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LARGE Data Collection with EMG Sensor for Training a Recurrent Neural Network

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***Abstract*—This research presents the development of a data acquisition system based on surface electromyography (sEMG) sensors for the recognition of hand gestures using a recurrent neural network (RNN). The system captures and classifies muscle activation signals corresponding to specific hand movements, enabling accurate gesture recognition. The experimental methodology involved the progressive training of the RNN across seven sessions, each incorporating 100 additional data samples from a diverse group of left-handed individuals, resulting in a total of 700 labeled instances per movement. The classification performance was systematically evaluated after each training iteration to assess the network's learning behavior and generalization capacity. Results indicate that the model reached a peak classification accuracy of 83.13%, with gesture number 3 consistently demonstrating the highest precision and reliability in detection. These findings highlight the potential of combining sEMG signals with RNN architectures for intuitive and responsive gesture recognition systems, particularly in applications such as prosthetic control and human-computer interaction.**

***Index Terms*—Keywords: EMG, Data Collection, RNN, Training**

I. Introduction

The research objective involves obtaining data through a force-detecting sensor during six different hand movements. A person must sit with their elbow at 90 degrees while extending their hand to execute each movement. The left forearm must have three sensor electrodes positioned to measure hand forces where two electrodes should be on the muscle area and one on the bony section. The Python programming system will perform data recording through an interface that enables users to choose movements and save each attempt in separate folders. The Arduino will handle both EMG sensor programming and data acquisition operations as a single control system. The system enables users to choose recording movements and manually input identification numbers for the test subjects. The research will gather data from people across all age groups and genders and physical abilities. The collected data will be used to train a recurrent neural network because this model excels at recognizing muscle activity patterns in hand movements.

II. State of art

A. Electromyography

The technique of Electromyography (EMG) detects myoelectric signals which emerge from muscle contractions and relaxations to identify muscle abnormalities [1]. The evaluation of muscle performance occurs through changes in amplitude and frequency which allow the detection of motor unit action potentials (MUAPs) from skin surface measurements [2].

The medical field uses EMG for neuromuscular disorder diagnosis while robotics employs it to create prosthetic devices and assistive technology. The technique requires signal amplification and analysis of muscle fiber activation from motor units [5]. The body's bioelectrical signals which stem from the brain and heart and muscles serve essential diagnostic purposes while EMG-based devices improve physical abilities and reduce injuries [6].

B. EMG Sensor

The EMG sensor detects electrical currents from muscle activity to assess movement and strength. It consists of electrodes, an instrumentation amplifier, filters, and a microcontroller [4]. The correct placement of electrodes on the muscle surface which should be in the center and parallel to the muscle fibers is essential for accurate signal detection because incorrect placement affects both intensity and efficiency [9].

The EMG sensors require three electrodes which include two electrodes positioned on the muscle and one ground electrode attached to a bone [10]. Sensor placement needs individual customization because muscle dimensions and arrangements between people differ, which affects both contact stability and control reliability [3].

The use of EMG sensors to track muscle force changes over time enables safer sports training and rehabilitation practices by identifying early signs of muscle injuries [7] [8].

C. Neural Network

Neural networks have received extensive research in various fields during recent years because they effectively solve complex problems. The computer vision field benefits from Convolutional neural networks (CNNs) because they achieve outstanding performance results [11]. RNNs have become essential for processing sequential data particularly in natural language processing applications [11].

Artificial neural networks (ANNs) function as computational models which use interconnected nodes called neurons to analyze and learn from input data [12]. The artificial neurons duplicate biological neurons through weighted connections [13]. Neural networks excel at learning from large datasets and identifying patterns that are difficult to define through conventional programming [13].

The technology applies to autonomous driving and security systems and industrial monitoring and medical applications which drive technological and clinical progress [12]. Neural networks have shown exceptional value in biomechanics so researchers have developed advanced architectures to process temporal and sequential data more effectively [15]. The image and video recognition tasks primarily use CNNs which belong to the feedforward neural network family through their combination of convolutional layers and pooling layers and fully connected layers [16].

III. METHOD

This project is focused on collecting data from different people with an EMG sensor that detects the electrical signals that our muscles emit. The idea is that they are completely different people, regardless of age, gender, or physical appearance of the people. The priority of the project is to collect all possible data on the strength in the left arm by performing a total of 6 hand movements on a total of 700 people. The approach of this project is quantitative since it focuses on the collection and compilation of data through the electrical signals emitted by the force of people, which are those detected by the EMG sensor. These signals are measured by the voltage peaks with respect to time.This research seeks to analyze the signals of 700 people in order to train a recurrent neural network based on data.

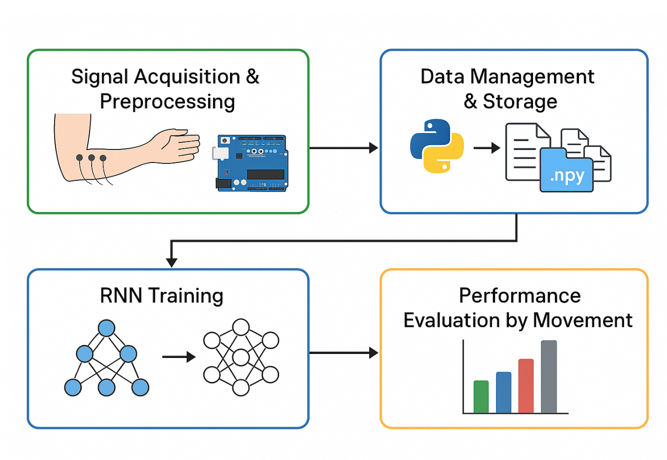

Fig. 1. Integrative Image

The research used an incremental methodology to study 700 participants who had different ages and genders and physical conditions. The participants completed six hand movements which included fist, peace sign, thumbs up, rock and roll, number three and grasping a tennis ball.

The EMG sensor received programming in Arduino IDE to execute analog signal processing with a high-pass filter before sending 20 filtered data points to Python.

Python interface built in Visual Studio Code enabled users to select movements while storing attempts in specific folders and provided a three-second countdown for preparation of the subject.

Analysis of force-over-time graphs eliminated attempts with exponential shapes because they were considered invalid. The valid data were averaged to represent each movement per participant.tasks.

IV. RESULTS

At last, training process received 100 data points from different people who performed the six predefined hand gestures. The participants performed each gesture four times before repeating it when they made errors or experienced long delays. The method produced well-defined average results for each movement and produced consistent signal graphs. The dataset included participants between 10 and 60 years old which produced a diverse collection of data points regarding age and gender and physical condition.

This ecurrent neural network achieved 95.19% accuracy on its training set while producing a training loss of 16.80% using the first 100 samples from each movement. The initial performance showed strong results while the error rates remained relatively low. The model demonstrated poor generalization to new data because validation accuracy reached 79.19% while maintaining the same loss value of 16.80%.

The ”number three” and ”peace sign” gestures achieved the highest precision and sensitivity rates among all six movements. The ”fist” movement achieved 80% accuracy and the ”thumbs up” movement achieved 75% accuracy when the hand was in a horizontal position. The ”rock & roll” gesture achieved 67% accuracy together with 50% sensitivity but the ”grasping a tennis ball” movement performed the worst at 50% for both metrics. The ”grasping a tennis ball” movement showed large performance variability because participants used different force levels which required multiple attempts to get reliable average results.

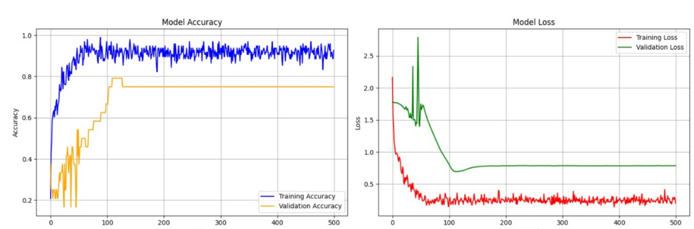

Fig. 2. Training with 100 data

In the movements, the one that obtained the greatest precision and sensitivity in capturing the data was the movement of the number three and the peace symbol, then with a precision of 80% it was the movement of the fist, and with a precision and sensitivity of 75 % the movement of the thumb up with the hand lying down, later the Rock Roll movement obtained 67 % precision and a sensitivity of 50 %, and finally the movement of catching a tennis ball that obtained 50 % in precision and sensitivity. The latter data came out very varied, since people applied completely different forces in each of the attempts, which is why even more attempts are made for each person.

TABLE I
CLASSIFICATION REPORT WITH 100 DATA

Class	Accuracy	Recall	F1-Score	Support
Fist	0.80	1.00	0.89	4
Peace Sign	1.00	1.00	1.00	4
Thumbs Up	0.75	0.75	0.75	4
Rock & Roll	0.67	0.50	0.57	4
Number 3	1.00	1.00	1.00	4
Ball	0.50	0.50	0.50	4

In the third training phase of the recurrent neural network, an additional 100 samples from new participants were added, reaching a total of 300 data points per movement. This iteration resulted in a training accuracy of 86.99%, representing a slight improvement over the second training phase. However, the training loss increased to 36.54%, indicating that the model still struggles to accurately predict some patterns and requires further refinement.

The validation accuracy reached 75%, with a notably high validation loss of 85.29%. Although this reflects a marginal improvement in accuracy compared to the previous training phase, the network still fails to generalize effectively to unseen data. These results suggest that the model would benefit from a broader and more diverse dataset, both in quantity and quality, to improve its learning capacity and reduce prediction errors.

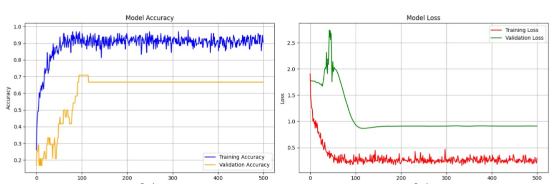

Fig. 3. Training with 300 data

Among the hand movements performed, the ”number three” gesture continued to show the highest precision and sensitivity in data capture. The ”peace sign” achieved 67% accuracy—a significant decrease compared to the first and second training—but showed an improvement in sensitivity. The ”fist” movement reached 75% sensitivity, along with a notable increase in accuracy. Similarly, the ”thumbs up” gesture (with the hand positioned horizontally) achieved both 75% accuracy and sensitivity.

The ”rock & roll” movement maintained 67% accuracy and 50% sensitivity, consistent with previous training results. Lastly, the ”grasping a tennis ball” movement remained the lowest in performance, with 50% accuracy and sensitivity. However, this represented a slight improvement over the second training phase.

TABLE II
CLASSIFICATION REPORT WITH 300 DATA

Class	Accuracy	Recall	F1-Score	Support
Fist	1.00	0.75	0.86	4
Peace Sign	0.67	1.00	0.80	4
Thumbs Up	0.75	0.75	0.75	4
Rock & Roll	0.67	0.50	0.57	4
Number 3	1.00	1.00	1.00	4
Ball	0.50	0.50	0.50	4

In the fifth training of the recurrent neural network, it was fed with another 100 more data points from different people, with the network having a total of 500 data points collected for each movement, where an accuracy of 91.90% was obtained, remaining the same as the fourth training, with a small increase in the training accuracy. This indicates that the recurrent neural network is learning the movement patterns better, and a loss of 24.91% was also obtained in the training model, resulting in a large reduction in the loss compared to the fourth training. This indicates that it is necessary to improve a little more in the predictions in the data, so it is necessary to feed it with more data. The accuracy in the validation set is 75% and the loss in validation is 74.52%. With this accuracy in validation, compared to the fourth training, it increased a lot but so did the losses in validation, so that the recurrent neural network is not yet learning patterns to generalize.

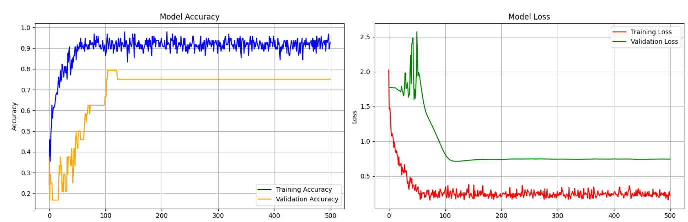

Fig. 4. Training with 500 data

TABLE III
CLASSIFICATION REPORT WITH 500 DATA

Class	Accuracy	Recall	F1-Score	Support
Fist	0.75	0.75	0.75	4
Peace Sign	0.80	1.00	0.89	4
Thumbs Up	0.75	0.75	0.75	4
Rock & Roll	0.67	0.50	0.57	4
Number 3	1.00	1.00	1.00	4
Ball	0.50	0.50	0.50	4

In the seventh and final training phase of the recurrent neural network, an additional 100 samples from new individuals were added, bringing the total to 700 data points per movement. The model achieved a training accuracy of 83.13%, representing a notable decrease compared to the sixth training, suggesting the network still struggles to identify certain movement patterns. The training loss also increased to 36.30%, indicating reduced performance in prediction and the need for further data refinement.

In the validation set, the network achieved 75% accuracy—an improvement over the sixth training and consistent with earlier training sessions. The validation loss was 73.31%, which, although relatively high, showed a significant decrease compared to the sixth training. These results suggest better generalization but also highlight the need for more and higher-quality data to reduce loss and improve overall model robustness.

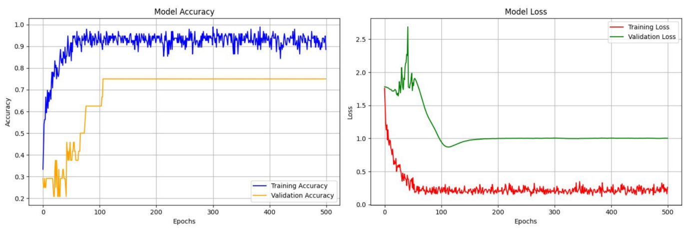

Fig. 5. Training with 700 data

TABLE IV
CLASSIFICATION REPORT WITH 700 DATA

Class	Accuracy	Recall	F1-Score	Support
Fist	0.75	0.75	0.75	4
Peace Sign	0.80	1.00	0.89	4
Thumbs Up	0.75	0.75	0.75	4
Rock & Roll	0.67	0.50	0.57	4
Number 3	1.00	1.00	1.00	4
Ball	0.50	0.50	0.50	4

As a result, the recurrent neural network got a total of 156 neurons. In the LSTM 1 layer there are 50 neurons where each neuron will generate an output at each temporal step of the sequence with the purpose of processing the temporal sequence and generating representations for each step with respect to time. The BatchNormalization layer normalizes the outputs of the neurons in the LSTM layer to speed up training and prevent activations from getting out of control. The Dropout layer reduces the risk of overfitting by forcing the model to learn. The LSTM 2 layer contains another 50 neurons just like the first, extracting more complex features. The LSTM 3 layer also has 50 neurons, but instead of returning output for each time step, it returns only one output with the aim of condensing all the information in the sequence. The dense layer contains 6 neurons, one for each output class, with the purpose of generating the final prediction of the movements for each input sample. The architecture of the recurrent neural network was composed of a stacked LSTM layer, each layer capturing the complex patterns in the sequence; then there are the BatchNormalization and Dropout layers, which guarantee stability and regularization. Finally, the final softmax layer is ideal for multiclass classification problems. With this data that was collected, this architecture has the potential to achieve high performance in hand gesture classification.

V. CONCLUSIONS

- An accuracy of 83.13% was achieved in the recurrent neural network in which it learned to identify patterns in the training data.
- A recurrent neural network was trained with the collection of data from a total of 700 different people, obtaining greater precision and detection in the movement of the number 3.
- The architecture of the recurrent neural network obtained a total of 156 neurons, achieving high performance in the classification of hand movements.

VI. RECOMMENDATIONS

- If the graph generated at the end of data collection presents anomalies, it is likely that the sensor is not connected or that it is poorly connected. In this case, check the electrode connections and make sure that all cables are securely fastened in their correct position.
- If the serial monitor of the Arduino IDE is open while you are trying to run the Python program, this will prevent the program from starting. Close the serial monitor before running the Python program.
- For the recurrent neural network, increase or decrease the number of neurons in the layers depending on the complexity of the data that has been collected.

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