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HAND GESTURE RECOGNITION USING SEMG WITH LSTM

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Using electromyography (EMG) signals has spread in many fields. LSTM networks is one of the most suitable methods for processing EMG because of their structure. In this work, two LSTM models were build, one layer (1L-LSTM) and multi-layers ML-LSTM. They were trained using Ninapro-DB5 dataset after augmenting it by averaging. Different input sizes were tested. 1L-LSTM and ML-LSTM scored an accuracy of 98.5% and 99.7% respectively. Moreover, they needed low testing time in the range of [60,240] mcs. In addition, the signal length was did not have much effect when using multi layers.

Keywords: LSTM, sEMG, hand gestures recognition, NinaPro-DB5, augmentation.

Introduction. In the middle of the 19th century, Emil du Bois was the first to measure the bioelectric currents in muscles. He used for that a galvanometer, and published his work and foundlings [1]. Later on, by the end of the century Etienne-Jules Marey was the first to record this electrical activity of the muscles graphically, which is considered the first EMG signal. Since then, EMG measuring tools and methods kept developing until today. Moreover, the usage of these signals has widely spread, from medical to industrial, even commercial applications.

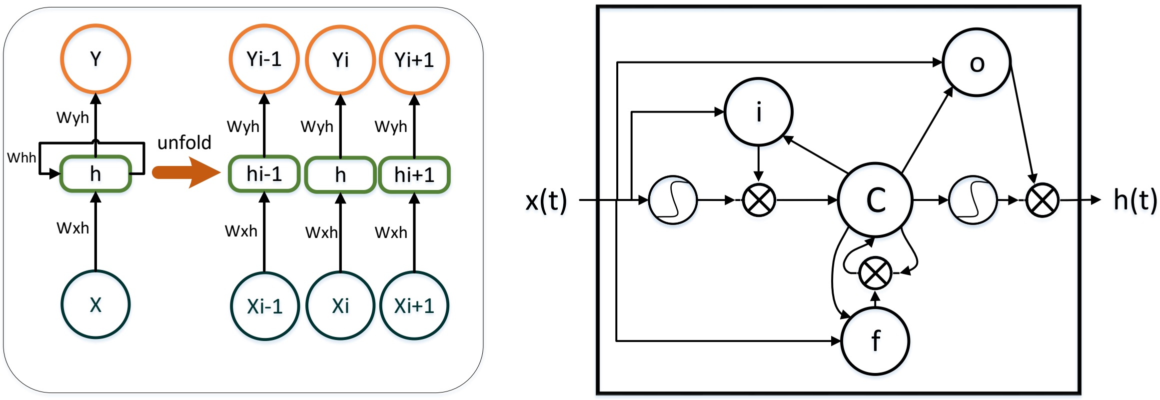
One of the first uses of EMG was to control prosthesis; the works of Ralph Alter [2] and Bottomley, A. H. [3] represent some of the earliest examples. It was also used as a biofeedback when treating patients, like the work of Crow, J. L., et al [4], where the studied EMG's effectiveness as biofeedback when treating a patient after a stroke. Di Girolamo's work [5] falls under the same category, but represents the continuation in modern times.

Nowadays, they play a key role in in medical and clinical applications. Researchers used them to diagnose neuromuscular disorders like [6] who worked on detecting motor unit abnormalities in Amyotrophic Lateral Sclerosis **(**ALS) using high density EMG. Visser, L. H., Smidt, M. H., & Lee, M. L in their work [7], used to diagnose carpal tunnel syndrome and compared it to sonography. Another clinical usage is to detect muscle fatigue, as O'Bryan et al did in their work [8]. Prosthetics a, an example of this is the work of Kaluf, Brian, et al [9]. Another application is exoskeleton like the work of Cisnal, Ana, et al [10]. Human computer interfaces HCI also use EMG, the work of Sugiarto et al [11] for gesture recognition, and Wang et al [12] for silent speech recognition. In sports, researches inspect the effectiveness of EMG for optimizing athletic performance [13] and preventing injuries [14]. For sure, industry is also invests in EMG in many ways, like smart gloves [15], and sign language translation [16].

Hand gesture recognition is one of the widely inspected domains, and LSTM networks are one of the most important tools. Using LSTM in this field is not new, but it is still developing. Many researchers succeeded in building high performance models using LSTM on its own or within hybrid models with other types of networks. Sun et al used for dilation [17], Karnam et al build a hybrid CNN and Bi-LSTM architecture [18]. Cheng Yang and Chenxuan Zhang [19], Wang et al [20], and Kishore et al [21] used CNN-LSTM for their models.

NinaPro was the dataset for training and evaluating the models we built. We used the values of the sEMG signals as the features to reduce the complexity of the model. Moreover, we augmented the dataset to dataset using averaging; we followed the same methodology from our previous work [22]. Where we chose the suitable signal length, following the same steps, then we augmented the dataset in two ways: Doubling the dataset size by averaging every two successive samples of each class, and Doubling the dataset size by $C_n = \frac{n(n-1)}{2}$, by averaging each sample of each class with each sample of the rest samples of the same class.

Long Short-Term Memory Networks (LSTM). LSTM is a special type of RNN, it shares with it the same general structure, but differs in the structure of the cell, fig. 1 shows this structure.



a

b

Fig. 1. LSTM structure: a) general LSTM structure, b) LSTM memory cell

Next are the main functions of an LSTM cell.

- Input gate:

$$i(t) = \sigma_g\left(w_i * x(t) + u_i * h(t-1) + b_i\right)$$

- Output gate:

$$o(t) = \sigma_g\left(w_o * x(t) + u_o * h(t-1) + b_o\right)$$

- Forget gate:

$$f(t) = \sigma_g\left(w_f * x(t) + u_f * h(t-1) + b_f\right)$$

- Memory cell:

$$c(t) = f(t) * c(t-1) + i(t) * \sigma_h\left(w_c * x(t) + u_c * h(t-1) + b_c\right)$$

- Output:

$$h(t) = o(t) * c(t)$$

Where:

x: input, *c*: excitation / LSTM cell, *h*: activation coefficient, *w*: feedback coefficient, *b*: bias, *σ*: feedback nonlinearity.

The dataset. NinaPro-DB5 is the dataset used in this work. It contains samples that represents 52 hand gestures and the rest sample, which counts up to 53 classes. The samples are obtained using two Myo armbands, each with 8 sensors; we used the samples of one Myo armband only; to reduce processing complexity during training stage by considering a fewer number of values, and taking into simplicity of use for the future user by requesting wearing one armband rather than two. The rest signal samples form about half the total number, but to avoid the problems caused by unbalanced classes we choose randomly a set of these rest samples with a size close to that of the other classes.

Our approach. We used the raw signals, without any further feature extraction. We examined the effect of signal length (time-steps) on the performance, and the effect of augmentation too.

The suggested approach includes follows four steps, the first step is choosing the sample's size, aiming at having the biggest number of samples and keeping as much time-steps in each sample as possible since they represent the features for the model to learn. Second, we doubled the samples by two/ multi-times. Then, comes the training stage. Finally, we tested model and evaluated the performance.

Evaluation criteria are accuracy, loss, training time and testing time.

The structure of the 1L-LSTM, as shown in fig. 2, consists of three layers:

- Input layer with 8 channels,
- LStM layer,
- Output layer with 53 units.

The size of the layers decreases right wise (from input to output).

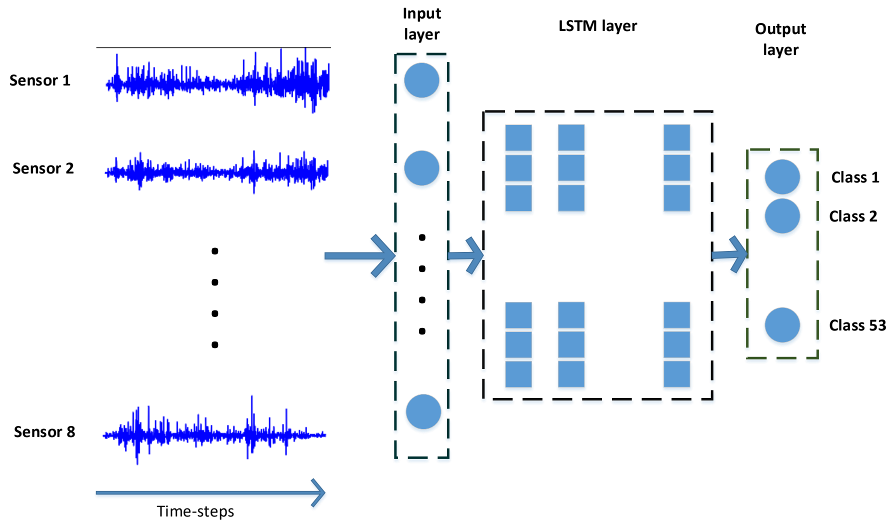


Fig. 2. 1L-LSTM model structure

To build ML-LSTM, two layers were added:

- Simple RNN layer right after the input layer
- Simple RNN layer right after the LSTM layer

This structure, shown in fig. 3, was inspired by concept formation or conceptualization**,** which is the process by which our brains decompose information and then recompose it to create our own concepts. This involves decomposition**,** that is breaking down complex information or experiences into simpler parts (more components), then, re-composition, where the brain recomposes these elements to form new concepts or ideas (less components).

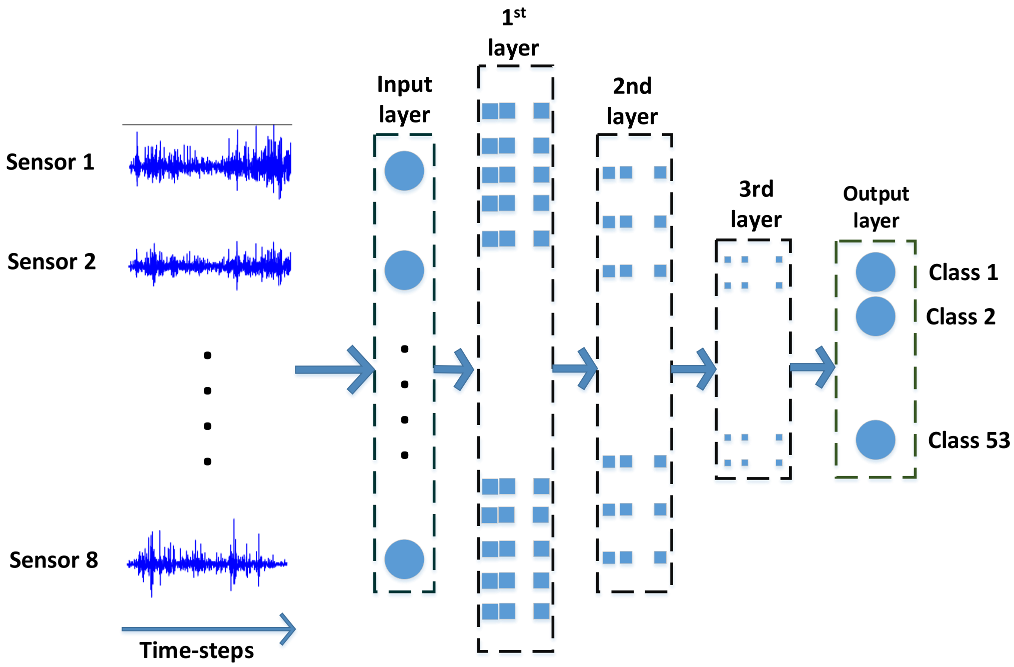


Fig. 3. ML-LSTM model structure

We built a special library for preprocessing the NP-DB5 dataset. Python libraries are the tool used for training and evaluating. Intel(R) Core(TM) i7-10870H CPU is the processor used in all the stages: preprocessing, augmenting, training and testing.

Augmentation effect. The first experiment was training the model using the original NinaPro-DB5 dataset without augmentation. Three signal lengths were tested: 200, 300 and 650 time-steps. However, the model could not learn, even when using longer signals. Fig. 4 shows the accuracy and loss of the model 1L-LSTM.

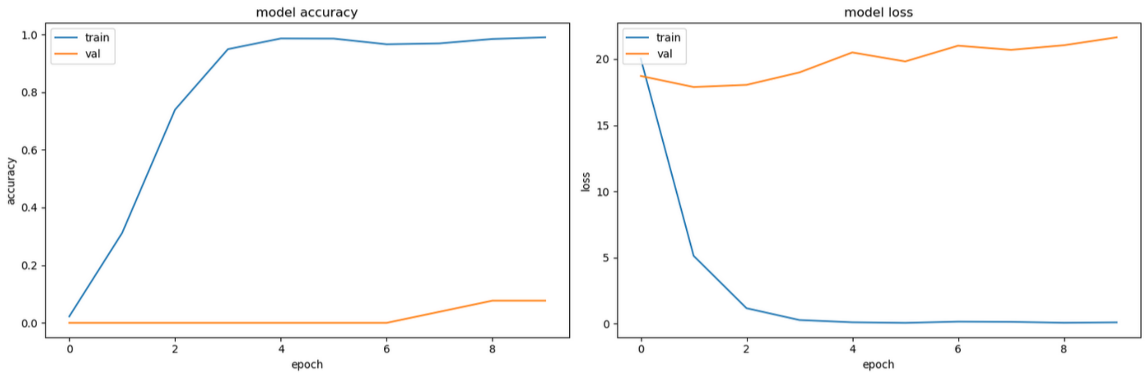


Fig. 4. 1L-LSTM model accuracy and loss when trained using the original NinaPro-DB5 dataset (signal length 650 time-steps)

Second experiment was performed using the doubled dataset, which we got by averaging every two successive sample in each class, and adding the result to the corresponding class. This helped the model learn, and the performance was significantly elevated; but it was still much less than the desired performance. However, the longer the signal the better the performance was. As fig. 5 shows, the model still over fits, and fails to generalize during the evaluation stage.

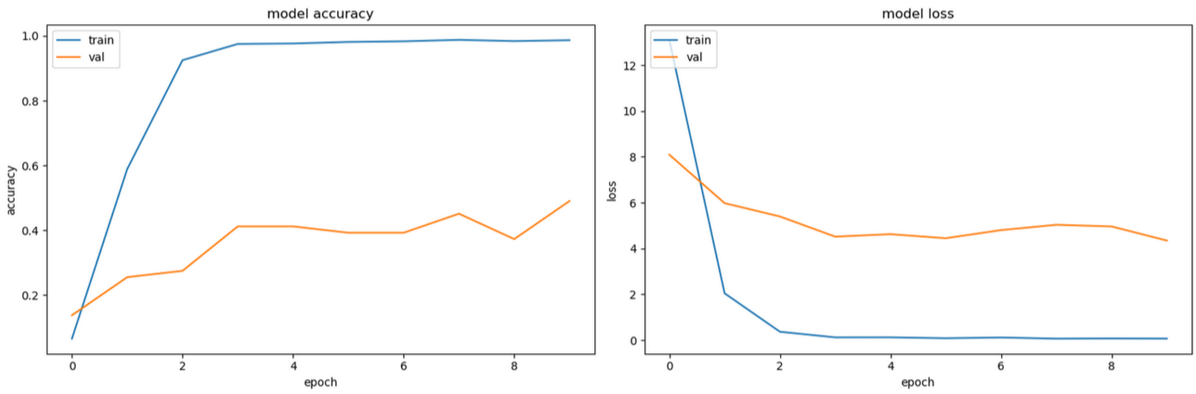


Fig. 5. ML-LSTM model accuracy and loss when trained using the doubled dataset
(signal's length: 650 time-steps)

Thirdly, we doubled the dataset many times, by averaging every two samples of the same class, and adding the new sample to the class. Training the two models using this dataset gave the set goal. The signal's length effect was noticeable with 1L-LSTM, but it slightly affected ML-LSTM.

This result is expected; having enough samples compared to the considered features (original values: 200*8, 400*8 or 650*8) certainly helps the model learn better and achieve the desired performance. Next, we present the results for each model when trained using the multi-times doubled datasets with different input sizes.

One layer LSTM (1L-LSTM). As fig. 6a shows, the1L-LSTM model accuracy, the model reached the highest accuracy value of 98.5% when we used the dataset of signals with the size of 650 time-steps. Moreover, it differs by 2.1% and 2.5% from the results when using signals of the size 400 time-steps and 200 time-steps respectively, this difference could affect the result of any EMG-based control system that uses such a model for recognition. Again, taking into account that the features in our case are the raw values of the signals from the eight different sensors, this result is expected, since having more features and longer signals with more relations to time would help the model build more connections and hence improve its performance. Again, this is obvious in fig. 6b, which shows that training the model with the longest signals allowed the model to decrease the testing loss to about 0.01.

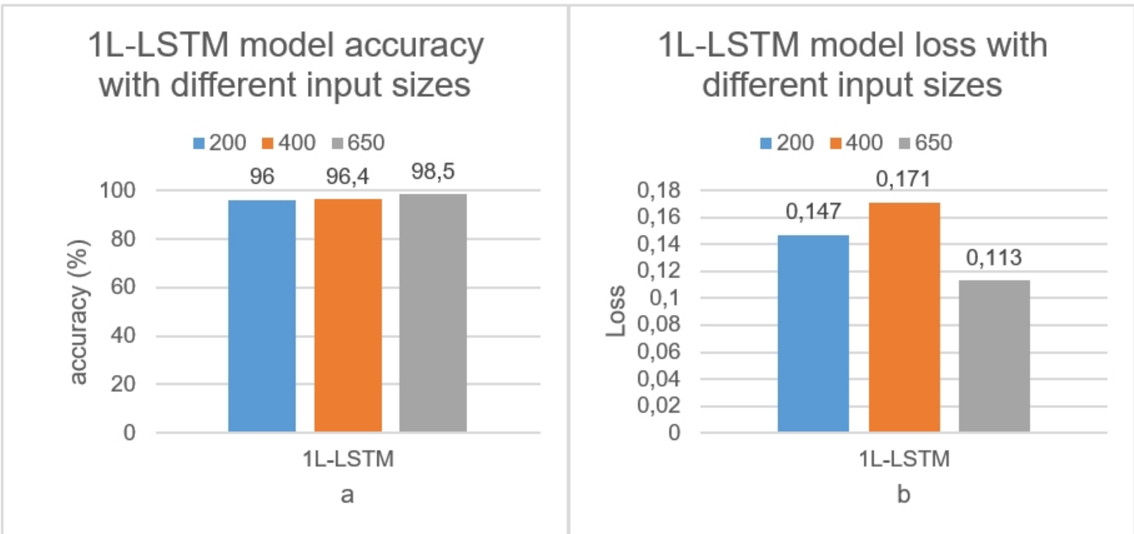


Fig. 6. 1L-LSTM model's accuracy using the multi-times doubles datasets with different input sizes:
a) 1L-LSTM model accuracy, b) 1L-LSTM loss

Unfortunately, the model spends a lot more time in the testing stage when the signal length is 650 time-steps, compared to the time it needs when the signal's length is 200 time-steps or 400 time-steps. In the training stage, the model needed the minimum time when the signal's length was 400 time-steps, yet the difference is not that big since the training is static and performed off-line and will not affect the future system if used with a control system. Fig. 7a shows the training time of the model when trained with different input sizes, and fig. 7b shows the testing time.

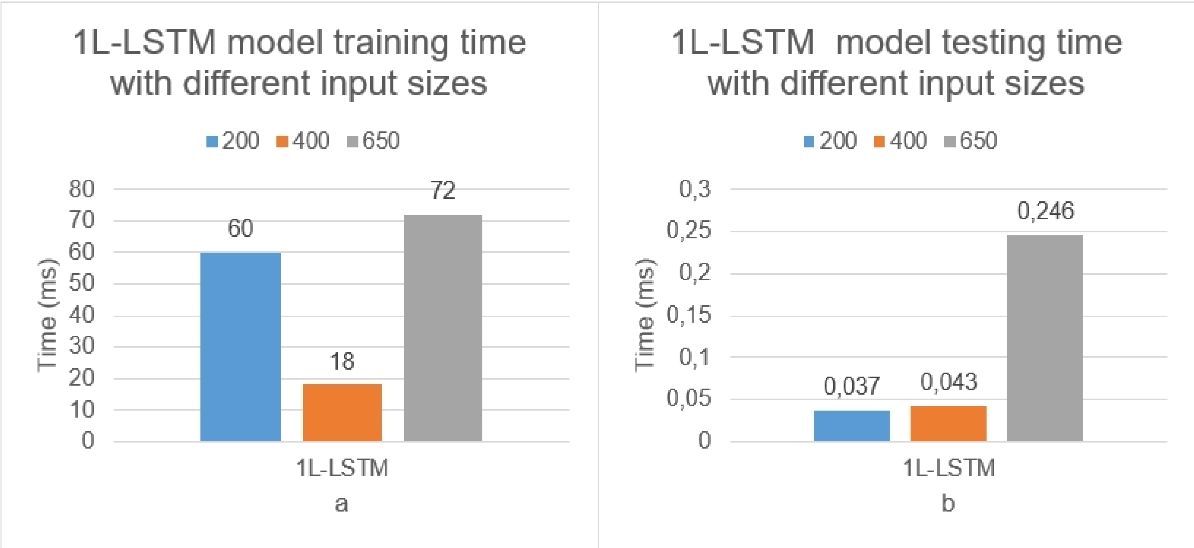


Fig. 7. 1L-LSTM training and testing time when trained using multi-times doubled datasets with different input sizes: a) training time, b) testing time

Multi-layer LSTM (ML-LSTM). Fig. 8a and fig. 8b show the model accuracy and loss respectively. The longer the signal the better the accuracy, and the lower the loss. As shown in fig. 9a the minimum training time was when the signal's length was 650 time-steps. While the differences in testing time were not that significant, as shown in fig. 9b.

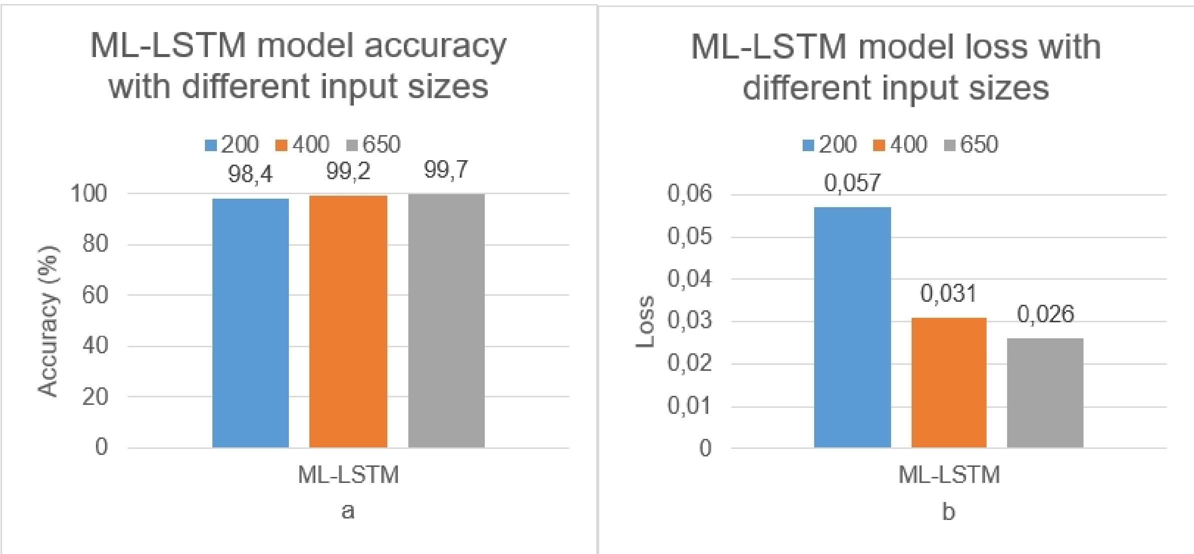


Fig. 8. ML-LSTM model accuracy using the multi-times doubled datasets with different input sizes: a) ML-LSTM model accuracy, b) ML-LSTM loss

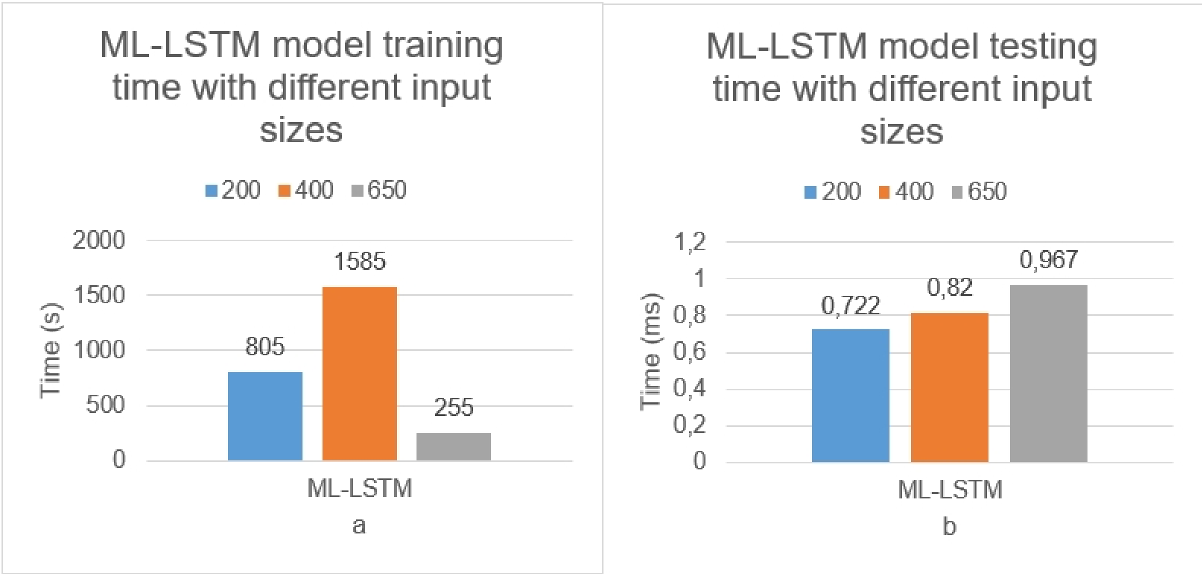


Fig. 9. ML-LSTM model training time and testing time when trained using the multi-times doubled datasets with different input sizes: a) training time, b) testing time

Comparing 1L-LSTM to ML-LSTM. Table 1 shows that ML-LSTM outperformed 1L-LSTM model in two out of four of the evaluation categories considered, it scored higher accuracy, with less loss, but it needed much more time to train and test, which is expected since it has much more parameters to update and modify.

Table 1. Comparing 1L-LSTM and ML-LSTM performance

Model	Accuracy (%)	Loss	Training time (sec)	Testing time (μsec)
1L-LSTM	98.5	0.11	72	246
ML-LSTM	99.7	0.03	255	970

Results discussion. Table 2 shows the results of our approach and some of the state-of-the-art researches in the field. Compared to the first five approaches, which use LSTM and DL, the suggested approach in this work outperformed them, although it had to classify the samples into 53 classes, which is more complex.

Table 2. Model accuracy of our approach and some of the state-of-the-art approaches

Approach	Dataset	Gestures num (classes num)	Model accuracy
4-layer 3rd Order Dilation (pure LSTM) [17]	NinaPro-DB2(B)	17	79.9%
CNN& Bi-LSTM[18]	NinaPro-DB2 UCI Gestures	50 7	95.93% 98.33%
CNN-LSTM[19]	NinaPro-DB2/DB3	13	89.37%
4-stream DL[15]	NinaPro-DB1 NinaPro-DB9	18	94.31% 98.96%
Res-LSTM[16]	NinaPro-DB1	52	91.03%
WaveFormer[23]	NinaPro-DB5	52	87,53%
CNN-transformer[24]	HD-sEMG	65	97,75%
CNN-transformer[25]	HD-sEMG	65	91,98%
TCN-transformer-LSTM[26] TCN [26]	experimental	5	98,82% 96,32%
1L-LSTM	NinaPro-DB5	53	98.5%
ML_LSTM	NinaPro-DB5	53	99.7%

The next four methods (WaveFormer [23], CNN-Transformer [24, 25], TCN [26]) are examples of lightweight models. Developing such models has spread widely recently to provide suitable systems for low-power devices; because of their low computational cost and small size which leads to higher energy efficiency and scalability. The suggested approaches in the work still outperformed these models in terms of accuracy, as expected because LSTM are capable of sequential modeling and has a built in memory that can chose what to drop and what to remember. In addition, they have the ability of learning long-range dependencies dynamically (unlike TCN, which can obtain this only after training. Moreover, they can handle variable-length input. However, although the lightweight models are more suitable for a low-power device in the training stage; they still draw back behind LSTM in the final real-life usage when handling a sample at a time. LSTM must perform only a fixed number of operations, which means the complexity is O(1), while for CNN-Transformer for example to process a new sample at time \`t\`, a standard Transformer requires the entire sequence from time \`0\` to \`t\` to be re-processed to compute new self-attention scores(O(t^2) complexity). Moreover, some of them use HD-sEMG (high-density sEMG) to build image like input data, which is less comfortable for the end user as it requires using a net of many sEMG sensors rather than an armband with a few sensors.

To get the best of the two worlds, one can adopt the following strategy:

Train the suggested models (1L-LSTM / ML-LSTM) off-device in a powerful environment (high performance workstation, cloud storage); then implement the optimized model on the MCU or any other low-power device needed.

Use lightweight-models for online training to improve the performance continuously, or schedule Re-training sessions off-device in a powerful environment, then again implement the improved model with the new parameters.

Conclusion. In this work, we build two LSTM based models to use them for hand gesture recognition using sEMG signals. We studied different situations: different signals' length, different training dataset size. The results show that high performance using signals' original values without any further feature extraction requires having enough data samples. In addition, it shows that augmenting the dataset, using averaging, was a suitable solution; it helps overcome the lack of big datasets for such type of biomedical signals, and helps elevate the performance. When adding more layers, the model performs better in terms of accuracy and loss regardless of the signals' length. The special structure we suggested form ML-LSTM, which was inspired by concept formation, allowed it to outperform the 1L-LSTM in terms of accuracy and loss. However, because it had much more parameters to modify it needs more training and testing time.

1L-LSTM and ML-LSTM scored an accuracy of 98.5% and 99.8% respectively. Compared to other researches, they outperformed them, although the task was to classify 53 hand gestures, while some other researches scored less even though the number of classified hand gestures was less. The models were compared to other lightweight models, and a future approach was suggested to make use of the powerful processing abilities of the LSTM models and the power friendly characteristics of the lightweight methods. These results prove that this approach is a promising one, when considering building a sEMG-based control system, by providing high performance with low complexity.

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ДОЛГОСРОЧНАЯ КРАТКОСРОЧНАЯ ПАМЯТЬ ДЛЯ РАСПОЗНАВАНИЯ ЖЕСТОВ РУК С ИСПОЛЬЗОВАНИЕМ ПОВЕРХНОСТНОЙ ЭЛЕКТРОМИОГРАФИИ

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Сигналы электромиографии (ЭМГ) нашли широкое применение в различных областях. Сети долгой краткосрочной памяти (LSTM) являются одним из наиболее подходящих методов для обработки ЭМГ-сигналов благодаря своей архитектуре. В данной работе были разработаны две модели LSTM: однослойная (1L-LSTM) и многослойная (ML-LSTM). Обучение проводилось на наборе данных Ninapro-DB5, предварительно аугментированном методом усреднения. Были протестированы различные размеры входных данных. Точность моделей составила 98,5% для 1L-LSTM и 99,7% для ML-LSTM соответственно. Время тестирования находилось в диапазоне [60,240] мкс. Кроме того, было установлено, что длина сигнала не оказывает значительного влияния при использовании многослойной архитектуры.

Ключевые слова: LSTM, поверхностная электромиография (пЭМГ), распознавание жестов рук, Ninapro-DB5, аугментация данных.

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