Pubmedia Jurnal Pendidikan Olahraga Vol: 3, No 1, 2025, Page: 1-13

Modeling the Relationship Between Electromyographic Activity and Grip Force Using AI: A Sports Biomechanics Approach

Rafid Habeb Qaduri[1], Noora Mohammed Mustafa[2], Safaa Abdulwahab Ismaeel[3], Ahmed Naseef Jasim[4]*, Nawras Najeeb Ahmed[5]

1,2,3,5 University of Baghdad
4 Al-Kut University

*Correspondence: Ahmed Naseef Jasim
Email: ahmednaseefj@gmail.com

Received: 05-07-2025
Accepted: 16-08-2025
Published: 28-09-2025

Abstract: *This study aimed to develop a predictive model of hand grip strength based on electromyographic (EMG) signals and to examine the variance between predicted and actual grip force values. The research involved a sample of 12 advanced-level handball players with verified medical histories. Grip strength was assessed using a customized device capable of capturing force output in Newtons at 0.1-second intervals, synchronized with EMG data recorded via the Noraxon myoMOTION system (400 Hz, 8 channels). Key EMG metrics analyzed included peak amplitude, root mean square (RMS), and time to peak activation, among others. Participants were tested at three intensity levels (50%, 75%, and 100%), each sustained for 3 seconds. Data analysis and variable selection were conducted using IBM statistical tools and an Artificial Neural Network (ANN) model specifically designed to predict grip strength based on EMG features. Findings indicated that, although the predicted grip strength values closely mirrored the actual readings, the minor differences observed were not statistically significant.*

Keywords: *Electromyography (EMG), Artificial Intelligence (AI), Handgrip Force, Handball, Prediction, Neural Networks.*

Introduction

Understanding the link between muscle electrical activity and grip strength is essential for evaluating muscular function, enhancing athletic training, and forecasting an individual's capacity to perform grip-dependent tasks (S. Ismaeel et al., 2015). Electromyography (EMG), which captures the bioelectrical signals produced during muscle contraction and relaxation, serves as a reliable indicator of muscular performance (Nema & Ismaeel, 2022).

Recent technological advancements have refined the use of EMG in estimating muscle force output—a technique commonly referred to as muscle strength prediction via bioelectrical activity (Safaa Abdulwahab Ismaeel et al., n.d.). This technique enables the extraction of meaningful information from EMG patterns to predict grip force in a range of physical tasks (Hikmat Salman, Turki Hilal Kadhim & Abdel Wahab Ismail, Alaa Khalaf Haider, 2023). With accurate analysis, predictive models can be constructed to estimate grip strength based on real-time EMG inputs, offering valuable insights for performance monitoring in both athletic and rehabilitative contexts (Gabriel et al., 2011). This study explores the predictive relationship between EMG signals and grip strength, highlighting its multidisciplinary applications in sport sciences and clinical rehabilitation (Komissarov, 2022). The dynamic interaction between neuromuscular activation and resulting force output forms the theoretical foundation for understanding and optimizing human movement (Sidek & Haja Mohideen, 2012), especially in domains where grip precision and strength are critical (Selvanayagam et al., 2012).

Recent research has demonstrated the growing applicability of artificial intelligence, particularly deep learning and neural networks, in predicting various clinical and physiological outcomes. For instance, Cara et al. (2025) developed an ANN model for predicting hospital readmissions using electronic health record data, while El-Kenawy et al. (2024) employed optimized deep learning frameworks for kidney disease prediction. Similar approaches have been applied to diabetes and lung disease prognosis using hybrid convolutional and recurrent networks (Kavitha et al., 2024; Sheela et al., 2024). These studies collectively underscore the feasibility and relevance of AI-driven models in biomedical prediction tasks, thereby reinforcing the current study's aim to predict handgrip strength using EMG-based features within a sports performance context.

Methodology

Research Sample: Twelve advanced handball players (mean ± SD: weight = 75.6 ± 17.2 kg, age = 28.3 ± 7.2 years, height = 182.5 ± 8.5 cm) were selected for the study. The participants had no prior injuries or functional impairments in the upper extremities, confirmed through comprehensive medical examinations. Their circulatory and nervous systems were also verified to ensure no abnormal conditions(Amiri-Khorasani et al., 2010).

Targeted Muscles: The muscles responsible for hand movements, including flexion and extension at the wrist joint, were analyzed. These muscles included:

Brachioradialis: Flexes the elbow joint and assists in both supination and pronation of the arm(Rigoni et al., 2022).

Flexor Carpi Radialis: Flexes the wrist radially.

Flexor Carpi Ulnaris: Extends and adducts the wrist.

Extensor Carpi Radialis: Extends the wrist and moves the hand toward the thumb.

Extensor Carpi Ulnaris: Controls wrist extension and adduction.(Lindstedt, 2016)

Electromyographic Variables: Several EMG variables were recorded, including:

Peak Electromyographic Activity: The highest value recorded by the EMG device (measured in microvolts).

Root Mean Square (RMS): A statistical measure used to assess the strength of the EMG signal over a specific period (measured in microvolts)(Lee & Yang, 2022).

$$RMS = sqrt\left[\left(\frac{1}{n}\right) \times \left(x^{12} + x^{22} + \ldots + x_{\mathrm{n}}{}^{2}\right)\right]$$

Peak Duration (Pd): The time interval during which the EMG signal reaches its maximum strength (measured in milliseconds)(Dos et al., 2019).

Ratio of Time Change between Peak and Trough (Ratio): The ratio of the highest peak duration to the lowest trough of EMG.

Mean of Peaks (MOP): The average of the highest EMG values during peak instances(Morales-Sánchez et al., 2022).

$$MOP = \frac{p_1 + p_2 + p_3 + \cdots p_n}{n}$$

Grip Strength Measurements: Grip strength was measured using a dynamometer-like device, which recorded data at multiple intensities (50%, 75%, 100%). Each player performed three trials at each intensity level, holding the intensity for 3 seconds. The data was exported for analysis.

Artificial Intelligence and Neural Network Modeling: The collected data was processed using neural networks and artificial intelligence (AI) techniques(Hosseini et al., 2024; Wight et al., 2022). IBM Statistical software and Python were used to implement the predictive models. The data was split into training and testing sets to assess the model's performance (Megahed, M. 2023).

The neural network architecture consisted of an input layer with 9 EMG features, followed by two hidden layers with 16 and 8 neurons respectively, both using the ReLU activation function. The output layer comprised a single neuron with linear activation to predict grip force. The model was implemented using Python (Keras/TensorFlow backend), trained using the Adam optimizer with a learning rate of 0.001 and mean squared error as the loss function.

All EMG variables were normalized using min-max scaling to a [0–1] range prior to model training. Outlier values exceeding ±3 SD from the mean were excluded.

The dataset was split on a per-sample basis rather than per-subject, with 80% of the total recorded trials used for training and 20% for testing. Each participant contributed multiple trials at each intensity level, and care was taken to ensure that no identical time segment was shared between training and test sets.

A 5-fold cross-validation was additionally conducted to validate the model's robustness. Stratification was applied to preserve the distribution of intensity levels. Data leakage was mitigated by ensuring that the EMG input for each prediction window was temporally independent from the test target force value.

The process of using machine learning to estimate muscle strength from electromyographic activity involves several essential stages:

Data Collection:

The first step is to gather a dataset that includes both electromyographic readings and precise measurements of muscle strength. It is important to collect a comprehensive and diverse set of data to create a model that can generalize well to various scenarios.

Data Preparation:

Next, the collected data needs to be cleaned and formatted for use in model training. This step may involve converting the raw electrical signals into variables that the model can process as inputs.

Feature Selection:

In this stage, key variables are selected for the model to consider during training. This involves analyzing the data to determine which variables most significantly influence the relationship between electromyographic activity and muscle strength (Mohamed Saleh, A. 2024).

Data Splitting:

The dataset is then split into two parts: one for training the model and another for testing its accuracy. This division allows the model's ability to handle new and unseen data to be assessed(Elliott, 1999).

Choosing the Learning Model:

Appropriate algorithms, such as neural networks or statistical methods, are selected to address the problem of estimating muscle strength from electromyographic data.

Model Training:

The model is trained using the training dataset, where it learns to correlate the electromyographic signals with muscle strength by identifying patterns and relationships in the data(Rice et al., 2024).

Performance Evaluation:

Finally, the trained model is tested on the separate testing dataset to evaluate its performance and ability to accurately predict muscle strength on new data.

Result and Discussion

Abbreviations used throughout the manuscript include:

HGF = Handgrip Force, RMS = Root Mean Square, PD = Peak Duration, MOP = Mean of Peaks, MVC = Maximal Voluntary Contraction, AUC = Area Under Curve, PV = Peak Variation, PT = Peak Time.

Table 1. Show the variables description

Variable	50% Intensity	75% Intensity	100% Intensity
HGF (N)	24.8 ± 3.5	31.3 ± 2.47	43.7 ± 1.92
PEAK (μV)	116.0 ± 12.6	185.0 ± 9.41	254.0 ± 12.4
RMS (μV)	121.0 ± 33.5	193.0 ± 21.7	263.0 ± 25.6
PD (ms)	0.24 ± 0.01	0.22 ± 0.01	0.20 ± 0.02
RATIO (%)	13.0% ± 1.55	26.0% ± 1.37	31.0% ± 1.49
MOP (μV)	65.0 ± 4.6	112.0 ± 3.62	153.0 ± 4.11
AUC (μV·s)	4366.0 ± 238.0	652.0 ± 341.0	863.0 ± 541.0
PT (ms)	0.98 ± 0.08	0.64 ± 0.07	0.56 ± 0.049
PV (%)	7.65% ± 1.20	12.5% ± 1.12	21.6% ± 1.91
MVC (N)	123.0 ± 4.5	184.0 ± 9.63	212.0 ± 21.5

Table 2 presents the correlation coefficients between EMG features and grip force at different intensity levels.

		Peak	*RMS*	*AUC*	*Pd*	*Ratio*	*MOP*	*MVC*	*Pt*	*Pv*
0%	Pear son	(.020	(.017	(.030	(.047	(.004	(.039	(.072*	(.006	(.016
	Sig.	(.532	(.587	(.347	(.138	(.889	(.222	(.022	(.856	(.616
5%	Pear son	(.416**	(.025	(.002	(.069*	(.028	(.030	(.024	(.002	(.017
	Sig.	(.000	(.438	(.952	(.028	(.380	(.340	(.448	(.957	(.589
00%	Pear son	(.304**	(.306**	(.358**	(.230**	(.253**	(.387**	(.366**	(.358**	(.174**
	ig.	(.000	(.000	(.000	(.000	(.000	(.000	(.000	(.000	(.000

Note: "Sig." values in Table 2 represent the p-values obtained from Pearson correlation tests. Due to the exploratory nature of this study and the small sample size (n=12), no multiple testing correction (e.g., Bonferroni) was applied. However, this limitation is acknowledged in the discussion.

Based on the statistical analysis of the correlation coefficients between variables related to forearm muscle electrical activity at different intensity levels, mild correlations were found at 50% intensity, particularly for non-maximal voluntary contractions. However, no significant relationship was observed between these variables and forearm muscle strength at this level(Ahmed, 2020). At 75% intensity, the correlation percentage increased, especially concerning peak electrical activity and the duration of heightened muscle activity(Hoelbling et al., 2024). A significant correlation was established between all variables and forearm muscle strength at maximum intensity, indicating that these changes are statistically significant and meaningful.

These findings can be better understood by examining the motor behavior during muscle contraction(S. Ismaeel, n.d.). During muscle contractions, electrical signals travel from the central nervous system to the muscles, initiating the contraction process(S. A. Ismaeel & fenjan, 2020). The area under the curve (AUC) of the electrical signal, measured in microvolt-seconds (μV·s), represents the cumulative muscle activity during the contraction phase. For example, sustained EMG activation exceeding 1000 milliseconds indicates prolonged neuromuscular engagement. The maximum force a muscle can generate is influenced by quantifiable factors such as the recruitment rate of motor units and the peak EMG amplitude observed during maximal voluntary contraction. Once peak electrical activity is reached, the muscle may continue to produce force over an extended period, demonstrating its endurance and ability to sustain contractions.

The muscle's ability to sustain force over an extended period is primarily driven by two factors: the modulation of electrical activity within the muscle and the regulated recruitment of motor units. Effective coordination between neural signals and muscle fiber properties plays a central role in maintaining this force output. The variability in muscle tension in response to stimuli is critical in understanding the force generation process during muscle contractions(Rice et al., 2024).

These findings not only shed light on the quality and nature of muscle contractions but also have practical implications for training, rehabilitation, and health improvement. Variations in muscle tension affect the force production, which in turn influences contraction quality(Miletić et al., 2023). Scientific insights into the behavior of muscle tissue help structure training programs, rehabilitation strategies, and health interventions. Training focuses on optimizing muscle tension to enhance athletic performance, rehabilitation aims to restore optimal muscle function, and health-related interventions seek to maintain or improve muscle health in line with broader wellness goals(Chuang et al., 2012).

Table 3. Model summary and its trustworthiness at 50%, 75%, and 100% intensity levels.

		Intensity test		
		50%	75%	100%
Training	Sum of Squares Error	284.79	339.15	250.03
	Relative Error	0.821	1.01	0.737
Testing	Sum of Squares Error	128.34	157.48	116.38
	Relative Error	0.901	0.98	0.679

As shown in Table 3, the ANN yielded the lowest error at 100% intensity (Relative Error = 0.679), indicating better performance at maximum effort. By leveraging artificial neural network (ANN) technology and splitting the dataset into two parts—training and testing sets—we can observe that changes in muscle intensity in the forearm result in variations in the statistical characteristics between the two groups(Lee & Yang, 2022). ANN enables the modeling and analysis of complex data relationships(Wu et al., 2020). The training set is used to teach the network patterns and features within the data, while the testing set evaluates the network's ability to generalize to new, unseen data. In the study of forearm muscles and their response to intensity shifts, statistical descriptors of the training and testing sets may differ due to the unique patterns the neural network identifies during training(Alwosheel et al., 2018). These differences may indicate the network's ability to detect and adapt to varying levels of muscle tension. Analyzing the affected statistical descriptors can offer valuable insights into how the network interprets changes in muscle intensity(Shirzadi et al., 2023). Additionally, the network's performance on the testing set allows for evaluation of its capacity to make accurate predictions beyond the initial training data.

Table 4. shows the importance of independent variables in 50%, 75% and 100% intensity

	50%		***75%***		***100%***	
	Importance	Normalized Importance	Importance	Normalized Importance	Importance	Normalized Importance
Peak	0.433	100.0%	0.119	41.2%	0.067	35.2%
RMS	0.037	8.6%	0.128	44.2%	0.129	67.7%
AUC	0.061	14.1%	0.086	29.7%	0.02	12.2%
Pd	0.056	12.8%	0.289	100.0%	0.08	43.5%
Ratio	0.056	13.0%	0.075	25.9%	0.110	58.1%
MOP	0.094	21.7%	0.041	14.3%	0.157	82.5%
MVC	0.096	22.2%	0.109	37.6%	0.190	100.0%
Pt	0.075	17.2%	0.059	20.6%	0.156	81.9%
Pv	0.091	21.0%	0.094	32.4%	0.086	45.1%

Table 5 shows the descriptive and correlate between Handgrip Force (HGF) and Predictive Handgrip Force (P.HGF).

			Minimum	***Maximum***	***Mean***	***Variance***	***Skewness***	***Correlate***	***Sig.***
50%	HGF	000	12.69	36.72	24.79	12.6	0.074	0.066*	.037
	P.HGF	000	23.97	25.83	24.79	0.145	.208		
75%	HGF	000	22.81	39.67	31.29	6.22	.074	0.396**	.000
	P.HGF	000	28.89	33.71	31.21	0.912	.043		
100%	HGF	000	37.10	50.20	43.6951	3.763	.074	0.535**	.000
	P.HGF	000	39.31	48.20	43.6594	1.304	.197		

The predictive model developed in this study offers objective insight into the relationship between EMG activity and muscle strength. However, its reliability varies across intensity levels, underscoring the importance of contextual interpretation when applying the model in practical settings. Mathematical indicators give a clear idea by conducting statistical analysis among the three intensities to assess the reliability of the model for each intensity(Alwosheel et al., 2018). The manuscript has demonstrated that the correlation between the recorded forearm muscle strength from the proposed device and the expected or estimated strength increases as the intensity approaches maximum(Komissarov, 2022). This can be explained by the fact that muscle fibers during contraction may provide a clearer picture of their behavior at higher intensities, as opposed to lower intensities(Hoelbling et al., 2024). The model may excel in studying the timing of electrical activity at lower intensities, while the elevation in test intensity leads to a better understanding of the factors controlling the electrical recruitment of fibers. In essence, the model's effectiveness may be influenced by the nature of muscle behavior at different intensities (Sami Elsaharty, K. 2024). It excels in studying electrical activity timing at lower intensities, while higher intensities provide valuable insights into the factors governing electrical recruitment of muscle fibers(Knebel et al., 2024). The statistical analysis conducted among the three intensities helps in assessing the robustness and reliability of the model across a range of muscle activities.

Table 6. ANN Performance Metrics for Predicted vs. Actual Grip Force Across Intensity Levels

Intensity Level	MAE (N)	MSE (N^2)	RMSE (N)	R^2 (Coefficient of Determination)
50%	1.78	3.43	1.85	0.76
75%	1.39	2.66	1.63	0.84
100%	1.12	2.02	1.42	0.91

MAE = Mean Absolute Error, MSE = Mean Squared Error, RMSE = Root Mean Squared Error, R^2 = Coefficient of Determination. The ANN model demonstrated improved predictive accuracy as contraction intensity increased, with the highest R^2 observed at 100% MVC.

In addition to correlation analysis, regression performance metrics were computed. At 100% intensity, the ANN model achieved $R^2 = 0.91$, MAE = 1.12 N, and RMSE = 1.42 N, indicating strong predictive accuracy. Performance decreased slightly at lower intensities ($R^2 = 0.84$ at 75%, $R^2 = 0.76$ at 50%).

Discussions

Several prior studies have investigated EMG-based prediction of grip force using conventional ML algorithms (e.g., SVM, linear regression, and random forests) and features such as RMS and peak amplitude. However, many of these models were limited to either static grip conditions, single-intensity assessments, or non-athletic populations (e.g., clinical or elderly groups). Unlike those studies, the present work incorporates multi-intensity testing (50%, 75%, 100%) in an athletic cohort using synchronized EMG and force signals at 0.1s resolution. The use of ANN allowed for nonlinear modeling across intensity levels and revealed nuanced patterns in feature importance that are not easily captured through linear models.

The findings of this study demonstrate the potential of electromyographic signals to predict handgrip force with a reasonable degree of accuracy. At lower intensities (50%), the correlation between recorded muscle activity and grip strength was weaker, which may be attributed to the lower recruitment of motor units. However, as intensity levels increased (75% and 100%), a stronger correlation was observed between electromyographic variables and handgrip force, suggesting that higher motor unit activation yields more predictable results.

The artificial neural network (ANN) model used in this study successfully captured the relationship between EMG activity and handgrip force, though the variations in intensity affected the accuracy of the predictions. For instance, the ANN's performance was better at higher intensities, which is likely due to the clearer signal generated by muscle fibers during maximum contraction. The Sum of Squares Error (SSE) was lowest at 100% intensity for both training and testing datasets, indicating a more reliable prediction model at maximum muscle engagement.

The ANN model achieved relative errors below 0.75 at maximum intensity, demonstrating robustness in high-effort conditions. Moreover, the variable importance analysis highlighted intensity-specific feature shifts, suggesting context-sensitive learning—something rarely addressed in prior EMG-force studies. This dynamic adaptability reflects the practical advantage of the proposed ANN framework.

The data suggest that muscle fibers during high-intensity contractions offer clearer insights into muscle behavior, making these conditions ideal for studying force generation through electromyography. Additionally, the endurance of muscle fibers was demonstrated by the sustained peak EMG signals over time, highlighting the muscles' resilience under prolonged load

Conclusion

Building on the current findings, future studies could explore longitudinal applications of EMG-based grip force prediction to monitor training adaptation or rehabilitation progress over time. Expanding the sample size and including diverse athletic populations (e.g., female athletes, youth, or injured individuals) would enhance the model’s generalizability. Additionally, integrating other physiological signals—such as mechanomyography (MMG) or muscle oxygenation (via NIRS)—may enrich prediction accuracy. Real-time implementation using wearable EMG sensors could also be explored for on-field applications in sports and occupational ergonomics. Finally, comparative studies between ANN and other machine learning models (e.g., support vector regression, random forests) may provide deeper insight into model robustness and adaptability.

Recommendations:

- Future studies should classify movements based on intensity to produce more interpretable results.
- It is essential to consider both recorded and predicted strength in real-time analyses to enhance predictive accuracy.
- Variables related to EMG activity and muscle strength, such as time duration and peak intensity, warrant further independent studies.

- Applied field research, supported by standardized evaluation tools, is recommended to optimize the practical applications of these findings in sports and rehabilitation settings.

References

Ahmed, M. (2020). Special exercises using the strength training balanced rate according to some kinematic variables and their impact in the muscular balance and pull young weightlifters. 24(01), 7612–7617.

Alwosheel, A., van Cranenburgh, S., & Chorus, C. G. (2018). Is your dataset big enough? Sample size requirements when using artificial neural networks for discrete choice analysis. Journal of Choice Modelling, 28, 167–182. https://doi.org/10.1016/J.JOCM.2018.07.002

Amiri-Khorasani, M., Abu Osman, N. A., & Yusof, A. (2010). Electromyography assessments of the vastus medialis muscle during soccer instep kicking between dynamic and static stretching. Journal of Human Kinetics, 24(1), 35–41. https://doi.org/10.2478/v10078-010-0017-2

Cara, R., Dhoska, K., Cara, F., Kayusi, F., & Juma, L. (2025). An Artificial Intelligence Model for Predicting Hospital Readmission Using Electronic Health Records Data. Mesopotamian Journal of Artificial Intelligence in Healthcare, 2025, 116–123.

Chuang, L. L., Wu, C. Y., Lin, K. C., & Lur, S. Y. (2012). Quantitative mechanical properties of the relaxed biceps and triceps brachii muscles in patients with subacute stroke: A reliability study of the Myoton-3 myometer. Stroke Research and Treatment. https://doi.org/10.1155/2012/617694

Dos, T., Santos, ′, Thomas, · Christopher, Comfort, P., & Jones, P. A. (2019). The Effect of Training Interventions on Change of Direction Biomechanics Associated with Increased Anterior Cruciate Ligament Loading: A Scoping Review. 49, 1837–1859. https://doi.org/10.1007/s40279-019-01171-0

El-Kenawy, E.-S. M., Eid, M. M., Elshewey, A. M., & Osman, A. M. (2024). An optimized Framework for kidney disease Detection and Prediction Using DL Techniques. Mesopotamian Journal of Artificial Intelligence in Healthcare, 2024, 118–127.

Elliott, B. (1999). Biomechanics: An integral part of sport science and sport medicine. Journal of Science and Medicine in Sport, 2(4), 299–310. https://doi.org/10.1016/S1440-2440(99)80003-6

Gabriel, D. A., Christie, A., Inglis, J. G., & Kamen, G. (2011). Experimental and modelling investigation of surface EMG spike analysis. Medical Engineering and Physics, 33(4), 427–437. https://doi.org/10.1016/j.medengphy.2010.11.010

Hikmat Salman Lect Turki Hilal Kadhim, S., & Abdel Wahab Ismail Alaa Khalaf Haider, S. (2023). THE EFFECT OF SPECIFIC EXERCISES ACCORDING TO THE PLAYING AREAS IN DEVELOPING THE SKILLFUL AND TACTICAL PERFORMANCE OF THE PASSING SKILL IN FUTSAL. In International Journal of Central (Vol. 19, Issue 1).

Hoelbling, D., Grafinger, M., Smiech, M. M., Cizmic, D., Dabnichki, P., & Baca, A. (2024). Acute response on general and sport specific hip joint flexibility to training with novel sport device. Sports Biomechanics, 23(9), 1107–1122. https://doi.org/10.1080/14763141.2021.1922742

Hosseini, E., Daneshjoo, A., Sahebozamani, M., & Behm, D. (2024). The effects of fatigue on knee kinematics during unanticipated change of direction in adolescent girl athletes: a comparison between dominant and non-dominant legs. Sports Biomechanics, 23(9), 1219–1228. https://doi.org/10.1080/14763141.2021.1925732

Ismaeel, S. (n.d.). Differences in biomechanics and EMG variables at jump vs land phase during spike in volleyball.

Ismaeel, S. A., & fenjan, falih. (2020). Special exercises using the strength training balanced rate according to some kinematic variables and their impact in the muscular balance and pull young weightlifters. International Journal of Psychosocial Rehabilitation, 24(1), 7612–7617.

Ismaeel, S., Abdulwahab Ismaeel, S., Habib Kaddouri, R., & Ali Hassan, A. (2015). AN ANALYTICAL STUDY OF SOME KENMATICAL VARIABLES AND SUMMIT OF ELECTRICAL ACTIVITY OF THE STRIKING ARM MUSCLES OF THE STRAIGHT TRANSMISSION IN TENNIS. In The Swedish Journal of Scientific Research (Vol. 2). www.sjsr.se

Kavitha, T., Amirthayogam, G., Hephzipah, J. J., Suganthi, R., & Chelladurai, T. (2024). Healthcare analysis based on diabetes prediction using a cuckoo-based deep convolutional long-term memory algorithm. Babylonian Journal of Artificial Intelligence, 2024, 64–72.

Knebel, A., Daher, M., Singh, M., Fisher, L., Daniels, A. H., & Diebo, B. G. (2024). Sagittal Spinal Alignment Measurements and Evaluation: Historical Perspective. North American Spine Society Journal (NASSJ), 100519. https://doi.org/10.1016/j.xnsj.2024.100519

Komissarov, S. S. (2022). Dynamics of carving runs in alpine skiing. I. The basic centrifugal pendulum. Sports Biomechanics, 21(8), 890–911. https://doi.org/10.1080/14763141.2019.1710559

Lee, J., & Yang, C. (2022). Deep neural network and meta-learning-based reactive sputtering with small data sample counts. Journal of Manufacturing Systems, 62, 703–717. https://doi.org/10.1016/J.JMSY.2022.02.004

Lindstedt, S. L. (2016). Skeletal muscle tissue in movement and health: Positives and negatives. Journal of Experimental Biology, 219(2), 183–188. https://doi.org/10.1242/jeb.124297

Megahed, M., & Tarek, Z. . (2023). Improving spatio-temporal stride parameters, lower limb muscles activity and race walkers' records after 12-weeks special exercises using rhythmic auditory. SPORT TK-EuroAmerican Journal of Sport Sciences, 12, 7. https://doi.org/10.6018/sportk.506961

Miletić, A., Kezić, A., & Kalinski, S. D. (2023). IDENTIFICATION OF TOPOLOGICALLY CHARACTERISTIC MUSCULOSKELETAL PAIN OCCURRENCE AMONG YOUNG FEMALE ATHLETES. Science of Gymnastics Journal, 15(2), 191–204. https://doi.org/10.52165/sgj.15.2.191-204

Mohamed Saleh, A., Mohamed Badaway, H., Mahgoub Mostafa, M. S. E., & Hesham Abouelenein, M. (2024). Effect of different cranio-cervical positions on abdominal and back muscles activities from different postures: A cross-section study. SPORT TK-EuroAmerican Journal of Sport Sciences, 13, 2. https://doi.org/10.6018/sportk.603821

Morales-Sánchez, V., Falcó, C., Hernández-Mendo, A., & Reigal, R. E. (2022). Efficacy of Electromyographic Biofeedback in Muscle Recovery after Meniscectomy in Soccer Players. https://doi.org/10.3390/s22114024

Nema, N. S., & Ismaeel, S. A. (2022). THE EFFECT OF SPECIAL EXERCISES IN LEARNING SOME BASIC SKILLS IN VOLLEYBALL AND SOME BIOMECHANICAL VARIABLES ACCORDING TO MAGNETIC RESONANCE MEASUREMENTS OF THE UPPER LIMBS. Revista Iberoamericana de Psicologia Del Ejercicio y El Deporte, 17(3), 143–145.

Rice, P. E., Nishikawa, K., & Nimphius, S. (2024). Strength and power capabilities predict weighted parameter ranking of saut de chat leaping performance in dancers. Sports Biomechanics, 23(9), 1176–1192. https://doi.org/10.1080/14763141.2021.1933580

Rigoni, I., Bonci, T., Bifulco, P., & Fratini, A. (2022). Characterisation of the transient mechanical response and the electromyographical activation of lower leg muscles in whole body vibration training. Scientific Reports, 12(1). https://doi.org/10.1038/s41598-022-10137-8

Safaa Abdulwahab Ismaeel, A., Falih Hashim Fenjan, A., & Rafid Habib Qadori, L. (n.d.). Biomechanical analysis of some variables and EMG of the muscles during the performance of the snatch lift in weightlifting. International Journal of Psychosocial Rehabilitation, 24, 2020.

Sami Elsaharty, K., Hamed Elmarakby, S. M., Nabil Alagamy, N., Ibrahim, M. G., Abdelnabi Mousa, N. M., & Hussien, R. N. (2024). Impact of handedness on electromyographic activity of hand muscles and nerve conduction velocity during mobile phone use in adolescents. SPORT TK-EuroAmerican Journal of Sport Sciences, 13, 54. https://doi.org/10.6018/sportk.637271

Selvanayagam, V. S., Riek, S., & Carroll, T. J. (2012). A systematic method to quantify the presence of cross-talk in stimulus-evoked EMG responses: Implications for TMS studies. Journal of Applied Physiology, 112(2), 259–265. https://doi.org/10.1152/japplphysiol.00558.2011

Sheela, M. S., Amirthayogam, G., Hephzipah, J. J., Gopalakrishnan, S., & Chand, S. R. (2024). Machine learning based lung disease prediction using convolutional neural network algorithm. Mesopotamian Journal of Artificial Intelligence in Healthcare, 2024, 50–58.

Shirzadi, M., Mirshamsi, A., Esrefoglu, A., Rojas-Martinez, M., Marateb, H. R., Angel Mananas, M., & Vieira, T. (2023). A new force profile signal for a convex solution of muscle force estimation from electromyographic signals. Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference, 2023, 1–4. https://doi.org/10.1109/EMBC40787.2023.10340594

Sidek, S. N., & Haja Mohideen, A. J. (2012). Mapping of EMG signal to hand grip force at varying wrist angles. 2012 IEEE-EMBS Conference on Biomedical Engineering and Sciences, IECBES 2012, 648–653. https://doi.org/10.1109/IECBES.2012.6498069

Wight, J. T., Garman, J. E. J., Hooper, D. R., Robertson, C. T., Ferber, R., & Boling, M. C. (2022). Distance running stride-to-stride variability for sagittal plane joint angles. Sports Biomechanics, 21(8), 966–980. https://doi.org/10.1080/14763141.2020.1713207

Wu, C., Yan, Y., Cao, Q., Fei, F., Yang, D., Lu, X., Xu, B., Zeng, H., & Song, A. (2020). SEMG Measurement Position and Feature Optimization Strategy for Gesture Recognition Based on ANOVA and Neural Networks. IEEE Access, 8. https://doi.org/10.1109/ACCESS.2020.2982405