IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 14, No. 4, August 2025, pp. 3228~3240
ISSN: 2252-8938, DOI: 10.11591/ijai.v14.i4.pp3228-3240

Myoelectric grip force prediction using deep learning for hand robot

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Article Info

Article history:

Received Feb 15, 2024
Revised Apr 21, 2025
Accepted Jun 8, 2025

Keywords:

Assistive robot
Deep learning
Grip force
Hand robot
Myoelectric

ABSTRACT

Artificial intelligence (AI) has been widely applied in the medical world. One such application is a hand-driven robot based on user intention prediction. The purpose of this research is to control the grip strength of a robot based on the user's intention by predicting the grip strength of the user using deep learning and electromyographic signals. The grip strength of the target hand is obtained from a handgrip dynamometer paired with electromyographic signals as training data. We evaluated a convolutional neural network (CNN) with two different architectures. The input to CNN was the root mean square (RMS) and mean absolute value (MAV). The grip strength of the hand dynamometer was used as a reference value for a low-level controller for the robotic hand. The experimental results show that CNN succeeded in predicting hand grip strength and controlling grip strength with a root mean square error (RMSE) of 2.35 N using the RMS feature. A comparison with a state-of-the-art regression method also shows that a CNN can better predict the grip strength.

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1. INTRODUCTION

The combination of artificial intelligence (AI) and biosensors within assistive systems has yielded promising outcomes across various research endeavors. AI-enhanced biosensors have demonstrated potential for rapid diagnostics, precision therapeutics, and disease management [1]. These technologies leverage machine learning, neural networks, and other AI techniques to improve biosensor functionality, connectivity, and point-of-care adoption [2]. Wearable biosensing technologies, empowered by AI, enable the monitoring of physiological signals and aid in disease diagnosis, supporting the trend toward personalized medicine [3]. The combination of AI with sensing technology has led to the development of intelligent biosensors capable of rapid target detection with high sensitivity, accuracy, and precision [4]. Jin *et al.* [5] delve into the challenges and prospects associated with AI-driven biosensors, highlighting the significance of material advancements, biorecognition components, and data processing techniques. These insights offer valuable guidance for the future evolution of AI-based biosensors tailored for assistive applications.

Electromyography (EMG) is a method for recording muscle signals. EMG has various applications, including controlling prosthetic robots for amputee patients to improve the robot-user interaction [6]–[11]. Anam and Al-Jumaily [6] focused on developing an amputation robot that moves according to the user’s wishes, paying attention to the user’s comfort and as if the robot were a part of his body. A prosthetic robot is ideally used to replace the patient's hand and move smoothly and with specific strength according to the user’s intention [12]. To ensure that a robot's hand can hold objects correctly and precisely according to grip strength, it is crucial to predict the grip strength. There have been various approaches proposed to predict grip strength. Lo *et al.* [13] investigated the use of grip strength to predict other hand exertions, finding it less effective for palmar pinch and thumb press.

Lv *et al.* [14] proposed a method based on surface EMG signals, optimizing a support vector regression model through the sparrow search algorithm to accurately predict hand grip strength. Sayadizadeh *et al.* [15] utilized artificial neural networks to predict grip and pinch strength based on hand anthropometric parameters, identifying key predictors such as hand length, width, and shape index. Chihi *et al.* [16] used a technique based on the nonlinear Hammerstein-Wiener model. Some researchers are also starting to use deep learning to predict grip strength. Su *et al.* [17] proposed a convolutional neural network (CNN) to predict the strength of the EMG signal. However, this study did not specifically focus on hand-grip strength. Hwang *et al.* [18] presented deep neural networks that can predict hand grip strength, but the results have not yet been used to control robots directly. It is necessary to further evaluate the implementation of force prediction on robotic hands. Several investigations have delved into utilizing deep learning models to forecast grip strength through EMG signals.

Xu *et al.* [19] introduced impedance signals to predict grip force, achieving high accuracy with a long short-term memory (LSTM) model. Jiang *et al.* [20] devised an adaptive neural fuzzy inference system employing surface EMG signals, effectively predicting grip strength and offering insights into rehabilitative therapy. Ma *et al.* [21] utilized a gene expression programming algorithm and a back propagation neural network to construct a prediction model for grasping force based on sEMG signals, achieving impressive accuracy. However, the results were not directly used to control the robot. These studies demonstrate the potential of deep learning models in accurately forecasting grip strength through EMG signals. However, it should be noted that the results were not directly applied to robot control.

This article aims to design a grip strength control system for hand robots using deep learning, specifically the CNN. This research presents a novel framework for robotic hand control through grasp force prediction, advancing the state-of-the-art in dexterous manipulation. The framework incorporates a comprehensive comparative analysis of deep learning architectures, specifically evaluating various CNN models against traditional approaches, including LSTM networks and classical machine learning algorithms such as random forest (RF), k-nearest neighbors (k-NN), and decision trees (DT). The experimental results demonstrate the framework's effectiveness in enhancing grip precision and control efficiency, providing valuable insights for the development of more sophisticated robotic manipulation systems. In addition to its application in robotic control, CNNs have been widely utilized in other domains. Examples include early stroke disease prediction [22] and detecting student attention levels [23]. These examples highlight the versatility of CNNs in addressing diverse challenges across fields.

The article's structure is as follows. Section 2 discusses the methods used in this study. Section 3 presents the results and discussion. Finally, the article concludes with key findings and future directions.

2. METHODS

This research aims to design a robot control system based on predictions of the user's grip strength based on muscle signals using deep learning methods. The deep learning method used is a CNN. The general design of the system is shown in Figure 1. The proposed control system appears to be an open loop because there are no pressure sensors on the robot or the robot’s fingertips. However, the detected strength sensor comes directly from the user, namely from the muscle signals decoded by CNN. Details of each stage will be explained in the following sections.

2.1. Acquisition and pre-processing data

The Myo armband collected muscle signals, or EMG. The Myo armband was attached to the participant's forearm while the hand gripped the hand dynamometer. Data were collected from five respondents who were instructed to move their hands through opening and grasping motions at predetermined intervals of 15 seconds for each strength parameter. The study participants were men aged 20 to 25 years with good hand muscle condition based on the diameter of their arms. This research included respondents who had physical and mental health without a history of illness. The EMG device was installed on the forearm of the respondent's right hand, which held the hand dynamometer. Efforts were made to ensure that the respondents were as comfortable as possible so they could focus on moving their hands. The conditions of the respondents during data collection are shown in Figure 2. This data collection procedure was approved by the Ethics Commission of the University of Jember under number 960/UN25.8/KEPK/DL/2020.

The steps in preprocessing EMG signal data are signal filtering and windowing, that is, taking a signal at a certain time. The EMG signal filtering process uses a bandpass filter by entering the upper limit and lower limit value parameters and a notch filter to overcome the disturbance of the mains voltage. A bandpass filter ensures that the signal being processed is an EMG signal, which usually ranges from 10 to 500 Hz. The strength prediction system is an overview of the data processing system shown in Figure 3. The prediction system consists of three stages: data acquisition, preprocessing, and prediction. Data acquisition collects muscle electrical activity and handgrip strength (N). Preprocessing involves EMG signal filtering (bandpass and notch filters), windowing for structured sampling, and feature extraction using root mean square (RMS) and mean absolute value (MAV). Finally, CNN is used to predict EMG data, generating an accurate prediction model.

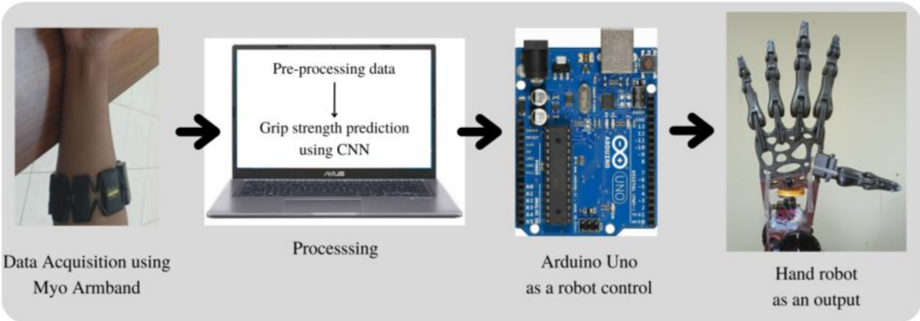


Figure 1. The proposed control system

Figure 2. Data collection

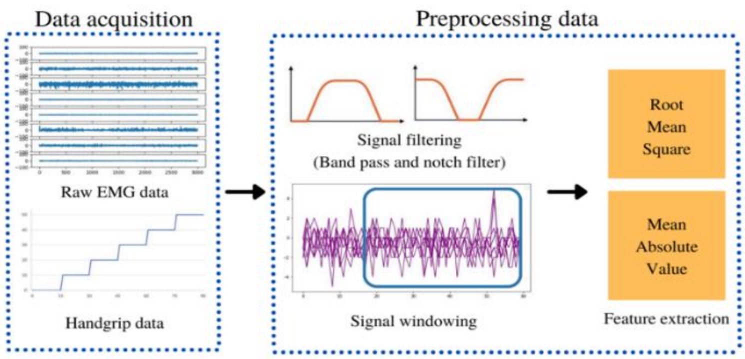


Figure 3. Data processing

2.2. Feature extraction

Feature extraction is performed before the forecasting stage using a CNN. The feature extraction used in this investigation is the RMS and MAV. Apart from that, raw signals will also be tested without going through the extraction feature. The mathematical formula for the RMS feature extraction is shown in (1).

$$RMS = \sqrt{\frac{1}{T}\int_{to}^{to+T} x(t)^2 dt} \tag{1}$$

The MAV extraction feature is widely used to process EMG signals digitally. MAV describes the signal features using the formula for average and absolute values. The mathematical formula for the MAV feature extraction is shown in (2).

$$MAV = \frac{1}{N}\sum_{i=1}^{N}|x_i| \tag{2}$$

2.3. CNN architecture design for grip strength prediction

The CNN architecture is comprised of two main parts: feature learning and classification. The feature learning process involves a series of layers, including convolutional and pooling layers. The classification process includes flattened and fully connected layers. This research investigates two CNN architectures, each with parameters such as input shape, filter, kernel size, pooling size, and fully connected layer. The study utilizes a one-dimensional CNN (1D CNN), and the parameter values are presented in Table 1.

Table 1. CNN architecture configuration

	Convolution layer			Kernel size			Pooling size		
Architecture	Layer 1	Layer 2	Layer 3	Layer 1	Layer 2	Layer 3	Layer 1	Layer 2	Layer 3
CNNs 1	128	64	32	4	2	1	2	1	1
CNNs 2	128	64	-	4	2	-	2	1	-

In Table 1, the values of the architectural parameters remain the same, and the only difference is in the input shape. The input shape of the raw data is 40.8, which is obtained from the windowing results. On the other hand, the input shape of the RMS and MAV data is 8.1, which is obtained after reshaping the windowing data. This is necessary because feature extraction using RMS and MAV is not sequential. The original windowing data was a 3-dimensional matrix, and it became two-dimensional due to the loss of sequence. Therefore, reshaping is necessary to change the RMS and MAV data matrices to match the CNN. The CNN architecture can be described in Figures 4 and 5. Figure 4 shows 8 depth layers starting from input shape, convolution 1, pooling 1, convolution 2, pooling 2, convolution 3, pooling 3, flatten, and dense, and Figure 5 shows the architecture 2 raw data has 2 convolution layers, 2 pooling layers, flatten, and dense.

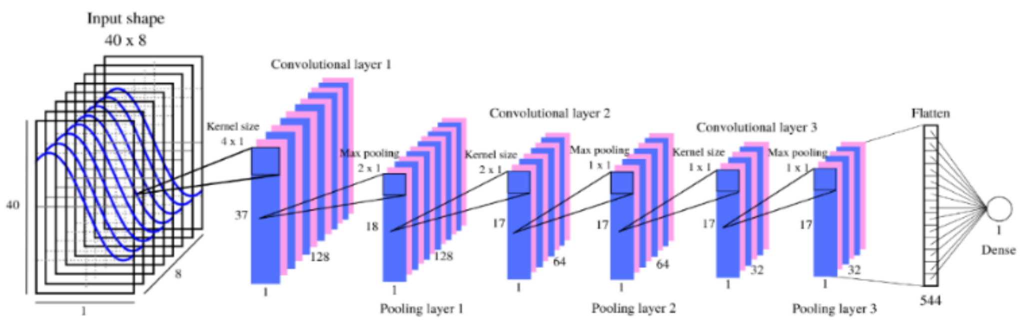


Figure 4. CNN architecture 1

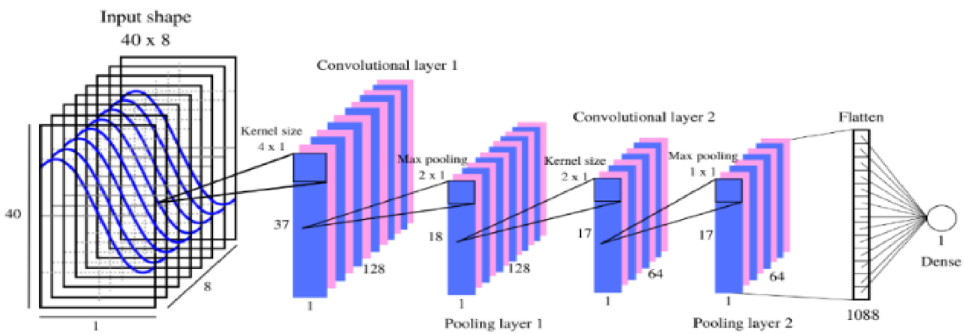


Figure 5. CNN architecture 2

2.4. Predict hand grip strength with CNN

The input for CNN is from the feature extraction process on the EMG signal using RMS and MAV. This research utilized a 1D CNN with several layers: the input, convolutional, sampling, and output layers. A schematic representation of the CNN method for predicting muscle grip strength is shown in the Figure 6 illustrates the prediction methodology using raw EMG data and CNN. The Myo armband records muscle electrical activity from eight sensor channels, which undergo bandpass and notch filtering before being windowed. Features are extracted using RMS and MAV, serving as CNN input. The CNN process includes convolution, pooling, and fully connected layers, transforming data from two to three dimensions (x, y, z) with filters (z-axis) and kernel size adjustments. The resulting feature map predicts handgrip strength, which is recorded alongside EMG signals.

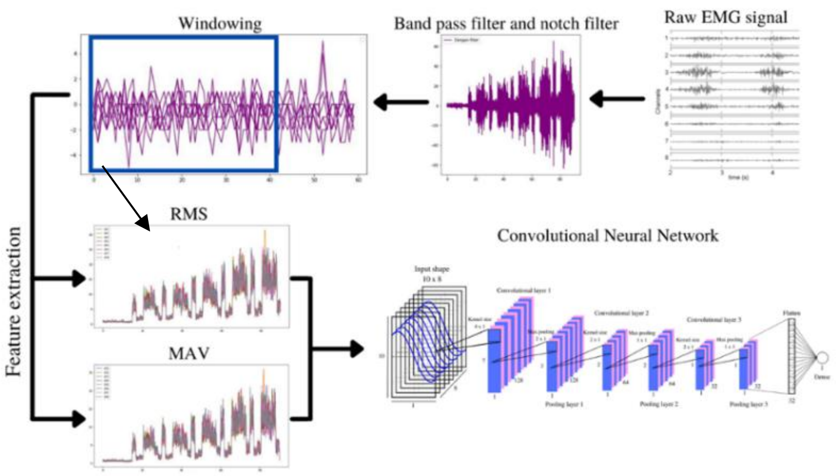


Figure 6. Schematic representation of the prediction of the grip force

2.5. Low-cost prosthetic hand

A hand prosthetic robot is a robotic hand that is used for gripping. This type of prosthetic is designed to excel at grasping rather than manipulating tasks. It features high dexterity, sophisticated sensors, and advanced control strategies. Five servo motors are used on the five robot fingers with the Arduino, as shown in Figure 7. In this figure, the configuration of the servo motor pins on the robot's finger is as follows: thumb on pin 3, index finger on pin 4, middle finger on pin 5, ring finger on pin 6, and little finger on pin 7. The Myo Armband dongle connects to a PC via Bluetooth, which is serially linked to an Arduino Uno for transmitting servo motor angle control data. Five servomotors share parallel VCC and ground connections, powered through an LM2596 step-down module with a 3-cell 2200 mAh LiPo battery. The 11.1 V battery input is regulated to 5 V, matching the servo motor's operating voltage.

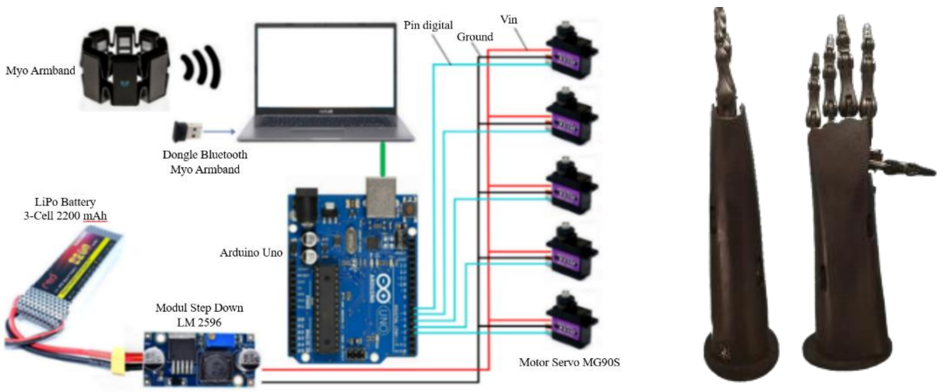


Figure 7. Electronic circuit design of hand robot

3. RESULTS AND DISCUSSION

3.1. Offline testing results of CNN data RAW, RMS, and MAV architecture

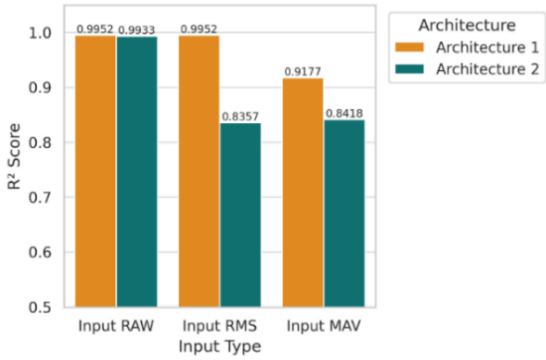
Once the parameters of the CNN and its architecture are defined, experiments are conducted on the RAW, RMS, and MAV data to identify the most accurate predictive results from the pre-determined architecture. To achieve this, a training and testing ratio of 7:3 was utilized. The outcomes of the experiments conducted on the RAW, RMS, and MAV data from the two architectures, namely architecture 1 and architecture 2, are presented in Table 2.

Based on the data obtained, a comparison has been made of three pre-processing methods: raw data, RMS, and MAV. With raw data, the CNN1 architecture achieves an average accuracy that exceeds that of the CNN2 architecture, recording a value of 0.9952 and a low MSE of 0.777. The second test with RMS shows results nearly identical to CNN1, with an accuracy of 0.8358 and CNN2 at 0.8357; however, the MSE values differ significantly, with CNN1 at 19.142 and CNN2 at 41.971. In the third test, using MAV, notable results were achieved, with CNN1 attaining an R^2 score of 0.9177 and CNN2 an R^2 score of 0.8418.

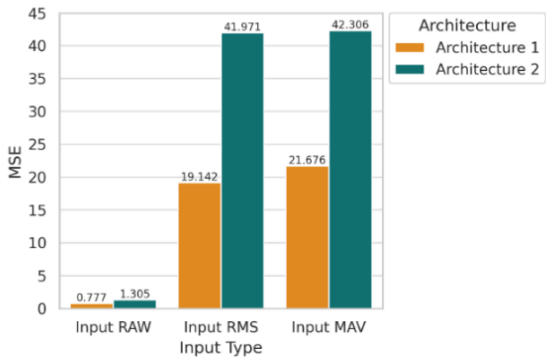
Figure 8 describes the performance comparison of CNN architecture based on input features. Figure 8(a) depict a comparison chart of the R^2 and Figure 8(b) depict a comparison chart of the RMSE of architectures 1 and 2, based on three input features. CNN1 architecture performs significantly better with raw data than RMS or MAV, suggesting that raw data contains more relevant information for precise predictions. However, real-time implementation on robots must consider processing power and memory constraints, requiring a balance between accuracy and practicality. Future research could explore alternative or combined input features to enhance CNN performance. Overall, architecture 1 with raw data appears to be the optimal choice for real-time robotic applications.

Table 2. CNN architecture testing results

Subject	RAW				RMS				MAV			
	R^2		MSE		R^2		MSE		R^2		MSE	
	CNN1	CNN2	CNN1	CNN2	CNN1	CNN2	CNN1	CNN2	CNN1	CNN2	CNN1	CNN2
1	0.9967	0.9964	0.640	0.880	0.8376	0.8376	18.019	40.122	0.9202	0.8611	20.381	33.972
2	0.9949	0.9899	1,100	2,131	0.8165	0.8165	23.145	45.430	0.8800	0.8565	29.642	39.805
3	0.9933	0.9908	0.784	0.935	0.8184	0.8184	20.632	43.787	0.9338	0.8410	17.020	45.176
4	0.9967	0.9952	0.646	1.198	0.8217	0.8217	15.925	47.623	0.9201	0.8171	20.874	48.346
5	0.9948	0.9943	0.717	1.385	0.8846	0.8846	17.990	32.896	0.9345	0.8337	17.921	44.231
Mean	0.9952	0.9933	0.777	1.305	0.8358	0.8357	19.142	41.971	0.9177	0.8418	21.676	42.306



(a)

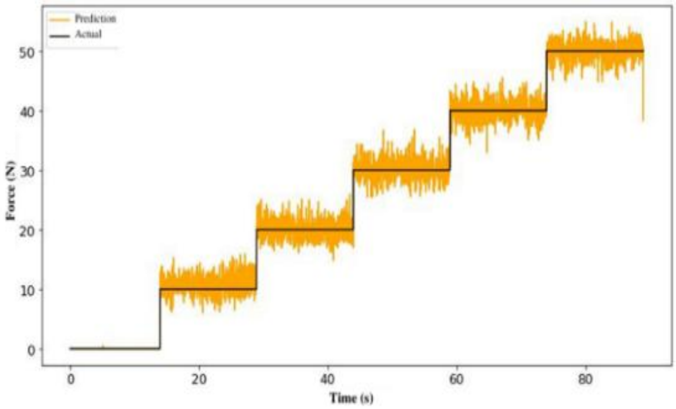


(b)

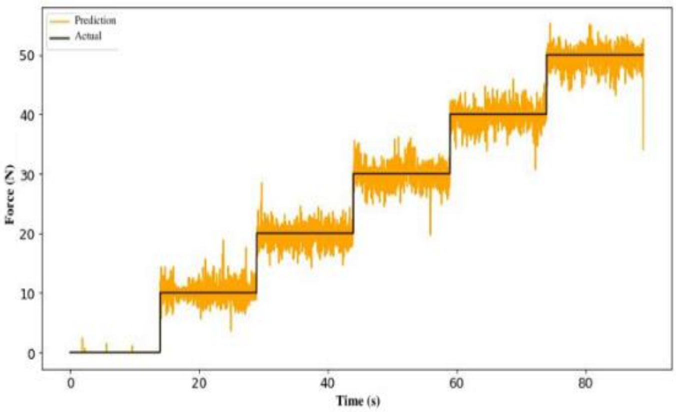
Figure 8. Comparison of average performance between architecture 1 and architecture 2: (a) R^2 and (b) MSE

3.2. Grip strength prediction testing

After experimenting with various types of architecture, the predictive results of grip strength were tested. The tests were carried out on the input data from RMS and MAV using the first CNN architecture. Figure 9 predict the results of CNN model in Figure 9(a) using RMS and Figure 9(b) using MAV features can follow the target but produces oscillating predictions. For instance, at a target of 10 N, the predicted output fluctuates around this value rather than being exact. Smoothing techniques like moving averages can improve real-time performance. While it is unclear whether RMS or MAV performs better, the RMS-based model exhibited fewer oscillations. Raw data was excluded to minimize processing demands for real-time control. Overall, the CNN architecture effectively predicts grip strength, though minor deviations from target values remain.



(a)

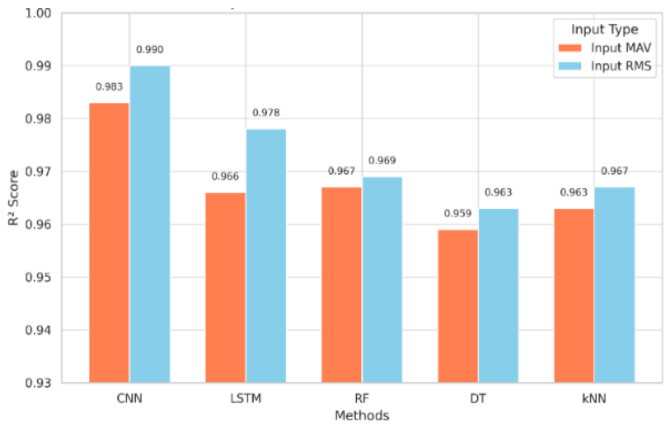


(b)

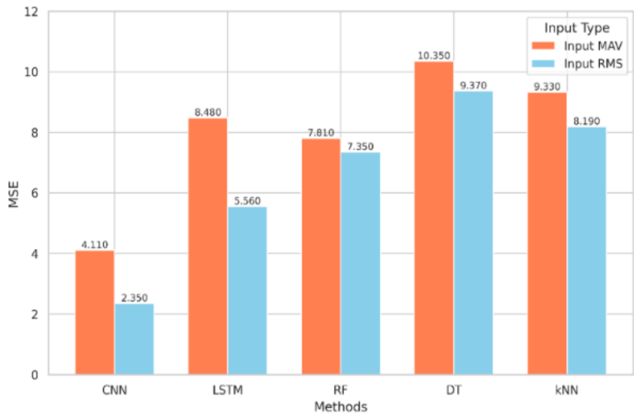
Figure 9. CNN prediction results with feature extraction using (a) RMS and (b) MAV

3.3. CNN and other methods

Figure 10 presents the results of a comparison of the CNN method with four other methods, namely LSTM, RF, DT, and KNN. Figure 10(a) illustrated the comparison measures use R^2 and Figure 10(b) illustrated MSE. These figures provide a detailed comparison of the five different methods. Figure 10 show two interesting things to discuss: the effect of features on model performance and the model's performance. In terms of features, the RMS feature is better than the MAV in all models. Thus, the RMS feature is most recommended compared to the MAV feature. As for model performance, deep learning models are generally better than machine learning models, with the CNN model being the best. If we look at the performance of the models from the R^2 side, it seems that the difference in the performance of the CNN model and the other models is not too significant. However, the difference is quite significant when viewed from the RMSE value. The CNN model with the RMS feature produces an RMSE error of about 2 Newtons, whereas the LSTM is around 6 Newtons. Even in the DT, it can be up to 10 Newtons. Meanwhile, the highest force value measured by the sensor is 50 Newton. Therefore, the RMSE error value of 10 Newtons is very large. With an RMSE error value of around 2 Newtons, the performance of the CNN mode will look very good.



(a)

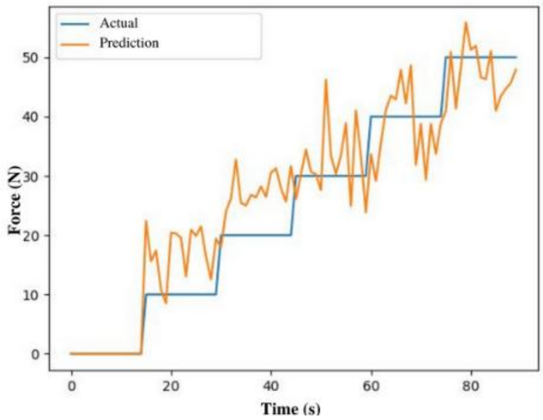


(b)

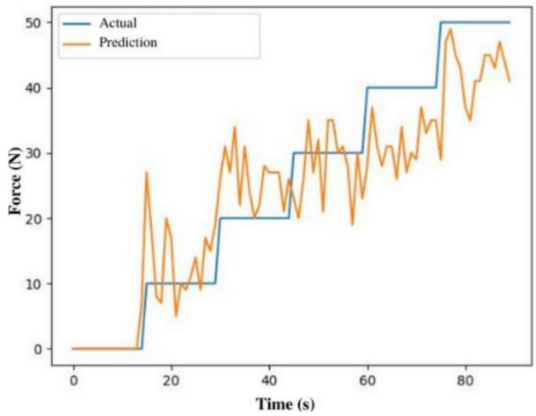
Figure 10. Comparison between five methods based on: (a) R^2 and (b) MSE

3.4. Online experiments

The process of testing predictions directly before they are applied to the hand robot is called online testing. This test makes use of EMG data, with RMS and MAV extraction features, using the CNN method that was previously trained in the offline experiment. Figure 11 present the results for the online test of the CNN method using RMS are presented in Figure 11(a) and MAV extraction features as shown in Figure 11(b) are very similar. However, upon closer comparison, the online test with RMS feature extraction has a predicted value that is almost identical to the actual value.



(a)



(b)

Figure 11. Online test results with (a) RMS and (b) MAV feature extraction

3.5. Robot implementation

3.5.1. Actuator testing

Servomotor actuator testing is performed to calibrate the angle of rotation of the servomotor. A parallel arc is placed at an angle of 0 to obtain an angle that corresponds to the angular parameters for each strength. The angle measurement data from the servo motor is then averaged, and the percent error value is calculated. The resulting measurement of the angle of the servo motor in the hand robot is presented in Table 3.

Table 3. Actuator testing

Force (N)	Angles (°)	Servo angle measurement (°)					Average angle (°)	Average error (%)
		Thumb	Index finger	Middle finger	Ring fingers	Little finger		
0	50	48	50	48	49	49	48.8	2.45
10	70	65	68	65	67	67	66.4	5.42
20	90	85	85	80	80	85	84	7.14
30	110	100	105	100	100	105	103	6.79
40	130	120	120	120	120	120	120	8.3
50	150	140	140	140	140	140	140	7.14

In this evaluation, we determined the accuracy parameter of the servo rotation with a maximum error value of 10%. The test results revealed that the highest percentage error observed was 8.3%. Our measurements of the angles on the robot's finger produced slightly different average values for each angle measurement compared to the actual angle. This is supported by the percentage of error values that fall below 10%. As such, we can confidently affirm that all the servo rotations of each finger work with utmost accuracy.

3.5.2. Hand grip strength testing in robots

The CNN prediction results are sent to Arduino to drive the strength of the robot grip. The results of the grip test on the robot are shown in Figure 12. For the predicted strength of 0 and 10 N, the operator should hold the cup because it is not strong enough for the robot to grip the plastic cup. The robot can grip plastic cups well for grip strength greater than 20 N.

0 Newtons 10 Newtons 20 Newtons 30 Newtons 40 Newtons 50 Newtons

Figure 12. Robot hand's grip strength measured in experiment

3.6. Discussion and limitation

The investigation of grip strength prediction through advanced CNN architectures represents a significant advancement in robotic hand control and biomechanical signal processing. Our proposed methodology demonstrates remarkable predictive performance, achieving an R^2 score of 0.99, which substantially outperforms previous methodological approaches in the field of grip strength estimation. A critical examination of existing research reveals a progressive improvement in predictive accuracy across various machine-learning techniques. As illustrated in the comparative performance Table 4, the performance of grip strength prediction methods has evolved from linear regression (R^2=0.82) to increasingly sophisticated neural network approaches. Our CNN-based method represents the current pinnacle of performance, significantly advancing the state-of-the-art in grip strength prediction.

Table 4. Comparative performance of grip strength prediction methods

Research methods	R^2 score
Regression [24]	0.82
MLP [18]	0.88
LSTM [25]	0.90
NN [26]	0.98
CNN (proposed method)	0.99

Despite the promising results, several critical limitations must be addressed in future research. The current system's prediction results, while generally accurate, exhibit occasional fluctuations that could pose risks when handling delicate objects. This variability necessitates further refinement to ensure consistent and precise grip strength prediction. Moreover, the study's current scope is limited to testing on healthy subjects, creating a significant research gap in understanding the system's effectiveness for amputee populations. Future studies should prioritize extending the research to diverse subject groups, particularly individuals with limb differences, to validate and optimize the proposed methodology. The study's findings extend beyond mere technical achievement, offering profound insights into the potential of deep learning methods for grip strength prediction. The proposed CNN architecture not only demonstrates superior predictive capabilities but also opens new avenues for advanced prosthetic control, rehabilitation technologies, and human-robot interaction interfaces. By bridging the gap between biomechanical signal processing and machine learning, this research contributes to the broader scientific understanding of precise force control in robotic and assistive technologies. Future research should focus on refining the predictive model, exploring transfer learning capabilities, and conducting extensive real-world validation trials to unlock the full potential of this innovative approach.

4. CONCLUSION

The aim of the study was to assess the effectiveness of CNN in controlling the grip strength of a robotic hand by predicting user grip strength through EMG signals. EMG signals are generated when muscles contract, and they can provide an accurate measurement of grip strength. The study evaluated two different CNN architectures, CNN1 and CNN2, to determine the best approach. CNN1 was designed with eight depth layers, while CNN2 had six depth layers and utilized raw and RMS input data. After analyzing the results, CNN1 proved to be the superior architecture. The predicted grip strength was successfully transmitted to the robotic hand, but the system did not maintain a consistent level of strength. Therefore, future research will focus on addressing this issue to improve the system's performance. The study highlights the potential of deep learning techniques, such as CNN, in controlling robotic hand grip strength. With further advancements in this area, this technology can have a significant impact on improving the quality of life for individuals with limited hand functionality.

FUNDING INFORMATION

This research is financially supported by Grant of International Collaboration Research 2022, Institute for Research and Community Service, University of Jember, under contract number 4393/UN25.3.1/LT/2022.

AUTHOR CONTRIBUTIONS STATEMENT

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Va : **Va**lidation
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I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are not publicly available due to privacy or ethical restrictions.

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