient were smaller than (0.05). This indicates the significance of the correlation coefficient, and therefore it can be said that the results of all tests are valid.

Second - Stability of the results of the measurement tools

The stability of the test results was verified by finding the correlation relationship between the results of the first measurement and the second measurement that were applied to the standardization sample of the tests - that is, using the (measurement and measurement) method.

To verify the significance of the correlations between the results of the first measurement and the results of the second measurement (measurement), the (F) statistic was used for the significance of the correlation, as all the values of the significance level (F) accompanying the values of the correlation coefficient were smaller than (0.05). This indicates the significance of the correlation coefficient between the results of the two measurements, and therefore the results of the skill tests enjoy high stability. Table (5) shows this.

Table 5: Values of correlation coefficients between the scores of the first measurement and the second measurement (re-measurement)

Test	Correlation coefficient value	F-test		
		Calculated F	Degree of Freedom	Statistical Significance
Suppressing the ball with all parts of the body except the arms inside a square of dimensions (2 x 2) meters	0.682	5.286	47	47
Rebound handling to a target drawn on a wall	0.656	4.814	47	47
Shooting with the foot at overlapping rectangles	0576	3.715	47	47
Rolling the ball for a distance of (15) meters	0.756	7.158	47	47
Heading the ball into circles drawn on the ground	0.782	8.155	47	47
Passing the ball between the markers (dribbling) for a distance of (15) meters	0.459	0.697	47	47

Third - Objectivity of the results of measurement tools

The objectivity coefficient of the measurement tools in the current research was extracted by finding the correlation between the results of three arbitrators, who recorded the results of the players in the tests concerned with the current research. It appears from Table (6) that there is agreement between the arbitrators when they evaluate the skill capabilities because the values of the significance level (F) accompanying all the values of the correlation coefficients were smaller than (0.05). This indicates the significance of the correlation coefficients, and therefore it can be said that the results of all tests enjoy high objectivity.

Table 6: Values of the correlation coefficients between the arbitrators' scores

Test	Correlation coefficient value	F-test		
		Calculated F	Degree of Freedom	Statistical Significance
Suppressing the ball with all parts of the body except the arms inside a square of dimensions (2 x 2) meters	0.876	22.693	47	94
Rebound handling to a target drawn on a wall	0.924	38.040	47	94
Shooting with the foot at overlapping rectangles	0.723	8.718	47	94
Rolling the ball for a distance of (15) meters	0.733	9.141	47	94
Hitting the ball with the head into circles drawn on the ground	0.893	24.938	47	94
Passing the ball between the markers (dribbling) for a distance of (15) meters	0.816	14.306	47	94

Table 7: Plan for implementing the final measurement of skill capabilities

Total	Number of players	Location	Date	School Name	Day
16	4	Local Administrative Stadium	19 / 3 / 2023	Central Preparatory School	First
	4	Local Administrative Stadium	19 / 3 / 2023	Qutaiba First Preparatory School	
	4	Local Administrative Stadium	19 / 3 / 2023	Qutaiba Second Preparatory School	
	4	Local Administrative Stadium	19 / 3 / 2023	Al-Jawahiri Preparatory School	
16	4	Local Administrative Stadium	20 / 3 / 2023	Al-Sadrain Preparatory School	Second
	4	Local Administrative Stadium	20 / 3 / 2023	Al-Mutamayizin Preparatory School	
	4	Local Administrative Stadium	20 / 3 / 2023	Al-Karamah Preparatory School	
	4	Local Administrative Stadium	20 / 3 / 2023	Abi Turab Preparatory School	
	32	Total			

Final measurement of research variables

After extracting the results of the pilot experiment and ensuring the validity (standardization) of the measurement tools, the final measurement of the research variables (skill capabilities) was initiated on the remaining research sample, which numbered (32) players, according to the following plan.

Classification of the research sample according to playing positions (initial classification)

The researchers relied in the initial classification of players according to playing lines, on the classification approved by the team coaches. (10) players were selected from each team distributed on the playing lines with (3) attacking players, (4) midfielders and (3) defenders. Thus, the total number of players is (80) players, with (24) players for the defense line, (32) players for the midfield line, and (24) players for the attack line. Table (8) shows this.

Statistical methods used in the research: The researchers used the statistical program (IMB - SPSS version 27) to process the data and display the results.

Table 8: Playing lines symbols Number of players in each line

Number	The symbol	Playing lines
24	1	Defense
32	2	Midfield
24	3	Attack
80	Total	

Table 9: Arithmetic means, standard deviations and standard errors of the research variables

Sample size	Standard error	Standard deviation	Arithmetic mean	Variables
80	0.125	1.121	7.4000	Dribbling
80	0.181	1.611	11.3671	Passing
80	0.082	0.733	8.2785	Scoring
80	0.077	0.682	8.6124	Dribbling
80	0.159	1.413	5.4810	Heading
80	0.277	2.464	4.3291	Dribbling

Statistical description of the results of the skill abilities tests: It appears from Table (9) that the standard error values were small, which indicates the good selection of the sample and its correctness in representing the studied community (for football players in the teams of Diwaniyah Education Schools). The results of Table (10) also indicate the good spread of players' scores for each of the research variables, because all the values of the standard scores (Z)(*) for skewness and convexity were smaller than (1.96) at a probability of (0.05 >P). The researcher indicates here that the positive values of asymmetry indicate the accumulation of scores in the left part of the distribution, while the negative values indicate their accumulation in the right part of the distribution. The positive values of convexity indicate a convex distribution, while the negative values indicate a flat distribution.

Table 10: Asymmetry and convexity values and the accompanying (Z) values

Distribution nature	Z values	Standard error	Flattening	Distribution nature	Z values	Standard error	twist	Variables
Moderate	1.44	0.535	-0.772	Moderate	0.39	0.271	-0.106	Dribbling
Moderate	0.38	0.535	-0.205	Moderate	0.28	0.271	0.076	Passing
Moderate	1.85	0.535	-0.986	Moderate	1.77	0.271	-0.481	Scoring
Moderate	0.88	0.535	-0.472	Moderate	1.48	0.271	0.402	Dribbling
Moderate	1.42	0.535	-0.759	Moderate	0.266	0.271	-0.072	Heading
Moderate	1.96	0.535	-1.046	Moderate	0.31	0.271	-0.083	Cutting

Artificial Neural Network Model for Classification Prediction: The current study aims to examine whether the MLP neural network can help football coaches correctly predict the classification of players according to the playing lines (defense, midfield, attack) by analyzing the data obtained from the skill tests applied to them.To achieve this goal, the researchers used the Multilayer Perceptron (MLP) module of IBM SPSS Statistics 27 to build the neural network model and test its accuracy. The MLP neural networks were trained using the back propagation learning algorithm that uses gradient descent to update the weights to minimize the error function.The data were randomly assigned based on the relative numbers of cases, for training (70%), testing (30%), and exclusion (0%). The training data set is used to find the weights and build the model. The testing data is used to find errors and prevent overtraining during training mode. While the exclusion data is used to validate the model.

First - Summary of case processing

Table (11) provides information about the data sets used to build the ANN model.

Table 11: Information used to build the artificial neural network model

Percentage	Number	Sample
70.0%	56	Training
30.0%	24	Test
100.0%	80	Valid
0.0%	0	Excluded
	80	Total

Second - Network information

Table (12) shows the number of neurons in each layer and the six independent variables (X1, X2, X3, X4, X5, X6). The automatic structure selection was chosen, so the network includes (5) nodes for the hidden layer, while the output layer contains (3) nodes to encode the results of the dependent variable cycle.

For the hidden layer, the activation function was the hyperbolic tangent, while in the output layer, the softmax function was used, while the cross entropy was used as an error function due to the use of the softmax function.

Table 12: Information about the artificial neural network

Output layer		hidden layer		Input layer	
1	Dependent variables	1	Number of layers	Variable name	Variable number
Y	Variable name	5	Number of units	X1	1
3	Number of units	Hyperbolic tangent	Activation function	X2	2
Soft max	Activation function			X3	3
Cross-entropy	Error function			X4	4
				X5	5
				X6	6
				6	Number of units
				normative	Measurement method

Figure (1) shows the network diagram used by SPSS to predict the classification of players according to the playing lines (defense = 1, center = 2, attack = 3) from (6) skill abilities. The diagram shows the six input nodes, the five hidden nodes, and the three output nodes representing the playing lines (defense, center, attack). Blue links or connections mean that the entanglement weights are less than zero (negative values), while gray links or connections mean that the entanglement weights are greater than zero (positive values). The thicker the line, the stronger the links or connections, and the thinner the line, the weaker the links. This will be shown in Table (15).

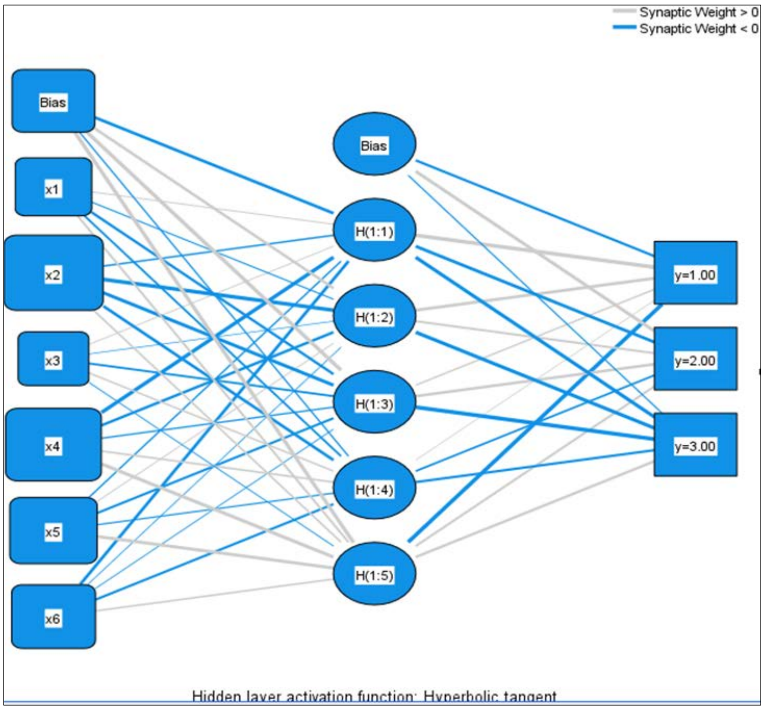

Fig 1: Artificial Neural Network Diagram

Third - Model Summary

The model summary, shown in Table (13), provides information related to the results of training, testing, and the excluded sample. The small value of the cross-entropy error for the training sample, which is equal to (13.190), indicates the model's ability to predict the outcome of the cycle. When the cross-entropy error is lower for the exclusion sample compared to the training and testing data set, which means that the network model is not overfitted to the training data. The result justifies the role of the testing sample, which is to prevent overtraining. According to the table, the percentage of incorrect predictions based on the training and testing sample, respectively, is (3.6%, 8.3%), while the percentage of incorrect predictions in the rejecting data set decreases to (0%). The researchers indicate that the learning procedure was implemented by achieving (10) consecutive steps with no decrease in the error function from the testing sample

Table 13: Summary of the Artificial Neural Network Model

Test	Training	Information
13.104	13.190	Cross entropy error
8.3%	3.6%	Percentage of incorrect predictions
	(10) consecutive steps without a decrease in error(*)	Stopping rule used
	0:00:00:01	Training time

Fourth - Parameter estimates

Table 14: Estimating the coefficients of the interconnections of the neural network

Expectation								The prophet	
Output layer					Hidden layer				
[y=3.00]	[y=2.00]	[y=1.00]	H(1:5)	H(1:4)	H(1:3)	H(1:2)	H(1:1)		
			0.582	-0.205	0.974	0.575	-0.690.	Constant	Hidden Layer
			0.332	-0.284	0.473-	-0.193	0.192	X1	
			0.275	-0.682	-0.811	1.053	-.0.236	X2	
			-0.064	0.239	-0.292	-0.003.	0.075	X3	
			0.818	0.279	-0.217	-0.534.	-0.935	X4	
			0.780	-0.197	-0.392	0.116	-0.221	X5	
			0.245	-0.409	-0.061	-0.010	-0.684	X6	
-0.197	0.797	-0.463						Constant	Output Layer
-0.825	-0.743	1.078						H(1:1)	
-0.845	0.385	0.743						H(1:2)	
-1.433	0.678	0.230						H(1:3)	
-0.448	-0.281	-0.004						H(1:4)	
0.533	0.387	-1.433						H(1:5)	

Table (14) shows the interlayer synaptic weights that were calculated using the training set data. It appears from the table that there are (53) synaptic weights that are borne on the connections, (35) of which are synaptic weights for the hidden layer - (5) weights that are borne on the connections between the five hidden layer nodes and the model constant and (30) connections between the hidden layer nodes and the predictive variables (mental abilities). It appears from the table that the number of negative weights (less than zero) for the hidden layer is (20) weights, while the remaining weights, which are (15) weights, are positive values (greater than zero). As for the remaining synaptic weights, which are (18) synaptic weights, they are for the output layer, including three weights that are borne on the connections between the three output layer nodes and the model constant and (15) weights that are borne on the connection between the output layer nodes and the five hidden layer nodes. The number of negative weights (less than zero) for the output layer is (9) weights, while the number of positive weights (values greater than zero) is also (9) weights. It is noted that the largest synaptic weight is between the fifth nodes of the hidden layer and the first nodes of the output layer, and the value of this synaptic weight is (-1.433). The lowest weight is between the second node of the hidden layer and the predictive variable (X3), and the value of this weight is (-0.003).

Fifth - Classification of the dependent variable (according to the game lines)

Table 15: Player classification results (Number of correctly classified cases and incorrectly classified cases.

Expectation				Category	Sample
Percentage	**3.00**	**2.00**	**1.00**		
100.0%	0	0	17	1.00	Training
65.5%	0	21	1	2.00	
94.1%	16	1	0	3.00	
96.4%	28.6%	39.3%	32.1%	Probability ratio	
85.7%	1	0	6	1.00	Test
100.0%	0	10	0	2.00	
85.7%	6	1	0	3.00	
91.7%	25.0%	45.8%	29.2%	Probability ratio	

Table (15) shows the classification of the results of the categorical dependent variable cycle (confusion rate) by section. In general, for each case, the expected result is defined as success if the expected probability is greater than (0.5). As is clear, the MLP network correctly classified ((54 players out of (56) in the training sample. And (22) out of (24) in the test sample. In general, (96%) of the training cases were correctly classified and (92%) of the test cases were correctly classified.

Sixth: The impact of the independent variables (inputs) on how the network classifies players

Table (17) gives the impact of each independent variable in the ANN model in terms of relative and normal importance. It seems that there is a difference in the impact of each independent variable. For example, we find that the variable (passing the ball) had the greatest impact, as it affected by (100%), while the variable (scoring) had the least impact, as it affected by (14.1%).

Table 16: The relative and normal importance of the independent variables in the classification of players by the artificial neural network

Natural relative importance	Relative importance	Variables
31.5%	0.089	x1
100%	0.283	x2
14.1%	0.040	x3
89.9%	0.254	x4
64.5%	0.182	x5
53.5%	0.151	x6

The graph in Figure (2) also depicts the importance of the independent variables - i.e. how sensitive the model is to changes in each independent variable (input layer). It shows that the most influential variable is (passing the ball), followed by (dribbling) in second place, (heading the ball) in third place, followed by (dribbling) in fourth place, while (suppression) ranked fifth, and (scoring) came in sixth and last place.

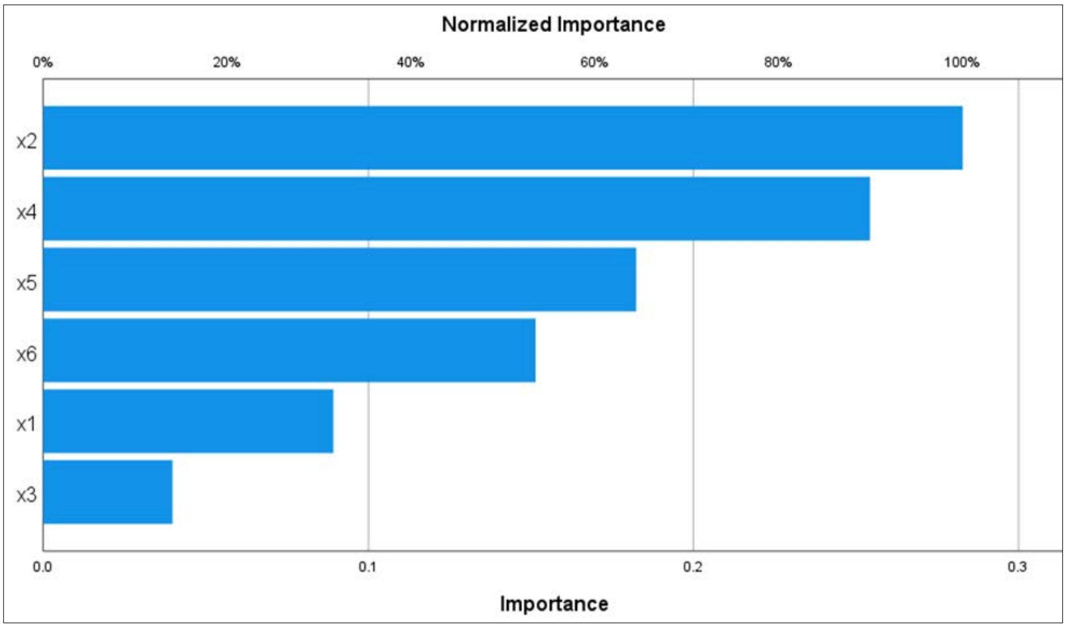

Fig 2: The importance of independent variables in the classification of players by the artificial neural network

Seventh: Player membership according to the actual classification and the expected classification using artificial neural networks:

It appears from Table (18) that there are (4) cases that were incorrectly classified, and these cases are: (17, 40, 48, 53). As for the remaining cases, numbering (76) cases, they were correctly classified*.*

Table 17: Player membership according to the actual classification and the expected classification using the neural network

Views	Form	Cases	Views	Form	Cases	Views	Form	Cases
2	2	55	3	3	28	1	1	1
2	2	56	3	3	29	1	1	2
2	2	57	3	3	30	1	1	3
3	3	58	1	1	31	2	2	4
3	3	59	1	1	32	2	2	5
3	3	60	1	1	33	2	2	6
1	1	61	2	2	34	2	2	7
1	1	62	2	2	35	3	3	8
1	1	63	2	2	36	3	3	9
2	2	64	2	2	37	3	3	10
2	2	65	3	3	38	1	1	11
2	2	66	3	3	39	1	1	12
2	2	67	2	3	40	1	1	13
3	3	68	1	1	41	2	2	14
3	3	69	1	1	42	2	2	15
3	3	70	1	1	43	2	2	16
1	1	71	2	2	44	1	2	17
1	1	72	2	2	45	3	3	18
1	1	73	2	2	46	3	3	19
2	2	74	2	2	47	3	3	20
2	2	75	2	3	48	1	1	21
2	2	76	3	3	49	1	1	22
2	2	77	3	3	50	1	1	23
3	3	78	1	1	51	2	2	24
3	3	79	1	1	52	2	2	25
3	3	80	3	1	53	2	2	26
			2	2	54	2	2	27

Conclusions

Based on the data collected on the skill capabilities of football players, it was shown that artificial neural networks are effective in predicting the classification of players according to the playing lines (defense, midfield, and attack). The results also showed that the strongest factors predicting the classification of players according to the playing lines were in the variable (Passing the ball).

Recommendations

- Verify the results of the current research through future work with larger and more diverse samples*.*
- Adopt scientific methods and avoid random methods in the classification and selection processes of football players.
- Use computer techniques and programs in the classification and selection processes of football players**.**
- Benefit from the results of the current research and generalize them to other sports games and clubs.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

1. Mortada Al-Yassari A. The effect of the playing field on developing motor performance according to individual and collective tactical sentences for young football players, Master's thesis, College of Education, Al-Qadisiyah University; c2008.
2. Mohsen T, *et al*. Testing and Analysis of Football, Mosul, Mosul University Press; c1999.
3. Qasim Al-Khashab Z, *et al*. Football, 2nd ed., Mosul, Dar Al-Kutub for Printing and Publishing; c1999**.**