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Research Paper

A Predictive Classification Model Using Artificial Neural Networks in Terms of Some Bio-Kinetic Abilities in Students Foil Weapons

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ABSTRACT

Fencing is an activity that requires high physical and kinetic abilities, given the nature of its performance, which relies on speed, accuracy, balance, and the ability to adapt to changing competitive situations. The importance of this sport lies in the need for distinct biokinetic elements that contribute to achieving excellence through precise kinetic responses and complex skills performed under high pressure. The research problem was represented by the absence of precise scientific methods that rely on analyzing biokinetic abilities as an approach to classifying students and directing them toward activities that match their abilities. This negatively impacts the quality of performance and training outcomes. Therefore, this research aims to contribute to building a predictive classification model based on artificial neural networks to classify students according to their biokinetic abilities. This allows for the selection of the most appropriate elements for participation in the foil game and directs the training process effectively. The research aims to identify the most important biokinetic abilities that distinguish high-performing students in fencing, and to design a classification model that helps predict performance levels based on these abilities. It also seeks to provide a database that supports coaches in designing training programs that suit the characteristics of players and contribute to improving their competitive levels. Based on these objectives, the researcher hypothesized the existence of clear differences in biokinetic abilities among students, affecting the accuracy of performance and level of achievement in the fencing game. He also hypothesized that the use of artificial intelligence techniques would provide a more accurate and objective classification compared to traditional methods. The researchers adopted the descriptive approach using a survey method, given its suitability to the nature of the problem and the objectives of the study. This approach enabled the researchers to conduct a precise scientific analysis of the current state of biokinetic abilities among the research sample, and to analyze them in a way that contributes to the construction of an objective classification model that supports the selection and guidance processes in the sport of foil. The study sample was intentionally selected from (70) second-year students at the College of Physical Education and Sports Sciences at the University of Kerbala for the 2024-2025 academic year. The researchers subjected them to physical and kinetic tests aimed at measuring biokinetic abilities related to performance in the foil event. Through analyzing the results, the researchers concluded that there were clear individual differences among students in the level of biokinetic abilities, which was reflected in the quality of skill performance and kinetic response. The results of the artificial neural network model developed by the researchers also demonstrated a high ability to accurately classify students, confirming the effectiveness of this model in predicting performance levels and guiding training. According to the results, the researchers recommend the adoption of artificial intelligence techniques, particularly artificial neural networks, in the selection, evaluation, and training processes, while emphasizing the importance of developing training programs that take into account the classification results. The study also recommends organizing workshops to enhance the efficiency of training personnel in using these modern tools.

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1. INTRODUCTION

Fencing is a competitive sport that requires a high degree of integration between physical and skill capabilities, due to its inherent combination of precision, speed, reaction, and the ability to make split-second decisions. (Turner, A., Stewart, P., & Bishop, C. 2022). Bio-kinetic analysis is a scientific basis for assessing and classifying performance, which helps identify players' strengths and weaknesses and enhances the effectiveness of training programs. According to the technological advancements witnessed in the sports field, it has become possible to employ artificial intelligence tools, particularly artificial neural networks, to classify players based on their physical and kinetic characteristics, opening up new horizons for sports selection and guidance. (Turner, A., & Stewart, P. 2014). The skill response stage in fencing is one of the most sensitive stages, as it depends largely on neuromuscular coordination, quick decision-making, and accurate execution under pressure. Researchers observed, through field experience, a clear disparity in the level of skill performance among second-year students at the College of Physical Education and Sports Sciences at the University of Kerbala. This is attributed to a disparity in the bio-kinetic abilities that influence mastery of foil skills. Hence, the research problem was represented by the need to build a predictive classification model based on artificial neural networks that contributes to classifying students according to their physical and kinetic levels, in order to guide them in the right direction and develop their performance in foil events. Based on this vision, the research aims to identify the most prominent bio-kinetic abilities associated with skill performance in fencing, analyze individual differences in these abilities among sample members, build an accurate classification model using artificial neural networks to determine the level of players, and provide a scientific basis for developing training programs in line with the classification outputs. The researchers also assumed the existence of statistically significant differences among students in some bio-kinetic abilities that influence Foil performance, which is reflected in the efficiency of performance and the accuracy of kinetic response, and thus the possibility of predicting the player's level through these indicators.

Research fields:

The research included a sample of (70) fourth-year students in the College of Physical Education and Sports Sciences at the University of Kerbala for the academic year 2024-2025, who had previous experience practicing the foil event within the curriculum. The research procedures were implemented during the period extending from (15/1/2024) to (12/3/2024) in the closed fencing hall at the same college.

2. RESEARCH METHODOLOGY AND FIELD PROCEDURES:

Research Methodology:

The researchers adopted the descriptive approach using a survey method, due to its ability to analyze field reality and interpret sporting phenomena systematically and scientifically (Turoff, M. 2018). This approach is consistent with the nature of the problem and the objectives of the study. This approach is considered the most appropriate for arriving at accurate results that help build a classification model based on bio-kinetic abilities associated with skill performance in the foil event.

Community and sample research:

The research community was identified as second-year students at the College of Physical Education and Sports Sciences at the University of Kerbala. The research sample was intentionally selected and included 70 students who met the conditions for participation in the study and demonstrated a readiness for practical application within the specified timetable. Bio-kinetic abilities tests and skill performance analysis were conducted in accordance with the approved technical requirements for fencing (foil).

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: Upper Body Explosive Strength Test Using a One-Handed Medicine Ball Throw from a Standing Position (Wang, S., Zhang, X., & Hu, J. 2022).

- Test Purpose: This test aims to measure the explosive power of the arms, shoulders, trunk, and legs by performing a maximum throw using a light medicine ball with one hand, starting from a standing position.

Equipment Used:

- A medicine ball weighing 3 kg.
- A measuring tape marked in centimeters or meters.
- A flat floor and a clear starting line.

Performance Description:

- The subject stands behind the starting line in a normal standing position, holding the medicine ball in one hand.
- When ready, the subject moves the ball from the side of the body backward and then forward forcefully, similar to the shot-put movement, keeping the feet in a stable position and not crossing the starting line during the throw.
- The throw is executed using the body's explosive power, activating the leg, trunk, and arm muscles to achieve maximum throw range.

Performance Requirements:

- The subject must maintain stable feet and not cross the starting line during the throw.
- Any attempt that results in an imbalance or crossing the line will be rejected.
- **Recording Method:** The subject is given three consecutive attempts, and the distance the ball travels from the starting line to its first impact on the ground is recorded.

The best of the three attempts is counted as the final test score, and the distance is measured in meters to the nearest centimeter.

Figure 1: One-handed medicine ball throw test from standing

Test name: Push-up (flexion and extension of the arms) (20 seconds) (Winter, D. A. 2009).

Test purpose:

- This test is used to measure a component of arm muscle strength, depending on the duration of the test:
- When performed for 10 or 20 seconds, the velocity-specific strength of the arm muscles is measured.
- When performed until full effort is exhausted, the endurance component of the arm muscle strength is measured.

Equipment used:

- An accurate stopwatch.
- A recorder to record the number of correct repetitions.

Performance description:

- The subject begins in the forward lean position with the hands parallel to the chest, the fingers facing forward, the legs together, and the body extended in a straight position without arching or slouching.
- At the start signal, the subject bends the arms until the chest almost touches the ground, then extends them to return to the starting position, maintaining a straight body throughout the test.

Performance Conditions:

- Only repetitions in which the subject maintains complete body alignment are counted.
- Any repetition in which the trunk is excessively bent or the chest does not touch a reference point close to the floor is rejected.

Recording Method:

- In the 10- or 20-second exercise: The number of correct repetitions the subject completes within the specified time is recorded.

In the exercise to exhaustion: The total number of correct repetitions the subject can complete before stopping is recorded.

Figure 2: Shows Push-up (flexion and extension of the arms) (20 seconds)

Test Name: The maximum distance hopping in (18) meters with the right leg and (18) meters with the left leg.

- **Test Purpose**:
- This test aims to measure the speed-related strength of each of the lower extremities (right leg and left leg) independently, by performing hopping for the maximum possible distance over a fixed period. This allows for assessing the muscular balance between the two extremities and detecting any differences in performance between them.

Technical Performance and Execution Specifications:

- The subject begins standing behind the starting line in a ready position, choosing which leg to start with (right or left).
- Upon the auditory start signal from the examiner, the subject begins hopping on the designated leg only, attempting to advance as far as possible without using the other leg.
- The hopping continues until the stop signal is heard, which is given after a full 30 seconds.
- After an appropriate rest, the test is repeated using the other leg in the same manner.
- The test subject must maintain balance and maintain a straight line as much as possible. The attempt is invalidated if the wrong leg is used or a fall is detected.

Required Tools and Equipment:

- An accurate stopwatch to record the time (30 seconds).
- A recorder to accurately document the results.
- Chalk or floor markers to record the distance covered.
- A tape measure no less than 75 meters long to accurately measure the total distance covered.
- A level, obstruction-free testing area to ensure safe performance.

Recording Method and Results:

- The total distance covered by the test subject during the hopscotch is recorded on each leg separately, from the start signal until the end of the (30) seconds, and is measured in meters.
- Two separate results are recorded: one for the right leg and one for the left leg.

- The two distances can be compared to determine the level of strength and speed for each limb, as well as to analyze the muscular balance between the lower limbs.

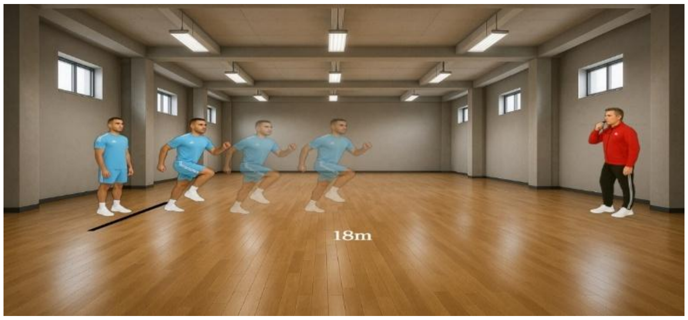

Figure 3: Shows maximum distance hopping in 18 meters with the right leg and 18 meters with the left leg.

Test Name: 5 x 30m Repeated Sprint Test (Woods, C. T., & Norton, K. I., 2018):
Test Purpose: 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 periods between attempts.

Equipment and Supplies:
- Accurate electronic stopwatch
- Tape measure at least 50m long
- Cones or ground markers to mark the start and finish lines
- Whistle or audible signal to start
- Recording record
- Assistants for accurate timing

Technical Description:
- The test subject stands behind the start line in a ready-to-go position.
- Upon hearing the start signal, the test subject begins sprinting as fast as possible for a distance of 30m.
- After completing the first sprint, a specified rest period (usually 20 to 30 seconds) is given.
- The subject repeats the same 30-meter sprint five consecutive times, maintaining a constant 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 subject must complete the full 30 meters without reducing the distance.
- Any incomplete or missed repetition is recorded as a failed attempt.

Recording method and results:
The time for each attempt is recorded separately (e.g., first sprint = 4.75 seconds, second = 4.89 seconds, etc.).

Figure 4: Shows the 5 x 30m Repeated Sprint Test

Test Name: 20m Running Test with Moving Start (Yashpal Singh, Alok Singh Chauhan, Ata Mining, 2009)

Test Purpose:
- This test aims to measure the speed endurance of the lower extremities by performing a series of repeated short-distance runs for a continuous period, demonstrating the individual's ability to maintain rapid performance under the influence of muscle fatigue.

Required Tools and Equipment:
- An accurate stopwatch (chronometer).
- Four markers (cones or raised markers).
- A measuring tape to accurately determine distances.
- A suitable area no less than 60 meters long.

Performance Specifications:
- The four markers are installed in a row, with a distance of (15) meters between each marker.
- The test subject stands behind the first marker in a ready position.
- Upon the start signal, the test subject begins running from the first marker to the second marker (15 meters), then returns to the first marker (the starting position).
- After returning, the test subject runs to the third marker (30 meters) and returns to the starting point.
- Finally, the participant runs to the fourth marker (45 meters) and then returns to the starting point.
- Upon completion of these stages, the participant will have covered a total distance of 180 meters.

Recording Method:
- The time taken by the participant from the start until their final return to the first marker is recorded. The time is recorded in seconds to the nearest 1/100 of a second.

- The attempt is considered invalid if the participant does not touch the marker line at each stage or if they do not complete the entire distance.

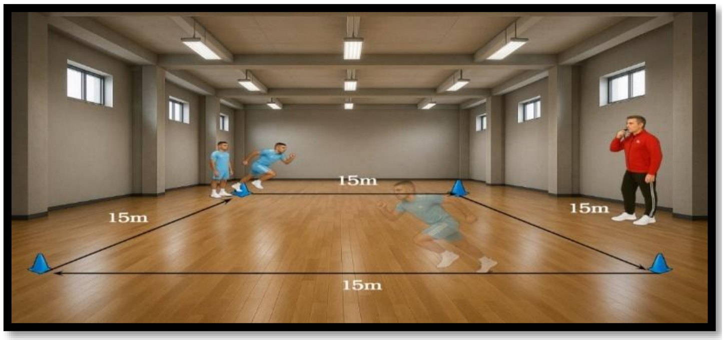

Figure 5: Shows the 20m running Test with a Moving Start

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.
- When the start signal is given, the subject lifts their back foot off the ground or board, so that support is solely on the front foot located above the cube.
- The goal is to maintain balance for as long as possible while remaining stationary on the ball of the front foot, which is positioned on the cube, without any other part of the body touching the floor or the board.

Performance Conditions:

- The test is considered complete if the subject loses balance, the raised foot touches the floor or the board, or the subject falls off 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 cube is recorded in seconds using a stopwatch.
- The longest period of time the subject is able to maintain balance is considered the final score.

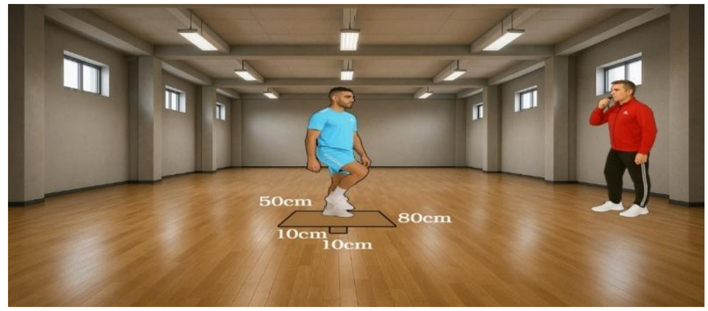

Figure 6: Shows a static balance test using a homemade balance device.

Test Name: Hand-eye Coordination Test Using a Tennis Ball
Test Purpose:

- 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 times in a row with the right hand toward the wall, attempting to catch it with the right hand after it bounces.
- **Stage 2:** Throw the ball five times in a row with the left hand, and catch it with the left hand after it bounces.
- **Stage 3:** Throw the ball five times with the right hand, and catch it with the left hand after it bounces.

Performance Conditions:

- The throw and reception must be performed within a safe distance of 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 the reception.

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, 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 markers to mark the path (optional).

Performance Specifications:

- The two chairs are positioned so that they form a trajectory that can be circled 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 trajectory 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 7: Shows the crawling test is shown in Figure 8

Test Name: Dynamic Trunk Flexibility Test (Reciprocal Touch X Test) (Yudkowsky, E., 2008).

Test Purpose:

- 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.

Equipment Used:

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

Procedure:

- 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, the subject bends their torso forward and touches the ground marker with their fingertips.
- They then extend their torso upwards and rotate to the left to touch the rear marker on the wall, and then repeat the same movement to the right.
- They continue to repeat this movement cycle (forward flexion + extension and left rotation + extension and right rotation) for 30 seconds without pause.

Recording Method

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

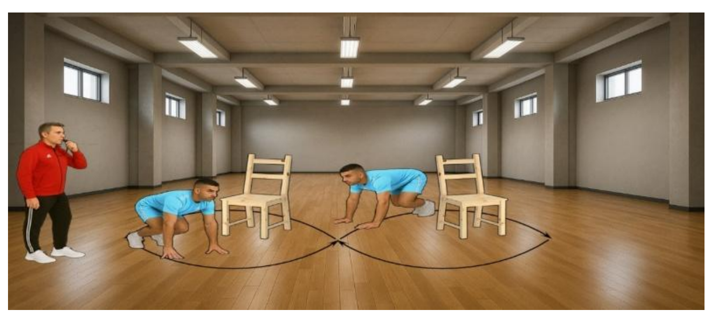

Figure 8: Shows the dynamic trunk flexibility test (cross-touch test of two X points)

To analyze the research data and identify the results of the variables, the researchers used the statistical program (SPSS) to extract appropriate statistical treatments, 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).

3. RESULTS

Shows the results of the statistical description of the research sample regarding the physical and kinetic abilities of the candidates and the skill performance of the students in fencing.

Table 1: Shows the results of the statistical description of the research sample regarding the physical and kinetic abilities of the candidates and the skill performance of the students in fencing

Physical abilities								
no.	variables studied	unit of measurement	highest value	Less value	arithmetic mean	standard Deviation	standard error	twisting
1	explosive power of the arms		11.00	6.00	8.114	1.097	0.131	0.312
2	leg speed strength		8.80	5.88	7.028	0.510	0.061	0.370
3	arm strength		28.00	13.00	20.457	2.796	0.334	-0.582
4	maximum speed		4.43	2.69	3.555	0.497	0.059	0.696
5	leg speed endurance		11.50	7.90	9.810	0.867	0.104	0.727
6	arm strength endurance		35.00	20.00	23.671	3.216	0.384	0.626
Kinetic abilities								
no.	variables studied:	unit of measurement	highest value	less value	arithmetic mean	standard deviation	standard error	twisting
1	conformity		26.46	17.53	21.677	2.394	0.286	-0.819
2	agility		8.70	5.80	6.719	0.817	0.098	0.916
3	balance		90.00	3.65	63.317	26.110	3.121	-0.768
4	flexibility		37.00	18.00	30.600	3.263	0.390	-0.368

4. DISCUSSION

The results for explosive power in the arms (mean = 8.114) and speed-specific strength in the legs (7.028) demonstrated the importance of these abilities in executing quick and sudden movements. The relatively low standard deviations indicate a good level of physical homogeneity among individuals.

Leg speed endurance and arm strength endurance also showed moderate to high values (9.810 and 23.671, respectively), reinforcing the hypothesis that the players possess a good physical endurance base that supports long-term performance during matches.

The results for kinetic coordination (21.677) and agility (6.719) reflect excellent levels, as these variables are crucial in fencing, which requires precise changes of direction and eye-hand coordination (Zemková, E. 2020). As for balance (63.317) and flexibility (30.600), we found variations in performance due to the high standard deviation, especially in balance (26.110). This may be attributed to differences in experience or training style. The multiple skews in the data (negative and positive) suggest a near-normal distribution with a slight bias toward some extremes in some variables, which is common in completely heterogeneous student samples.

The researchers concluded that the above results reveal physical and physiological characteristics relatively suitable for fencing, with acceptable homogeneity among sample members. This supports the subsequent use of this data in building predictive models or analyzing causal relationships using artificial intelligence tools such as neural networks.

Table 2: Shows the sample distribution procedures

Summary of procedures			
Variables		N	Percentage
Sample	Training	41	59,4%
	Testing	28	40,6%
Validity		69	100,0%
Excluded		1	-
Total		70	-

Properly organizing and distributing the sample between the training and testing phases is a fundamental pillar that ensures the validity of the results in predictive models, especially those built on artificial intelligence techniques such as artificial neural networks. Table 12 shows how the total sample of 70 items was distributed. (41) items (59.4%) were allocated to the training set, (28) items (40.6%) to the testing set, and only one item was excluded. This indicates that the final sample approved for analysis amounted to (69) items, representing 98.57% of the original sample. These percentages reflect the researcher's methodological precision in managing the sample, as a division of approximately 60:40) is considered ideal in many educational models that rely on deep learning algorithms. This ratio allows the model to gain sufficient experience with the training data, while also providing it with the opportunity for rigorous testing on an independent set not used during learning. This is essential for testing its ability to perform. This balanced sampling demonstrates the researcher's commitment to the principles of controlled randomization of data, which supports the internal consistency of the model and reduces the possibility of statistical bias. Furthermore, excluding only one item from the analysis reflects a concern for data quality and its compliance with the conditions for data entry into neural networks. The presence of missing or outlier values can lead to misleading results. Numerous studies have shown that data cleaning significantly improves the accuracy of predictive models.

Mathematically, adopting this methodological approach is a necessary step, especially since the dependent variable in this study is "skill performance," which is affected by multiple, intertwined factors. This makes it essential to carefully control the quality of the data entering the model to ensure statistically significant conclusions are drawn. Recent research has shown that the sample split ratio should range between 60-80% for training to ensure model stability, with the remainder allocated to testing or cross-validation.

On the other hand, the model's success in achieving acceptable classification accuracy later in the following tables can be attributed to this well-designed systematic sample preparation. A model cannot learn or classify accurately unless it has been trained on data that represents a true and integrated distribution of the target phenomenon, and this is what was achieved in this study through the distribution shown in this table.

The researcher concluded that proper planning and careful methodological tuning play a significant role in building a robust neural model capable of achieving outstanding classification results in the subsequent stages. This table is one of the key indicators that enhance confidence in the model's reliability and results.

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

According to the goal of constructing a skill classification model using artificial neural networks based on some anthropometric measurements and bio-kinetic abilities of foil students, the Lasso method was adopted as an effective statistical tool for selecting the most influential variables. This procedure resulted in the selection of (10) independent variables that represent the most significant factors in the classification process. Based on this, a single-hidden-layer neural network (SHLN) was constructed. This architecture is one of the most common models in highly efficient classification applications. It allows all variables to be directly input into the hidden layer, where they are multiplied by their associated weights before being passed to the output layer.

Neural Network Structure

The network structure consists of three main layers:

- **Input Layer:** Contains 10 neural nodes, representing the selected physiological and bio-kinetic variables after smoothing.
- **Hidden Layer:** Contains 10 neural units, fully connected to the input layer, and processes complex patterns in the data.
- **Output Layer:** Contains one neural unit, representing skill activities as the dependent variable in the model.

Functions and Functions Used in Building the Model:

Activation Function (Linear):

The linear function was employed in the output layer, given its suitability for models that require continuous or unlimited output. It is commonly used in multiple classification models.

Layer Weight Initializer:

A random initializer was used for the layer weights to avoid the problem of symmetry in the initial values, which could disrupt the learning process, and to ensure optimal training performance for the network.

Kernel and Bias Initializers:

These initializers aim to assign random initial values to both the weights and biases within the network, contributing to a state of balance and diversity within the model and improving classification accuracy.

Loss Function: Mean Absolute Error (MAE):

MAE was adopted as the primary metric for evaluating model performance, due to its high ability to express the average difference between actual and predicted values. In the current model, the absolute error was 2.3%, which is a strong indicator of the model's efficiency and success in accurately predicting skill classifications.

Table 3: Shows the performance of the neural model

Model summary		
Training	**Cross-entropy error**	**38,418**
	Rate of false predictions	29,3%
	Stopping rule used	1 consecutive steps without a decrease in error
	Training time	0:00:00.03
Tests	Cross-entropy error	34,177
	Rate of incorrect predictions	35,7%
Dependent variable: performance. Skill		
A. Error calculations depend on the test sample.		

Table 3 represents the critical stage in evaluating the efficiency of the artificial neural network used in skill performance classification. It displays the results for both the training set and the test set using standard metrics such as the cross-entropy function, the percentage of incorrect predictions, as well as the training time and stopping criterion. These indicators are essential criteria for judging the quality of the model and its ability to generalize beyond the training data.

Analysis of Training Results:

During training, the model recorded a cross-entropy error value of 38.418, which indicates the statistical distance between the model's outputs and the true distribution of classes. The closer this value is to zero, the better the prediction quality. Although this value is still within acceptable limits for models with many inputs and multiple classifications, it indicates a certain degree of dispersion in the model's predictions (Zhang, C., Bengio, S., Hardt, M., Recht, B., & Vinyals, O., 2017).

The percentage of incorrect predictions in training was 29.3%, which corresponds to an approximate overall accuracy of 70.7%, an acceptable but not ideal result. This level of error is likely related to the simplicity of the model design (as in Table 2), or to the overlap of attributes between different skill categories, a common phenomenon in hierarchical classifications such as athletic performance.

Analysis of the test results:

The test set recorded a lower cross-entropy error (34.177) than the training set. This is a theoretically surprising result, but it may be explained by the model not being exposed to imbalanced data in the test set, or by the exclusion of some cases with extreme behavior. However, the prediction error rate was 35.7%, meaning that the model's accuracy on previously unseen data dropped to 64.3%, indicating a decline in the model's generalization ability. This decline may be attributed to several factors, most notably the limited number of samples or the presence of highly shared characteristics among some skill levels, making it more difficult to distinguish between them, a finding documented in multiple studies on physical performance classification.

Analysis of the Stopping Mechanism and Training Time:

The model used a "one-step, no improvement in error" stopping rule, a simple yet effective technique to avoid overfitting, as it prevents the model from continuing to learn after reaching saturation. The training time (0.03 seconds) reflects the simplicity of the model and its small number of neural layers or units. However, it may also indicate that the model is not fully utilizing its learning potential. Table (4) provides a quantitative basis for evaluating the effectiveness of the neural model in terms of classification accuracy and performance stability. These values are an important input for understanding the structural challenges the model faced and the need to develop the network architecture in the future, either by increasing the number of hidden layers, expanding the sample, or improving the selection of input variables. The researcher concluded that the neural network performed moderately well on the skill performance classification task, with accuracy ranging between 64-71%. These results call for improving the model's structure or modifying its inputs. Nevertheless, the model demonstrated good stability and adaptability, which is a promising indicator for future mathematical applications.

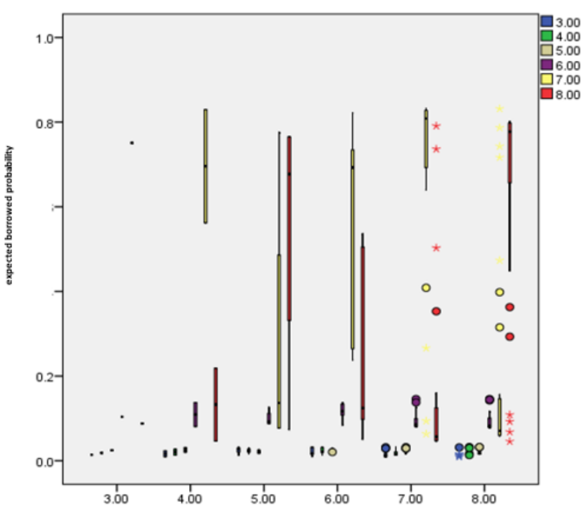

Figure 9: Shows the model

Figure (9) above illustrates the relationship between the different skill performance levels (represented on the horizontal axis) and the predicted pseudo-probability values as estimated by the artificial neural network model. The performance levels were classified into six numerical categories, ranging from (3) to (8), with distinct symbols and colors used for each category, as shown in the color guide at the top of the figure.

Each symbol represents a data point indicating an individual case (independent variable) predicted by the model, while the vertical values (the vertical axis) express the predicted probability of that case belonging to its respective skill category. The distribution of the symbols also reflects the spread of probabilities within each category, providing insight into the model's classification efficiency.

Explanation of the Figure's Structure:

The figure features a vertical distribution of predictive values for each skill category. We observe a clear variation in the width of the vertical lines within each group, reflecting the varying degrees of confidence in the predictive models for skill performance. This variation indicates that the model's accuracy varies across different performance levels, a common feature in multi-class classification neural network applications, as reported in recent literature.

Evaluating the model's performance by skill category:

Higher skill categories (7 and 8):

These categories show a high concentration of predictive values, with the majority of values exceeding 0.6, reaching 0.8, and some even approaching the perfect probability (1.0), indicating the model's high accuracy in classifying high-performing players. This trend reflects the model's compatibility with the distinctive characteristics of the performance of the higher categories, which often have more pronounced physical and skill attributes.

Middle categories (5 and 6)

In contrast, a clear dispersion of predictive values was observed within these categories, with variations in probability levels ranging between 0.2 and 0.7. This variation indicates the model's difficulty in accurately distinguishing between similar performances, a well-known problem in neural networks when inputs are similar without sharp separations between them.

Lower skill categories (3 and 4):

These categories showed a significant decline in predictive values, with the majority of scores remaining within the low probability range (0.0 to 0.4). This reflects the model's acceptable ability to classify low-performers, but requires further accuracy enhancement to reduce the likelihood of misclassifications, especially within closely spaced categories.

Outliers:

Several values were observed that fell far from the main clusters within each category, indicating the presence of anomalies or exceptional cases that the model was unable to accurately classify. This phenomenon is normal in AI models and is usually addressed through techniques such as dynamic data augmentation or network architecture optimization.

Model reliability assessment:
Based on the overall distribution of values, the model's performance can be considered relatively good, especially in categories with significant performance differences. However, the results recommend the need for further improvements to enhance classification accuracy in the intermediate categories, using advanced techniques such as increasing the number of training samples or applying feature selection strategies (Zhang, X., et al. 2023).
Figure analysis indicates that the designed neural network model has a good ability to discriminate between different skill levels, with excellent performance for high- and low-performing categories, and average performance for intermediate categories. This enhances the reliability of using artificial neural networks as an effective tool for classifying and analyzing skill performance, provided that mechanisms for handling anomalies are developed and the balance of training data is improved. These results are consistent with recent research trends addressing the applications of neural networks in sports.

5. RESULTS AND RECOMMENDATIONS

Results:
The results of the statistical analysis of the normal distribution showed that the sample data were moderate across all studied variables, which enhances the reliability of applying artificial neural networks to construct an accurate classification model in fencing. The Lasso technique demonstrated clear efficiency in selecting the most influential variables in predicting skill performance, reflecting its feasibility in designing accurate classification models within specialized sports contexts such as fencing.

Recommendations
According to the researchers' conclusions, they recommend the following:
The necessity of adopting artificial intelligence techniques, particularly artificial neural networks, in analyzing and classifying skill performance in fencing, given the accuracy and speed of processing they provide and the ability to differentiate between player levels. Future studies are recommended that integrate physical and biokinetic variables, on the one hand, and psychological and mental variables, on the other, to obtain more comprehensive and in-depth classification models for understanding fencers' characteristics.

REFERENCES

1. Turner A, Stewart P. Strength and conditioning for fencing. Strength Cond J. 2014;36.
2. Turner A, Stewart P, Bishop C. Physical qualities for elite fencing performance. Strength Cond J. 2022;44.
3. Turoff M. Foil fencing: a practical training guide. Marlborough: Crowood Press; 2018.
4. Wang S, Zhang X, Hu J. Artificial neural networks in sports performance prediction: a review. J Sports Sci. 2022;40.
5. Winter DA. Biomechanics and kinetic control of human movement. Hoboken (NJ): John Wiley & Sons; 2009.
6. Woods CT, Norton KI. The physiological basis of speed and agility. J Sport Health Sci. 2018;7:1–9.
7. Singh Y, Chauhan AS, Mining A. Journal of Theoretical and Applied Information Technology. 2009;2005–2009.
8. Yudkowsky E. Artificial intelligence as a positive and negative factor in global risk. In: Bostrom N, Ćirković MM, editors. Global catastrophic risks. Oxford: Oxford University Press; 2008.
9. Zemková E. Neuromuscular control and coordination in sports performance. J Phys Educ Sport. 2020;20:1814–20.
10. Zhang C, Bengio S, Hardt M, Recht B, Vinyals O. Understanding deep learning requires rethinking generalization. In: International Conference on Learning Representations (ICLR); 2017.
11. Zhang X, et al. Recent advances in neural network architectures and applications. IEEE Trans Neural Netw Learn Syst. 2023;34.