Attention-Based Bidirectional LSTM for Multi-Class Hand Gesture Recognition Using sEMG Signals from NinaPro DB2

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Surface electromyography (sEMG) offers a non-invasive format of recording muscle activation signals and is thus essential in hand gesture recognition of human-computer interaction and assistive technologies. The proposed paper presents an attention-based bi-directional long-short-term memory (BiLSTM) structure, on which the multi-class hand gesture recognition can be realized, on the basis of the NinaPro Database2 (DB2). The given model capitalizes on the dynamics of temporal dependencies of sEMG signals and uses the mechanisms of dynamic attention to the attention of the learnt discriminative temporal features. When using a sample size of 40 individuals, and 49 gestures, results on the subjects are 67.65 percent +/-.76 percent (range: 53.87 percent to 81.68 percent). The attention mechanism is used to increase the interpretability of the model by visualization of the time pieces with the most significant contribution to gesture classification. These findings indicate that attention temporal modelling enhances myoelectric control system recognition performance and explainibility. The future direction of the research will be on subject-adaptation techniques and multi-sensors fusion to strengthen the issue of robustness and generalization among users.

Keywords— *Surface electromyography, Hand gesture recognition, Bidirectional LSTM, Attention mechanism, Deep learning, NinaPro database*

I. Introduction

The problem of hand gesture recognition has been a subject of interest to human-computer interaction and prosthetic control systems, rehabilitation engineering, and wearable assistive applications [1][2][3]. Surface electromyography (sEMG) is the most common tool in this task since it is a non-invasive tool used to record neuromuscular activity that is highly linked to human motor intention [2][3]. The sEMG signals indicate the movement of human body which can be analyzed and identified using deep learning models [4]. Nevertheless, accurate gesture recognition based on sEMG is still not it is not possible because of the non-stationary characteristics of the signal, the inter-subject variability, sensitivity to the location of the electrodes used and the effects of noise and muscle fatigue [5][6]. Surface electromyography (sEMG) is one of such modalities that have been of much interest because it is a non-invasive technique and operating under the principle of recording neuromuscular activity that directly reflects the human motive [4]. Nevertheless, gesture recognition based on reliable sEMG data is defiantly hard due to non-stationary nature of sEMG data, high subject dependability, and sensitivity of sEMG signals to electrode arrangements, muscle fatigue, and noise of the environment [7][1][6]. The initial sEMG gesture recognition systems used time or frequency domain features handcrafted and traditional machine learning classifiers. Although these methods succeeded in a controlled environment, they frequently failed to apply to large-scale, multi-class, and multi-subject data. The current developments in the field of deep learning have enhanced the analysis of sEMG by allowing automatic feature acquisition and enhanced time modeling. Specifically, recurrent neural networks like long short-term memory (LSTM) and bidirectional long short-term memory (BiLSTM) models have shown a high ability to encode temporal performance of sEMG sequences. However, temporal muscle parts of an sEMG signal do not add equally to gesture differentiation. Attention mechanisms mitigate this limitation by laying more emphasis to informative time-steps and hold back less meaningful areas [8]. This work is inspired by this; hence, it explores an attention-based BiLSTM model to sEMG-based hand gesture recognition and tests it on the difficult NinaPro DB2 data set comprising of recordings of 40 subjects practicing 49 hand gestures [1]. Instead of trying to achieve state of the art accuracy, systematic preprocessing, model design stability, and multi-subject evaluation have been examined in this research granting practical information on the performance threshold of attention based recurrent models due to realistic computational and time constraints.

II. related Work

In medical sector, the use of machine learning and deep learning models have increased exponentially in last few years for their easier application and human-machine interaction. Surface electromyography (sEMG) is a famous technique mostly used to detect muscle movement using electrophysiological signals and it's very beneficial for acquiring robust muscle information and the functionality [9], [10]. There's been many studies conducted on sEMG using deep learning models.

Most recently, Sakinala et al. [6] achieved raw accuracy 85% using stacking ensemble method constituting CNN, LSTM and Random Forest for only 29 gestures of NinaPro DB1 dataset. Similarly, Doostkam et al. [11] showed ViEMGT, a Vision-EMG Transformer that was able to bring 95.2% accuracy on 22 gestures. Though, this model is heavily dependable on high density sEMG hardware, it's application for light weight prosthetic devices is limited. To cop up with the problems raised by signal variations, Liu et al. [2] introduced a Dual-Model Adaptive Continuous Learning (DM-ACL) technique using k-Nearest Neighbors(kNN), CNN and LSTM, achieving 95.33% on 5 gestures. Later, Aarotale and Rattani [12] published their research showing 97% accuracy using 1D dilated CNN and 94.95% using Random Forest. However, the dataset contained only 12-16 gestures only. Nahid et al. [13] classified sEMG as an Image Recognition Problem, where he used CNN-LSTM architecture to gain 99.83% on Rami Khusaba repository (10 gestures) and 99.72% (6 gestures) in UCI machine learning repository using only 2 channel sEMG system. Then, Gouda et al. [3] worked on two staged architecture using SVM and ANN and achieved 99% accuracy on dataset containing 6 subjects and 7 gestures. Again, Marbán Salgado et al. [14] using ESP 32 microcontroller on a single sEMG channel for 6-8 gestures having a state of an art accuracy. On the other hand, we researched on high-dimensional 49 class hand gestures applying Attention based BiLSTM architecture. We focused on maintaining a stability of our framework efficiency and its capability of complex explainibility and applied attention algorithm to differentiate muscle movement pattern rather than depending on 'black-box' interpretability.

III. METHODOLOGY

A deep learning architecture relying on attention models of surface electromyography (sEMG)-based hand gesture recognition was created and evaluated under the structured approach. The approach also involves dataset selection, preprocessing of signals, temporal segmentation, model architecture development, training and performance measures based on subject-wise accuracy and statistical variability measures. To deal with the challenges of inter-subject variability and non-stationarity of signals with large-scale sEMG data as NinaPro DB2.

A. Dataset Description

This study uses the NinaPro Database 2 (DB2), the general benchmark data when training a surface electromyography (sEMG)-based hand gesture recognition system. The dataset includes the sEMG signals which are preprocessed and filtered with band-pass filter with 10-1000 Hz and notch filter with 50 Hz [15]. The multi-channel sEMG records provided by NinaPro DB2 were and measured in 40 healthy individuals where each individual performed a predefined replication of motions involving hands and wrists under strictly supervised conditions in the laboratory [13]. The dataset is a good choice of model evaluation since it is specifically designed to test gesture recognition algorithms in the real condition of the inter-subject variation. The sEMG data were recorded by applying 12 Delsys Trigno electrodes over the forearm, flexor, biceps, triceps and extensor muscles to record the movements of dynamic muscle action of each of the individual subjects [1]. Besides the raw sEMG signals, the dataset includes synchronized annotation data with gesture labels (restimulus) and repetition indices (repetition) of each time sample that allow the accurate segmentation and regular means of learning.

Besides a rest, NinaPro DB2 has 6 repetitions of 49 gesture classes that are carried out by 40 individuals; this category includes great diversity of hand, wrist, and finger movements of human beings, robotic, and prosthetic hand, open sources to carry out research [8]. The data may be partitioned into training, validation, and testing subsets based on the repetition indices as every motion is done a few times per person. Although we maintain subject-dependents consistency, our split of evaluation described by repetitions ensures that we evaluate unseen executions of gestures. The gestures in NinaPro DB2 make the gesture recognition models using a deep learning-based approach hard and that too very exacting due to its large gesture set, non-stationarity of signals, and large inter-subject variability.

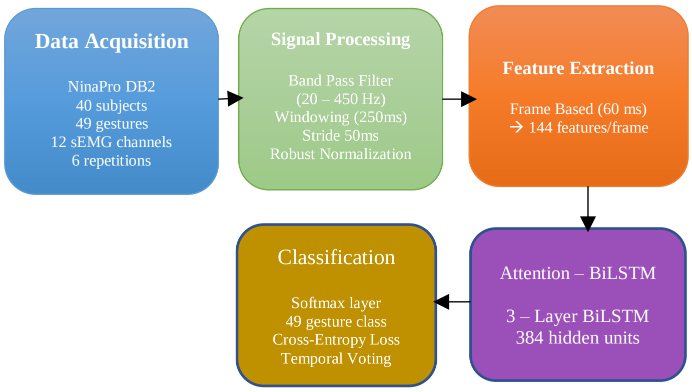

Figure 1 : Flow Chart of Data processing

B. Data Preprocessing

The unprocessed (raw) electromyography (sEMG) data retrieved by NinaPro DB2 require detailed post-processing steps to ensure the reliability of signals, get rid of noise, and be able to analyze subject variability. The preprocessing normally includes amplification, windowing, and filtering [13]. Ensuring the necessary computational efficiency needed to perform high-level processing might therefore be a challenge especially in terms of low-latency sEMG model processing [16]. Since the sEMG recordings are strongly vulnerable to motion artefacts, electrode movement and mains disturbance, medical practices must be strict in their preprocessing to increase the strength and applicability of the suggested learning system. The pipeline used in this article is specifically obtained to maintain discriminative patterns of muscle activation and remove artefactual and corrupted signal components.

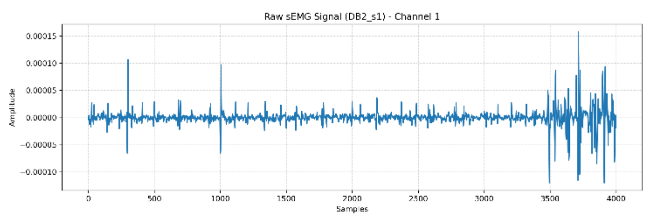

Figure 2 -raw sEMG signals

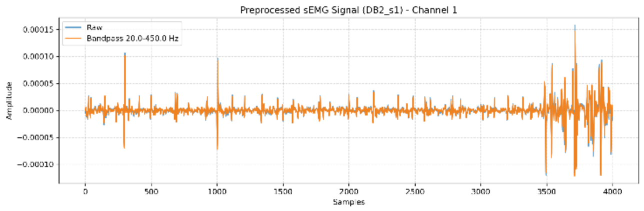

Figure 3- sEMG signal after processing and filtering

1) Signal Alignment and Integrity Checking

First, sEMG channels are verified in terms of the temporal alignment and data completeness are examined respect to each other. Samples that display gaps or a rotted sample and corrupted samples are removed so as to maintain signal continuity among the samples.

2) Band-Pass Filtering

The sEMG recordings are processed using a fourth-order Butterworth band-pass filter where the limits are 20 Hz and 450 Hz to silence motion artefacts and high frequency electrical noise of the sEMG signal but leave the original muscle activation dynamics intact. Temporal fidelity and phase distortion prevention Zero-phase filtering (bidirectionally) is used.

Equation (Butterworth filter transfer function):

$$H(s) = \frac{1}{\sqrt{1 + (\frac{s}{\omega_c})^{2n}}}$$

where n=4, and ω_c corresponds to the band-pass cutoff frequencies.

3) Windowing and Segmentation

The sEMG signals are divided into parts after filtering by using a sliding-window scheme. The windows represent independent samples of muscular activity, overlapping windows are added to enjoy sample variability and preserve the context.

Equation (Window extraction):

$$X_k = x\,[t_k : t_k + L]$$

Where L is window length and $t_{k+1} = t_k + S$ with stride $S < L$.

4) Rest Class Removal and Gesture Purity Control

The null or rest gesture (label 0) is thrown off so that learning will focus on active hand gestures. A gesture-purity criterion is also needed whereby a window is maintained only if most of the samples making up it are the same gesture thus avoiding contamination of mixed-gesture material.

Equation (Purity condition):

$$\frac{1}{L}\sum_{i=1}^{L} 1(y_i = g) \geq \tau$$

Where τ is defined as purity threshold. (e.g., 0.9).

5)Feature Normalization

Per-channel normalization of feature vectors extracted by each window is on basis of statistics calculated using training partition only. This plan reduces the inter-subject deviation and prevents information leakage hence stabilizing the optimization process, and increasing the convergence rates. Equation (Z-score normalization):

$$\hat{x} = \frac{x - \mu_{train}}{\sigma_{train}}$$

6)Feature Level Augmentation

In order to enhance generalization and inhibit overfitting, when training, the Gaussian perturbations are added at the level of the feature. The method reacts to natural variability in muscular response without ruining any semantic meaning of the gestures. Equation (Noise injection):

$$\tilde{x} = x + \epsilon, \epsilon \sim N(0, \sigma^2)$$

C. Deep Learning Model

1) Overview of Proposed Architecture

A long short-term memory network, which has been extended with an attention mechanism (Attn -BiLSTM) is used to detect hand gestures using the temporal dynamics of sEMG signals. The sequential disparate nature of sEMG makes discriminative information to be scattered over time. Conventional machine-learning algorithms can only approximate such temporal representations hence supporting the use of recurrent neural network based structures.

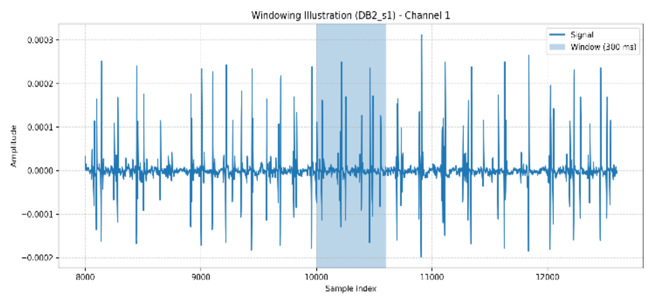

Figure 4-framing the features with windows classification

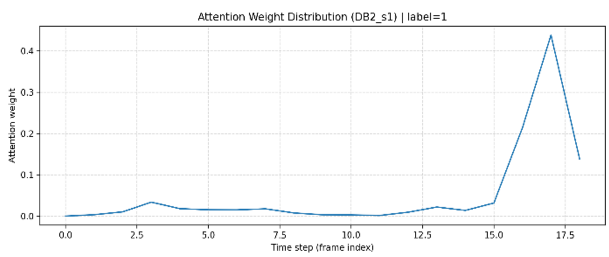

Figure 5-Attention weight distribution is illustrated in different time intervals

The architecture proposed in our research proposes three main key points:

1. Consecutive portrayal of input features.
2. A BiLSTM structure for temporal modeling of the channels.
3. And before classifying, an Attention based algorithm to highlight the time intervals of each steps.

2) Long Short-Term Memory (LSTM)

LSTM is a particular recurrent neural network designed with attempts to solve the vanishing -gradient problem of regular RNNs that contains gated memory units. The LSTM cell adapts its memory state inside by incorporating or excluding information at time step t, based on the signal being fed into it, x t. The LSTM uses the gating mechanisms; input, forget, and output gates to coordinate the information flow in order to compute the memory state, the LSTM calculates the following gates:

$$
\begin{aligned}
f_t &= \sigma\left(W_f x_i + U_f h_{t-1} + b_f\right) \\
i_t &= \sigma(W_i x_i + U_i h_{t-1} + b_i) \\
\tilde{c} &= \tanh(W_c x_t + U_c h_{t-1} + b_c) \\
c_t &= f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \\
o_t &= \sigma(W_o x_t + U_o h_{t-1} + b_o) \\
h_t &= o_t \odot \tanh(c_t)
\end{aligned}
$$

where σ (·) denotes the sigmoid activation function, ⊙ represents element-wise multiplication, and h_t and c_t are the hidden and cell states, respectively.

3) Bidirectional LSTM (Bi-LSTM)

Bi-LSTM allows the exploration of temporal contexts of the past and the future at the same time. The Bi-LSTM uses two directions of sequence processing forward and backward at both current and past time steps, producing an output hidden state with each time step; one is called the forward and the other backward state concealed state t is given for a given time step t:

$$
\begin{aligned}
\vec{h}_t &= LSTM_{forward}(x_t) \\
\overleftarrow{h}_t &= LSTM_{backward}(x_t)
\end{aligned}
$$

By adding both of these states the final Bidirectional LSTM output is generated:

$$h_t = \left[\vec{h}_t; \overleftarrow{h}_t\right]$$

This is a bidirectional rendering enabling a more in-depth representation of gestures dynamics since the model could consider the complete context of signals, thus especially it is beneficial to the characterization of complex hand or body movements.

4) Attention Mechanism

Although Bi-LSTMs are sensitive to time relationships, they do not give the same predictive influence to every time step. In order to alleviate this shortcoming, an attention mechanism is proposed that incorporates more influence to the more informative portions of the sEMG sequence. To compute the attention score, AT t, is obtained as:

$$
\begin{aligned}
e_t &= \tanh(W_a h_t + b_a) \\
\alpha_t &= \frac{\exp(e_t)}{\sum_{k=1}^{T} \exp(e_k)}
\end{aligned}
$$

In this context, αt is represented as the normalized version of attention weight of the signals and the total number of time steps is denoted as T. The weighted sum which is calculated from Bi-LSTM output is classified as context vector c below:

$$c = \sum_{t=1}^{T} \alpha_t h_t$$

This algorithm helps the model to improve against noise and increase its robustness and applicability.

5)Classification Layer

Class probabilities are generated by passing a context vector c with the softmax activation in fully connected layer:

$$y = Softmax(W_s c + b_s)$$

By applying the categorical cross-entropy loss method the model is trained:

$$L = -\sum_{i=1}^{C} y_i \log(\tilde{y}_i)$$

where y_i represents the ground-truth label, and $\hat{y}_i$ represented as the predicted probability and C is number of gestures.

IV. EXPERIMENTS

A. *Experiment Setup*

All testing was done in Python 3.10 using PyTorch to perform deep-learning inference, NumPy, and SciPy to perform signal-processing operations and scikit-learn to calculate evaluation measures, and Matplotlib to depict data. Training and evaluation processes were done using a regular desktop machine with the specification of AMD Ryzen 7 CPU, 32GB RAM, and Windows 11 (64 bits). The performance was also improved with the help of NVIDIA GeForce 4050 RTX-GPU that showed the model computational efficiency with regular hardware resources.

B. *Experimental Design*

The offered architecture was considered with regards to NinaPro DB2 dataset that consists 12-channel surface electromyography (sEMG) records of 40 participants, performing 49 different hand gestures. The applied validation strategy was subject-dependent, where repetitions (repetition) 1-4 were used in the training, repetition 5 in the validation, and 6 in the test sets. Because of the inter-subject variability in muscle activation patterns, each subject was trained independently. The optimizer used in training was AdamW, and early stopping which was measured by validation accuracy was used to control overfitting. Classification accuracy as well as weighted precision, weighted recall, and weighted F1-score (commonly applied in multi-class gesture recognition) were considered as the measures of model performance.

V. Results

A. Subject-Wise Classification Performance

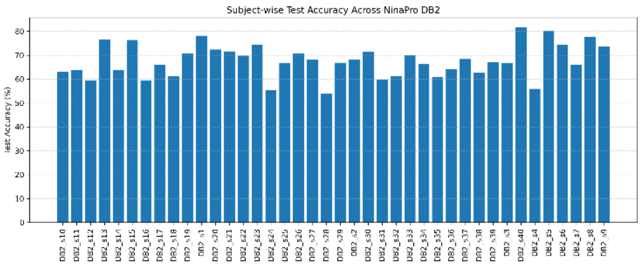

Figure 6-Each subject's accuracy for whole NinaPro Dataset

Figure 6 (Accuracy per Subject) shows the accuracy in the classification of gestures received on each of the 40 subjects. The findings indicate observable inter-subject variability which is a popular feature of sEMG-based systems because of disparities in physiology of muscles, electrode positioning, and electrode signal quality.

A number of subjects (e.g., DB2s1, DB2s40, DB2s55, DB2s58) realized more than 75% accuracy with maximum accuracy reached at 80 and above, which suggests that the proposed model can be trained to learn high levels of discriminative temporal patterns using sEMG. On the other hand, there were few subjects, with lower accuracies (approximately 55-60%), and this could be explained by the noise acquisition of the signals, weak muscle responses, or high intra-class variation. The findings point to the realistic and difficulty of subject-specific sEMG gesture classification whereby a zero-error performance is almost impossible to achieve without subject adaptation or calibration.

B. Distribution of Accuracy Across Subjects

To further examine the strength of the proposed approach, the spread of the classification accuracy in all subjects is plotted by using a histogram in Figure 6. The findings reveal that the majority of the subjects obtain the accuracies of 60%-75% with a minor proportion reaching above 80 percent. This dispersion implies that the performance can be rather consistent among subjects and the suggested attention-conditioned BiLSTM does not assume high accuracy of a small group of people.

C. Discussion of Attention Mechanism Effectiveness

The addition of an attention-mechanism to the BiLSTM based system helps the model to adhere more significance to the more informative temporal sections of individual sEMG windows. This is particularly advantageous during gestures recognition wherein discriminatory patterns of muscle activity are only developed within short temporal patterns. The model specifically lays emphasis on the time steps that represent active muscle contractions and suppresses the undesirable or unnecessary information, which is also indicated by the visualizations of the attention weights. The advantage of such biased attention increases generalization as this is especially effective in subtle gestures, which are also slightly different across classes.

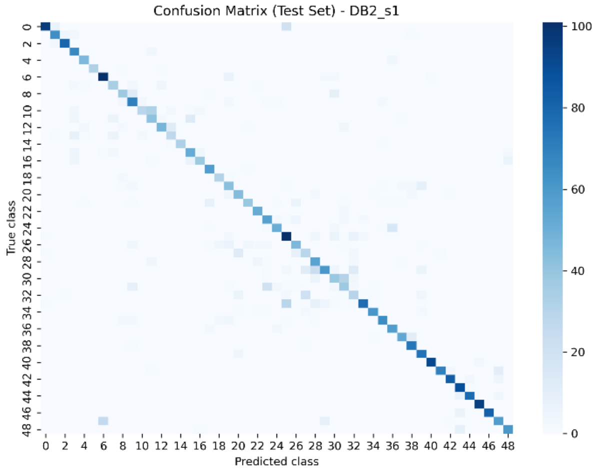

Figure 7-Confusion matrix of all subjects

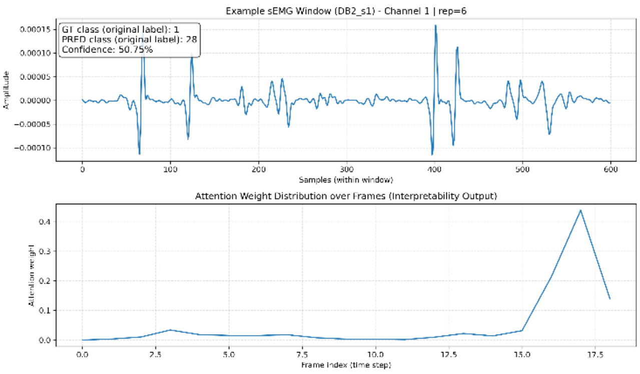

Figure 8-gesture recognition and interpretability for DB2_s1 (subject 1)

The figure of the sample sEMG window and the weight distribution of attention belonging to subject DB2_s1 is shown in Figure 8. The attention mechanism gives greater weights to the time segments related to strong muscle activation therefore showing the ability of the model to focus on, the discriminative time areas to predict gestures.

D. Comparative and Practical Analysis

It has been found that though higher classification accuracies have been achieved in previous research, most of them have been when lower sets of gestures are used, when the sub-sets are used or highly controlled experimental procedures. Conversely, the current experiment assesses the 49 gestures in a sample of 40 participants, and hence significantly more demanding and practical environment. In the given framework, the suggested framework can be proven to be having a balanced trade-off of model complexity, computational efficiency, and classification performance, hence obtaining favorable acceptability to real-time human-machine interaction and assistive technology implementation.

VI. CONCLUSIONS AND FUTURE WORKS

In this paper, an attention based BiLSTM architecture was used to recognize hand gestures using surface electromyography (sEMG) and tested on NinaPro DB2. Combining the strong signal preprocessing, time-frequency feature representation and a temporal attention mechanism, the proposed approach demonstrated consistent and stable performance on the 40 subjects. In spite of the fact the achieved accuracy is not the best compared to all the recent large-scale or strongly optimized state-of-the-art models, the framework has proven a viable trade-off between recognition performance and computational efficiency, and model interpretability. Attention mechanism increases explainibility of the model as it points at the temporally salient patterns of muscle activity, which is especially useful in biomedical and assistive use. These properties allow the suggested approach to be applicable to the situations in which transparent decision-making and the moderate level of complexity of computations are needed. In the future, one will work on the problem of enhancing cross-subject generalization by domain adaptation and subject-invariant learning or hybrid methods that combine CNN and RNN or transformer-based models. It will also be inquired to determine how to support useful prosthetic and human-computer interaction systems through real time deployment and validation on embedded or wearable platforms.

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