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Using artificial intelligence as an indicator to classify students' javelin throwing effectiveness in athletics Based on some physical and motor skills and body measurements

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Abstract

Study purpose. To determine the authenticity of the sample based on the physical and athletic skills and body measurements of some students, with the goal of classifying them into homogeneous groups and to group pupils according to their body measurements and certain athletic and physical attributes.

Materials and methods. The researchers described the concept of his current research in a comprehensive manner within the theoretical framework. Methodologically, the opted for descriptive research and correlational methods because of his compatibility and the problem he wanted to address. The research team was comprised of third year students (115 students) from the faculty of Sport and Exercise Sciences at the University of Babylon during the academic year 2022/23. The researcher described the procedures used to accomplish his research and achieve his goals

Results. The table indicates that the explosive power of the legs x the fourth cell had the highest coefficient value in the negative direction, reaching -1.117, and the explosive power of the arms x the ninth cell had the highest coefficient value, reaching 0.886 in the positive direction. The other coefficient values varied between these values

Conclusions. Using statistical metrics associated with normal distribution, these estimates suggest that the sample components are approximately distributed across all of the study variables, this enables the researchers to create models for categorization purposes and the researchers were able to create models of how various variables influence class: (weight, arm length, hand length**,** chest width, upper arm circumference, leg power, arm power, balance and coordination)**.**

Keywords: Artificial intelligence, javelin, throwing, motor skills**.**

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Introduction

Life has witnessed remarkable development in all areas, and this development has come to meet human needs. Physical education has had a share of this development. Once limited to entertainment and recreation, sports have evolved to reach higher levels, achieve results, and break previous records. It has also fostered competition among individuals in general. Among these developments, sports are considered a fundamental means of advancing nations, elevating societies, and elevating their standing among other societies. Therefore, specialists in the field of physical education have sought to find ways to develop this field and keep pace with modern developments, working to develop and advance it, whether in team or individual sports.

Athletics competitions are the foundation of athletics, as their races vary between running, jumping, and throwing (Rubin, 2014). These are all skills that showcase an individual's physical performance in a manner that reflects their potential. They are a collection of individual and team races, and throwing events are among the most important events in the field of track and field sports, given the enjoyment they bring to players and spectators, as well as the entertainment they provide. Throwing events are among the most popular athletics events Many countries participate in this activity, including the javelin throw, discus throw, and shot put. Increasingly, these events have been attended by both men and women, they are both enjoyable and fascinating for both sexes. These events have recorded a lot of progress. This increase is caused by the utilization of accurate and comprehensive scientific approaches, especially during the process of classifying players according to the sporting activity they practice, to achieve the full rhythm of the athlete's sporting activity requirements. Players in various types of throwing events are characterized by their control of neuromuscular activity, represented by coordination, speed of reaction, strength, speed, rotation, sliding, strength of the upper and lower extremities, explosive ability, flexibility, agility, large physical and muscular size, and the ability to relax. The assessment and improvement of student abilities in throwing activities is not confined to the confines of training sessions, despite their significance. Instead, the increase in, improvement of, and evaluation of the degree of success is dependent on the classification of students, their physical and motor abilities, and the specific body measurements associated with each activity (Carballo-Fazanes, 2022).Because of the variety of statistical methods and techniques and scientific methods and their diverse fields of application, sciences have a variety of degrees of dependence on them and utilize different levels of statistical methodology. Certain statistical techniques have gained widespread use after proving their efficacy in a particular field, but they have not been investigated in other domains. Among the most popular modern technological innovations in the world is artificial intelligence, which was designed for many uses, the most important of which are the recognition of people, situations, voice, image, fingerprint, handwriting recognition, system simulation, and the construction of a future vision. (Predictive) of any performance. The more the field differs, the more different the technology and method of implementation that researchers and those in charge of this field seek to develop and bring to the highest degree of perfection and idealism. There is no doubt that the tangible development in the speed of obtaining data and its accuracy saves time and effort. With this development, it keeps pace with the very large volume of data, as it is difficult to process it using traditional methods or may not lead us to the desired goal in a satisfactory and honest manner (He, 2024).

While artificial intelligence has a significant role its application in a number of scientific domains, such as health and finance, as well as in humanitarian sports education is still limited—in part, this is based on the research conducted by scientists. As a result, it's crucial to investigate the potential benefits of this technology in sports education and science, and to determine its effectiveness through one of its components, artificial neurons.

There is no doubt that human intelligence cannot be replaced by artificial intelligence, but we must also acknowledge that artificial intelligence is more stable than natural intelligence, which allows it to be distributed and copied at a lower cost. It is also characterized by its speed of implementation and predictability of results, as knowledge in the field of artificial intelligence relies on data and information, and it is one of the most prominent technologies that mimics human neural networks in its operation. Therefore, the researcher decided to build an artificial neural network (profile) by tapping into the world of artificial intelligence to overcome some of the obstacles facing researchers and specialists, and to benefit from it in the correction process, relying on the results of the model for classification with variables taken from the actual performance of students, so that he can shed light on the physical motor abilities appropriate for each activity and determine the extent of their compatibility with the requirements of the activity, as well as reveal the body measurements of each player through player classification and studied objective guidance. Consequently, the researcher aimed to clarify artificial intelligence etworks, which classify variables (body measurements, physical and motor abilities) into homogeneous groups based on common characteristics (Wood, 2022). Hence, in trying to establish correct scientific foundations by employing artificial intelligence techniques in the service of the sports field. This is the goal that the researcher seeks to achieve in order to bring about development in the level of achievement in light of the studied variables in order to choose the most appropriate type of activity and avoid randomness, especially if the students are among those who have specifications that enable them to achieve high-level achievements. Learning with the help of artificial intelligence will be a new gateway in the modern sports field to get rid of obstacles and reach results with high accuracy and the lowest percentage of error.

Materials and methods

Study participants

A. Human Area: Students in their second year at the University of Babylon's College of Physical Education and Sports Sciences during the 2022–2023 academic year.
B. Time Area: October 16th, 2022, to April 10th, 2023.
C. Spatial Area: The University of Babylon's College of Physical Education and Sports Sciences' indoor hall, weight room, and outdoor courts.

Study organization

Field Research Procedures

Determining the Body Measurements for the Effectiveness of the Javelin

Access to body measuring tests that are pertinent to the research and the model is necessary to finish the research procedures and meet objectives. In order to gather information about experts and other professionals working in testing, measuring, sports training, and athletics, the researcher created a survey. There were nine experts and professionals. The table 1 shows that the measures that achieved a percentage of 82.21% were deemed valid after the forms were collected, the data was obtained, and their validity was confirmed using Chi-square.

Table 1. shows the number of those who agreed and disagreed, the percentage, and the calculated and tabulated (Chi-square) value for the measurements studied

Tests	Units	Agree	%	Disagree	%	CHI-SQUARE Calcila-ted	CHI-SQUARE Tabul-ated*	Statistical significance
Body weight	Kg	8	88.89	1	11.12	5.46	3.84	Sig.
Total body length	Cm	9	100	0	0	9	3.84	Sig.
Torso length	Cm	8	88.89	1	11.12	5.46	3.84	Sig.
Torso length with head	Cm	6	66.67	3	33.34	1	3.84	No sig.
Upper arm length	Cm	8	88.89	1	11.12	5.46	3.84	Sig.
Forearm length	Cm	8	88.89	1	11.12	5.46	3.84	Sig.
Foot length	Cm	3	33.34	6	66.67	1	3.84	No sig.
Hand length	Cm	9	100	0	0	9	3.84	Sig.
Forearm length	Cm	8	88.89	1	11.12	5.46	3.84	Sig.

	with palm								
0	Arm length	Cm	8	88.89	1	11.12	5.46	3.84	Sig.
1	Lower limb length	Cm	8	88.89	1	11.12	5.46	3.84	Sig.
2	Thigh length	Cm	8	88.89	1	11.12	5.46	3.84	Sig.
3	Leg length	Cm	8	88.89	1	11.12	5.46	3.84	Sig.
4	Wrist width	Cm	6	66.67	3	33.34	1	3.84	No sig.
5	Abdominal width	Cm	2	22.23	7	77.78	2.78	3.84	No sig.
6	Shoulder breadth	Cm	9	100	0	0	9	3.84	Sig.
7	Abdominal width	Cm	0	0	9	100	9	3.84	No sig.
8	Hip width	Cm	0	0	9	100	9	3.84	No sig.
9	Hand width	Cm	6	66.67	3	33.34	1	3.84	No sig.
0	Hip width	Cm	3	33.34	6	66.67	1	3.84	No sig.
1	Chest width	Cm	1	11.12	8	88.89	5.46	3.84	No sig.
2	Shoulder width	Cm	1	11.12	8	88.89	5.46	3.84	No sig.
3	Chest breadth	Cm	9	100	0	0	9	3.84	Sig.
4	Pelvis breadth	Cm	9	100	0	0	9	3.84	Sig.
5	Thigh circumference	Cm	8	88.89	1	11.12	5.46	3.84	Sig.
6	Upper arm circumference	Cm	9	100	0	0	9	3.84	Sig.
7	Upper arm circumference (extended)	Cm	1	11.12	8	88.89	5.46	3.84	No sig.
8	Forearm circumference (flexed)	Cm	8	88.89	1	11.12	5.46	3.84	Sig.
9	Upper arm circumference (flexed)	Cm	0	0	9	100	9	3.84	No sig.
0	Abdominal circumference	Cm	2	22.23	7	77.78	2.78	3.84	No sig.

* At a significance level of 0.05 and a degree of freedom of (1), the tabular Chi-square value is 3.84.

Determining the physical and motor abilities specific to javelin throwing activities

Table 2. shows the number of those who agree and disagree, the percentage, and the calculated and tabulated value of (CHI-SQUARE) for the physical and motor abilities studied

Abilities	Units	Agreed	%	Disagree	%	CHI-SQUARE Calcila-ted	CHI-SQUARE Tabul-ated*	Statistical significance
Physical abilities								
Explosive power for arms	Meter	8	88.89	1	11.12	5.46	3.84	Sig.
Explosive power for legs	Meter	9	100	0	0	9	3.84	Sig.

Speed-power for arms	Number	8	88.89	1	11.12	5.46	3.84	Sig.
Speed-power for strength	Meter	1	11.12	8	88.89	5.46	3.84	No sig.
Speed-power for legs	Meter	8	88.89	1	11.12	5.46	3.84	Sig.
Force endurance for legs	Number	8	88.89	1	11.12	5.46	3.84	Sig.
General force endurance for arms	Meter	3	33.34	6	66.67	1	3.84	No sig.
Speed endurance for legs and arms	Number	9	100	0	0	9	3.84	Sig.
Explosive power for arms	Number	8	88.89	1	11.12	5.46	3.84	Sig.
Abilities and mobility								
Agility	Meter	8	88.89	1	11.12	5.46	3.84	Sig.
Eye-Arm Coordination	Number	8	88.89	1	11.12	5.46	3.84	Sig.
Eye-Leg Coordination	Number	6	66.67	3	33.34	1	3.84	No sig.
Accuracy	Meter	2	22.23	7	77.78	2.78	3.84	No sig.
Leg-Arm Coordination	Time	9	100	0	0	9	3.84	Sig.
Balance	Time	8	88.89	1	11.12	5.46	3.84	Sig.
Motor Flexibility	Cm	9	100	0	0	9	3.84	Sig.

With a degree of freedom of (1) and a significance level of 0.05, the table 2 chi-square value is 3.84.

Ultimately, there were twelve acceptable abilities: agility, balance, coordination (eye-arm, coordination (leg-arm), motor flexibility), explosive ability of the arms, explosive ability of the legs, speed-specific strength of the legs, force endurance of the legs, and speed endurance of the legs and arms.

Determining the tests for physical and motor abilities in javelin throwing

Table 3. shows the number of those who agree and disagree, the percentage, and the calculated Chi-square value for the physical and motor tests and abilities

Test	Units	Agreed	%	Disagree	%	CHI-SQUARE Calcila-ted	CHI-SQUARE Tabul-ated*	Statistical significance
Throwing a 2 kg medicine ball with one hand from a standing position	Meter	9	100	0	0	9	3.84	Sig.
Grip Strength Measurement	N	1	11.12	8	88.89	5.46	3.84	No sig.
Long Jump from Standing	Meter	9	100	0	0	9	3.84	Sig.
Sargent's Vertical Jump	Cm	8	88.89	1	11.12	5.46	3.84	Sig.
Vertical Jump from Standing with Half Bent Knees	Meter	3	33.34	6	66.67	1	3.84	No sig.
Forward Sit (Arm Flexion and Extension) (10 seconds)	Meter	9	100	0	0	9	3.84	Sig.
Forward Sit (Arm Flexion and Extension) (20 seconds)	Meter	8	88.89	1	11.12	5.46	3.84	Sig.
Forward Sit (Arm Flexion and Extension for (15) seconds)	Meter	6	66.67	3	33.34	1	3.84	No sig.
Three consecutive forward jumps	Meter	3	33.34	6	66.67	1	3.84	No sig.
Dubney for (10) seconds	Meter	2	22.23	7	77.78	2.78	3.84	No sig.

with the barbell only								
From a standing position, fully bend and extend the knees within (20) seconds	Meter	3	33.34	6	66.67	1	3.84	No sig.
Hop the maximum distance in (30) seconds on one leg	Meter	9	100	0	0	9	3.84	Sig.
Bend and extend the knees within 20 seconds	Meter	5	55.56	4	44.45	0.12	3.84	No sig.
Lateral jump off the bench	Meter	9	100	0	0	9	3.84	Sig.
Full Dubbin test	Meter	5	55.56	4	44.45	0.12	3.84	No sig.
Front stadium until exhausted	Meter	8	88.89	1	11.12	5.46	3.84	Sig.
Hanging with Bent Arms	Time	1	11.12	8	88.89	5.46	3.84	No sig.
Pen Press to Exhaustion (Barbell Only)	Meter	2	22.23	7	77.78	2.78	3.84	No sig.
Medicine Ball Throw and Catch for 30 Seconds	Meter	9	100	0	0	9	3.84	Sig.
Lying Bench Press	Meter	6	66.67	3	33.34	1	3.84	No sig.
180m Rebound Run Test	Time	8	88.89	1	11.12	5.46	3.84	Sig.
300m High Start Run	Time	5	55.56	4	44.45	0.12	3.84	No sig.
4x9m Shuttle Run	Time	8	88.89	1	11.12	5.46	3.84	Sig.
Solo-Foot Stand	Time	8	88.89	1	11.12	5.46	3.84	Sig.
Balance Beam Run	Time	6	66.67	3	33.34	1	3.84	No sig.
Figure 8 Crawl Test	Time	9	100	0	0	9	3.84	Sig.
Numbered Circles Test	Time	0	0	9	100	9	3.84	No sig.
Tennis Ball Throw and Catch Test	Meter	8	88.89	1	11.12	5.46	3.84	Sig.
Light Touch Test	Meter	2	22.23	7	77.78	2.78	3.84	No sig.
Skipping Rope Test	Meter	3	33.34	6	66.67	1	3.84	No sig.
Spine Flexibility Test (Bridge)	Cm	8	88.89	1	11.12	5.46	3.84	Sig.
Jumping test from a 60cm platform and touching the ground with the feet	Meter	6	66.67	3	33.34	1	3.84	No sig.
Dynamic flexibility test: touching the X mark	Cm	8	88.89	1	11.12	5.46	3.84	Sig.
Bridge arch or back arch	Cm	3	33.34	6	66.67	1	3.84	No sig.

At a significance level of 0.05 and a degree of freedom of (1), the table 3 chi-square value was 3.84. (16) was the final acceptable test count.

The Main Experiment

The investigator initiated his primary experiment on the research community (students in the second year of the University of Babylon's College of Physical Education and Sports Sciences, numbering 115 students, from November 1st, 2022, to December 1st,20th. The researcher conducted the experiment, utilizing scientific sources in order to test, measure, and train sports, as well as the supervision's and researcher's expertise in this field. The program details are as follows (Baumgartner, 2020).

The experiment lasted for four weeks. The students' body measurements were determined by experts in the weight room of the Institute of Sports Sciences of the University of Babylon. To measure symptoms, researchers used a vernier and a measuring tape (linen). In addition, selected tests of physical fitness and sports skills were conducted in the hall of the Institute of Sports Sciences and on the outdoor court. The tests were conducted on the outdoor (indoor) throwing court of the Institute of Sports Sciences of the University of Babylon.

Statistical analysis

The statistical package (SPSS) was used to process the research data and extract the results.

Results

Results (presentation, analysis, and discussion)

Statistical explanation of the study variables (the sample's actual physical and motor skills as well as body measures that students possess in order to categorize them into homogenous groups) table 4.

Table 4. displays the results of the statistical analysis of the physical and motor skills, body measurements, and project throwing success of the research participants

Variables	Units	highest value	Minimum value	Mean	Std	Standard	Skewness
			Body measurements				
Body mass	Kg	102.00	64.00	75.81	5.48	0.66	0.93
Total height	Cm	190	170.00	177.01	5.35	0.65	0.56
Trunk length	Cm	70	45	55.1	4.6	0.6	0.6
Upper arm length	Cm	36.00	27.00	30.94	2.07	0.25	0.26
Forearm length	Cm	34.00	26.00	30.31	1.67	0.20	-0.41
Hand length	Cm	28	16	19.8	1.5	0.2	0.1
Forearm and palm length	Cm	57	42	48.2	3.1	0.4	0.4
Arm length	Cm	98	70	78.1	4.6	0.6	0.9
Lower limb length	Cm	106	80.00	94.46	4.94	0.60	-0.30
Thigh length	Cm	53	40	45.4	3.2	0.4	0.6
Leg length	Cm	52	38	44.4	3.2	0.4	0.4
Shoulder width	Cm	48.00	30.00	43.60	2.94	0.36	-0.54
Chest width	Cm	38	23.00	28.65	3.01	0.37	0.87
Pelvis width	Cm	54	25.00	32.12	3.63	0.44	0.21
Thigh circumference	Cm	67	46.00	53.90	5.06	0.61	0.54

Upper arm circumference	Cm	37.00	23.00	30.22	3.20	0.39	-0.08
Forearm circumference	Cm	33	23	27.9	2.2	0.3	0.2
Achievement in the researched activities							
Weightlifting	Meter	10.5	5.2	8.2	0.1	0.9	-0.5
Disc throwing	Meter	20.12	10.2	15.6	0.2	0.7	-0.3
Spear throwing	Meter	30.3	13.12	18.9	0.5	0.1	0.4
physical abilities							
Explosive arm power	Meter	10	8	8.9	0.6	0.1	0.00
Explosive leg power	Meter	2.6	1.9	2.3	0.3	0.1	-0.1
Explosive leg power	Cm	50	30	37.3	7.2	0.9	0.6
Speed-specific arm power	Number	14.00	8.00	11.31	1.42	0.17	-0.21
Speed-specific arm power	Number	22.00	14.00	18.16	2.53	0.31	-0.18
Speed-specific leg power	Meter	99.00	45.00	79.65	16.25	0.97	-0.70
Strength endurance for arms	Number	37.00	20.00	28.19	5.12	0.62	0.11
Strength endurance for legs	Number	37.00	15.00	25.10	6.65	0.81	0.16
Speed endurance for arms	Number	52.00	38.00	46.47	4.32	0.52	-0.41
Speed endurance for legs	Sec.	52.2	36.8	45.1	4.2	0.4	-0.11
Motor abilities							
4x9m shuttle run	Sec.	12.14	9.11	10.82	0.80	0.10	-0.70
Standing on one foot	Sec.	45.13	22.75	33.01	5.94	0.72	0.57
Figure 8 crawl test	Sec.	1.47	1.06	1.26	0.11	0.01	-0.04
Tennis ball throw and catch	Number	14.00	10.00	12.07	1.15	0.14	-0.21
Spinal flexibility test (bridge)	Cm	48.00	23.00	33.63	6.37	0.77	0.07
Dynamic flexibility test (touching X)	Number	41.00	28.00	35.88	3.69	0.45	-0.24

Steps for building an artificial neural network for classification:

Displaying and analyzing the results of the correlation matrix:

Without a doubt, neural network analysis is dedicated to expressing association statistics with specific variables. To attain these values, they must be derived from the data matrix using the simple equation for the Pearson correlation coefficient. The matrix of intercorrelation had

(630) associated correlation coefficients. See (The Intercorrelation Matrix) and the Table 5 in the appendix for more information.

Table 5. shows the numbers and percentages of positive, negative, significant, and random correlations included in the intercorrelation matrix

Correlation	Positive		Negative		Zero		Total	Percentage
	Number	%	Number	%	Number	%		
Moral	282	43.59	253	9.60	/	0	318	% 53.20
Random	36	20.93	58	25.86	1	0.24	312	% 46.79
Total	318	64.52	311	35.46	1	0.24	630	100 %

The degree of freedom is 66, the significance level is 0.05, and the largest random number (r) is 0.24. Significant correlations between a number of covariates and the dependent variable (weight, disc, and javelin thrust performance) are displayed in Table 5. This example illustrates a basic correlation matrix that uses the numerical expansion rule = n × (n + 1) / 2 and displays the derived correlation values. The total of the values acquired in both the positive and negative directions between the significant and non-significant values (630), With a significance level of 0.05 and a degree of freedom of 66, the table value is 0.24. Since the values are dispersed between substantial and insignificant, the presence of a meaningful link is indicated by an increase in one of the estimated correlation values with the table value. The direction of the relationship is therefore classified as either positive or negative based on the value information. The first party (direct connection) has several (282) positive significant values for direct or indirect significant values, with the largest being (forearm circumference x circumference). With computed values of 0.703, 0.644, and 0.579, respectively, the upper arm is the first variable, followed by the length of the leg and lower limbs (Vazou, 2020).

Conversely, the inverse relationship is derived from the relationships (speed endurance, two legs x chest width) and (agility x strength, characterized by speed, two arms, thigh circumference x forearm length), with calculated values of (-0.449), (-0.346), and (-0.338), respectively, totaling (253) negative significant values.

Weight, hand length and strength endurance, and two-leg strength were the factors that had a positive and significant association with the dependent variable (throwing and javelin throwing success rate). These correlations were calculated as (0.282), (0.210), and (0.238), respectively.

Displaying and analyzing the results of variable selection using the LASSO method:

This is an abbreviated form of the selection and shrinking operator, which employs a penalty function or threshold to choose variables. Its fundamental concept is that it functions on the principle of reducing the values' squares in comparison to the error in a particular imposed limit, which is the total sum of the parameters (Majeed, 1988). Because of the nature of the restriction, the Lasso estimator will reduce the number of parameters by a specific amount while keeping the others the same.

Table 6. Transaction values after reduction

Variables	Coefficients	Standard coefficient sum
Body mass	- 0.04	- 0.1
Total height	0.000	0,000
Trunk length	0.000	0.000
Upper arm length	0.000	0.000
Forearm length	0.000	0.000
Hand length	0.03	0.097
Forearm and hand length	0.000	0.000

Arm length	0.1	0.42
Lower limb length	0.000	0.000
Thigh length	0.000	0.000
Leg length	0.000	0.000
Shoulder width	0.000	0.000
Chest width	- 0.07	- 0.31
Pelvis width	0.000	0.000
Thigh circumference	0.000	0.000
Upper arm circumference	0.06	0.18
Forearm circumference	0.000	0.000
Explosive power of the arms	0.05	0.1
Explosive power of the legs	0.038	0.067
Explosive power of the legs	0.000	0.000
Speed-strength of the arms	0.000	0.000
Speed-strength of the arms	0.16	0.012
Speed-strength of the legs	0.000	0.000
Strength endurance of the arms	0.000	0.000
Strength endurance of the legs	0.000	0.000
Speed endurance of the arms	0.000	0.000
Speed endurance of the legs	0.000	0.000
Agility	0.000	0.000
Balance	0.03	0.24
Coordination	0.000	0.000
Coordination 2	0.02	0.005
Motor agility 1	0.000	0.000
Motor agility 2	0.000	0.000

Table 6 shows the values of the coefficients after reduction. This is achieved through a series of equations that reduce the number of coefficients to 0, thereby eliminating them from the selection process. The other coefficients that cannot be reduced to 0 retain their original values. These values represent the coefficients of the variables after filtering. The values of non-standard and standard parameters are shown. Both values represent acceptable variables, i.e., h. Variables with coefficient values greater than zero. As a result, the values of (33) variables were reduced to 23 variables. The meaning of these variables changes depending on the absolute value of the parameter (Al-Tkhayneh, 2023). The first variable (driven by speed) is the highest, followed by the variable (driven by length) and the variable that is on the border between simplified and non-simplified parameters (Compatibility 2). The numbers in the table are the coefficients on the y-axis, while the overall standardized coefficients represent the x-axis. Therefore, the coefficients (y-axis) have the final say in choosing one variable and ignoring another (Chow, 2023).

Demonstration and discussion of splitting samples into two groups (training, testing):

After the data processing process, which includes (10) additional variables besides the (Bias) bias coefficient, this process moves the line of intersection of the slope with the y-axis, which has the effect of providing flexibility in altering the position without negatively affecting the display of the best slope. This coefficient is associated with the input layer (individuals) as well as the hidden layers. It's included in the calculation formula and is considered like any other trainable variable. Its value is always increased by one (+1). It has an effect on subsequent variables, however, those variables do not have an effect on it. The dependent variables (the activity of throwing) are the ultimate consequence and are incorporated into the creation of the neural network, which has a hidden layer that facilitates the improvement of the process of training on the data in question. Table 7 gives the percentage of samples that were utilized in the network.

Table 7. Percentage of samples used in the network

Samples	Number		Ratio
Training Set	44		%64
Test Set	24		%35.3
Total Number	68		%100
Training Error Rate		%2.3	
Test Error Rate		%4.2	

From Table 7, we can see that the entire sample of (68) people is divided into two groups: a training group, used to train input and output data, and a test group, used to evaluate weights. The existence of a hidden layer is observed. The first group (training group) has (44 people), accounting for 64% of the total population, and the second group (test group) has 24 people, accounting for 35.3% of the total population. It is also evident that all data correlated with the statistical analysis and that no data was missed. Once the training process was complete, the results were evident. The error rate for both testing and prediction was 4.2%, meaning that the predictive power of the network was quite high. The error rate for the training cohort was 2.3%, indicating that the data was adequately captured, resulting in successful results (Bellows, 2013).

Discussion

Presentation, analysis, and discussion of the artificial neural network structure.

After the process of selection and smoothing took place using Laaso on the sample, (10) data were gathered and then inputted into the neural network. The researcher developed an integrated network of neurons of the single-layer type (Neural network). This network's purpose is to increase the weight of each input by its respective value.

First // Number of layers:

The two completely linked layers that make up the network's structure each feature a hidden layer with ten units. The dependent variable—the throwing behavior—represents each of the three units in the second layer, the second layer consists of ten units, each of which is represented by an independent variable.

Second // Functions used:

Linear activation function: The linear activation function was employed in the output layer. This function is similar to the Input-Output function, but instead of having an image of the output variables' appearance, it has an image of the input variables' appearance. This function provides multiple and unlimited classifications. The function of the layer weight initializer is to:

This is the layer's weight initializer that causes the weights to be random, this results in a good training outcome. If the weights are identical, the results will be identical.

Kernel initializer and bias initializer:

This function employs the initializer for the kernel and the bias initializer, both of which are intended to randomize the bias in order to achieve optimal weights that result in accurate results.

Mean absolute error (=loss):

This function was employed. It's one of the most significant functions associated with deep neural networks. It's represented by (MAE), which in statistics means the absolute mean error, a figure of errors that is used to calculate the average error between the actual values and the expected values (hitoshi, nasimul 2020:111). As a result, it's the primary factor in determining if or not to accept the network. In our instance, it increased to 2.3%.

Third/The final shape of the artificial neural network

Body weight, palm length, arm length, chest breadth, upper arm circumference, leg explosiveness, and uniqueness of strength with speed in the arms are the ten independent variables that are shown. Furthermore, the bias coefficient (BIAS), which is equivalent to the regression equation's value of (bo), is shown. Since it is a part of the mathematical equation, it is regarded like any other number and has a coefficient that is used in all computations. like a result, it influences the variables that follow, but those variables have no effect on it (Youssef, 2000). It complements both the hidden layers and the layer of independent variables. Three related variables and a hidden layer are also present: the effectiveness of the toss (javelin). The weight of each variable is equal to its respective importance and the percentage of its contribution to the next variable; the weight in blue has a negative value, i.e., negative values, and the gray line has the opposite value. The lines each represent the weight point (weight) or the value of the coefficient that connects all cells; the value usually falls between (±1). The first hidden layer consists of 10 cells plus the bias term value (bias). The input value (X), which is the independent variable, is multiplied by a random weight value to determine each value. In order to get optimal weights and the lowest error rate, the result is then fed into an equation known as the activation function. As a result, each cell's values from the hidden layer show up, which also shows the values of each cell, which are the input values for the second output layer, represented by (den Uil, 2023). The procedure remains the same, except the output is fed into the linear activation function. The delta value is then used to determine the difference between the actual values extracted from the sample results and the expected output values.(Δ). Then the network performs a reverse regression (Backward) by using the delta values of the outputs to extract the delta values of the hidden layer, and thus using each delta value used to extract a new weight (Δ^{new}) from During the equation, the new delta is used with the old weight to extract the new weight:

$$W^{new} = W^{old} - \Delta^{new}$$

The process continues until the stability level is reached, where the weights do not change, and the network is ready to operate.

Fourth // Presentation and discussion of the weight values between the layers and the contribution ratio

After completing the construction of the network, two sets of weights were extracted, as shown in The weight values, which are the coefficients for the variables or contribution ratios, are in two stages:

1-Coefficients of the effect of the independent variables in the hidden layer

(Lee, 2021) ten (10) cells are present. According to the formula (Z = X * W), the values of the independent variables were multiplied by their random weights to create the hidden layer. The resulting value (Z) was then entered into the Sigmoid equation using the formula (1 + e – z / g = 1). The predicted values of the dependent variable are revealed by multiplying the newly computed values for the hidden layers by the hidden layer's random weights. As a result, (110) coefficients. The table indicates that the explosive power of the legs x the fourth cell had the highest coefficient value in the negative direction, reaching -1.117, and the explosive power of the arms x the ninth cell had the highest coefficient value, reaching 0.886 in the positive direction. The other coefficient values varied between these values (Basil Younis Al-Khayat, 2005).

2- Coefficients of the effect of the hidden layer on the dependent variable:

While the highest value in the negative direction was (-0.293), and this coefficient was between (the tenth layer x the spear).

Conclusions

Using metrics associated with normal distribution, the sample's items were found to be distributed across all studied variables, enabling the researcher to develop a categorization model. By applying neural networks and the Lasso method, a classification model was developed based on variables such as weight, arm length, palm length, chest width, upper arm circumference, leg explosive power, arm strength specific to speed, arm explosive power, balance, and coordination. These physical and motor abilities, along with body measurements, proved significant in classifying students during javelin throw practice in athletics. The researcher concluded that the Lasso method is one of the most effective techniques for identifying fundamental common traits when building a classification model using neural networks.

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Conflict of interest

There is none.

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