International Journal of Artificial Intelegence Research
Vol. 9, No. 1, June 2025
ISSN 2579-7298

Research on the Application of Artificial Intelligence in Hand Rehabilitation by Estimating Hand Grip Force using EMG Data

Tien Manh Nguyen [a,1], Motoki Takagi [a,2], Trung Thanh Nguyen [b,3], Hieu Huy Tran [b,3], Khanh Viet Trong Dao [b,3]

[a] Shibaura Institute of Technology Graduate School, 307 Fukasaku, Minumaku, Saitama-city, Saitama, Japan
[b] National Research Institute of Mechanical Engineering, 4 Pham Van Dong, Cau Giay, Hanoi, Vietnam
[c] HaNoi University of Science and Technology, 1 Dai Co Viet Street, Bach Khoa, Hai Ba Trung, Hanoi, Vietnam
[1] nb23103@shibaura-it.ac.jp*; [2] takagim@shibaura-it.ac.jp; [3] trung.nguyenthanh@hust.edu.vn; [4] hieu.lth210355@sis.hust.edu.vn; [5] khanh.dvt216154@sis.hust.edu.vn
* corresponding author

ARTICLE INFO

Article history
Received
Revised
Accepted

Keywords
Grip Force
EMG
Rehabilitation
Machine Learning

ABSTRACT

The human hand is a complex and functionally significant anatomical structure, playing a critical role in daily activities, communication, and professional tasks. Any impairment due to injury, neurological disorders, or musculoskeletal diseases can severely affect an individual's quality of life. Conditions such as stroke-induced hemiparesis, arthritis, carpal tunnel syndrome, and tendon injuries often necessitate rehabilitation to restore function, minimize pain, and prevent secondary complications. Traditional rehabilitation approaches, while beneficial, generally follow a standardized methodology, failing to account for individual variations in muscle strength, neuroplasticity, and adaptive capacity.Modern rehabilitation methods leverage advanced technologies such as electromyography (EMG) and hand grip force measurement to enhance therapy effectiveness. Additionally, artificial intelligence (AI) applications, particularly Long Short-Term Memory (LSTM) networks and Transformer models, have emerged as promising tools for personalized rehabilitation. These models analyze EMG signals to predict hand movement intentions, enabling adaptive rehabilitation strategies tailored to individual needs. This study focuses on the construction of a real-time EMG signal acquisition system and uses them as input to LSTM and Transformer models to compare and analyze the performance of the two types of models. By demonstrating the superiority of applying AI for personalization over the general AI approach, this study highlights the potential of AI in hand rehabilitation in particular and healthcare in general with its ability to specialize for each individual patient..

1. Introduction

The human hand is one of the most intricate and functionally significant anatomical structures, enabling complex movements essential for daily living, work, and social interactions. The hand consists of 27 bones, numerous muscles, tendons, ligaments, and an extensive network of sensory and motor neurons that allow for precise control of grip strength, dexterity, and tactile feedback [1]. Its functionality extends beyond simple grasping and manipulation; it plays a pivotal role in communication, particularly in sign language and non-verbal cues. Given its crucial role, any disorder or injury affecting the hand necessitates effective rehabilitation to restore function and improve overall well-being. Hand dysfunction can result from various conditions, including traumatic injuries, musculoskeletal disorders, and neurological impairments. Common conditions requiring rehabilitation include stroke. arthritis, carpal tunnel syndrome, Dupuytren’s contracture, and peripheral nerve injuries

[2]. Rehabilitation plays a critical role in restoring function, minimizing pain, and preventing secondary complications following injury or disease. The primary goals of rehabilitation include improving muscle strength, restoring joint mobility, enhancing coordination, and promoting neuroplasticity for functional recovery [3]. Here is a list of some typical cases of hand dysfunction that require hand rehabilitation:

- Stroke-Induced Hemiparesis: Stroke is a leading cause of disability worldwide, frequently resulting in hemiparesis or hemiplegia, which impairs hand function on one side of the body [4]. Post-stroke rehabilitation aims to restore motor control and hand dexterity.
- Arthritis and Degenerative Disorders: Osteoarthritis and rheumatoid arthritis lead to joint stiffness, pain, and progressive loss of movement in the hand, requiring rehabilitation to maintain mobility and reduce discomfort [5].
- Carpal Tunnel Syndrome (CTS): CTS results from median nerve compression, leading to numbness, weakness, and pain. Conservative and post-surgical rehabilitation strategies focus on restoring grip strength and reducing symptoms [6].
- Hand Trauma and Tendon Injuries: Fractures, lacerations, and tendon injuries significantly impact grip force and dexterity. Rehabilitation for such injuries includes exercises to restore strength and flexibility [7].

Rehabilitation is particularly crucial for individuals recovering from stroke, neurological disorders, or musculoskeletal injuries, where loss of fine motor skills can severely impact independence. Research suggests that early and intensive rehabilitation leads to better functional outcomes by stimulating neural pathways and preventing muscle atrophy [8].

Modern rehabilitation approaches incorporate electromyography (EMG) and hand grip force measurement to monitor and enhance the effectiveness of exercises. EMG measures muscle electrical activity, providing real-time feedback for neuromuscular training, while grip force measurement assesses strength levels and functional improvements. EMG biofeedback has been used in stroke and neuromuscular rehabilitation to improve voluntary muscle activation. EMG-driven robotic exoskeletons help restore hand movement by assisting weakened muscles [9]. Devices measuring grip force are commonly used in rehabilitation for conditions like stroke and arthritis. They help track improvements in hand strength and allow personalized training programs tailored to the patient's needs [10]. Studies have demonstrated that EMG-controlled robotic gloves and exoskeletons significantly improve hand function in stroke survivors by promoting repetitive task practice and neuroplasticity [11].

Traditional hand rehabilitation programs often follow a standardized approach, applying the same therapy protocols to a broad patient population. While effective for general recovery, this method fails to address individual differences in muscle strength, neuroplasticity, and adaptive capacity [12]. Personalized rehabilitation, in contrast, considers each patient’s specific impairments, progress rate, and adaptive responses. Several studies emphasize the drawbacks of generalized rehabilitation, highlighting the importance of tailoring therapy to an individual’s specific deficits. Personalized rehabilitation can optimize treatment outcomes by adjusting intensity, duration, and type of exercises based on real-time feedback from EMG and grip force sensors [13].

Artificial intelligence (AI) has gained significant attention in rehabilitation due to its potential to provide adaptive and personalized therapy. Machine learning models, such as Long Short-Term Memory (LSTM) and Transformer architectures, are being increasingly utilized for movement prediction, rehabilitation monitoring, and biofeedback analysis. LSTM networks, a type of recurrent neural network (RNN), have been used to analyze EMG signals for predicting hand movement intentions in individuals with neuromuscular impairments. These models enhance prosthetic and exoskeleton control, providing more natural hand movements [15]. Transformers, known for their efficiency in processing sequential data, have been applied in motion prediction and rehabilitation robotics. By analyzing grip force patterns and muscle activity, Transformer-based models can optimize therapy by adjusting rehabilitation exercises dynamically [16]. Recent advancements in AI- driven rehabilitation suggest that combining EMG biofeedback with machine learning models can lead to more effective and adaptive therapies, improving patient outcomes [17]. There have been several studies using AI to predict hand grip force, such as in the study by Hongxin Cao, which used extreme learning machine (ELM), support vector machine (SVM), and multiple nonlinear regression (MNLR)

 ISSN 2579-7298

with the input of EMG signals to predict hand grip force with a maximum accuracy of up to 80.6% [18]. Pan Xu's study used electrical impedance myography (EIM) applying a weak alternating current signal of known frequency to obtain muscle impedance parameters, combined with LSTM to predict hand grip force with a maximum accuracy of up to 90.23% [19]. Betzalel Fialkoff's study used the Logarithmic Transformer with an input of 8 EMG signals to predict handgrip force with a maximum accuracy of up to 97% [20]. Chang Liu's research developed a flexible EMG sensor for muscle strength assessment and rehabilitation training, through extracting EMG features according to different muscle strengths, the project realized the research of muscle strength feedback through EMG, using LSTM model and back propagation network (BP- ANN) with a maximum accuracy of 98.81% [21]. As of this study, Chang Liu's research shows the state-of-art of using AI to estimate handgrip force with EMG as input data.

The hand is an essential organ for human functionality, and its impairment due to disease or injury necessitates effective rehabilitation strategies. Traditional rehabilitation approaches, while beneficial, often lack personalization, highlighting the need for individualized therapy. EMG and grip force- based methods have improved rehabilitation effectiveness, and AI applications, such as LSTM and Transformer models, offer promising advancements for adaptive rehabilitation. Our research focuses on applying AI in rehabilitation to further personalized hand therapy, ultimately enhancing patient recovery and quality of life.

The works and contributions of our papers are summarized as follows:

- Fabricate a system to capture EMG signals from the hand at 200Hz frequency continuously in real time. Design LSTM and Transformer models specifically for that EMG input data.
- Performance comparison between LSTM Model and Transformer Model when input is continuous EMG data over time.
- Comparing the accuracy between applying personalized AI to a specific person with AI generalized to a group of people. Confirming the vast potential of AI personalization in Rehabilitation

2. Method

2.1 Collecting EMG data

Based on the anatomical study of the flexor digitorum superficialis (FDS) muscle, the electrode placement positions were precisely determined. One electrode is placed at the innervation zone [22] of the FDS muscle, identified in this case as the area near the wrist. Another electrode is positioned on the muscle belly. Both locations are considered optimal for obtaining high-quality EMG signals

[23] which are labeled as green and red, respectively. To obtain clear signals, a yellow reference electrode was placed at a low potential position on the elbow. The electrode placement positions are illustrated on Fig.1.

Ten subjects were instructed to perform gradually increasing and decreasing grip force levels at evenly spaced time intervals. The force levels were chosen to be sufficiently different so that the measurement tool's error would not significantly impact the results. Additionally, the required grip force was not too high to avoid discomfort for the participants. After careful consideration of these conditions, the study employed grip force levels of 3, 6, 9, and 12 kg. Each grip force level was maintained for 10 seconds, with a rest period (muscle relaxation) of 10 seconds between grips. The gripping and releasing process was performed continuously during a single EMG signal measurement to ensure the continuity and accuracy of the collected data.

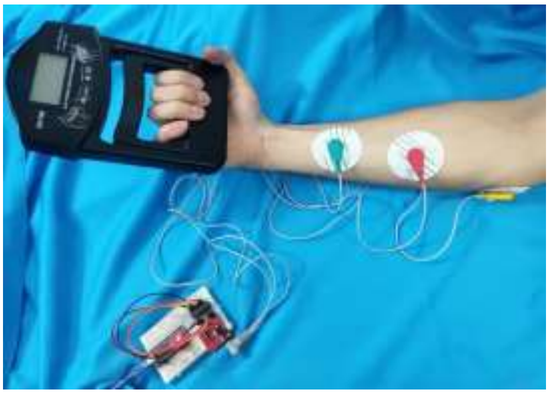


Fig. 1.EMG data collection process

2.2 Encoding EMG data

Encoding a single EMG signal for hand grip force estimation involves preprocessing raw signals into a structured format suitable for machine learning models. The EMG data, collected at different force levels (0Kg, 3Kg, 6Kg, 9Kg, 12Kg), is segmented into time windows with 50 EMG values per window, since the sampling frequency is 200Hz, one window corresponds to 0.25 seconds. This structured encoding enables accurate force estimation by capturing the relationship between EMG signal variations and corresponding grip force intensities. The EMG data of multiple individuals were pooled into one group and the EMG data of each individual was encoded corresponding to the hand grip force as shown in Fig.2.

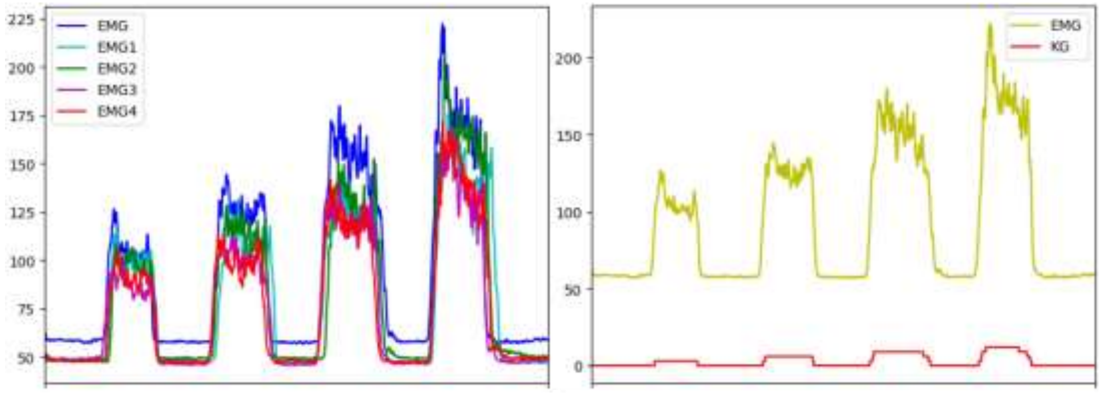


Fig. 2.EMG data set of multiple people (left) and Encoding EMG from a single object (right)

2.3 LSTM Model and Transformer Model for One EMG Signal Input

The LSTM Model is a powerful deep learning architecture designed to capture temporal dependencies in sequential data, making it well-suited for processing EMG signals. When estimating hand grip force, LSTMs could effectively learn patterns from multi-channel EMG inputs, preserving long-term dependencies while mitigating vanishing gradient issues. By leveraging recurrent connections and memory cells, the model refines its predictions, enhancing real-time grip force estimation for prosthetic control or rehabilitation applications. However, since the input is only from one single EMG signal, the model will not have any Normalization or Convolution layers to minimize the possibility of noise in the input data. The structure of the LSTM Model in this study is shown through the characteristics shown in Fig.3 and Table 1.

 ISSN 2579-7298

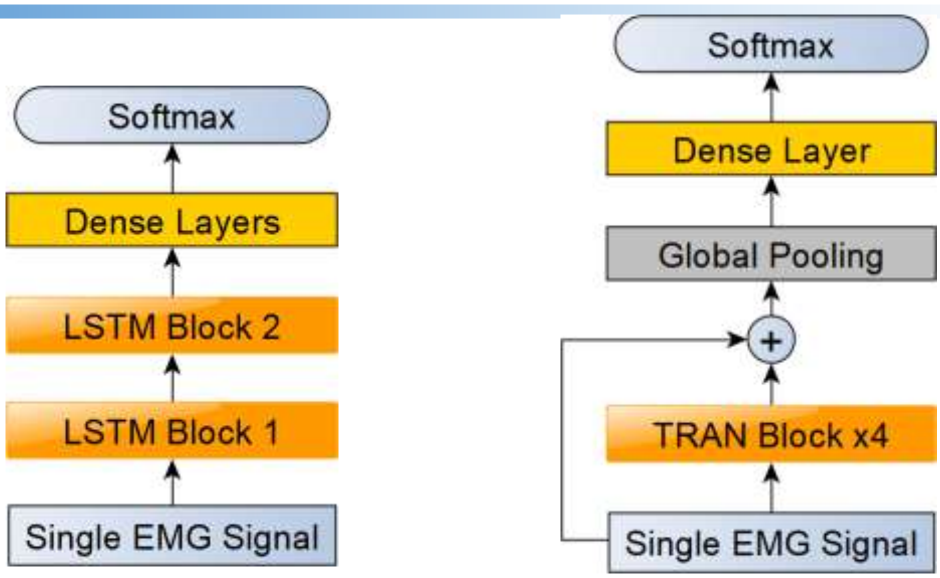


Fig. 3. Architecture of LSTM Model (left) and Transformer Model (right)

The Transformer Model, known for its self-attention mechanism, has shown great potential in processing EMG signals for hand grip force estimation. Unlike recurrent models, Transformers capture long-range dependencies efficiently by attending to all time steps simultaneously, improving feature extraction from complex muscle activation patterns. This architecture enables precise grip force estimation by learning intricate spatial-temporal relationships in EMG data. Its parallel processing capability enhances computational efficiency, making it suitable for real-time applications in prosthetics and rehabilitation. Similar to LSTM Model, with input data from only one single EMG signal, Transformer Model will not have any Normalization layer (a layer often present in segments of a standard Transformer) to minimize the possibility of noise for input data. The structure of the Transformer Model in the study is shown in Fig.3 and Table 1.

Table 1. Specifications of Training Models

Specifications	LSTM Model	Transformer Model
Optimizer	Adam	Adam
Loss	Categorical Cross Entropy	Categorical Cross Entropy
Metrics	Categorical Accuracy	Categorical Accuracy
Epochs	200	200
Drop Out	0.1	0.4
Total Parameter	30789	22581

3. Results and Discussion

Our research results show promising results when using LSTM and Transformer models with EMG data of an individual or multiple individuals as input to estimate Hand Grip Force for Hand Rehabilitation. We observed the models' ability to estimate Hand Grip Force for a single subject or a group of people, assessing the strengths and limitations of each model and different inputs. The overall F1-score accuracy for an individual of each model and input are shown in Table 2., and detailed information of other metrics such as Loss, Validation and Confusion Matrix are shown in the sections below.

Table 2. F1-Socre Accuracy of all Models and Inputs

	F1 – Score			
Indicators	***LSTM-Individual***	***STM-MultiPerson***	***Transformer-Individual***	***sformer-Multiperson***
Micro average	**1.00**	0.92	0.75	0.80
	F1 – Score			
Indicators	***LSTM-Individual***	***STM-MultiPerson***	***Transformer-Individual***	***sformer-Multiperson***

Macro average	**0.99**	0.85	0.45	0.60
Weightedaverage	**0.99**	0.92	0.72	0.79
Samples average	**0.99**	0.92	0.75	0.80

.

3.1. LSTM Model

Training results of the LSTM Model using individual data and multi person data through the Loss graphs are indicated in Fig.4 and Accuracy graphs in Fig.5. The evaluation results, the Confusion Matrix of using LSTM Model to estimate Hand Grip Force for a single subject and a group of people are shown in Fig.6 and Fig.7.

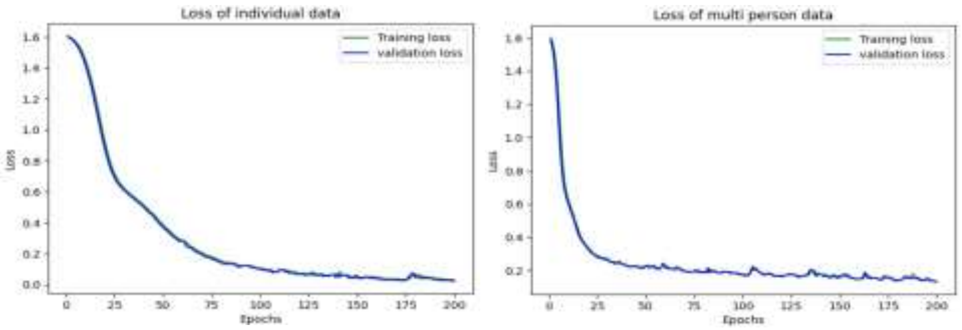


Fig. 4. Plot of the training and validation loss using individual data (left) and multi person data (right)

In Fig.4, both the individual data and multi person data inputs of LSTM Model have a decreasing training loss and a decreasing validation loss, eventually stabilizing at a low value, which means that both inputs of LSTM Model are Good Fits, but the right graph stabilizes faster. In the last epoch, the training loss value from individual data is 0.0288 and that of multi person data is 0.1350, the validation loss value from individual data is 0.0226 and that from multi person data is 0.1371.

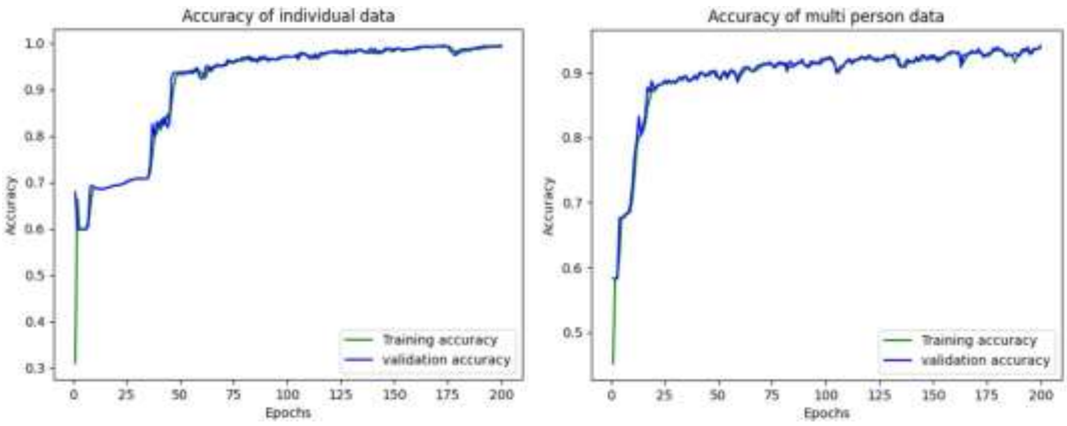


Fig. 5. Plot of the training and validation accuracy using individual data (left) and multi person data (right)

In Fig.5, both the individual data and multi person data inputs of LSTM Model have an increasing training accuracy and an increasing validation accuracy that eventually stabilizes at a high value, it means both inputs of LSTM Model are Good Fits, but the right graph stabilizes faster. In the last epoch, the training accuracy value from individual data is 0.9925 and from multi person data is 0.9388, the validation accuracy value from individual data is 0.9905 and from multi person data is 0.9408

 ISSN 2579-7298

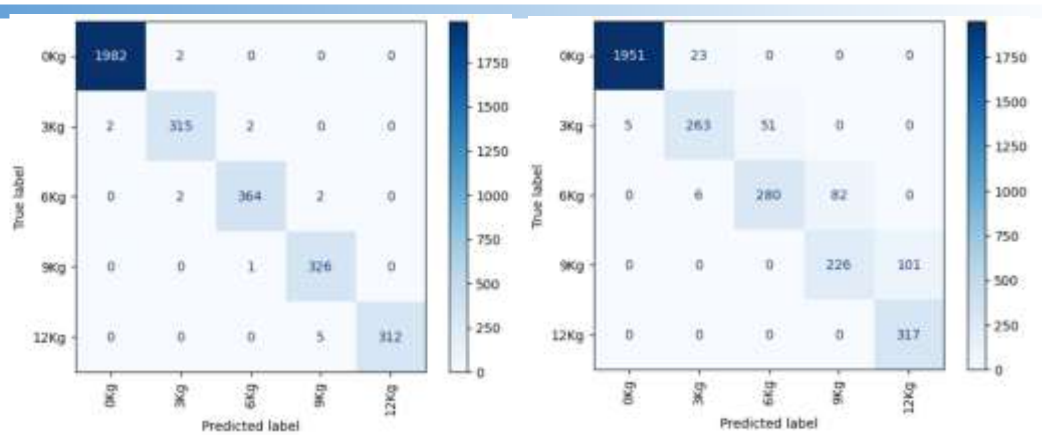


Fig. 6. Confusion matrix of estimating a single subject hand grip force using individual data (left) and multi person data (right)

Fig.6 shows that both the individual and multi person input data of the LSTM Model recognize the resting state - 0Kg very well, the grip force estimation from the individual data is very good while that from the multi person data is relatively good. The right confusion matrix shows that the grip force estimation has a part that predicts higher force than the actual force, this is because the EMG value of this individual is higher than the average. The details of the accuracy index of all 5 grip force markers and the averages of the individual and multi person input data of the LSTM Model are shown in Table 3.

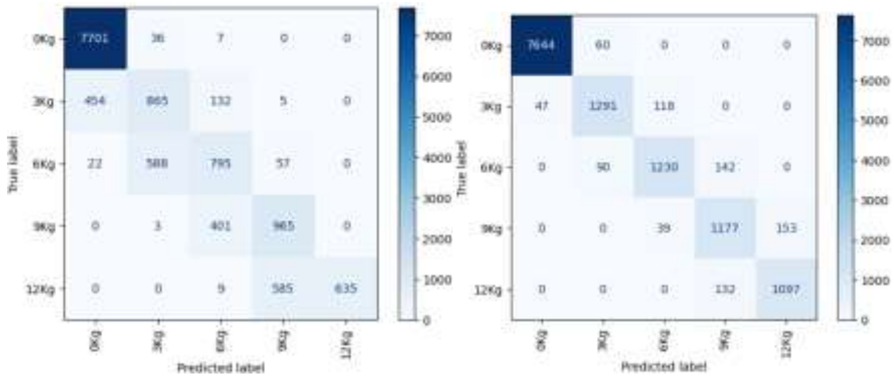


Fig. 7. Confusion matrix of estimating a group of people hand grip force using individual data (left) and multi person data (right)

Fig.7 shows that both individual and multi person data input of the LSTM Model recognize the resting state - 0Kg very well, the grip force estimation from the individual data is slightly inaccurate while that from the multi person data is relatively good. The left confusion matrix shows that the grip force estimate has a fair amount of predicted force that is higher than the actual force, this is because this individual's EMG value is higher than the average value. The accuracy of left confusion matrix is 83% and that of right confusion matrix is 94%.

Using individual EMG data as input to LSTM Model to estimate a single subject's handgrip force gives better results than using multiple person EMG data. Using multiple person EMG data as input to LSTM Model to estimate a group of people's hand grip force gives better results than using individual EMG data. The F1-score of LSTM Model in this study has the highest value of 99.99%, higher than the score of other AI models and state-of-art model mentioned in the study: Hongxin Cao Model – 80.6% [18], Pan Xu's Model – 90.23% [19], Betzalel Fialkoff's Model - 97% [20], Chang Liu's Model – 98.81% [21].

Table 3. Accuracy of LSTM Model estimating a single subject hand grip force

Indicator	Individual			Multi person		
	Precision	*Recall*	*F1-score*	*Precision*	*Recall*	*F1-score*
0Kg	1.00	1.00	1.00	1.00	0.99	0.99
3Kg	0.99	0.99	0.99	0.90	0.82	0.86

6Kg	0.99	0.99	0.99	0.85	0.76	0.80
9Kg	0.98	1.00	0.99	0.73	0.69	0.71
12Kg	1.00	0.98	0.99	0.76	1.00	0.86
Micro average	1.00	1.00	1.00	0.92	0.92	0.92
Macro average	0.99	0.99	0.99	0.85	0.85	0.85
Weighted average	1.00	1.00	1.00	0.92	0.92	0.92
Samples average	1.00	1.00	1.00	0.92	0.92	0.92

3.2. Transformer Model

Training results of the Transformer Model using individual data and multi person data through the Loss graphs are indicated in Fig.8 and Accuracy graphs in Fig.9. The evaluation results, the Confusion Matrix of using Transformer Model to estimate Hand Grip Force for a single subject and a group of people are shown in Fig.10 and Fig.11.

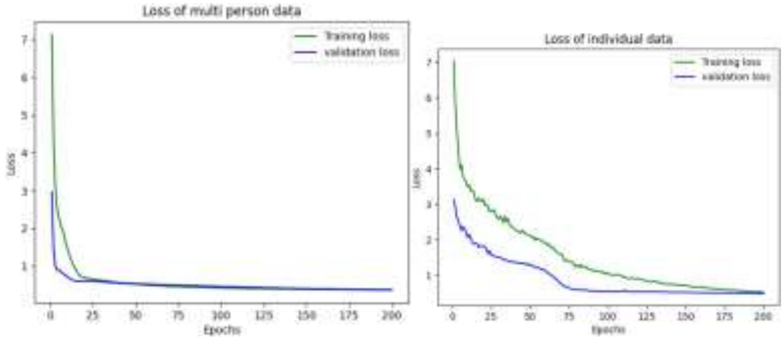


Fig. 8. Plot of the training and validation loss using individual data (left) and multi person data (right)

In Fig.8, both the individual data and multi person data inputs of Transformer Model have a decreasing training loss and a decreasing validation loss, eventually stabilizing at a low value, which means that both inputs of Transformer Model are Good Fits, but the right graph stabilizes faster. In the last epoch, the training loss value from individual data is 0.5206 and that of multi person data is 0.3609, the validation loss value from individual data is 0.4827 and that from multi person data is 0.3625.

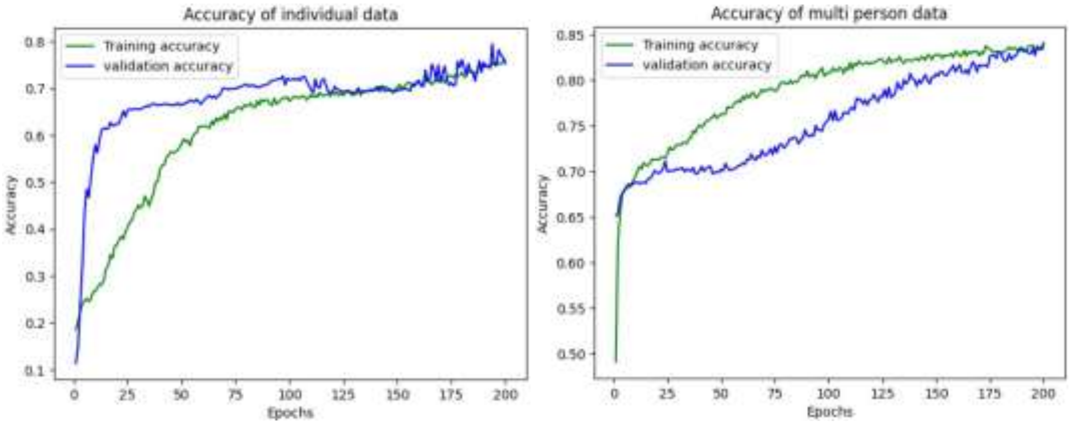
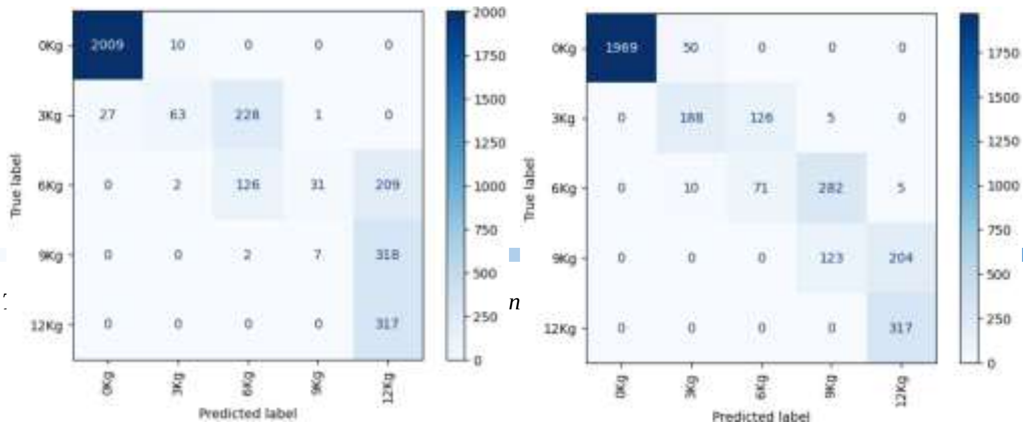


Fig. 9. Plot of the training and validation accuracy using individual data (left) and multi person data (right)

In Fig.9, both the individual data and multi person data inputs of Transformer Model have an increasing training accuracy and an increasing validation accuracy that eventually end at a high value,



it means both inputs of Transformer Model are Good Fits. In the last epoch, the training accuracy value from individual data is 0.7600 and from multi person data is 0.8360, the validation accuracy value from individual data is 0.7528 and from multi person data is 0.8405.

Fig. 10. Confusion matrix of estimating a single subject hand grip force using individual data (left) and multi person data (right)

Fig.10 shows that both the individual and multi-person input data of the Transformer Model recognize the resting state - 0Kg very well, the grip force estimation from the individual data is severely inaccurate while that from the multi-person data is relatively inaccurate. Both confusion matrices have misclassification with adjacent handgrip force values, the right confusion matrix has higher accuracy. The details of the accuracy index of all 5 grip force markers and the averages of the individual and multi person input data of the Transformer Model are shown in Table 4.

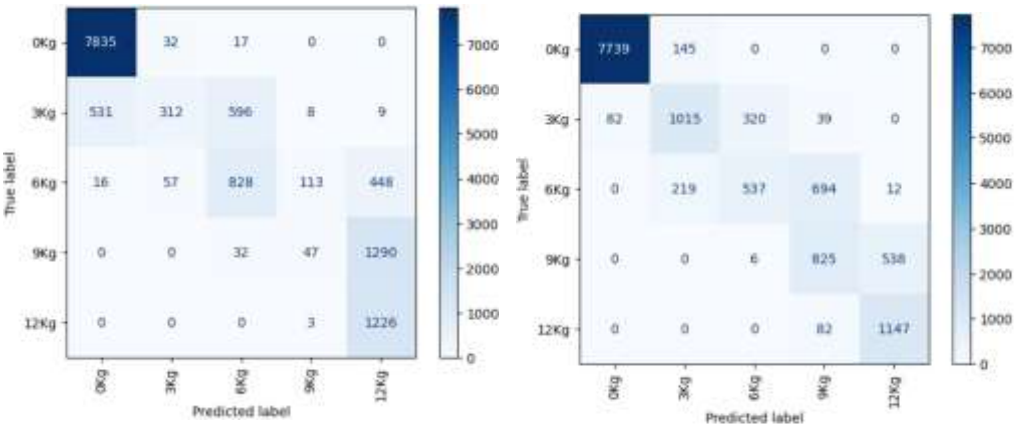


Fig. 11. Confusion matrix of estimating a group of people hand grip force using individual data (left) and multi person data (right)

Fig.11 shows that both the individual and multi-person input data of the Transformer Model recognize the resting state - 0Kg very well, the grip force estimation from the individual data is severely inaccurate while that from the multi-person data is relatively inaccurate. Both confusion matrices have misclassification with adjacent handgrip force values, the right confusion matrix has higher accuracy. The accuracy of left confusion matrix is 76% and that of right confusion matrix is 84%.

Using multiple person EMG data as input to Transformer Model gives better results than using individual EMG data in estimating both single object and a group of people hand grip force.

Table 4. Accuracy of Transformer estimating a single subject hand grip force

Indicator	Individual			Multi person		
	Precision	***Recall***	***F1-score***	***Precision***	***Recall***	***F1-score***
3Kg	0.84	0.20	0.32	0.76	0.59	0.66
6Kg	0.35	0.34	0.34	0.36	0.19	0.25
9Kg	0.18	0.02	0.04	0.30	0.38	0.33
12Kg	0.38	1.00	0.55	0.60	1.00	0.75
Micro average	0.75	0.75	0.75	0.80	0.80	0.80
Macro average	0.55	0.51	0.45	0.60	0.63	0.60
Weighted average	0.77	0.75	0.72	0.80	0.80	0.79
Samples average	0.75	0.75	0.75	0.80	0.80	0.80

4. Conclusion

LSTM Model performed significantly better than the Transformer Model in this study, specifically LSTM Model had an accuracy of nearly 100% in estimating the grip force of single subject and 94% of a group of people compared to 80% for a single subject and 84% for a group of people of Transformer Model. Transformer Model gives much better results with input data of EMG of many people than EMG of a single subject. From the above, we can draw the following conclusions:

- When the input is just one EMG signal, with such low input dimensionality, using LSTM Model is more optimal than using Transformer Model.
- With low input dimensionality, the Transformer Model with more diverse input data gives better results whether it is to estimate the grip force of a single subject or a group of people.
- This study took approximately 1 to 2 hours from EMG data collection to training the Model to estimate grip force. Combined with the accuracy of nearly 100% when applied to a single subject, significantly higher than 94% for a group of people, **the Application of Artificial Intelligence in Rehabilitation should focus on developing support for a single specific subject** instead of a group of people like other traditional methods.

To continue to develop further into AI research for Hand Rehabilitation, there are recommendations below:

- Increasing the input number of EMG signals instead of just one EMG signal as in this study to be able to recognize more complex states of the human hand, which should be the strength of Transformer Model with its ability to receive diverse inputs for complex outputs.
- Grip force is one of the most basic states of hand activity, future studies will combine the recognition of other complex hand activities together with grip force, by using a multi-label classification model instead of multiclass classification for only hand grip force as in this study.

References

[1] Fraser J. Leversedge, Thomas J. Moore, Bret C. Peterson, John G. Seiler, "Compartment Syndrome of the Upper Extremity", 1 March 2011, https://doi.org/10.1016/j.jhsa.2010.12.008.

[2] Michael Darowish, Jyoti Sharma, "Evaluation and Treatment of Chronic Hand Conditions", Medical Clinics, 14 April 2023, Vol 98, Isssue 4, July 2014, pp. 801-815

[3] Alexander A. Frolov, Olesya Mokienko, Olesya Mokienko, Roman Lyukmanov, Elena Biryukova, Sergey Kotov, Lydia Turbina, Georgy Nadareyshvily, Yulia Bushkova, "Post-stroke Rehabilitation Training with a Motor-Imagery-Based Brain-Computer Interface (BCI)-Controlled Hand Exoskeleton: A Randomized Controlled Multicenter Trial", Futuristic Neural Prostheses, 20 July 2017, https://doi.org/10.3389/fnins.2017.00400.

[4] Jean-Michel Gracies, Maud Pradines, Mouna Ghédira, Catherine-Marie Loche, Valentina Mardale, Catherine Hennegrave, Caroline Gault-Colas, Etienne Audureau, Emilie Hutin, Marjolaine Baude, Nicolas

[5] Bayle & the Neurorestore Study Group, "Guided Self-rehabilitation Contract vs conventional therapy in chronic stroke-induced hemiparesis: NEURORESTORE, a multicenter randomized controlled trial", BMC Neurology, Vol 19, 12 March 2019, https://doi.org/10.1186/s12883-019-1257-y.

[6] Jon A. Jacobson, Gandikota Girish, Yebin Jiang, Brian J. Sabb, "Radiographic Evaluation of Arthritis: Degenerative Joint Disease and Variations", Radiology, 1 August 2008, https://doi.org/10.1148/radiol.2483062112.

[7] Benjamin M. Sucher, "Carpal Tunnel Syndrome: Ultrasonographic Imaging and Pathologic Mechanisms of Median Nerve Compression", Journal of Osteopathic Medicine, 1 December 2009, https://doi.org/10.7556/jaoa.2009.109.12.641.

[8] Johanna P. de Jong, Jesse T. Nguyen, Anne J. M. Sonnema, Emily C. Nguyen, Peter C. Amadio, Steven

[9] L. Moran, "The Incidence of Acute Traumatic Tendon Injuries in the Hand and Wrist: A 10-Year Population-based Study", 16 May 2014, https://doi.org/10.4055/cios.2014.6.2.196.

[10] Jacqueline Hochstenbach, “Rehabilitation is more than functional recovery”, Disability and Rehabilitation, 07 Jul 2009, DOI 10.1088/1742-6596/1267/1/012044, pp. 201-204

[11] Yassine Bouteraa, Ismail Ben Abdallah, Ahmed Elmogy, “Design and control of an exoskeleton robot with EMG-driven electrical stimulation for upper limb rehabilitation”, Industrial Robot, 19 June 2020, https://doi.org/10.1108/IR-02-2020-0041.

[12] Jeffrey Henderson, Joan Condell,mJames Connolly, Daniel Kelly, Kevin Curran, “Review of Wearable Sensor-Based Health Monitoring Glove Devices for Rheumatoid Arthritis”, Sensors 2021, 24 February 2021, https://doi.org/10.3390/s21051576

[13] Saad M. Sarhana, Mohammed Z. Al-Faizb, Ayad M. Takhakh, “A review on EMG/EEG based control scheme of upper limb rehabilitation robots for stroke patients”, Heliyon, 21 August 2023, Volume 9, Issue 8, e18308

[14] Joy C. MacDermid, “An introduction to evidence-based practice for hand therapists”, Volume 17, Issue 2, April–June 2004, Pages 105-117, https://doi.org/10.1197/j.jht.2004.02.001.

[15] Gillian Barry, Brook Galna, Lynn Rochester, “The role of exergaming in Parkinson’s disease rehabilitation: a systematic review of the evidence”, Journal of NeuroEngineering and Rehabilitation, 07 March 2014, https://doi.org/10.1186/1743-0003-11-33

[16] Daniele Leonardis, Michele Barsotti, Claudio Loconsole, Massimiliano Solazzi, Marco Troncossi, Claudio Mazzotti, An EMG-Controlled Robotic Hand Exoskeleton for Bilateral Rehabilitation”, IEEE Transactions on Neural Systems and Rehabilitation Engineering, 23(6), 1030–1039, 30 March 2015, DOI: 10.1109/TOH.2015.2417570

[17] Houcheng Li, Long Cheng, “A Systematic Review on Hand Exoskeletons From the Mechatronics Aspect”,

[18] IEEE/ASME Transactions on Mechatronics, 05 December 2024, 10.1109/TMECH.2024.3500585

[19] [16] N. A. Khan, T. Goyal, F. Hussain, P. K. Jamwal and S. Hussain, "Transformer-Based Approach for Predicting Transactive Energy in Neurorehabilitation," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 33, pp. 46-57, 2025, doi: 10.1109/TNSRE.2024.3515175

[20] Kumar, Sanjeev;Pandey, Dilkeshwar;Chandra, Saurav, “REVOLUTIONIZING BIOFEEDBACK AND BEYOND : A JOURNEY THROUGH THE EVOLVING LANDSCAPE OF BIOMECHANICS”

[21] Biochemical & Cellular Archives,2023 Suppl1, DOI: 10.51470/bca.2023.23.S1.1625

[22] Cao, H., Sun, S. & Zhang, K., “Modified EMG-based handgrip force prediction using extreme learning machine”, Soft Comput 21, 491–500 (2017), https://doi.org/10.1007/s00500-015-1800-8

[23] Pan Xu, Xudong Yang, Wei Ma, Wanting He, Željka Lučev Vasić, Mario Cifrek, "A Study of Handgrip Force Prediction Scheme Based on Electrical Impedance Myography", in IEEE Journal of Electromagnetics, RF and Microwaves in Medicine and Biology, vol. 7, no. 1, pp. 90-98, March 2023, doi: 10.1109/JERM.2023.3241769

[24] Betzalel Fialkoff, Harel Hadad, Darío Santos, Franco Simini, Marcelo David, " Hand grip force estimation via EMG imaging", in Biomedical Signal Processing and Control, vol. 74, April 2022, https://doi.org/10.1016/j.bspc.2022.103550

ISSN 2579-7298

12 International Journal of Artificial Intelligence Research ISSN 2579-7298

Vol. 9, No. 1, June 2025, pp. xx-xx

[17] Chang Liu, Jiuqiang Li, Senhao Zhang, Hongbo Yang, Kai Guo., "Study on Flexible sEMG Acquisition System and Its Application in Muscle Strength Evaluation and Hand Rehabilitation", Micromachines 2022, https://doi.org/10.3390/mi13122047

[22] A. Rainoldi, G. Melchiorri, and I. Caruso, "A method for positioning electrodes during surface EMG recordings in lower limb muscles," J Neurosci Methods, vol. 134, no. 1, pp. 37–43, Mar. 2004, doi: 10.1016/j.jneumeth.2003.10.014

[23] H. J. Hermens, B. Freriks, C. Disselhorst-Klug, and G. Rau, "Development of recommendations for SEMG sensors and sensor placement procedures," 2000, (last revised 10 Feb, 2025). [Online]. Available: www.elsevier.com/locate/jelekin