Predicting a Biomechanical Model Using Neural Networks for the Serving Skill of Iraqi National Volleyball Players

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Abstract
The biomechanical-physiological model, structured according to its variables, involves the collection and analysis of components using advanced technologies. This study utilises cutting-edge equipment, including the Electromyography (EMG) device, which measures muscle electrical activity, and the Biosyn system, which provides data on body height and angular positioning through its integrated sensors. Among the most significant artificial intelligence techniques are artificial neural networks, which serve multiple purposes, including the recognition of individuals, scenarios, speech, images, fingerprints, handwriting, and patterns. Additionally, they facilitate system simulation and predictive modelling of performance. The application of artificial neural networks in learning offers valuable insights for athletes, coaches, and sports specialists, enabling them to assess performance levels, evaluate technical and skill-based execution, obtain results, and generalise findings within the field. Moreover, this model allows for future reference and refinement. This study aimed to develop a model based on artificial neural networks to enhance the analysis of volleyball serving skills, integrating physiological and biomechanical compatibility outcomes. It sought to predict the most critical physiological and biomechanical variables influencing the serve performance of the Iraqi national volleyball team. The research population comprised 18 national team players, from whom a sample of 8 players (44.44% of the total) was selected. Each participant was given 10 attempts in the serve test, resulting in a total of 80 observations. The findings indicate that volleyball players can be categorised in terms of serving skills based on physiological and biomechanical variables.
Keywords: Prediction, Physiological Biomechanical Model, Artificial Neural Network, Serve Skill, Volleyball.

Introduction

The world is undergoing rapid advancements, experiencing a significant transformation across various domains due to the ongoing technological revolution, which continues to expand and flourish. This progress is evident across all fields, including sports (Balmer, 2021; Lee & Lim, 2021). Models play a crucial role in sports by enhancing technical performance, identifying strengths and weaknesses in execution, assessing training levels, and evaluating psychological and motor aspects. Additionally, physiological analysis is fundamental in studying the athlete's bodily functions in relation to skill execution (Nicholls & Culpepper, 2021). Biomechanics, as a complementary discipline, enables motor analysis for the theoretical examination of movement patterns, making it one of the most critical analytical approaches.
Serving is a fundamental offensive skill in volleyball, allowing players to score directly with minimal effort and time while significantly influencing match outcomes and disrupting opponents' strategies (Drikos et al., 2025; Oliinyk et al., 2021; Yousif, Almogami, & Khadim, 2023). This study aims to develop a biomechanical-physiological model by analysing relevant variables. Data is collected and examined using advanced technologies such as the EMG device, which measures muscle electrical activity, and the Biosyn system, which provides insights into body height and angular positioning through integrated sensors. Artificial intelligence, particularly artificial neural networks, plays a pivotal role in various applications, including the recognition of individuals, scenarios, speech, images, fingerprints, handwriting, and movement patterns, as well as in system simulation and predictive modelling of performance (Boujdi et al., 2023). The application of artificial neural networks in training sports offers insightful advice to athletes, coaches, and experts, which allows for an evaluation of performance levels, technical performance, and skill levels. Additionally, this model is able to perform result generalisation, improves decision-making, and is repeatable, ultimately saving time, energy, and resources (Janyga et al., 2024; Yousif, Almogami, & Khadim, 2023).
The value of this study comes from using artificial intelligence to address issues that puzzle researchers and experts, aiding in correctional process support while establishing a performance outcome prediction framework. Through technical performance simulation from national volleyball players' genuine performance data, the model predicts biomechanical and physiological variables more precisely (Aversano et al., 2023; Kolanu et al., 2024; Zhao, Li, Gan, & Wang, 2023). This study adds an artificial neural network approach in creating a biomechanical-physiological sports model for the serving action in volleyball, helping players overcome their dilemmas and coaches with insightful

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recommendations for training. It also helps predict performance outcomes and improve technical performance, ensuring efficient and effective athletic development.

Significance of Study

The novelty of this research is in creating a physiological-biomechanical model based on artificial neural networks (ANNs) to improve national volleyball players' serving skill. It is intended to solve performance issues of athletes and offer coaches a quantitative means of optimizing training. By constructing a predictive framework, the study enables the simulation of technical performance based on empirical results, contributing to performance enhancement and long-term player development. This study is of significant relevance to sports biomechanics, physiology, and artificial intelligence-based performance analysis. By investigating how an interplay between physiological and biomechanical properties affects volleyball serves, it deepens knowledge of determinants contributing to efficient serving. Of particular interest, this study investigates muscle activation, specifically triceps brachii and rectus femoris, in relation to torque, angular velocity, and power for optimal serving biomechanics. From this, knowledge will be advanced about which variables influence speed, accuracy, and overall performance of serves, ultimately leading to planning evidence-based training programs for coaches and athletes.

A novel feature of this study is the application of ANNs to sports performance analysis, utilizing machine learning models to estimate service accuracy and performance. AI-based biomechanical modelling allows accurate performance assessment and supports systems of instant feedback, sharply enhancing training methods. Bridging sports science with AI developments, this research advances data-driven, precision-based training intervention in volleyball, along with other professional sports. Moreover, the study establishes a conceptual and empirical foundation for the design of training programmes that enhance physiological and biomechanical attributes. It provides practical insights for coaches, sports scientists, and athletic trainers, identifying critical elements of serve execution that mitigate performance inconsistencies and reduce injury risks. This contribution enhances athlete efficiency, productivity, and career longevity. By advancing both theoretical and practical aspects of sports science, this research underscores the role of AI-driven biomechanical approaches in sports performance evaluation. The integration of machine learning with physiological and biomechanical data introduces a novel framework for assessing athletic performance, demonstrating the impact of technological innovation on athlete training and development.

Objectives of the Study

This study aims to develop a biomechanical model using neural networks to enhance the serving skill of Iraqi national volleyball players. The research will address the following objectives:

- Analyse biomechanical patterns in volleyball serving by evaluating variations in torque, angular velocity, and power production under different conditions.
- Examine muscle activation of the triceps brachii and rectus femoris in elite players to assess their relationship with serve performance metrics.
- Assess the predictive accuracy of ANNs in forecasting serve speed and accuracy based on biomechanical and physiological variables.
- Identify the most influential physiological and biomechanical factors contributing to improved volleyball serve performance.

Research Questions

- How do torque, angular velocity, and power affect the biomechanics of volleyball serving?
- What is the relationship between muscle activation of the triceps brachii and rectus femoris and serve performance in elite volleyball players?
- How accurately can ANNs predict serve speed and accuracy using biomechanical and physiological variables?
- What is the relative impact of physiological and biomechanical factors on the effectiveness of a volleyball serve?

Literature Review

A volleyball serve involves accurate control of various physiological and biomechanical factors, which affect team performance and competition outcome. This paper reviews literature on volleyball serving performance with focus on biomechanics and physiology using ANNs to predict outcome of sports. ANNs have increasingly been popular in sports biomechanics studies over the last few years due to the technical nature of volleyball. Biomechanics modelling is vital in determining performance variables, particularly in serving, which involves optimal performance based on synchrony between muscle activity, production of force, and angular motion to produce maximum speed and accuracy (Lee, Lee, & Rainbow, 2024). Biomechanics and physiology literature review of volleyball is carried out for prediction of feedback with neural networks, which depicts the applications of artificial intelligence in movement mechanics. Effective motor skills in a volleyball serve are influenced by mechanical factors in integration with physical attributes such as muscle control, turning speed, torque, and production of power. Relationships between these aspects of performance have been investigated in some studies. Simultaneous muscle activation to produce a good serve is required, with triceps brachii and rectus femoris playing primary roles (Yamakawa, Nishiwaki, & Sengoku, 2024). Triceps brachii aids in application of force together with arm extension, with rectus femoris helping in production of power along with stability from activation of the lower limbs (Khalaf, 2024).

Electromyography (EMG) tests have substantiated that high-performance volleyball players exhibit high levels of muscle activation for serves, especially for accelerating movements (Holonec, Grindei, & Rápolti, 2024). Increased muscle strength increases three basic mechanical factors: force torques, body momentum, and acceleration (Slovák et al., 2024). Executing rotation movement due to torque guarantees smooth performance and efficient technical accomplishment in volleyball. Torque and angular velocity are pivotal factors in controlling speed of serve and accuracy based on biomechanics. During torque development, rotation force transmitted to joints of the wrist and shoulder affects speed of the ball and direction of flight (Manzi et al., 2025). Torque and angular acceleration also dictate transmitting force from bottom of body to upper limbs, enabling optimal service mechanics (Guatibonza et al., 2024). Investigations confirmed that serving performance was found to be positively correlated with strength output, with greater values in force-velocity resulting in unstable flight movements of balls with greater velocity (Wang, Qin, & Wei, 2024). Long-term investigations founded on volleyball serving biomechanics have established determinants of performance such as force, torque, acceleration, angle velocity, and acceleration (Jia et al., 2024). These determinants of these players play an important role in forming serves that are difficult to counter for their opponents. Torque dictates body's angular acceleration directly, which means their interrelation; their acceleration increases with torque but decreases with rotary inertia (Imura, Iino, & Koike, 2024). They prove this relation algebraically by employing angular torque and moment of inertia. Power production in volleyball serves relies on integration between speed of movement and forces applied, with force playing an important role in fast movements, with speed being extremely correlated with players' capability (Jankovic et al., 2024). Producing maximum force at maximum speed calls for short times in push movement of the serve.

Muscle electrical activity forms the basis of volleyball performance, providing information on physical demands of skill. Triceps brachii and rectus femoris generate high electrical activity in serving, facilitating forceful, accurate delivery of balls (HIREMATH, D'SOUZA, & TAGIMAUCIA, 2025). Leg movement in synchrony with arm movement forms serving as an integrated system. Triceps brachii, further, plays a role in providing force and speed required for efficient serves. Muscle electrical activity also aids in identification of weaknesses of opponents by athletes, facilitating direct scoring (Ozawa et al., 2021). Physiological factors along with biomechanics are understood from studying serving performance. Scientists apply quantitative, qualitative indicators to test assumptions or falsify them, which is critical in measuring such complex motor skills that involve multiple factors simultaneously (Rebelo et al., 2024). Standardization of measurement practices allows consistent databases to be established, evident from HIREMATH, D'SOUZA and TAGIMAUCIA (2025), who prioritize taking values from left- and right-muscle sides so that calculations based on physiology are precise.

ANNs have become strong tools for examining sport performance. Molavian, Fatahi, Abbasi and Khezri (2023) were the pioneers of applying ML and DL techniques to sports, showing that ANNs are highly predictable. ANNs, for example, have been used to make predictions of tennis serve speed based on key movement variables that dictate performance. The bias parameter in neural networks serves as a controlling parameter ensuring accuracy in models without loss of performance quality (Brinkjans, Memmert, Imkamp, & Perl, 2022). The bias parameter determines future values in analysis, regardless of whether other variables change. Performance in a network is optimized by changing weight and bias values until the system operates with minimal levels of error (Chmait & Westerbeek, 2021). Neural networks communicate information using various hidden layers with activation functions to produce forward and backward values. It acts as a shifting coefficient that affects additional variables without changing. Dense layers are popular in neural networks since each neuron from each layer connects to every neuron that lies ahead, addressing training issues that increase with network depth (Liu, Yang, Han, & Liu, 2021). Weighting each variable in a neural network portrays its relevance and contribution to future variables. While weighing is usually between ±1, it sometimes surpasses this range to represent strong weight relations (Zhang et al., 2022).

Neural networks are employed to predict volleyball serve outcomes by analysing muscular function and player mobility patterns. Studies utilising ANNs have demonstrated that these systems accurately classify serve types and predict serve accuracy based on kinematic data and ground reaction forces. The study proposes that AI can be applied to create personalized training programs for athletes. Presently, it is established that biomechanical modeling with ANNs allows for better performance evaluation integrating such variables as joint angles, muscle activation levels, and kinetic forces (Brinkjans et al., 2022). These systems offer players and coaches instant feedback that guides better strategy development with minimized injury risks. An ANN model was established to measure volleyball spike performance based on torque, angular acceleration, and speed. The model determined fixed prediction values, which confirmed the viability of biomechanical evaluation with AI. The process of measurement confirmed that AI and biomechanics are effective in enhancing sports performance measurement with heightened accuracy and speed (Chmait & Westerbeek, 2021; Zhang et al., 2022). With the digital age, AI technologies revolutionized biomechanical studies by allowing for accurate visualization of athletes' movements, muscle activity, and force application (Liu et al., 2021). These systems offer information based on optimal movement mechanics, reducing human analysis errors. AI-based biomechanics modeling enhances performance measurement by locating areas of wasteful movement contributing to injury. Creating an optimal ANN model for serving in volleyball is based on integrating high-quality kinematic and physiological measurements. Multi-layered, fully connected neural networks offer maximum accurate estimations of movement patterns in sports (Liu et al., 2021).

There is a great improvement in the integration of volleyball serve performance analysis with artificial intelligence training methods, which has made traditional training obsolete. Theory and empirical work have established torque, angular velocity, power generation, and muscle activation as key determinants in enhancing serve efficiency. With the use of AI programs, training programs can be revolutionised by creating prediction models, ultimately improving player performance (Chmait & Westerbeek, 2021). Future work could investigate the use of real-time AI feedback systems in training for volleyball, which could allow players to make instant performance adjustments. Further, investigating hybrid machine learning models that incorporate deep learning together with biomechanics simulations could improve further predictability of serves and advance injury prevention programs.

Methodology

In this chapter, we provide, analyse, and discuss the findings of the study. The SPSS package was used to obtain and process the outcome. Physiological and biomechanics variables were extracted from national volleyball players' performance of the serving skill, as shown in Figure 1.

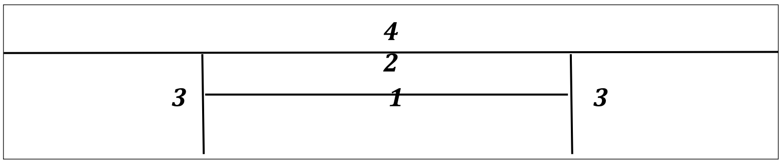

Figure 1: Volleyball Serve Accuracy Test.

Measurement of the Variables

To identify physiological and biomechanical factors that characterise the volleyball serve, several factors were tested in accordance with mechanical and physiological concepts of the game. These factors, based on theoretical models and related literature, were chosen due to their possible contribution to this offense skill and recorded at the same time via advanced analytical instruments. Physiological factors were recorded through EMG to measure the electrical muscle activity of major serving-related muscles such as triceps brachii of both sides and rectus femoris. Biomechanical factors were recorded with the use of the BIOSYN SYSTEM, which measured force, torque, angular velocity, power, and acceleration of different joints such as leg, trunk, wrist, head, foot, thigh, pelvis, and humerus. This holistic approach allowed for an all-encompassing measurement of muscle activation patterns and mechanical forces, providing deeper insight to an understanding of serve performance and efficacy.

Physiological Variables

Physiological variables were measured by an EMG device, namely Noraxon's MR3 system, fitted with eight electrodes (8-channel) and with application software version 3.16.68. This state-of-the-art portable laboratory equipment allows for real-time skeletal muscle electrical activity recording, transmitting over Bluetooth over 20 metres. A specialist selected the muscles to be analyzed, targeting the electrical activity of left and right brachialis muscles and left and right rectus femoris muscles.

Biomechanical Variables

Biomechanical parameters were determined with the BIOSYN SYSTEM, a three-dimensional sports movement analysis system that employs radio frequency (RF) to enable communication between its program—a three-dimensional skeletal model or human images—and sensors. It works effectively over an approximate 20-metre range in an open area, with longer range in indoor settings, appropriate for full-court volleyball. Measured were the following biomechanical parameters:

Force

It investigates the linear correlation of these effects according to the mechanical principle of force = acceleration × mass. Data were captured in relation to body parts using the Biosynsystem, with values made equivalent from device to axis for further analysis. The components under study are: (Tracy et al., 2023).

- Trunk Force (N)
- Left Knee Force (N)
- Right Knee Force (N)

Torque of Force

The study examines the circular effect according to mechanical law (torque = force x distance from axis of rotation). Measurement was carried out with the Biosyn system for body components, with readings from the equipment being converted to axis for calculation. Body components under examination are: (Sun & Zhang, 2022).

- Trunk Torque (Nm)
- Left Shoulder Torque (Nm)
- Right Shoulder Torque (Nm)
- Elbow Torque Left Elbow Torque (Nm)
- Right Elbow Torque (Nm)

Angular Velocity

The study examines the circular effect in accordance with

the mechanical law:
Angular velocity = angular distance / time.
Data were extracted using the Biosyn system for body parts, with values converted from the device to Excel for analysis. The investigated components include: (Saheb, 2024).

- Left Shoulder Angular velocity (deg/s)
- Right Shoulder Angular velocity (deg/s)
- Left Elbow Angular velocity (deg/s)
- Right Elbow Angular velocity (deg/s)

Power

The study investigates the circular effect based on the mechanical law:
Power = Work / Time.
Data were collected using the Biosynsystem for body parts, with values converted from the device to Excel for analysis. The examined components include:

- Trunk power (Watts)
- Right shoulder power Left shoulder power (Watts)
- Right shoulder power (Watts)
- Right elbow power (Watts)
- Right elbow power (Watts)

Acceleration

The acceleration variable was examined based on its circular effect, following the mechanical law:
Acceleration = Speed / Time
Data were extracted using the BIOSYN SYSTEM, converted into Excel format, and analysed for various body segments. The studied body parts included:

- Acceleration for the left shoulder Left Shoulder Acceleration (deg/s)
- Acceleration for the right shoulder Right Shoulder Acceleration (deg/s)
- Acceleration for the left elbow Left Elbow Acceleration (deg/s)
- Acceleration for the right elbow Right Elbow Acceleration (deg/s)

Main Experiment

The primary experiment was conducted on Monday, 6 March 2023, to assess the serving skill of Iraqi national volleyball team players. The evaluation included:

- Physiological measurements: Utilising an EMG device to record the electrical activity of the left and right triceps brachii and left and right rectus femoris muscles (Idrees, Yasir, & Rashied, 2022).
- Biomechanical measurements: Using the BIOSYN SYSTEM to assess key variables, including force, torque, angular velocity, acceleration, and power.

The experiment took place in the indoor sports hall of the College of Physical Education and Sports Sciences at the University of Al-Qadisiyah.

Data Collection Technique

For presentation of findings consistent with expected scientific practice, measurement standardisation of some of the variables is done. When considering physiological variables, numerical magnitudes of electrical activity of right and left triceps brachii, respectively, were averaged over to yield a single magnitude. Similarly, electrical activity of right and left rectus femoris, respectively, was averaged to yield a representative measurement of physiological activity. This is justifiable considering that movement by a serving player involves both limbs such that a single representation of activation of muscle is needed. Thus, the resulting dataset represents two physiological variables: electrical activity of triceps brachii muscle and rectus femoris muscle (Kukić, Mrdaković, Stanković, & Ilić, 2022).
For biomechanical variables, a collection of parameters was classified under chains, which included force, power, torque, angular velocity, and angular acceleration. Each chain covers several variables contributing to an overall series; hence, one singular representative value was necessitated for each chain. To standardize measurements, the researcher computed (variable/highest value), such that all units were normalized to 100 or an integer. This allowed calculation of the arithmetic mean for every chain to help present all biomechanical variables in one unified format. Since some chains had five variables, with others having four or three, the arithmetic mean was implemented instead of total sum after normalization. Consequently, dataset was formatted with a single column for each chain, which ensured similarity in all biomechanical variables. Ultimately, seven independent variables were determined, together with the dependent variable. Statistical presentation of these variables was in tables and graphical forms, providing lucidity in scientific interpretation and aiding in comprehensibility of findings. It is a mode of presentation that allows extraction of major scientific information and acts as an effective explanative tool. Data analysis aims to identify initial quantitative and qualitative indicators, which support research findings, validate or disprove theories, and offer empirical backup of study conclusions (Bowen, 2023). This aids in ensuring study objectives are achieved and theories are tested rigorously.

Estimations

Estimations of the Values of the Description of the Physiological and Biomechanical Variables of the Volleyball Serve

The basis of this study relies on the scientific principle that inferential coefficients based on statistics cannot be meaningfully applied before determining a thorough description of central tendency, dispersion, normal distribution, and homogeneity. Accurate characterization of these statistics is vital for ensuring that hypothesis testing that follows is valid, in addition to enabling determination of the right applicable statistic coefficients. Further, in examining quantitative estimations based on biomechanical variables, the nature of distribution of the data has to be evaluated to test whether it is moderated and reliable in representing the sample. Measurement of these estimations informs us of their implication, supporting credibility of findings. This process required a statistical description of values obtained by players on the team in all attempts made, which comprised 80.

Table 1

Descriptive Statistics

	Variables	Total Number	Arithmetic Mean	Standard Deviation	Skew	Kurtosis	Lowest Value	Highest Value
Physiological	Triceps Brachii	80	200.478	41.92423	0.201	-0.373	120.98	297.1
	Rectus Femoris	80	230.8446	57.91779	0.467	-1.081	140.88	355.87
Biomechanical	Force Series	80	0.6931	0.15715	0.126	-0.666	0.45	0.94
	Torque Series	80	0.57	0.18908	-.230	-0.036	0.16	0.86
	Power Series	80	0.6	0.10529	-.043	-0.722	0.42	0.8
	Angular Velocity Series	80	0.5613	0.2822	0.609	-0.320	0.15	1.08
	Angular Acceleration Series	80	0.57	0.20829	0.052	-0.367	0.2	0.91
Send		80	31.825	3.22088	0.188	-0.728	26	38

Based on the extracted data from the players' attempts, Table 1 presents the descriptive statistics for the physiological and biomechanical variables, as well as the volleyball serve skill test. The table includes values for the arithmetic mean, standard deviation, skewness, highest and lowest values, and kurtosis, providing insight into the distribution of the studied variables. The arithmetic mean was used to summarise the values of the variables into a single representative measure. To assess the accuracy of the mean in reflecting the dataset, the standard deviation was employed as a dispersion measure, indicating the spread of values around the mean. A reliable mean representation occurs when the majority of data points cluster around it, resulting in a relatively small standard deviation. Standard deviation values are considered acceptable if they do not exceed one-quarter of the arithmetic mean (first quartile). The table demonstrates that the standard deviation values for all variables were relatively small compared to their corresponding means, confirming that the mean serves as an appropriate representation of the data. This suggests that the observed values across player attempts were relatively consistent, reinforcing the suitability of the arithmetic mean as a model for the dataset.

Sample Level in Each of the Physiological and Biomechanical Variables of the Volleyball Serve

Table 2 displays descriptive statistics for the physiological and biomechanical variables together with calculated t-values comparing arithmetic mean with hypothetical mean to measure volleyball players' serving performance. From the findings, there are no differences in variables like triceps brachii muscle, series of force, series of angular velocity, and series of angular acceleration, indicating that arithmetic mean closely follows the hypothetical mean. The researcher credits this consistency with high training levels for players in the national team, which guarantees consistency in these variables. From the table, there are differences in electrical activity in the rectus femoris muscle, with hypothetical mean being greater than arithmetic mean. This means that players' performance in this variable is below desired levels, with an implication of a need for focused training aiming to improve performance in this variable.

Table 2

Sample Level in Each of the Physiological and Biomechanical Variables of the Volleyball Serve Skill Using the Test for One Sample

	Variables	Arithmetic Mean	Standard Deviation	Hypothetical Mean	Calculated T-Value	Degree of Freedom	Significance Level
Physiological	Triceps Brachii	200.478	41.924	209	-1.818	79	0.073
	Rectus Femoris	230.844	57.917	248.4	-2.7110	79	0.008
Biomechanical	Force Series	0.693	0.157	0.695	-0.107	79	0.915
	Torque Series	0.570	0.189	0.51	2.838	79	0.006
	Power Series	0.60	0.105	0.57	2.548	79	0.013
	Angular Velocity Series	0.561	0.282	0.615	-1.704	79	0.092
	Angular Acceleration Series	0.570	0.20829	0.555	0.644	79	0.521
Send		31.825	3.220	30	5.068	79	0.000

On the contrary, noteworthy differences existed in both the torque series and power series, with the arithmetic mean surpassing that of the hypothetical mean. This suggests an exceptional performance level in these variables based on players following physiological and biomechanics principles. This is attributed by the researcher to players' capability in effectively using mechanical laws in their performance in the serve, such as optimizing movement dynamics as well as targeting vulnerable spots in their opponents in an aim to maximize scoring. The variable values of serves were also significantly greater than that of the hypothetical mean, indicating that differentiation in testing player levels was effective. Variables that contributed to this difference included landing point, velocity, and spin speed, which reinforce their significant function in performing an effective serve.

Correlations of the Matrix

Table 3 reveals a significant correlation among certain physiological and biomechanical variables, as well as between these factors and the dependent variable (serving). The simple correlation matrix displays calculated correlation values, which vary between significant and non-significant, positive and non-negative relationships (Mocanu, Harabagiu, & Parvu, 2024). The researcher posits that the correlation between physiological variables—such as the electrical activity of the triceps brachii and rectus femoris muscles—highlights the integrated nature of the player's body during the serving skill. This integration arises from the coordinated movement of the legs and arms, indicating a unified mechanism that cannot be separated. A significant correlation was observed between the electrical activity of the triceps brachii and serving performance, whereas the rectus femoris showed no significant correlation. This suggests that while there is harmony between leg and arm movements, players predominantly focus on arm movements, making the triceps brachii's electrical activity the most influential factor.

Regarding biomechanical variables, the skill's requirements during performance necessitate consideration of mechanical characteristics and precise neuromuscular coordination. The application of mechanical laws ensures the correct execution of the skill. Significant correlations were found between force and torque variables, indicating that the kinetic transfer of force from the lower body (knee joint) to the upper body (shoulder) is crucial for effective serving. This underscores the importance of rotational movement and torque generation in achieving high technical performance. The findings suggest that players must possess substantial muscle strength to ensure fluid rotational movements and effective torque generation. Developing muscle strength can enhance force torque, body momentum, and force propulsion, which are interconnected mechanical factors critical to sports performance (Khalaf, 2024). These insights provide coaches with valuable guidance for training programs aimed at improving serving efficiency. The data presented in the Table 3 indicate a significant correlation between the power series and the execution of the volleyball serve. Given that this skill necessitates movement and jumping at specific intensities depending on the type of serve performed, an athlete's ability to generate mechanical work by combining force and speed is crucial for successful execution.

Table 3

Correlation Matrix for the Values of the Physiological and Biomechanical Variables of the Volleyball Serve Skill

Variables	Triceps Brachii	Rectus Femoris	Force Series	Torque Series	Power Series	Angular Velocity Series	Angular Acceleration Series	Transmission
Triceps Brachii	1							
Rectus Femoris	0.351**	1						
Force Series	0.062	0.209	1					
Torque Series	0.134	0.257*	0.770**	1				
Power Series	0.134	0.186	0.950**	0.728**	1			
Angular Velocity Series	0.130	0.216	0.964**	0.807**	0.919**	1		
Angular Acceleration Series	0.119	0.191	0.954**	0.763**	0.937**	0.981**	1	
Transmission	0.064	0.250*	0.300**	0.207	0.301**	0.317**	0.311**	1

* Significant at 78 degrees of freedom and 0.05 significance level.
** Significant at 78 degrees of freedom and 0.01 significance level.

According to the principle of power (power × speed), force exerts a greater effect when movement occurs rapidly within a short duration. This establishes a direct proportionality between an athlete's capability and movement speed. Consequently, coaches and athletes must integrate this principle into their training, particularly in phases such as the push phase of the volleyball serve. To maximise effectiveness, this phase must be executed within a minimal timeframe, ensuring that maximum force is applied at peak speed (Zhou, 2022). Furthermore, the table illustrates a direct relationship between torque and angular acceleration. The researcher posits that torque significantly influences both angular acceleration and the extent of angular motion. The magnitude of angular acceleration is contingent on the torque applied to the body and the degree to which the body resists variations in its rotational motion. When an external torque induces a change in rotational state, a greater torque results in a correspondingly higher angular acceleration. Additionally, the body's resistance to rotational changes plays a critical role in determining the extent of the variation induced by torque. Angular acceleration is directly proportional to torque and inversely proportional to the body's rotational inertia. In most cases, rotational inertia corresponds to the moment of inertia, forming a structured relationship between these mechanical variables (Hu, Rabenorosoa, & Ouisse, 2021).

Angular Acceleration = Angular Torque / Moment of Inertia

Steps to Build an Artificial Neural Network

Dividing the Sample into Two Groups (Training, Testing) for the National Volleyball Team Players

The dataset comprised seven variables in addition to the "Bias" coefficient, which serves to adjust the position where the slope line intersects the Y-axis. This adjustment ensures flexibility in positioning the slope line without adversely affecting the optimal representation of the best-fit line. The bias coefficient is intrinsically linked to both the input layer of independent variables and the hidden layers, influencing the overall model structure (Schrapf, Hassan, Wiesmeyr, & Tilp, 2022). The bias coefficient is incorporated into the computation formula in the same manner as any other trainable variable, with a default value of (+1). This default setting is essential, as subsequent variables are dependent on it rather than the reverse. The dependent variable in this analysis is the "serve," which represents the outcome. This variable is then utilised in constructing the neural network, which, in this case, comprises two hidden layers, thereby optimising the training process for the given dataset. Table 4 presents the division of the sample into two groups: the training set (59 data points) and the testing set (21 data points). The training phase involved iteratively adjusting weight and bias values to minimise error and enhance network performance. A specific point was identified to store the optimal weight parameters derived from the training process. Subsequently, a separate dataset was utilised to evaluate the machine learning algorithm's effectiveness.

Table 4

Percentages of the Totals, Errors and Information Used in the Network

Ratio	No.	Total Number
73.8%	**59**	Error Function
26.3%	**21**	Training Error Rate
100.0%	**80**	Test Error Rate
Sum of Squares		Error Function
0.050		Training Error Rate
0.034		Test Error Rate
7		Number of Independent Variables
Standardized		Method of Rescaling Independent Variables
1		Number of Hidden Layers
2		Number of Units of the First Hidden Layer
Hyperbolic Tangent		Activation Function for Independent Variables
Send		Dependent Variable
Standardized		Method of Rescaling Dependent Variable
Identity		Activation Function for Dependent Variable

The training process involved determining ideal weight values during the forward and backward propagation of network information within the presence of a hidden layer. The hyperbolic tangent function was employed as the activation function to compute the extracted z-value for each independent variable. This value was first multiplied by an initial weight and then passed through another activation function, the identity function, to compute the dependent variable (serve). The estimated outcome was then compared with the actual value, and in the case of a discrepancy, the assumed weights were adjusted accordingly. The process of weight modification followed the backpropagation mechanism, beginning with the first weight linking the initial independent variable to the first cell of the hidden layer. Recalculations were performed using the adjusted weights iteratively until reaching a threshold beyond which further weight refinement was ineffective (Rácz, Bajusz, & Héberger, 2021). This process was repeated across all independent variables and all cells within the two hidden layers until the dependent variable was determined, with an indefinite number of iterations aimed at minimising error. The error rate was computed using the sum of squares function. The results from the table indicate that the training process concluded with an error rate of 0.050, which qualifies the network for application to the test sample. Upon testing, the network achieved an error rate of 0.034, which is considered highly acceptable based on established network performance standards. This outcome is particularly significant given the relatively small number of samples used for both training and testing.

Structural Representation of the Artificial Neural Network

Following the identification of the seven features, these were utilised in constructing the network. The researcher developed a fully connected neural network, where each input is multiplied by its respective weight. The network consists of two fully connected layers. The first is a hidden layer comprising two units, while the second layer contains a single unit representing the dependent variable, the serve. The input layer includes seven units corresponding to the independent variables, as illustrated in Table 5. Moreover, Table 5 outlines the network layer construction, detailing their types, output structures, and coefficients. All layers were configured as dense layers, the most prevalent type in neural networks. These layers consist of interconnected neurons, ensuring that each neuron in a given layer is linked to every neuron in the subsequent layer. Consequently, the output from one layer serves as the input for the next. This configuration effectively mitigates training challenges that arise as network depth increases.

Table 5

Construction of the Layers of the Neural Network

Type of Layers	Output Format	Coefficient
First Layer (Thick)	*2*	*14*
Second Layer (Thick)	*1*	*8*
Total Parameters		*22*
Trainable Parameters		*22*
Untrainable Parameters		0

Regarding the output structure, the first hidden layer comprised two units, with each unit corresponding to an input. The initial values of the seven primary variables were multiplied by their respective weight values, which were initially assumed by the algorithm and subsequently adjusted during training to achieve optimal values (Giustino & Patti, 2025). This process also accounted for the bias term, resulting in 14 parameters across the two hidden layers. The second layer, representing the output, contained a single unit corresponding to the dependent variable (effectiveness). This unit was multiplied by the number of primary variables, yielding a total of 22 parameters. Thus, the model had 22 trainable parameters and no non-trainable parameters.

The Last Shape of the Neural Network

After determining the structure of the variables, segmenting the sample into groups, and configuring the network layers while ensuring all prerequisites for training and testing were met—including activation functions and optimisation algorithms—the final network architecture is illustrated in Figure 2.

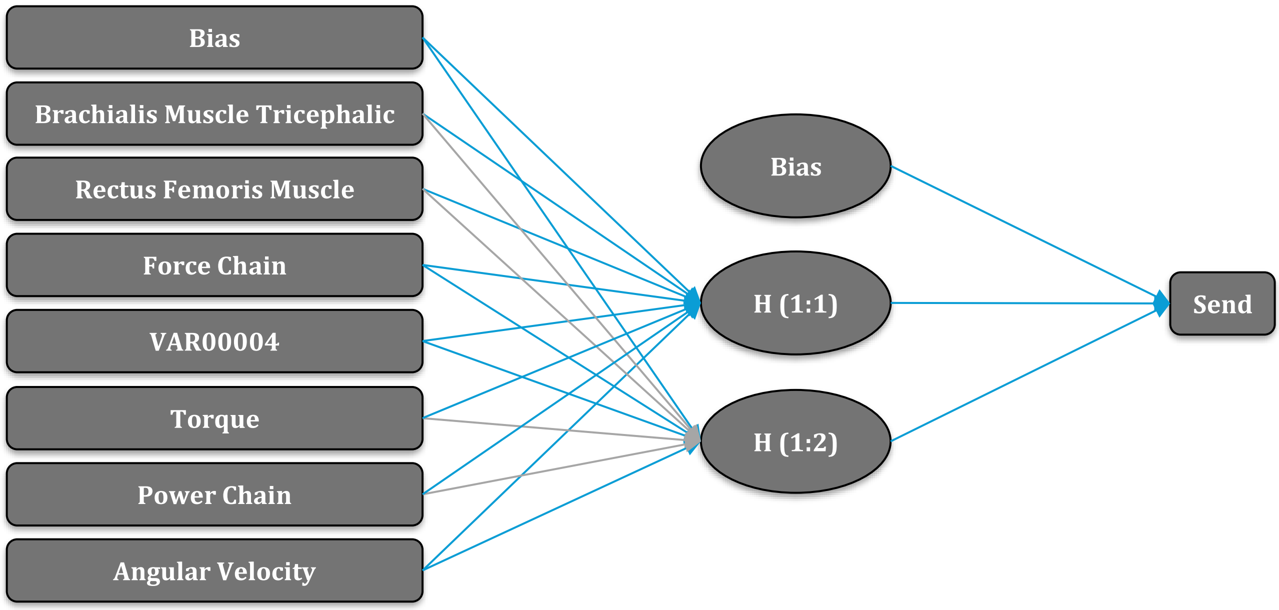

Figure 2: The Final Shape of the Neural Network.

Figure 2 illustrates the seven independent variables alongside the bias coefficient, which functions as b_0 in the regression equation. This coefficient is incorporated into all calculations like any other variable but remains unaffected by subsequent variables, as indicated by the blue lines (Ma, Li, & He, 2023). It acts as the driver for shifting within the network. The diagram also presents two hidden layers and a single dependent variable. The connecting lines represent weight points, also known as coefficient values, which establish relationships between all units. These weights are generally bounded by ±1, though some may exceed this range, indicating high significance in the model (Mizumoto, 2023). The magnitude of each weight reflects its importance and its contribution to the subsequent variable.

Within the first hidden layer, an additional bias unit is denoted as 2. Each computation follows this process: x × (stochastic weight value) → in → activation function.

The hyperbolic tangent function is applied to optimise weights and minimise error, producing values for each unit within the hidden layer. These values are then propagated as input to the second layer, where they are denoted as z. The same process is repeated, with the final outcome passing through the identity activation function to generate the predicted output values. To measure accuracy, the delta value is derived by comparing the predicted outputs with actual values from the sample. The network then undergoes backpropagation, where delta values from the output layer are used to calculate delta values in the hidden layer. These values adjust the previous weights (Wold) to generate updated weights (Wnew), ensuring continuous optimisation through iterative recalibration.

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

This iterative process continues until the network reaches a stability level where the weight values no longer change. At this point, the model is considered fully trained and ready for operation, ensuring optimal performance in processing new input data.

The Final Equation for the Sending Skill of the National Volleyball Team Players

Table 6 presents the contribution ratios of the independent variables influencing the sending skill of national volleyball team players, highlighting their relative impact on performance. Table 6 presents the contribution percentages of the seven independent variables influencing the dependent variable (transmission) within the network. The variables with the highest relative importance were the triceps brachii muscle, rectus femoris muscle, and force chain, respectively. In contrast, the power chain, angular velocity chain, torque, and angular acceleration exhibited the lowest relative importance. The variation in these values among the variables is further illustrated in Figure 3.

Table 6

Ratios for the Independent Variables

Variables	Importance	Natural Importance
Triceps Brachii	0.295	100.0%
Rectus Femoris	0.192	64.9%
Force Series	0.184	62.1%
Torque Series	0.033	11.1%
Power Series	0.144	48.8%
Angular Velocity Series	0.125	42.2%

Angular Acceleration Series	0.028	9.4%

Figure 3 illustrates the significance of the variables influencing the serving skill of national volleyball team players, based on their non-standard values. The seven variables—triceps brachii muscle, rectus femoris muscle, force chain, power chain, angular velocity chain, torque, and angular acceleration—are ranked by their relative importance. The increased electrical activity of the triceps brachii muscle suggests that players rely heavily on their arms during performance, enabling them to direct the ball with force and speed behind the net to score points or pressure opponents into weak returns. As projectile motion is crucial in volleyball, these relative importance values provide valuable insights for optimising skill performance. Therefore, they should be considered when developing future training strategies (Sun & Zhang, 2022).

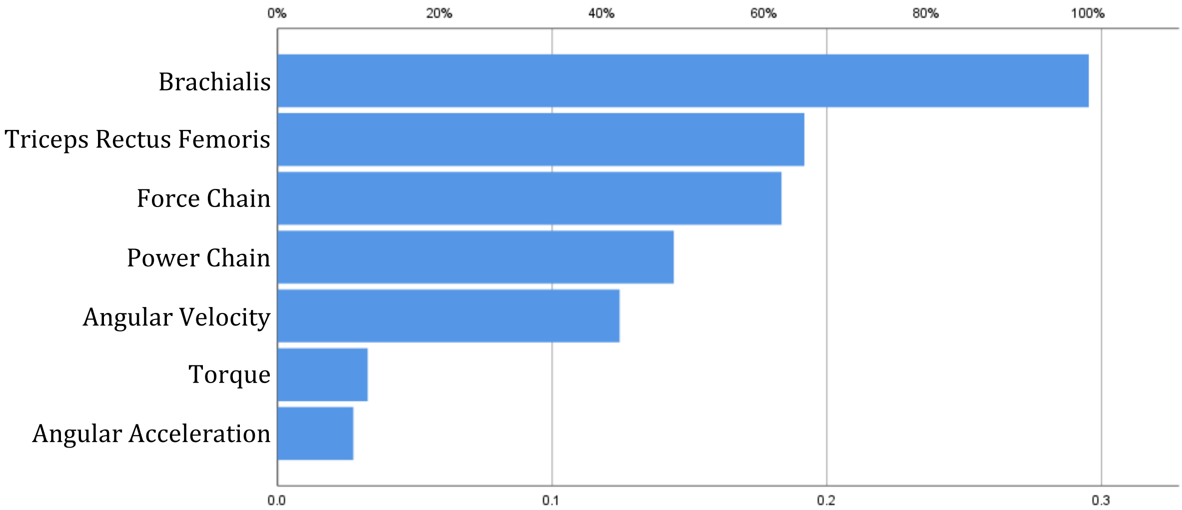

Figure 3: Variables Affecting the Skill of Sending for the National Volleyball Team Players.

Conclusion

The outcome of this study points to the strong contribution of physiological and biomechanical factors in determining successful volleyball serving. Specifically, recorded electrical activity of triceps brachii muscle was most effective on the performance of serving, illustrated by Iraqi national team players. In addition, the study explains in detail the role of torque, angular velocity, production of power, and muscle activation in improving serving skills and performance of athletes. Additionally, it confirms that volleyball players could systematically be graded according to physiological and mechanical variables describing serving. These indicators permit a systematic classification system that can enhance player efficacy and designing advanced training programs. Empirical examination also supports that different physiological and mechanical variables perform with varying degrees of influence on performance. Some of these indicators offer significant information that could be used for targeted training intervention to optimise performance of athletes. Further, this study confirms that an internal reference model is possible with which the dependent variable could be defined in volleyball serving. Standardizing all physiological and mechanical variable measurements permits developing a prediction model for performance. With an exceptionally low error rate, application of this model is an extremely reliable means to grade players according to their serving excellence.

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