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RESEARCH ARTICLE

Predicting Hand Grip Force Based on Muscle Electromyographic Activity Using Artificial Intelligence and Neural Networks

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Abstract
This study aimed to establish predictive values for hand grip strength based on electromyographic activity while exploring disparities between measured and predicted grip strength among 12 proficient handball players. Grip strength was quantified using a specialized device recording Newton force in real-time at a 0.1-second sampling window, synchronized with muscle electromyographic activity (sEMG) recorded using the Noraxon myoMOTION technique. Various electromyographic parameters were assessed, including peak activity, root mean square, time to peak, and area under the curve. Grip strength measurements were taken at three stages (50%, 75%, 100%) and maintained for 3 seconds each. The data were analyzed using IBM Statistical software, implementing neural networks and artificial intelligence methods. The results revealed statistically insignificant differences between recorded and anticipated grip strength (p>0.05), indicating a high level of predictive accuracy. Minor disparities were observed, suggesting potential avenues for further investigation. This study contributes to our understanding of predictive modeling for grip strength and highlights the importance of electromyographic activity in assessing muscular performance.

Keywords
EMG, AI, Handgrip Force, Handball, Prediction Force, Neural Network

INTRODUCTION

Hand grip strength is a fundamental measure of upper extremity function and overall muscular performance. It serves as a reliable indicator of an individual's physical health, functional capacity, and quality of life across various age groups and populations (Bohannon, 2008; Leong et al., 2015; Celis-Morales et al., 2018). Moreover, grip strength has been associated with numerous health outcomes, including mortality, cardiovascular disease, and disability (Wei et al., 2023).

In recent years, electromyography (EMG) has emerged as a valuable tool for assessing muscle function and neuromuscular activation patterns during grip strength testing (Merletti et al., 2002; Mesin et al., 2011; Vieira et al., 2011). By capturing the electrical activity generated by muscle fibers, EMG provides insights into the recruitment and coordination of motor units, thereby offering a deeper understanding of muscular performance.

Additionally, advancements in EMG technology, such as high-density surface EMG and wireless EMG systems, have enhanced the precision and reliability of muscle activity measurements (Hauraix et al., 2019). Despite the extensive research on grip strength and electromyographic activity, there remains a gap in our understanding of the predictive relationship between these parameters. While previous studies

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have examined the association between muscle activation patterns and grip strength, few have sought to establish predictive models based on electromyographic data. By elucidating the underlying mechanisms driving grip strength, predictive modeling can facilitate early detection of muscle dysfunction and inform targeted interventions to optimize muscular performance.

In this study, we aim to address this gap by investigating the predictive values of hand grip strength based on electromyographic activity. Specifically, we will examine the relationship between muscle activation patterns measured via surface electromyography (sEMG) and grip strength in a cohort of proficient handball players. By leveraging advanced analytical techniques, including neural networks and artificial intelligence methods, we seek to develop robust predictive models that account for individual variations in muscle activation and strength. Our findings have the potential to inform personalized training strategies and enhance athletic performance in competitive sports settings.

MATERIALS AND METHODS

***Research Sample*:**

The research sample consisted of 12 advanced-level handball players (Table1.). Comprehensive examinations were conducted to ensure the absence of previous injuries or functional impairments in the targeted research area. Additionally, the medical records of the research sample were reviewed to confirm the absence of high blood pressure signs or abnormal indicators in both the circulatory and nervous systems (Rufo et al., 2021). The research sample comprised athletes engaged in regular training and play. This case study followed ethical standards and received approval from the Ethics Committee of Second Artillery General Hospital PLA with reference number KY2017016 and date 10/03/2022.

Table 1. Show the demographic characteristics and statistics of the participants.

Characteristic	Mean ± SD
Weight (kg)	75.6 ± 17.2
Age (years)	28.3 ± 7.2
Height (cm)	182.5 ± 8.5

Procedures

Targeted Muscles (Kunc et al., 2019).

The muscles responsible for hand movements (flexion and extension) at the wrist joint were identified as follows:

Brachioradialis

The brachioradialis is an arm muscle responsible for flexing the arm and elbow joint. It can also perform both movements: supination (turning the palm upward) and pronation (turning the palm downward), depending on the arm's position. It connects to the distant radial tuberosity of the radius bone through the brachioradial ligament and to the dorsal epicondyle above the radial notch of the humerus.

Flexor Carpi Radialis

In anatomy, this muscle in the human forearm functions to flex the hand (radially). The Latin term "carpus" refers to the wrist, indicating its role in wrist flexion.

Flexor Carpi Ulnaris

This muscle has two heads: the humeral head and the ulnar head. The humeral head originates from the medial epicondyle of the humerus via the common flexor tendon, while the ulnar head arises from the middle border of the olecranon and the upper two-thirds of the dorsal border of the ulna. The ulnar nerve and ulnar artery pass between these heads.

Extensor Carpi Radialis

It is one of the five fundamental muscles controlling wrist movement. As a long muscle, it originates from the lateral side of the forearm, attaching to the base of the second metacarpal bone. Its function involves extension at the wrist joint, moving the hand towards the thumb and away from the ulnar side.

***Extensor Carpi Ulnaris*:**

In human anatomy, this muscle is a structural muscle located on the ulnar side of the forearm. It functions in extending and adducting the wrist from the anatomical position.

Electromyographic Variables (S. Ismaeel et al., 2015).

Peak Electromyographic Activity

Defined as the highest recorded value through an EMG device, represented by the peak of the electrical wave.Measured in microvolts.

Root Mean Square (RMS)

A statistical measure used in electromyographic (EMG) analysis. Employed to measure the intensity or strength of electrical signals recorded from muscles over a specific time period.

RMS is calculated as the square root of the mean of the squared values of the muscle's electrical signal. Measured in microvolts (Vieira et al., 2017).

$$RMS = \sqrt{\frac{1}{n(x_1^2 + x_2^2 + \cdots x_n^2)}}$$

Peak Duration (Pd)

The time interval extending from the onset to the end of EMG peak. Represents the period during which muscle electrical activity appears at its maximum strength. Measured in milliseconds (S. Ismaeel, n.d.).

Ratio of Time Change between Peak and Trough (Ratio)

A mathematical value obtained by calculating the change in time between the peak and trough of recorded electromyographic activity. Indicates the ratio of the duration of the highest peak of EMG to the duration of the lowest trough. Measured as a dimensionless ratio (Journal et al., 2020).

Mean of Peaks (MOP)

The arithmetic means of the highest EMG values. Calculated by dividing the sum of EMG values for each peak by the number of peaks. Provides an average measure of electrical activity during peak instances. Measured in the respective units of electromyographic activity.

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

The Area Under the Curve (AUC)

The Area Under the Curve (AUC) is a measure of the enclosed area beneath a curve on a graphical plot. In the context of EMG or signal analysis for other biological activities, AUC signifies the integrated activity of the muscle over a specific time period. Typically, the curve represents the electrical activity of the muscle, and the AUC represents the total force or energy expended by the muscle during a specific timeframe.

The AUC is a valuable metric for quantifying the overall muscle activity within a given time frame. It is measured in units of microvolts × milliseconds and is often used to assess the total muscle force or energy consumption during a specific activity (Selvanayagam et al., 2012).

$$AUC = \int_a^b f(x)\,dx$$

Peak Sustain Time (Pt)

Represents the duration required for the maximum EMG to remain visible. Indicates the time the muscle maintains its peak electrical activity. Measured in milliseconds.

Peak-to-Valley Difference (Pv)

The recorded difference between the highest peak and the lowest trough of EMG. Provides a percentage difference for each recording. Reflects the dynamic changes in EMG. Expressed as a percentage.

Maximum Voluntary Contraction (MVC)

Refers to the maximum force or effort that a muscle or muscle group can generate voluntarily during a specific contraction. It serves as a measure of the maximum force or muscle output achievable by an individual in a specific context. Measured in units relevant to force or contraction strength (Jan et al., 1999).

Data Collection Tools

Hand Grip Force (HGF) measure

A device designed similar to a dynamometer was employed for measuring grip strength. This device allows data recording in multiple time windows with intervals as short as 0.1 seconds between each recording, as described by (Duque et al. 1995). The apparatus enables clear graphical representation for momentary evaluation, and it facilitates easy data export to Excel, as illustrated in Figure (1). Using the device, three attempts were given to each player, with each attempt executed at different intensities (50%, 75%, and 100%).

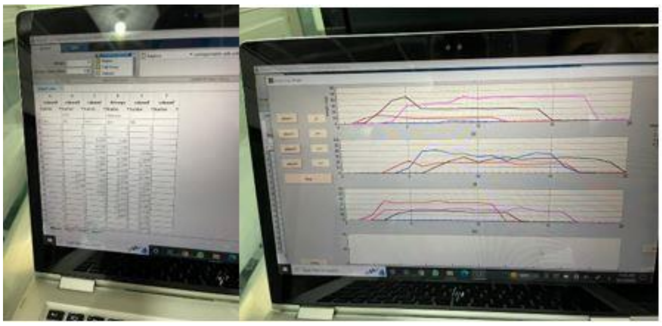

Figure 1. show the software

Stages of Applying Artificial Intelligence in the Research (Alwosheel et al., 2018)

Utilizing machine learning to estimate muscle strength based on electromyographicactivity involves several key steps

Data Collection

Begin by gathering a dataset containing electromyographic readings and accurately measured muscle strength. Comprehensive and diverse data are preferred to establish a robust and generalizable model.

Data Preparation

Preparing the data involves cleaning and formatting it for model training. This may include transforming electrical signals into variables usable as inputs for the model.

Feature Selection:

Choose important variables that the model should consider during training. This might involve analyzing the data to identify which variables have the most significant impact on electromyographic activity and muscle strength.

Data Splitting (Bonato et al., 2001)

Divide the data into two sets: one for training the model and another for testing its performance. This allows evaluating the model's ability to handle new, unseen data not used during training.

Selecting the Learning Model:

Use neural networks, statistical methods, and other suitable algorithms for addressing the estimation problem.

Model Training

Train the model using the training dataset, where it learns how to correlate electromyographic activity with muscle strength. The model aims to identify relationships and patterns in the data that can be used for predicting muscle strength.

Performance Evaluation

Test the model using the testing dataset to assess its performance and its ability to handle new data

Statistical Analysis

A statistical program was used in the statistical analysis of the data obtained. Arithmetic mean, standard deviation, frequency, minimum and maximum values were used in statistical representations of the data. In the normality testing of the data, kurtosis and skewness values of ±1.5 were taken into consideration (Tabachnick & Fidell, 2013). Neural networks were utilized to determine the relative importance of each variable, alongside leveraging artificial intelligence for predicting numerical values.

RESULTS

Table 2. Show the viriables describtion

Var.	%50		%75		%100	
	m	**±s**	**m**	**±s**	**m**	**±s**
HGF (N)	24.8	3.5	31.3	2.47	43.7	1.92
Peak (μV)	116	12.6	185	9.41	254	12.4
Rms (μV)	121	33.5	193	21.7	263	25.6
Pd (ms)	0.24	0.01	0.22	0.01	0.20	0.02
Ratio %	13	1.55	26	1.37	31	1.49
MOP (μV)	65	4.6	112	3.62	153	4.11
AUC (μV.s)	4366	238	652	341	863	541
Pt (ms)	0.98	0.08	0.64	0.07	0.56	0.049
Pv %	7.65	1.2	12.5	1.12	21.6	1.91
MVC	123	4.5	184	9.63	212	21.5

HGF hand grip force, Peak the peak of wave, Rms root mean square, Pd peak delay, Ratio of muscle power, MOP mean of peak, AUC area under curve, Pt peak time, Pv peak variance, MVC maximum voluntric contraction

Table 3. Shows the correlate among variables and HGF in 50%, 75%, and 100%.

		Peak	RMS	AUC	Pd	Ratio	MOP	MVC	Pt	Pv
50%	Pearson	0.020	0.017	0.030	0.047	0.004	0.039	0.072*	0.006	0.016
	Sig.	0.532	0.587	0.347	0.138	0.889	0.222	0.022	0.856	0.616
75%	Pearson	0.416**	0.025	0.002	0.069*	0.028	0.030	0.024	0.002	0.017
	Sig.	0.000	0.438	0.952	0.028	0.380	0.340	0.448	0.957	0.589
100%	Pearson	0.304**	0.306**	0.358**	0.230**	0.253**	0.387**	0.366**	0.358**	0.174**
	Sig.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

*P<0.05

Table 4. Model summary and it's trusted in 50%, 75% and 100%

Groups	Varibles	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

Table 5. Shows the importance of independantvariables 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%	0.023	12.2%
Pd	0.056	12.8%	0.289	100.0%	0.083	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 6. shows the descriptive and correlate between Handgrip Force (HGF) and Predictive Handgrip Force (P.HGF)

		N	Minimum	Maximum	Mean	Variance	skewness	Correlate	Sig.
50%	HGF	1000	12.69	36.72	24.79	12.6	0.074	0.066*	0.037
	P.HGF	1000	23.97	25.83	24.79	0.145	.208		
75%	HGF	1000	22.81	39.67	31.29	6.22	.074	0.396**	0.000
	P.HGF	1000	28.89	33.71	31.21	0.912	.043		
100%	HGF	1000	37.10	50.20	43.6951	3.763	.074	0.535**	0.000
	P.HGF	1000	39.31	48.20	43.6594	1.304	.197		

*P<0.05

DISCUSSION

Through the statistical results of the correlation coefficients between the variables of forearm muscle electrical activity during the three intensities under investigation, (Ismaeel & Fenjan, 2020), it is observed that correlation coefficients were mildly present at 50% intensity and were significant for non-maximal voluntary contractions (Wei et al., 2023). Meanwhile, there was no significant correlation between the variables and forearm muscle strength. From the same table, a noticeable increase in the correlation percentage is observed at 75% intensity, with a focus on the peak electrical activity variable and the variable of the duration of higher activity. Additionally, a significant correlation is found between all variables and forearm muscle strength at maximum intensity, suggesting that the observed changes are statistically meaningful (Clancy et al., 2005). A substantive explanation of the motor behavior of the muscle contraction being measured can provide insight into these findings (Smaeel et al., 2015). As wel as During muscle contraction, electrical signals are sent from the central nervous system (brain and spinal cord) to the muscle via nerve fibers. Although area under curve were ment the area under the electrical signal curve reflects the total electrical activity of the muscle over a specific time period (Králová et al., 2020).

Till that maximum force and time durationcan explane the maximum force of muscle contraction depends on factors such as the number of responsive motor units and the activation of muscle fibers (Wakeling et al., 2002). After the peak of electrical activity, the muscle may maintain the ability to produce force for a longer period. This endurance can be attributed to the resilience of muscle fibers and their capacity for sustained contraction (Rufo et al., 2021).

Precise regulation of electrical activity may occur to sustain muscle force. Control over the activation of motor units and the distribution of electrical signals may contribute to this objective. In general, the prolonged maintenance of maximum force over time is explained by various factors, including the precise regulation of neural signals and the physiological properties of muscles (Forrester & Petrofsky, 2004). Neural and hormonal control, alongside the characteristics of muscle fibers, plays a crucial role in achieving this sustained force (Nema, 2022) . The emphasis on muscle tension variability in generating force parallel to the stimulus is considered a significant academic source for understanding the objective changes in muscle contraction. This can provide a scientific explanation for the quality of the contraction, interpreting the nature of muscle tissue, and addressing training, rehabilitation, or health scenarios to optimize sports performance while considering the achievement of set goals (Journal et al., 2020). Understanding the nuanced aspects of muscle contraction is crucial in tailoring interventions for training, rehabilitation, or health improvement. The variations in applied muscle tension contribute to the diversity in force production, influencing the quality of contractions. Scientific insights into the nature of muscle tissue guide how training programs, rehabilitation strategies (Duque et al., 1995), or health interventions are structured. Dealing with training involves optimizing muscle tension to enhance performance, considering the specific goals set for athletic endeavors. Rehabilitation interventions aim to restore optimal muscle function, taking into account the intricacies of muscle contraction. Health-related considerations involve maintaining or improving muscle health while aligning with broader wellness objectives (Gabriel et al., 2011).

By utilizing artificial neural network (ANN) technology and dividing the dataset into two subsets, namely the training set and the testing set, we can observe that variations in the intensity affecting the muscles of the forearm lead to changes in the statistical descriptors of the two groups. This is evident in the table above (Vieira et al., 2017). The use of artificial neural networks allows for the modeling and analysis of complex relationships within the data. The training set is employed to teach the neural network the patterns and features inherent in the data, while the testing set is used to assess the network's ability to generalize to new, unseen data (Sidek & Haja Mohideen, 2012). In the context of studying forearm muscles and their response to intensity variations, the statistical descriptors of the training and testing sets may exhibit differences due to the distinct patterns learned by the neural network during training. These differences could reflect the network's capacity to capture and adapt to the varying levels of muscle tension (Ismaeel & Fenjan, 2020). It's important to carefully analyze the specific statistical descriptors affected, as this can provide insights into how the neural network is interpreting and responding to the variations in muscle intensity.

Additionally, (Selvanayagam et al., 2012), the performance of the network on the testing set helps evaluate its generalization capabilities and ensures that it can make accurate predictions on new, unseen data beyond the training samples (Jan et al., 1999).

Building a model to predict muscle strength based on electrical activity variables can indeed provide objective insights and logical explanations (Kunc et al., 2019). However, the confidence in this model may vary with different intensities measured through it. Mathematical indicators give a clear idea by conducting statistical analysis among the three intensities to assess the reliability of the model for each intensity (Hou et al., 2007). 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 (Wei et al., 2023). 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. 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 (Bonato et al., 2001). In essence, the model's effectiveness may be influenced by the nature of muscle behavior at different intensities. 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 (Wang et al., 2021). The statistical analysis conducted among the three intensities helps in assessing the robustness and reliability of the model across a range of muscle activities.

Conclusions

Different models are verified for each muscle contraction intensity (50%, 75%, 100%), each with its independent characteristics. The level of muscle mobilization is a fundamental principle in predicting muscle strength. Opportunity to explore the mechanisms of muscle action.

Recommendations

Classify the types of movements to be measured for strength according to intensity to achieve more logical results. Give greater importance to examining recorded strength along with expected strength simultaneously, with the option to disable self-data generation from within the application. Some variables of electromyographic activity associated with time and muscle strength need independent study based on the nature of the movement. Conduct applied field research coupled with standardized examination and evaluation devices. Low-intensity models exhibit a presence of variables related to time periods, while high-intensity models have a more pronounced presence of variables related to peak activity. There is inverse (negative) interference of some variables, providing a greater. There is a non-significant difference between the resulting and expected muscle strength using artificial neural networks.

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Conflict of Interest

We declare that this article we wrote is not involved in any conflict of interest.

Ethics Statement

The writing of this article has gone through all ethical procedures related to the academic realm. All the principles of the Declaration of Helsinki were complied, with special emphasis on informed consent and the vulnerability of the study population.

Authors Contribution

Study Design, ASM, JKA, SI and MAH; Data Collection, ASM, JKA, MAH, and SI ; Statistical Analysis, SI, JKA, MAH, and ASM; Data Interpretation ASM, JKA, MAH, and SI Manuscript Preparation, ASM, JKA, MAH, and SI; Literature Search, ASM, JKA, MAH, and SI. All authors have read and agreed to the published version of the manuscript.

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