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Estimating The Parameters Of The Logistic Regression Model Using The Swam Algorithm For The Handball Team Of The College Of Physical Education And Sports Sciences Al-Mustansiriyah University

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Abstract. *This research investigated the biomechanical variables of movement analysis and its essential components for handball players at the College of Physical Education and Sports Sciences, Al-Mustansiriya University, during a league match and university qualifiers. The data was analyzed using binary logistic regression, a mathematical model that defines the link between a dependent variable, which takes the value of one when a goal is scored against the opposing team and zero when no goals are scored, and independent factors. The bird swarm algorithm will be used in this research. It is one of the artificial intelligence algorithms that rely on the intelligence of living flocks by monitoring their movements, such as birds, bees, cats, chickens, and many other swarm algorithms.The conclusions we reached from this study are as follows: When using logistic regression, we found only four explanatory variables that affect the dependent variable. They are detailed as follows: The two explanatory variables (The maximum height of the hip and Flight time until leaving the ball) and the dependent variable (shooting) have an inverse relationship and affect it. The two variables (Knee angle at the moment of thrust and The instantaneous speed of the ball) have a positive relationship with aiming and affect it. When we used the Bird Swarm algorithm, we found that all the explanatory variables included in the study had a significant effect on the dependent variable. The variables (Knee angle at the moment of thrust, Rising angle, Flight angle, The instantaneous speed of the ball, and the horizontal distance of the performance) have a positive relationship, with the dependent variable (shooting). In contrast (The maximum height of the hip and Flight time until leaving the ball) have an inverse relationship with the dependent variable.Using the logistic model helps sports coaches and researchers to estimate and predict models, especially when the dependent variable takes values (one or zero). In contrast, we noticed that the results were more accurate and objective when using the bird swarm algorithm. It further helps academics, those interested in sports, and coaches benefit from these results.*

Keywords: *logistic regression model , Artificial intelligence, Bird Swarm algorithm, Akaike Criterion, Kinematic variables , Biomechanic.*

Introduction

The logistic regression model is used in life research and is "the statistical method for modeling binary data." To estimate the parameters of the logistic regression model, we used artificial intelligence (AI) in this research because it is used in many essential applications in practical life and various natural, scientific, and human sciences. Optimization among the set of solutions to the problem, and these algorithms improve the solution's value according to the obstacles and variables.

This research aims to employ the bird's swarm approach to estimate the logistic regression parameters for the handball team at the College of Physical Education and Sports Sciences, Al-Mustansiriyah University.

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We will mention some authors who have written on logistic regression and artificial intelligence algorithms. (Mohammed, A., 2015) compared various classification models employing different estimation methods, concluding that the ridge estimation method exhibits greater reliability in predicting anemia classes than other iteratively reweighted least squares methods, such as Maximum Likelihood, Iterative Maximum Likelihood, and Neural Networks [1]. (Shelley, B., Juan P., and Sophia S., 2007) presented methodologies for constructing confidence intervals (CI) within a penalized polynomial logistic regression framework and assessed the CI coverage and length of PLE-based approaches in comparison to conventional MLE-based methods in trinomial logistic regression with both binary and continuous covariates. Simulation experiments were done on sparse datasets [2]. (Sandro, S., 2014) elucidated the logistic regression technique by employing examples to enhance comprehension. Following the definition of the technique, the essential interpretation of the results is emphasized, and several specific concerns are addressed [3]. (Jill, C., 2011) Diagnostic statistics are advised to evaluate the model's appropriateness further; findings for independent variables are generally presented as odds ratios (ORs) accompanied by 95% confidence intervals (CIs) [4]. (Kenned, J., Eberhart, R., 1997) The researcher advocates employing diagnostic statistics to evaluate the model's appropriateness. The outcomes of the independent variables are generally presented as odds ratios (ORs) accompanied by 95% confidence intervals (CIs) [5]. (Elif, V., Bilal, A., 2019) The two researchers incorporated chaos into standard BSA to enhance the advantage of global convergence by preventing early convergence and getting stuck in local solutions. Thus, a new research field of chaos dynamics was introduced. Generally, the results obtained from the proposed new chaotic BSAs can outperform the standard BSA in measurement functions and engineering design problems [6]. (Chuangbiao, X. and Renhuan, Y., 2017) the research used an improved parametric algorithm for flocking birds to estimate the parameters of chaotic systems, where they conducted experiments on the Lorenz system and the delivery engine system, and the numerical simulation results showed the effectiveness and desired performance of IBBSA to estimate the parameters of chaotic systems [7].

Research goal

1. This study aims to use the logistical model to help coaches of sports teams increase the chances of scoring goals against the opposing team.
2. Estimating the parameters of a logistic regression model for the biomechanical variables of handball players.
3. Improving the estimation of logistic regression model parameters using the bird flock algorithm to obtain the optimal parameters.

Logistic Regression (LR) :

Before initiating an examination of the logistic regression model, it is imperative to recognize that the objective of an analysis employing this model aligns with that of any other statistical regression model. The objective is to identify the most suitable and economical clinically interpretable model that elucidates the relationship between an outcome (dependent) variable and a collection of independent (predictor) variables.

Logistic regression is the most common method used for binary response modeling for data. When the response is binary, it takes the form 1/0, where one indicates success and 0 indicates failure. However, the actual values of 1 and 0 can vary depending on the type of study. The number 1 indicates the subject of interest for which a two-response research was designed.

Logistic regression is a statistical model consisting of one or more dependent variables. More take binary values and explanatory variables (independent variable). Logistic regression is a method for fitting a regression curve $Y = f(z)$ Where y consists of binary value (0, 1) data; when the response is a binary (dichotomous) variable, Logistic regression models (RL) the relationship between X and Y by fitting a logistic curve. A logistic curve is characterized by its S-shaped or sigmoid form. A logistic curve commences with gradual, linear growth, transitions to exponential growth, and subsequently decelerates to a stable pace [8].

A binary response model is based on a Bernoulli distribution, which is a specific case of the binomial probability density function when the binomial denominator equals 1. The Bernoulli probability density function is a constituent of the exponential family of probability distributions. It possesses characteristics that provide a far simpler estimation of its parameters compared to conventional Newton-Raphson-based maximum likelihood estimation (MLE) techniques.

A simple logistic function is defined by

$$f(z) = \frac{1}{1+e^{-z}} \quad (1)$$

The logistic function can be extended to the form :

$$f(z) = \frac{e^{(\alpha+\beta X)}}{1+e^{(\alpha+\beta X)}} = \frac{1}{1+\ e^{-(\alpha+\beta X)}} \quad (2)$$

where α and β determine the logistic intercept and slope.

To get the logistic model from the logistic function:

$$f(z) = \frac{1}{1+\ e^{-(\alpha+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_i x_i)}} = \frac{1}{1+\ e^{-(\alpha+\sum \beta_i x_i)}} \quad (3)$$

Where $i = 1,2,\ldots,k$

Now, We write the Bernoulli distribution function in the exponential family as follows:

$$f(y_i;\pi_i) = exp\{y_i\ ln(\pi_i/(1-\pi_i)) + ln(1-\pi_i)\} \quad (4)$$

Where :

$ln(\pi_i/(1-\pi))$: It is the link function.

$-ln(1-\pi)$ $\quad or \quad$ ln $(1/(1-\pi))$: is the cumulant.

π : In a Bernoulli distribution, it is defined as the likelihood of success.

Rather of multiplying, the natural logarithm of the function enables summing across observations in the estimate procedure. What follows is the binary-logistic model's log-likelihood function:

μ : is generally changed with π when Generalized Linear Models (GLM) estimate a logistic model.

$$L(\mu_i;y_i) = \sum_{i=1}^{n}\{y_i\ ln(\mu_i/(1-\mu_i)) + ln(1-\mu_i)\} \quad (5)$$

Or

$$L(\mu_i;y_i) = \sum_{i=1}^{n}\{y_i\ ln(\mu_i) + (1-y_i)ln(1-\mu_i)\} \quad (6)$$

Regression in logistic models based on the Bernoulli-logistic log-likelihood function. Instead of the log-likelihood function, we base convergence on the deviation. The logistic model uses the following expression for the deviance:

$$D = 2\sum_{i=1}^{n}\{y_i\ ln(y_i/\mu_i) + (1-y_i)ln\big((1-y_i)/(1-\mu_i)\big)\} \quad (7)$$

The value of μ for each observation in the model is derived from the linear predictor. $\acute{x}\beta$ Whether evaluated by maximum likelihood methods or as a generalized linear model (GLM). The link function expresses the response in the logistic model ln $(\mu_i/(1-\mu_i))$, then [9]

$$x_{\acute{\iota}}\,\acute{\beta} = \ln(\mu_i/(1-\mu_i)) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \qquad (8)$$

The value of μi , is calculated in the logistic model as follows:

$$\mu_i = 1/\left(1 + exp\left(-x_{\acute{\iota}}\beta\right)\right) = exp\left(x_{\acute{\iota}}\beta\right)/\left(1 + exp\left(x_{\acute{\iota}}\beta\right)\right) \qquad (9)$$

In the logistic model, μ represents a probability. We used Newton-Raphson to estimate logistic regression. The estimated fit is subsequently ascertained by calculating the first and second derivatives of the log-likelihood function.

$$\frac{\partial L(\beta)}{\partial \beta} = \sum_{i=1}^{n} (y_i - \mu_i)\, x_i \qquad (10)$$

$$\frac{\partial^2 L(\beta)}{\partial \beta \partial \acute{\beta}} = -\sum_{i=1}^{n} \{x_i \acute{x_\iota} \mu_i (1-\mu_i)\} \qquad (11)$$

Cox and Snell Pseudo R^2 :

It decreases variance by incorporating additional variables into the model. The Cox and Snell R^2 is an alternate, measure of goodness of fit associated with the R^2 result from linear regression. The formula is as follows:

$$R^2_{McF} = 1 - \left[\frac{l(0)}{l(\hat{\beta})}\right]^{\frac{2}{w}} \qquad (12)$$

Where: $l(\hat{\beta})$ represents the probability of the existing model; $l(0)$ is the likelihood of the initial model.

$$l(0) = W \log(0.5) \qquad (13)$$

And W is a vector with its elements the weight for the i^{th} case.

Nagelkerke Pseudo R^2 :

The Nagelkerke measure, adjusts the C and S measures for the maximum value so that one can be achieved:

$$R^2_N = \frac{R^2_{CS}}{\max(R^2_{CS})} \qquad (14)$$

Where

$$\max(R^2_{CS}) = 1 - \{l(0)\}^{\frac{2}{w}} \qquad (15)$$

The Nagelkerke Pseudo R2 base rate might be anything from 0 to 1.

Artificial intelligence algorithms – Swarm algorithms (SA) :

These algorithms are founded on the principles and concepts of artificial intelligence. They are distinguished by their capacity to formulate adaptive strategies aligned with the problem's nature and to discern a viable approach for selecting a suitable solution from the array of potential options. They are also characterized by improving the solution's value according to the obstacles and variables. Birds in some specific linear configurations can achieve collective aerodynamic efficiency. The resulting decrease in energy consumption Exhaustion leads to a greater chance of survival at the end of the migration. [10, 11,12].

Bird Swarm algorithm (BSA) :

Xian-Bing Meng proposed this algorithm as a way to solve optimization problems. It simulates the social behavior of bird swarms. The algorithm operates on the dual processes of searching and iterating to identify optimal solutions within a designated search domain, contingent upon the nature of the problem. Where the algorithm performs the process of exploration of the search space, and when finding the optimal solution, it turns to the operation of exploitation to obtain the solution. Then, the algorithm updates its components and repeats the iteration process according to the number of specified iterations to achieve all the conditions of the specified algorithm. It is used in the radar and Bluetooth network and in the field of network transmission, rebuilding, and expansion, and is used in drug design, diagnosis of Parkinson's disease, organization of genetic networks, prediction of the length of life, synthesis of electronic circuits, design of loudspeakers, filters, design of cars, design of energy systems, and solving problems related to similarly to max and min, It is also used in forecasting electrical works, indicating the flow of water channels, environmental models, meteorological forecasting, forecasting traffic flow in cities, and predicting time series [11, 13].

The essential components of the bird swarm algorithm

The BSA consists of [11, 13]:

1. Number of swarms (particles) N , $n = (n_i, n_i, \dots, n_i)$. These particles depend on their individual experiences as well as those of neighboring particles within the swarm.

2. The speed of the particle $V_i^t = (V_1^t, V_2^t, \dots, V_i^t)$.

3. particle position $X_i^t = (X_1^t, X, \dots, X_i^t)$.

4. The best position of the particle $P_{best,i}^t$.

5. The best particle position in the entire swarm $G_{best,i}^t$.

6. Dimensions of the problem $d = (d_1, d_2, \dots, d_j)$.

The following equations show how to adjust the velocity and position of each particle:

$$V_i^{t+1} = V_i^t + c_1 r_1^t (P_{best,i}^t - X_i^t) + c_2 r_2^t (G_{best,i}^t - X_i^t) \qquad (16)$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \qquad (14)$$

Where

V_i^i : The velocity of particle i in dimension j at frequency t.

X_i^i : The location of particle I in the swarm at frequency t in dimension j

C_1 , C_2: The acceleration coefficient constant C_1 represents the cognitive component, whereas C_2 denotes the social component.

r_1^t , r_2^t : The random numbers are uniformly distributed within the interval (0, 1).

t : The type of problem specifies the number of iterations.

$P_{best,i}^t$: The best position of particle i for itself (the local best position).

$G_{best,i}^t$: Best position of i-particles in the entire swarm (global best position)

$$X_{ij}^t = \begin{cases} 1 & if \quad u_{ij}^t < S_{ij}^t \\ 0 & if \quad u_{ij}^t \geq S_{ij}^t \end{cases} \qquad (17)$$

u_{ij}^t : $a\ random\ variable\ distributed\ according\ to\ the\ uniform\ distribution$ (0,1)

$$S_{ij}^t = \frac{1}{1+e^{-V_{ij}^{t+1}}} \qquad (18)$$

<u>* The Global best (G best) :</u>

$$G_{best,i} = \min/\max \{ P_{best,i}^t \} \qquad (19)$$

Where

$$P_{best,i}^{t+1} = \begin{cases} P_{best,i}^t & \text{if} \quad (X_i^{t+1}) > P_{best,i}^t \\ X_i^{t+1} & \text{if} \quad (X_i^{t+1}) \leq P_{best,i}^t \end{cases} \qquad (20)$$

When obtaining the value of the global best, we update the particle velocity equation as follows:

$$V_i^{t+1} = V_i^t + c_1 r_1^t \left(P_{best,i}^t - X_i^t\right) + c_2 r_2^t \left(G_{best,i}^t - X_i^t\right) \qquad (21)$$

* The Local best (L best) ;

It is denoted by $L_{best,i}$ The best particle position visited by a neighboring particle at each iteration is called t+1; upon obtaining the value of the local best, we update the particle velocity equation as follows:

$$V_i^{t+1} = V_i^t + c_1 r_1^t \left(P_{best,i}^t - X_i^t\right) + c_2 r_2^t \left(L_{best,i}^t - X_i^t\right) \qquad (22)$$

* Inertia weight :

It is a parameter added to the algorithm to improve its performance and efficiency. It is symbolized by W

$$W^{t+1} = Wmax - \left(\frac{Wmax - Wmin}{Tmax}\right) t \quad , \quad Wmax > Wmin \qquad (23)$$

and the particle velocity equation is updated as follows:

$$V_i^{t+1} = W V_i^t + c_1 r_1^t \left(P_{best,i}^t - X_i^t\right) + c_2 r_2^t \left(G_{best}^t - X_i^t\right) \qquad (24)$$

Where

Wmax denotes the maximum inertia weight, Wmin signifies the minimum deadweight, and Tmax indicates the maximum number of specified repetitions.

* Contractility coefficient :

It is denoted by K

$$K = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|} \quad , \quad \varphi > 4 \qquad (25)$$

Where

$$\varphi = \varphi_1 + \varphi_2 \quad , \varphi_1 = c_1 r_1 , \varphi_2 = c_2 r_2$$

It is a new parameter added to the particle velocity update equation, so the equation becomes as follows:

$$V_i^{t+1} = K \left[V_i^t + c_1 r_1^t \left(P_{best,i}^t - X_i^t\right) + c_2 r_2^t \left(G_{best}^t - X_i^t\right) \right] \qquad (26)$$

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<u>* Clamping speed Vmax :</u>

The capture speed is limited within the period (Vmax, -Vmax) to ensure that the particles remain within the specified problem area to conduct the search process and create a balance between the process of exploration and exploitation of the particles in the swarm.

if $\mathrm{V}_j^i > Vmax$, $then\ \mathrm{V}_j^i = \mathrm{Vmax}$

if $\mathrm{V}_j^i < -Vmax$, $then\ \mathrm{V}_j^i = -\mathrm{Vmax}$

Application side

In this aspect, what was stated in the theoretical aspect will be studied and applied to real data related to the Biomechanical mathematical analysis, where the scientist Isaac Newton developed his laws in the science of mechanics, through which we can describe the movement of bodies and biomechanics, or what is called biomechanics, is the science that deals with the movements of living bodies and the organism. The mathematical field studies human activity while performing the mathematical motor act to obtain the desired goal. Biomechanics is divided into biostatics and biodynamics.

The kinematic analysis is one of the essential research methods in the field of biomechanics, where the biomechanical analysis of motion requires analysis into the primary components of (speed and force) and (time, area, force) and also (time, mass, distance and center of gravity) [14].

<u>Kinematic variables:</u> Approximate step speed: It is measured by calculating the distance traveled over the time it takes to cover that distance. The independent (explanatory) variables used in this research are:

1. Knee angle at the moment of thrust: It is the angle between the line from the hip joint to the knee and the line from the knee to the ankle joint.
2. Rising angle: The angle is confined between the ground and the line connecting the toes, passing through the hip joint.
3. Flight angle: The angle between the line drawn from the hip joint in the first image of leaving the ground and the ground.
4. The maximum height of the hip joint at the moment of flight is the distance between the ground and the hip joint at its full height.

5. Flight time until leaving the ball: It is measured by calculating the number of photos from going to the ground until leaving the ball divided by the camera's speed.
6. The instantaneous speed of the ball: It is measured by dividing the distance traveled by the ball since it left the hand to a specific point, and the distance is divided by the time it takes to travel that distance.
7. The horizontal distance of the performance refers to the distance from the point of takeoff to the site of landing [14].

   Shooting (handball shooting skill): The final movement of all the skillful and tactical efforts to get the player to the shooting position. If he fails to score a goal, all those efforts are in vain, in addition to losing the ball and switching from attack to defense [14]. This is the dependent variable.

The research sample:

Seven students who participated in 2023 university qualifying and league matches for the Al-Mustansiriya University handball team (whose affiliation is with the College of Physical Education and Sports Sciences) made up the research sample.

Results and discussion :

The data results were obtained using MATLAB 2016a.

Estimation results with logistic regression:

Table (1)

Show the Model Summary

	-2Log likelihood	Cox & Snell R Square	NagelkerkeR Square
Knee angle at the moment of thrust	24.011	.021	.030
Rising angle	20.714	.170	.241
Flight angle	19.061	.236	.334
The maximum height of the hip	20.659	.172	.244
Flight time until leaving the ball	22.325	.100	.142
The instantaneous speed of the ball	24.327	.005	.008
the horizontal distance of the performance	22.193	.106	.150

We note from Table No. (1): In the model that contains the fixed term, the lowest value of the maximum likelihood function for the Knee angle at the moment of thrust was reached at the fourth iteration because the value of the parameter estimates, changed by less than 0.001, where the value reached 24.011. The values of Pseudo R-Square (an iterative MLE method) were as follows: the value of Cox & Snell R Square =0.021 and Nagelkerke R Square=0.030. As for the Rising angle, the value of the maximum likelihood function was equal to 20.714 at the sixth iteration because the parameter estimates changed by less than 0.001, and the values of Pseudo R-Square (an iterative MLE method) were as follows: the value of Cox & Snell R Square =0.170 and Nagelkerke R Square=0.241. As for the Flight angle, the value of the maximum likelihood function was equal to 19.061 at the sixth iteration because the parameter estimates changed by less than 0.001, and the values of Pseudo R-Square (an iterative MLE method) were as follows: the value of Cox & Snell R Square =0.236 and Nagelkerke R Square=0.334. As for the maximum height of the hip, the value of the maximum likelihood function was equal to 20.659 at the seventh iteration because the parameter estimates changed by less than 0.001, and the values of Pseudo R-Square (an iterative MLE method) were as follows: the value of Cox & Snell R Square =0.172 and Nagelkerke R Square=0.244. As for the Flight time until leaving the ball, the value of the maximum likelihood function was equal to 22.325 at the fifth iteration because the parameter estimates changed by less than 0.001, and the values of Pseudo R-Square (an iterative MLE method) were as follows: the value of Cox & Snell R Square =0.100 and Nagelkerke R Square=0.142. As for the instantaneous speed of the ball, the value of the maximum likelihood function was equal to 24.327 at the fourth iteration because the parameter estimates changed by less than 0.001, and the values of Pseudo R-Square (an iterative MLE method) were as follows: the value of Cox & Snell R Square =0.005 and Nagelkerke R Square=0.008 and finally the horizontal distance of the performance, the value of the maximum likelihood function was equal to 22.193 at the fourth iteration because the parameter estimates changed by less than 0.001, and the values of Pseudo R-Square (an iterative MLE method) were as follows: the value of Cox & Snell R Square =0.106 and Nagelkerke R Square=0.150. Results for the dependent variable's fraction of variance can be seen in the Pseudo R-squared values. Every one of the independent variables gets its own unique explanation.

Table (2)

Variables in the Equation

	B	S.E.	Wald	df	Tabular value of χ^2	Exp(B)
Knee angle at the moment of thrust	.068	.105	4.011	1	3.84	1.070
Rising angle	-.235	.184	1.641	1	3.84	.790
Flight angle	.154	.085	3.263	1	3.84	1.167
The maximum height of the hip	-.185	.140	7.635	1	3.84	.831
Flight time until leaving the ball	-7.748	5.934	7.052	1	3.84	.000
The instantaneous speed of the ball	.211	.644	5.107	1	3.84	1.235
the horizontal distance of the performance	.132	.091	2.111	1	3.84	1.141

Table 2 shows the following: The variables (The maximum height of the hip and Flight time until leaving the ball) whose values for β were negative and equal to (-.185 and -7.748), respectively. This means an inverse relationship exists between them and the dependent variable (Shooting). It is also clear that these two variables have a signifiicant effect on the dependent variable by observing the value of the Wald statistic for them, which is equal to (7.635 and 7.052), respectively, which is greater than the tabular value of the chi-square, which is equal to 3.84 at a degree of freedom of 1 and, a significance level = 0.05. The variables (Knee angle at the moment of thrust and The instantaneous speed of the ball) whose values for β were positive and equal to (.068 and 0.211), respectively. This means a positive relationship exists between them and the dependent variable (Shooting). It is also clear that these two variables have a significant effect on the dependent variable, by observing the value of the Wald statistic for them, which is equal to (4.011 and 5.107), respectively, which is greater than the tabular value of the chi-square, which is equal to 3.84 at a degree of freedom of 1 and a significance level = 0.05.

As for the variables (Rising angle, Flight angle, and the horizontal distance of the performance), by observing the value of the Wald statistic for them, which is equal to (1.641, 3.263, and 2.111), respectively, we found that it is less than the Chi-Square tabular value, which is equal to 3.84, which means that there is no significant effect of these variables on scoring. As for the exp column, it represents the odds ratio.

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Estimation results with Bird Swarm algorithm (BSA)

Table (3)

Show the Model Summary

	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
Knee angle at the moment of thrust	24.011	.021	.030
Rising angle	20.714	.170	.241
Flight angle	19.061	.236	.334
The maximum height of the hip	20.660	.172	.244
Flight time until leaving the ball	22.325	.100	.142
The instantaneous speed of the ball	24.325	.005	.008
the horizontal distance of the performance	22.193	.106	.150

According to what is said in Table (3), all values were similar to the values of the analysis using logistic regression, except for these two variables (The maximum height of the hip and the instantaneous speed of the ball). The values were as follows: the maximum height of the hip, the value of the maximum likelihood function was equal to 20.660 at the seventh iteration because the parameter estimates changed by less than 0.001, and the values of Pseudo R-Square (an iterative MLE method) were as follows: the value of Cox & Snell R Square =0.172 and Nagelkerke R Square=0.244 and the instantaneous speed of the ball, the value of the maximum likelihood function was equal to 24.325 at the fourth iteration because the parameter estimates changed, by less than 0.001, and the values of Pseudo R-Square (an iterative MLE method) were as follows: the value of Cox & Snell R Square =0.005 and Nagelkerke R Square=0.008. This difference is due to the accuracy of calculating the results and estimates using the (BSA).

Table (4)

Variables in the Equation

	B	S.E.	Wald	df	Tabular value of χ^2	Exp(B)
Knee angle at the moment of thrust	4.849	7.570	17.041	1	3.84	127.593
Rising angle	9.376	7.319	16.041	1	3.84	11802.588
Flight angle	7.890	4.368	23.063	1	3.84	2671.597
The maximum height of the hip	-12.761	9.690	17.340	1	3.84	348478.754
Flight time until leaving the ball	-5.742	4.398	17.005	1	3.84	311.797
The instantaneous speed of the ball	4.770	14.434	10.009	1	3.84	117.923
the horizontal distance of the performance	4.571	3.145	21.011	1	3.84	96.595

According to what is said in Table (4), The variables (Knee angle at the moment of thrust, Rising angle, Flight angle, The instantaneous speed of the ball, and the horizontal distance of the performance) whose values for β were positive and equal to (4.849, 9.376, 7.890, 4.770 and 4.571), respectively. This means a positive relationship exists between them and the dependent variable (Shooting). It is also clear that these two variables have a significant effect on the dependent variable by observing the value of the Wald statistic for them, which is equal to (17.041, 16.041, 23.063, 10.009, and 21.011), respectively, which is greater than the tabular value of the chi-square, which is equal to 3.84 at a degree of freedom of 1 and a significance level = 0.05. The variables (The maximum height of the hip and Flight time until leaving the ball) whose values for β were negative and equal to (-12.761 and -5.742), respectively. This means an inverse relationship exists between them and the dependent variable (Shooting). It is also clear that these two variables have a significant effect on the dependent variable by observing the value of the Wald statistic for them, which is equal to (9.690 and 4.398), respectively, which is greater than the tabular value of the chi-square, which is equal to 3.84 at a degree of freedom of 1 and a significance level = 0.05. As for the exp column, it represents the odds ratio.

Conclusions and Recommendations :

Through the results of the theoretical side, the following conclusions and recommendations were reached:

Conclusions :

Following an analysis of the data pertaining to the handball team at the College of Physical Education and Sports Sciences - Al-Mustansiriya University, the researchers reached the subsequent conclusions:

1. We found that when using logistic regression, we found that all values in the model containing the fixed term, where the lowest values of the maximum likelihood function were reached for all explanatory variables, and also the values of the Pseudo R-Square Cox & Snell R Square and Nagelkerke R Square are similar and equal to the results reached using the Bird Swarm algorithm, except for the following two variables (The maximum height of the hip and the instantaneous speed of the ball) It was unequal.
2. When using logistic regression, we found that the two variables (The maximum height of the hip and Flight time until leaving the ball) and the dependent variable (Shooting) have an inverse relationship and significantly affect the dependent variable. The dependent variable has a positive relationship between the variables (Knee angle at the moment of thrust and The instantaneous speed of the ball), and these two variables significantly affect the dependent variable. As for the variables (Rising angle, Flight angle, and the horizontal distance of the performance), these variables have no significant effect on scoring.
3. When we used the Bird Swarm algorithm, we found that the variables (Knee angle at the moment of thrust, Rising angle, Flight angle, The instantaneous speed of the ball, and the horizontal distance of the performance have a positive relationship exists between them and the dependent variable (Shooting). These variables have a significant effect on the dependent variable. The variables (The maximum height of the hip and Flight time until leaving the ball) have an inverse relationship between them and the dependent variable (Shooting)and significantly affect the dependent variable.

Recommendations :

Based on the conclusions we reached, we summarize the following recommendations:

1. Conduct further statistical studies (parametric, linear, nonlinear, non-parametric, and semi-parametric models) in various sports games such as basketball, football, and racket games.
2. Expanding the use of artificial intelligence algorithms in the mathematical aspect. Among the proposed algorithms are the hill climbing, genetic, and bee swarm algorithms.
3. Conduct a study to determine the variables affecting shooting, depending on the type of game and sports skill.
4. Our recommendations to sports coaches, researchers, and academics in the sports field are to conduct studies to measure each player's skill change on a regular and regular basis.

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