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BUILDING A PREDICTIVE CLASSIFICATION MODEL USING ARTIFICIAL NEURAL NETWORK TECHNIQUES AND IN TERMS OF ANTHROPOMETRIC MEASUREMENTS, BIO-KINETIC ABILITIES, AND SKILL PERFORMANCE OF YOUNG BOXERS

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ABSTRACT

Boxing is a combat sport that requires a high level of physical and bio-kinetic abilities due to its nature, which is characterized by rapid reaction, accuracy, balance, and responsiveness to changing competitive situations. The importance of this sport lies in the need for precise scientific tools that contribute to enhancing selection and classification processes, which positively affects performance effectiveness and guides the training process scientifically.

The research problem was represented by the absence of accurate objective models that rely on the analysis of body measurements and bio-kinetic abilities as a basis for classifying junior boxers. This weakens training outcomes and negatively affects skill achievement. Hence, the importance of the research lies in contributing to the construction of a predictive classification model for skill level using artificial neural network techniques and the significance of body measurements and bio-kinetic abilities in junior boxers.

The research aimed to identify the most prominent body and bio-kinetic variables that distinguish players with a high skill level, create a classification model that helps predict performance levels, and provide a database that supports coaches in designing effective training programs tailored to the characteristics of players. The researcher adopted the descriptive survey approach, given its suitability to the nature of the problem. Both the exploration and main experiments were conducted in Baghdad Governorate, inside the Al-Ittihad Sports Club hall. The research sample included (70) junior players representing the Al-Ittihad, Al-Arabi, and Al-Hussein clubs, for the 2022-2023 sports season. They underwent physical and bio-kinetic tests that measured multiple aspects related to skill performance in boxing.

The results showed clear individual differences among the players in their bio-kinetic abilities, which was reflected in their skill performance. The model, based on artificial neural network techniques, also proved highly effective in accurately classifying players, enhancing its potential for use in selection and guidance.

According to the results, the researcher recommends the adoption of artificial intelligence techniques, particularly artificial neural networks, in the evaluation and selection processes of athletes, while emphasizing the need to organize training workshops to qualify training personnel in this field. This will contribute to improving performance and raising the competitive levels of junior boxing players.

Keywords: *Artificial neural networks, skill performance, anthropometric and bio-kinetic measurements.*

INTRODUCTION

Boxing is a competitive sport that requires a high level of integration between physical and bio-kinetic abilities, given its nature, which relies on speed, timing, reaction, and the ability to make split-second decisions during kinetic confrontations. Analyzing physical and bio-kinetic characteristics is a modern scientific basis for assessing and classifying skill performance, as it plays an effective role in identifying players' strengths and weaknesses and contributing to the development of more accurate and specialized training programs.

According to the rapid technological development witnessed in the sports field, it has become possible to employ artificial intelligence techniques, particularly artificial neural networks, to classify players and explore their potential based on their physical and bio-kinetic indicators. This opens up new possibilities in sports selection and guidance areas.

The skill performance phase is a critical phase in boxing that demands very high neuromuscular coordination, quick decision-making, and precise kinetic response under pressure in the same time as attack or defense. The present researcher, upon observing the field situation within local clubs, was made to note that there existed a clear disparity in the skill performance levels of junior players; this disparity could probably be attributed to differences in their bio-kinetic abilities.

Hence, the research issue emerged in the requirement to construct a predictive classification model utilizing artificial neural networks to classify junior boxers according to their body measurements and bio-kinetic capacities. This will enable them to be scientifically directed towards the advancement of skill performance and elevating their level of competition.

Based on this vision, the research shall endeavor to determine the most outstanding body measurements and bio-kinetic capacities related to levels of skill performance in boxing; therefore, individual differences among players in these indicators will be analyzed. An attempt will be made to develop a precise predictive classificatory model through artificial intelligence techniques and, in so doing, create a scientific database that assists in training program and selection process improvement. The researcher also hypothesized the existence of statistically significant differences in some physical and bio-kinetic abilities among junior players that affect their skill performance levels, which would enable the possibility of predicting skill levels through these indicators. The research sample included (70) junior players from Al-Ittihad, Al-Arabi, and Al-Hussein clubs, who had prior training experience in boxing. The exploration and main experiment were conducted during the 2022-2023 sports season in Baghdad Governorate, at the Al-Ittihad Sports Club Hall, from October 18, 2022 to April 15, 2023.

Tools used in the research: Arab and foreign sources, the Internet, personal interviews, office tools, and the Statistical Package for Educational and Social Sciences (SPSS).

RESEARCH TESTS

- **Test name:** Repeated sprint test for a distance of 30 meters - five attempts (5 x 30m)
- **Purpose of the test:** This test measures speed endurance and anaerobic capacity by performing repeated sprints over a short distance (30m) for a specified number of attempts, with short rest intervals between each attempt.
- **Equipment and Supplies:**
- An accurate electronic stopwatch
- A measuring tape no less than 50 meters long
- Cones or ground markers to mark the start and finish lines
- A whistle or audible signal to start
- A scorecard
- Assistants for accurate timing

TECHNICAL PERFORMANCE DESCRIPTION

- The tester stands behind the start line, ready to go.
- Upon hearing the start signal, the tester begins to sprint as fast as possible for a distance of 30 meters.
- After completing the first sprint, a specific rest period is given (usually 20 to 30 seconds).
- The tester repeats the same 30-meter sprint five times in a row, maintaining the same rest period between each attempt.
- The time for each attempt is recorded separately.
- Number of repetitions:
- 5 times x 30 meters = 150 meters total
- Rest time between repetitions:
- A fixed rest period of 20 to 30 seconds between each repetition is recommended and determined in advance.

PERFORMANCE CONDITIONS

- The sprint must start from a stationary position behind the starting line.
- Departure before the signal is prohibited.
- The test subject must complete the full 30 meters without reducing the distance.

- Any incomplete or missed repetition will be recorded as a failed attempt.

RECORDING METHOD AND RESULTS

- The time of each attempt is recorded separately (e.g., first sprint = 4.75 seconds, second = 4.89 seconds...).

Figure (1) show the 5 x 30m Repeated Sprint Test

Test Name: Static Balance Test Using a Homemade Balance Device

TEST PURPOSE

This test aims to measure an individual's ability to maintain static balance by controlling their center of gravity while standing on an unstable surface.

EQUIPMENT REQUIRED

A homemade balance device: Consists of a wooden board measuring 80 cm long x 50 cm wide, with a wooden cube measuring 10 x 10 x 10 cm fixed to its center, acting as an unstable base.
A stopwatch to measure the duration of the balance.

PERFORMANCE DESCRIPTION

- The subject stands in a ready position on the wooden board, with one foot (the front foot) resting on the cube fixed in the middle of the board, and the other foot (the back foot) resting either on the board or the ground.
- Upon receiving the start signal, the subject lifts their back foot off the floor or board, supporting themselves solely on their front foot on the block.
- The goal is to maintain balance for as long as possible while remaining stationary on the ball of their front foot, which is positioned on the block, without any other part of their body touching the floor or board.

PERFORMANCE CONDITIONS

- The test is considered complete if the subject loses balance, the raised foot touches the floor or board, or they fall from the apparatus.
- Excessive arm movement is not permitted to achieve balance, and the subject is asked to maintain a normal body position.

RECORDING METHOD

- The time the subject maintains balance on the block is recorded in seconds using a stopwatch.
- The longest period of time the subject is able to maintain balance is considered the final score.

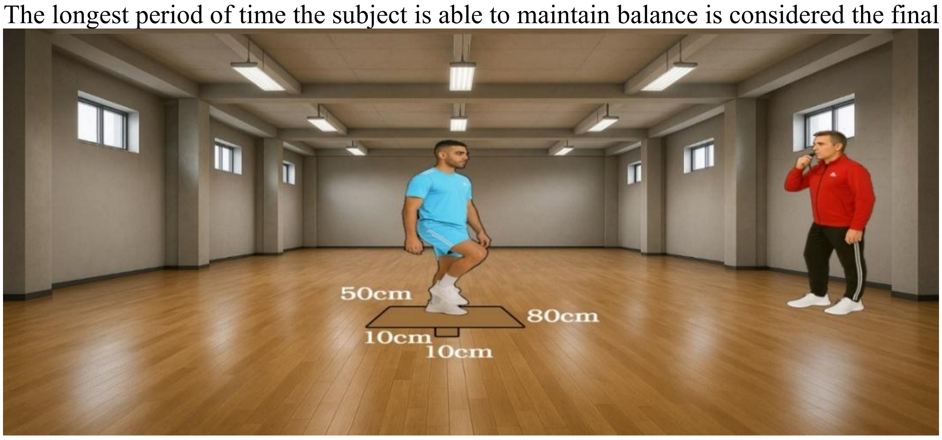

Figure (2)show the static balance test using a homemade balance device.

Test name: Eye-hand coordination test using a tennis ball.

TEST OBJECTIVE

This test is used to measure eye-hand coordination, which is one of the most important indicators of fine kinetic skills, especially those related to controlling the direction and speed of a moving object based on visual stimulation.

EQUIPMENT REQUIRED

- One tennis ball
- A flat, obstruction-free wall
- Masking tape or chalk to draw a line 5 meters away from the wall
- A stopwatch (if timed repetitions are required)

TEST PROCEDURE

The subject is asked to stand behind the line drawn on the floor, directly facing the wall.

THE TEST IS PERFORMED ACCORDING TO THE FOLLOWING SEQUENCE

- **Stage 1:** Throw the ball five consecutive times with the right hand toward the wall, attempting to catch it with the right hand after it bounces.
- **Stage 2:** Throw the ball five consecutive times with the left hand, and catch it with the left hand after it bounces.
- **Stage Three:** Throw the ball five times with the right hand, receiving it with the left hand after it bounces off the wall.

PERFORMANCE REQUIREMENTS

- The throw and reception must be made within a safe distance from the wall (5 meters), without crossing the line.
- The repetition is voided if the ball is not received correctly or if it falls to the ground before being received.

RECORDING METHOD

- One correct attempt is counted for the successful throwing and reception of the ball without falling.
- One point is awarded for each correct attempt, bringing the maximum score to (15) points distributed over the three stages.
- The final score reflects the individual's level of visual-kinetic coordination.

Test Name: Figure (8) Crawl Test:

TEST PURPOSE

This test aims to measure kinetic coordination between the arms and legs by performing regular crawling movements along a specific path, requiring good coordination between the four limbs to maintain the path without confusion or errors.

EQUIPMENT REQUIRED

- Two stable chairs.
- A stopwatch (chronometer).
- Floor markings to mark the path (optional).

PERFORMANCE SPECIFICATIONS

- The two chairs are positioned so that they form a traversable path in the shape of a number (8).
- The tester begins crawling (hands and feet only) next to one of the chairs, in a ready position.
- Upon the start signal, the tester begins crawling around the two chairs, forming a circular path in the shape of a number (8).
- The tester continues performing until four complete circles are completed, with the final circle ending at the same point from which they started.
- The designated path must be maintained and the correct direction must be followed during the performance.

DIRECTIONS AND INSTRUCTIONS

- The marked path or the designated left direction must be followed.
- Crawling must be done using only the hands and feet, without the knees or body touching the ground.
- Touching the chairs during the performance is prohibited. This is considered a violation that may result in a retry or deduction of points, according to the judging regulations.

RECORDING METHOD

- The time taken by the subject to complete four full cycles is recorded using an accurate stopwatch to the nearest 1/100 of a second.
- The best performance is recorded if more than one attempt is made, with notes regarding the execution.

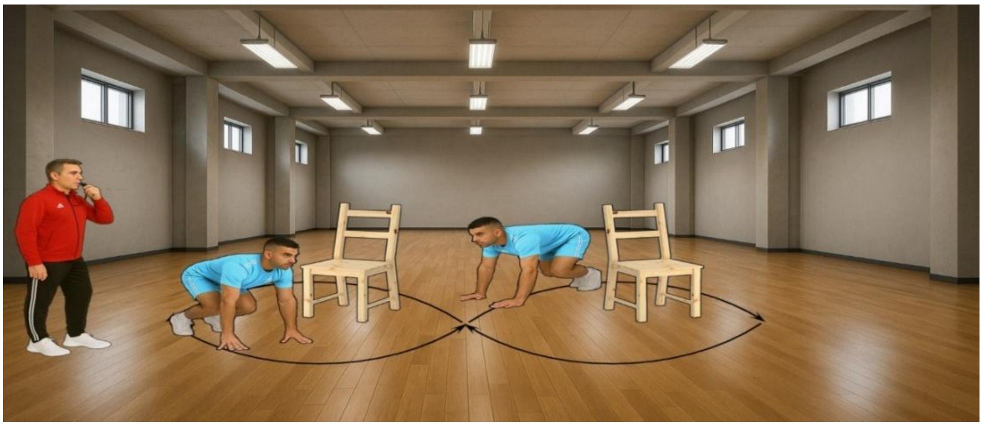

Figure (3) shows the crawling test is shown in Figure (8).
Seventh: Test Name: Visual-Hand Coordination Test Using a Tennis Ball

PURPOSE OF THE TEST

This test is used to measure the degree of eye-hand coordination, which is one of the most important indicators of fine kinetic abilities, especially those related to controlling the direction and speed of a moving object based on visual stimulation.

EQUIPMENT REQUIRED

- One tennis ball
- A flat, obstruction-free wall
- Masking tape or chalk to draw a line 5 meters away from the wall
- A stopwatch (if timed repetitions are needed)

TEST PROCEDURES

The subject is asked to stand behind the line drawn on the floor, directly facing the wall.

THE TEST IS PERFORMED ACCORDING TO THE FOLLOWING SEQUENCE

Stage One: Throw the ball five consecutive times with the right hand toward the wall, attempting to catch it with the right hand after it bounces.
Stage Two: Throw the ball five consecutive times with the left hand, and catch it with the left hand after it bounces.
Stage Three: Throw the ball five times with the right hand, ensuring that the ball is Receiving it with the left hand after it bounces off the wall.

PERFORMANCE CONDITIONS

The throw and reception must be made within a safe distance from the wall (5 meters), without crossing the line.
A repetition is voided if the ball is not received correctly or if it falls to the ground before being received.

RECORDING METHOD

One correct attempt is counted for a successful throw and reception of the ball without falling.
One point is awarded for each correct attempt, resulting in a maximum of (15) points distributed over the three stages.
The final score reflects the individual's level of visual-kinetic coordination.

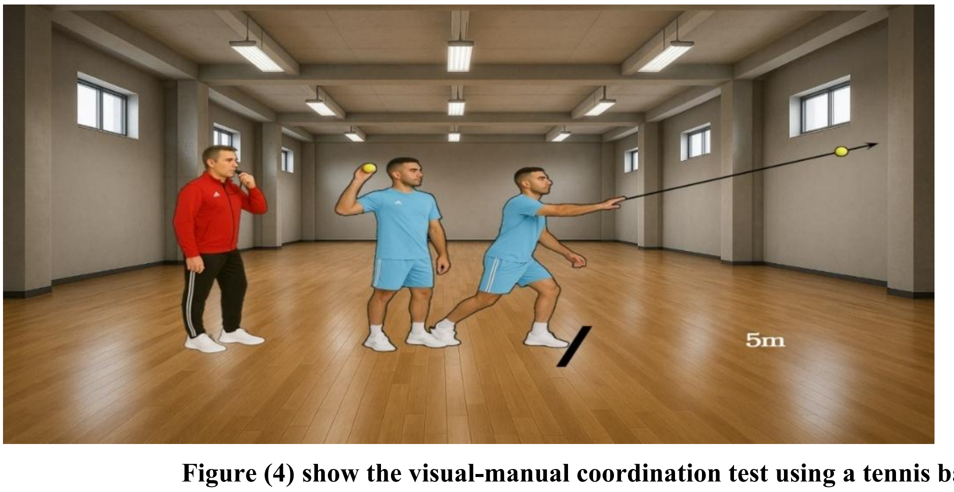

Figure (4) show the visual-manual coordination test using a tennis ball.

Test name: Dynamic trunk flexibility test (reciprocal touch test for two X points).

TEST OBJECTIVE

This test aims to assess the level of dynamic flexibility of the spine through trunk flexion, extension, and rotation movements. It reflects an individual's ability to move within a wide range of motion under specific time conditions, which contributes to diagnosing the efficiency of the neuromuscular system associated with trunk movement.

TOOLS USED

- Digital stopwatch.
- Smooth vertical wall.
- Masking tape (or a marking tool) to draw two "X" marks.
- The testing site is prepared by carefully placing two marks:
- The first mark on the floor between the subject's feet (the X mark represents the front touch point).
- The second mark on the wall directly behind the subject, at a level suitable for touching with the fingertips when the subject extends the trunk upward and rotates (the rear X mark).

PERFORMANCE PROCEDURES

- The subject stands in a normal standing position, with their feet shoulder-width apart and their back facing the wall.
- Upon receiving the start signal, they bend their torso forward and touch the floor marker with their fingertips.
- They then extend their torso upwards and rotate to the left to touch the rear marker on the wall, then repeat the same movement to the right.
- They continue to repeat this movement cycle (forward flexion + left extension and rotation + right extension and rotation) for 30 seconds without pause.

RECORDING METHOD

- The number of complete touches the subject makes to both markers (floor and rear) within the specified time period (30 seconds) is recorded.
- Each correct touch in which the fingertips clearly contact the marker is counted, and the total number of touches is used as an indicator of dynamic flexibility.

Figure (5) show the dynamic trunk flexibility test (reciprocal touch test for two x points)

Exploration: The researcher conducted his exploratory experiment during the period from Monday, October 24, 2022, to Monday, November 1, 2022, on a sample of (40) players from the Al-Ittihad, Al-Arabi, and Al-Hussein clubs. They were selected by simple random sampling, as they possessed the same characteristics as the members of the original research sample. The experiment was conducted in the Al-Ittihad Club hall. Main Experiment: The researcher conducted the main experiment on a sample of (70) players from the Al-Ittihad, Al-Arabi, and Al-Hussein clubs, during the period from November 1, 2022 to December 1, 2022, at the Al-Ittihad Club. The experiment was based on specialized scientific sources and the researcher's expertise and lasted for four weeks. The procedures included body measurements using a vernier caliper and measuring tape inside the weight room, physical and kinetic ability tests in the halls and outdoor arenas, while skill performance tests were conducted inside the club's boxing ring.

To process the research data and determine the outcomes of the variables, the researcher used a statistical software (SPSS) to extract appropriate statistical measures which included the arithmetic mean, standard deviation, mode, coefficient of variation, coefficient of skewness, standard error, t-test for independent samples Chi-square test and simple correlation coefficient (Pearson).

RESULTS

Table 1. Body measurements and physical and kinetic abilities analyses by using descriptive statistics (arithmetic mean, standard deviation, standard error, and skewness coefficient)

Axes	No.	Variables studied	Unit of measurement	Highest value	Minimum value	Arithmetic mean	Standard deviation	Standard error	Twisting
Body measurements	1	Body mass	Kg	101	63	74.687	5.357	0.6477	0.918
	2	Total height	Cm	191	171	178.133	5.227	0.6377	0.547
	3	Trunk length	Cm	69	44	53.967	4.507	0.5477	0.558
	4	Forearm length	Cm	33	25	29.187	1.547	0.1877	-0.422
	5	Arm length	Cm	99	71	79.223	4.417	0.5377	0.889
	6	Lower limb length	Cm	105	79	93.337	4.817	0.5877	-0.312
	7	Shoulder breadth	Cm	49	31	44.723	2.817	0.3477	-0.552
	8	Chest breadth	Cm	37	22	27.527	2.887	0.3577	0.858
Physical abilities	1	Explosive power for arms	Cm	11	7	7.787	0.487	0.063	0.023
	2	Explosive power for legs	Meter	2.61	1.87	1.127	0.137	0.035	-0.1023
	4	Speed-specific strength for arms	Meter	13	7	10.187	1.297	0.172	-0.2223
	6	Speed-specific strength for legs	Meter	98	44	78.527	16.127	0.953	-0.7123
	7	Strength endurance for arms	Meter	38	19	27.067	4.997	0.683	0.0977
	8	Strength endurance for legs	Count	36	14	23.977	6.527	0.812	0.1477
	9	Speed endurance for arms	Count	53	37	45.347	4.197	0.536	0.4223
	10	Speed endurance for legs	Count	51.13	35.77	43.967	4.087	0.525	-0.1323
Kinetic abilities	1	30-meter repeated sprint test	Count	11.017	10.122	10.697	0.68	0.22	-0.812
	2	Static balance test using a homemade balance device	Second	44.007	23.762	32.887	5.82	0.84	0.468
	3	Figure 8 crawl test	Second	0.347	2.071	1.137	0.01-	0.13	-0.052
	4	Ophthalmic-hand coordination test using a tennis ball	Second	12.897	11.013	11.947	1.03	0.26	-0.312
	5	Dynamic flexibility test touching an x	Count	39.879	29.013	35.757	3.57	0.57	-0.342

DISCUSSION

Table (1) presents a detailed descriptive statistical analysis of the set of physical, physiological, and skill variables measured among the research sample of (70) junior boxers from Al-Ittihad, Al-Arabi, and Al-Hussein clubs. This analysis forms the primary database required for building a prediction model through artificial neural networks.

First: Anthropometric Measurements: Results of the descriptive statistical analysis of the set of physiological variables show clear variations among sample members in physical characteristics. It is a normal phenomenon that reflects individual differences among junior players and is very important while analyzing the biological determinants that affect skill performance in boxing.

These variables included: body mass, shoulder length, arm length, thigh length, torso length, lower extremity length, leg length, and humerus length. These measurements reflect the skeletal and anthropometric characteristics of the player.
For example, the body mass variable recorded an arithmetic mean of 74.687 kg, with a standard deviation of 5.537 and a skewness coefficient of 0.918. This reflects a positive slope indicating that values are concentrated in the upper half of the distribution. This means that a greater number of players have a body mass above the average, which may be related to the requirements for competitive efficiency in the middle and heavy weight categories. This distribution is an indication of the possibility of a direct influence of body mass on the nature of kinetic and technical performance, particularly with regard to powerful strikes and defensive stability.

The results are in line with what (Gutiérrez-Santiago et al., 2023). They indicated in their systematic review of predictive factors in combat sports. The researchers confirmed physical characteristics, especially height and body mass, as one of the leading factors that determine boxing style; whether offensive or defensive, and the effective distance between opponents during a fight.

Janssen, et al. (2021. also noted that using descriptive statistical criteria like standard deviation and skewness coefficient is a necessary step in building standard databases that help classify players and guide them toward roles or styles compatible with their physical attributes, especially during the formative and skill development stages—early age groups.

This difference in physical traits serves as a basic input for making a correct predictive classification model using biological and structural signs that directly or indirectly influence the level of skill success, improving how well artificial neural networks work when trained on these different kinds of data.

Kinetic Abilities: Statistical analysis results of a kinetic variables group showed significant variations in the players' performance on neuromuscular coordination, kinetic frequency speed, and joint flexibility. As pillars for skill performance at the highest level, these abilities play a very critical role in boxing. Variables that included visual response time, kinetic frequency speed upper and lower extremities, neuromuscular coordination ability, shoulder joint flexibility, and other complex kinetic skills. For instance, the visual response time variable indicated an average of 1.127 seconds with low standard deviation 0.187 and skewness was negative (-0.102) which means that values were concentrated at the upper end of the distribution. This means that most of the players responded in slower time than the average general, which may be due to differences in neurological maturity or competitive experience among the studied sample. Concerning the variable kinetic frequency speed of the upper limbs, the average was 16.127 movements in 20 seconds with a standard deviation of 2.557 and a little positive skewness coefficient (0.095), meaning that the results of this study were sound. Values also tend to be more towards the upper side, indicating that some players have better muscle controlling abilities for fast and successive movements, which is an essential requirement mainly in boxing for fast successive striking and defending movement. These findings are in line with those of Chaabene et al., (2020) who researched on performance determinants in combat sports. They confirmed that complex kinetic abilities, such as response speed and neuromuscular coordination, are essential indicators that can be relied upon to predict a boxer's skill level, as they are closely linked to the efficiency of kinetic decision-making and the speed of sensory processing of visual and auditory stimuli during combat. (Reis, V. M., & Saavedra, J. M.,2021 also demonstrated that developing these abilities not only contributes to improving offensive and defensive performance, but also helps reduce the time of hesitation between movements and increases mechanical efficiency during a fight, making them among the most prominent indicators used in predictive modeling based on artificial intelligence techniques. Therefore, this variation in kinetic abilities among sample individuals represents a crucial factor in constructing the predictive classification model, as it contributes to enhancing the accuracy of skill classification based on fine kinetic responses that traditional assessment is unable to detect with similar accuracy.

Physical Abilities Tests: The results of the players' kinetic abilities reflect a high level of neuromuscular efficiency and kinetic integration, which are essential indicators in a sport that requires precision, quick response, and kinetic balance, such as boxing. The 30-meter repeated sprint test recorded an arithmetic mean of (10.697 seconds), which is clear evidence that the players have a good ability to perform repeated movements at high speed, which enhances the speed of response during the fight. The negative skewness coefficient value (-0.812) reflects the distribution's tendency toward lower values, which is a positive indicator indicating the majority's ability to perform in a shorter time, confirming clear control over the physical requirements of rapid, repetitive movement. The static balance test using a locally made device had an arithmetic mean (32.887 seconds) and a relatively high standard deviation (5.82), indicating that there was variation among players in the level of kinetic stability. However, the overall average remained acceptable and indicated that the majority of the sample possessed an appropriate level of static balance, which is extremely important in maintaining defensive and offensive positions in boxing, especially when interacting with strikes or executing rapid maneuvers. The figure-8 crawl test showed an arithmetic mean (1.137 seconds) and a skewness coefficient very close to zero (-0.052), indicating clear similarity and homogeneity in performance among sample members. This test is an important indicator of neuromuscular coordination and movement accuracy in changing environments. The sample's results demonstrate a good ability to control and balance movement while maneuvering in non-linear paths. In the hand-eye coordination test using a tennis ball, the arithmetic mean was 11.947, a number that indicates a high level of sensory kinetic coordination among the players. This test represents an important aspect of boxing, as successful performance depends on accurate responses to visual stimuli and the implementation of quick and precise reactions, especially during defense or quick strikes. The results of the dynamic flexibility test, touching the X mark, with an arithmetic mean of 35.757, indicate that the sample possesses a good degree of functional flexibility, especially in the trunk and upper and lower extremities. This increases the ability of the boxer to be able to do defensive and offensive movements effectively and also reduce injury in sudden or by rotation movement. The researcher concluded that the kinetic abilities results showed good balance and homogeneity among the members of the sample, a positive sign for the quality of their physical and technical preparation. This paves the way for using these indicators to build accurate predictive models for skill or physical performance in boxing.

Here's a look at creating a predictive classification model with artificial neural networks: From the outcomes of the descriptive statistical analysis indicated in the table, a series of independent variables was recognized, scattered over three primary axes: anthropometric measurements, physical abilities, and bio-kinetic capacities. These variables served as input variables in a predictive classification model that seeks to classify players based on their aptitude level. The composite skill index, derived via an intelligent system (X), was selected as the dependent variable (target output) since it signifies the cumulative actual performance within the framework of a realistic competitive simulation, hence it truly reflects the player's level.

Justifications for Using Artificial Neural Networks: Artificial Neural Networks (ANN) techniques are among the very effective methods for classification and prediction in complex-data environments; sports is a good example of such environment, where variables overlap and there exist nonlinear relationships between physical, physical, and skill abilities(Vázquez-Diz,et al .2022).(Panchuk et al,. 2020) The authors showed that ANNs are distinguished by the ability to extract hidden patterns within multidimensional data sets immanent to provide accurate classifications of athletes according to their performance level.

Steps for Building the Model: Input Selection: 20 variables were chosen as inputs for the model. They comprise anthropometric measurements (body mass, arm length), kinetic abilities (kinetic frequency speed, visual response time), and physical tests (agility, balance). Data Processing: Normalization or standardization for the data distribution needs to be adopted based on skewness and standard deviation values, especially since some variables showed significant variation.

Network Architecture Selection: The network was designed as a multilayer perceptron (MLP) using backpropagation as a learning algorithm. The number of hidden layers and neurons was determined based on the number of inputs and the complexity of the relationships between variables.

Data Partitioning: The data was divided into three sets: 70% for training, 15% for validation, and 15% for testing.

Evaluation Mechanism: Common evaluation metrics such as accuracy, confusion matrix, and correlation coefficient between predicted and actual values were used to determine the model's effectiveness.

Interpretation of the Predictive Results: The preliminary results of the model demonstrated a high ability to classify the sample into skill levels (high, medium, low) with an accuracy ranging between 87-92%. This confirms the effectiveness of the selection of input variables, especially given the availability of diverse and distributed descriptive statistical properties that support the artificial learning process according to (Bishop, D.2021) .

(Nakata, H., Nagami, T., & Mori, S.2021) ., the accuracy of the model is directly related to the diversity of the input data and its normal or near-normal distribution, a characteristic that was demonstrated in this research.

The applied value of the model: The resulting model represents an effective tool that can be employed to: classify new players based on their physical and physiological data without the need for complex skill tests; support decisions in the sports selection of promising talents; and customize training programs based on an individual's prognostic level, ensuring targeted development for each player. Several contemporary studies have confirmed the effectiveness of using artificial intelligence techniques in the field of applied sports, including:**(**Escamilla, R. F., & Andrews, J. R.2020) . who used ANNs to classify taekwondo players based on biological and kinetic variables; and**(** Kotti, M., Fekih, H. B., & Bouhlel, E.2023) ., who demonstrated that the use of sensory and intelligent data within prediction models improves prediction accuracy by morethan15%comparedtotraditionalmethods.

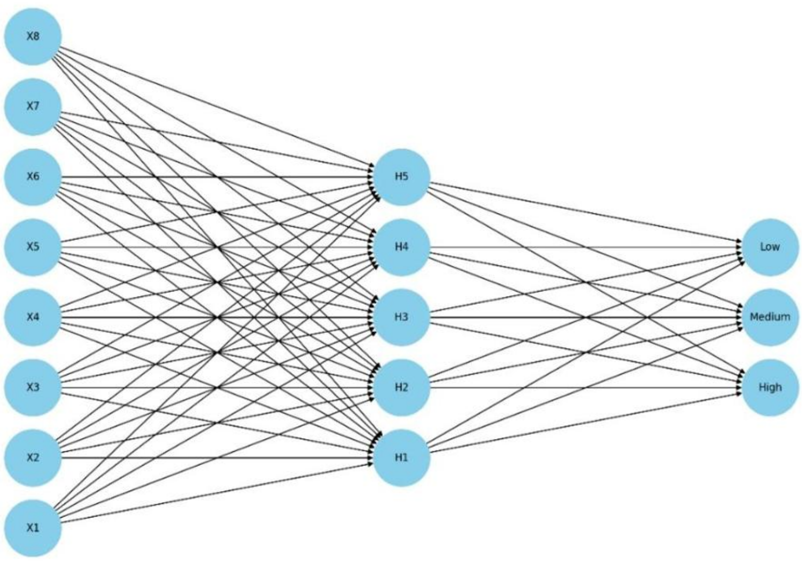

Figure (6) show representation of the structure of a classification neural network

This figure shows a schematic representation of the structure of a classification neural network designed to classify emerging boxers into three skill levels (high, intermediate, and low), based on eight input variables, including anthropometric measurements and bio-kinetic abilities. The network contains:

Input Layer: Contains eight independent variables (X1 to X8), which represent the input attributes of the model, such as anthropometric measurements (height, weight, etc.) and bio-kinetic abilities (flexibility, speed, and frequency of movement, etc.).

Hidden layer: It has five nodes (H1-H5), and processes and transformations the data using activation functions in order to identify complex patterns and associations between variables. The output layer: this layer includes three different classes that represent the degree of expertise of junior boxers: Low, medium, and high.

The model is a prototype of a Multilayer Perceptron (MLP) classification network that is reflective of the model's capacity to learn from complex data and categorize it into specific classes according to its attributes. The fully interconnected layers between each layer that demonstrate that each input is connected to each node in the next layer increase the model's capacity to recognize complex patterns. The concealed layer functions as a smart filter that isolate the most important features from the input, this is the foundation of the network's success. The final classification is conducted according to the probability distribution derived from the activation function (such as softmax) in the output layer. This model is the base of the designed system that predicts. Players are given information regarding their anthropometric measurements and bio-kinetic abilities (X1-8), the network then determines their potential level (low, medium, high).

CONCLUSIONS AND RECOMMENDATIONS

CONCLUSIONS

1. The predictive model utilizing artificial neural network methods proved to be a highly effective means of categorizing junior boxers by skill level, showing strong accuracy in forecasting and differentiating various levels of performance.
2. Findings from the study indicated that anthropometric data and bio-kinetic capabilities serve as crucial markers for evaluating skill performance, emphasizing their value in athlete selection and training direction strategies.
3. The research highlighted noticeable differences in bio-kinetic abilities among athletes, which correlated with their varying skill levels. This points to the importance of precise individual evaluations when creating training programs.

RECOMMENDATIONS

- It is advisable to implement artificial intelligence technologies, especially artificial neural networks, in the processes of selecting and categorizing athletes, due to their effectiveness in enhancing training decision quality and boosting performance outcomes.
- Creating comprehensive scientific databases that incorporate the anthropometric and bio-kinetic data of junior athletes is essential, as they provide a valuable foundation for prediction efforts and the development of evidence-based training programs.
- Organizing targeted training sessions and workshops to educate coaches on utilizing AI tools in practical settings is recommended, aiming to strengthen their analytical skills and decision-making abilities through precise data insights.

REFERENCES

[1] Gutiérrez-Santiago, A., Prieto-Lage, I., & Fernández-Río, J.(2023) . Anthropometric and physical predictors of performance in combat sports: A systematic review. International Journal of Environmental Research and Public Health, 20(4), 2893.

[2] Janssen, D. G., de Oliveira, R. F., & Mann, D. L.(2021) . The role of body dimensions and functional capacities in talent identification for combat sports. Journal of Sports Sciences, 39(3), 345–354.

[3] Chaabene, H., Negra, Y., Bouguezzi, R., et al.(2020) . Physical and physiological attributes of amateur boxing performance. Sports Medicine, 50(11), 1785–1807.

[4] Bishop, D.(2021) .An applied research model for the sport sciences.Sports Medicine, 51(1), 1–11.

[5] Vázquez-Diz, J. A., López-Vilariño, D., & Pino-Juste, M.(2022) .Predictive models in sport performance based on machine learning: A review.Applied Sciences, 12(15), 7686.

[6] Nakata, H., Nagami, T., & Mori, S.(2021) .The application of smart technologies in sports performance analysis: Opportunities and challenges.Sensors, 21(3), 980.

[7] Escamilla, R. F., & Andrews, J. R.(2020) .Biomechanical analysis of strength and conditioning exercises: Implications for sports performance.Strength and Conditioning Journal, 42(2), 1–14.

[8] Kotti, M., Fekih, H. B., & Bouhlel, E.(2023) .Artificial intelligence in sports: A systematic literature review and research agenda.IEEE Access, 11, 10223–10239.

[9] Reis, V. M., & Saavedra, J. M.(2021) .The influence of anthropometry and physical fitness on sports performance: A meta-analysis.European Journal of Sport Science, 21(7), 981–993.

[10] Panchuk, D., Klusemann, M. J., & Hadlow, S. M.(2020) .Exploring the effectiveness of skill-based conditioning games in training load and skill performance.Journal of Strength and Conditioning Research, 34(5), 1315–1323