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# EMG PATTERN RECOGNITION FOR THUMB MUSCLE STATES USING WEARABLE SENSING AND ADAPTIVE NEURAL NETWORK

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***Abstract.*** *Accurate classification of electrophysiological signals, particularly electromyographic (EMG) is essential for the development of advanced systems in sports medicine, biomechanical prosthetics, and neurocomputer interfaces. However, challenges such as signal noise, device portability, and real-time processing constraints limit the practical deployment of EMG-based interfaces. In this paper, we present a custom wearable device for EMG data acquisition and real-time classification of muscle activity. The device integrates an ESP32C6 microcontroller for wireless data transmission, an AD8232 analog sensor module for electrophysiological signal capture, and Ag/AgCl electrodes placed on antagonist muscles of the hand. EMG signals are sampled at 1000 Hz, preprocessed by normalization and filtering, and then classified using a two-layer feedforward neural network trained with the ADAM optimization algorithm. The dataset contains 4000 consecutive time series that reflect the dynamics of EMG signals across three thumb motor states: rest, abduction, and adduction. The neural network achieved a classification accuracy of 94% in real time, with high stability and minimal delay, demonstrating reliable detection of muscle activity patterns. The integration of low-cost hardware with an adaptive neural classifier enables efficient real-time EMG signal interpretation. The use of ADAM optimization ensures stable convergence and robustness to signal variability. This work contributes a compact and effective solution for real-time EMG classification, paving the way for its application in wearable rehabilitation systems, neuro-controlled prosthetics, and intelligent human–machine interfaces.*

***Key words:*** *data analysis, electrophysiological signals, EMG, wearable sensing, classification, neural network, optimization algorithm, pattern.*

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## 1. INTRODUCTION

In recent years there has been rapid development of technologies in the field of neuro prosthesis, exoskeletons and systems for the restoration and rehabilitation of patients with neurological disorders resulting from injuries to the brain and spinal cord, strokes and paralysis. At the same time, there is growing interest in creating the next generation of robotic prostheses capable of adapting to the individual characteristics of the user. The use of bioelectric signals, in particular electroencephalography (EEG), electrocardiography (ECG) and electromyography (EMG) [1, 2], is becoming increasingly important for building effective human-machine interfaces.

EMG, as a method of recording the electrical activity of muscles, plays a key role in monitoring muscle activity as well as studying neuromuscular connections. It allows not only the assessment of the functional state of muscles but also the indirect examination of nerve-cell activity. During muscle contraction, its cells generate electrical impulses that can be recorded using surface electrodes. The main characteristics of an EMG signal are intensity (amplitude), which reflects the force of contraction, and frequency, which characterizes the level of muscle activation. However, despite significant scientific progress, accurate and reliable classification of EMG signals in real time remains a challenge. This is hindered by signal instability, noise, limited hardware resources in portable devices and the complexity of interpreting signals across different motor states.

In this context, it is relevant to develop simple, reliable and accessible solutions that provide automatic recognition of muscle-activity patterns with high accuracy and minimal delay, for subsequent use in rehabilitation systems, sports medicine and neurocomputer interfaces.

The process of classifying electrophysiological signals and extracting vital information must be reliable, automatic and highly accurate, which is why many current studies are focused on finding methods that improve the results of data analysis and processing, including EMG [3–6].

In the paper [7], a two-layer Feedforward ANN was used to reproduce the activity of shoulder muscles; the RMSE was 0.33–0.84 for unreported data. The authors of the work [8] proposed a method for classifying multichannel EMG signals using DBN, which outperforms LDA and SVM by ~7.5% and ~2.9%, respectively. At the same time, a wavelet-based DBN was applied in the research [9] to recognize upper-limb movements. In the paper [10], a method for classifying multichannel neurosignals to improve the detection of brain diseases was proposed using the E-DBN architecture together with the Adam-COA method. The CNN model [11] analyses ECG representations where the Adam optimizer provided better accuracy and training stability compared with an optimizer such as SGD. The authors of work [12] compared several DNN architectures for classifying gestures from EMG signals, with the Adam optimizer providing the best results (~94% accuracy versus ~88% for other optimizers).

The analyzed studies demonstrate the scientific community's ongoing interest in improving the accuracy and stability of electrophysiological-signal classification, particularly EMG. The main trends include the use of deep neural networks (DBN, CNN, DNN) and optimizers such as ADAM, which provide better convergence and high accuracy. However, most work focuses either on multichannel data or on complex architectures that are not always compatible with real usage conditions, notably in portable or low-power devices for rehabilitation. Furthermore, there are no examples of complete integration of systems for real-time collection, processing and classification of signals on low-cost embedded solutions. This defines the relevance of the proposed approach, which combines compact hardware with an adaptive neural network optimized using the ADAM algorithm for practical use in sports medicine, prosthetics and neurointerfaces.

## 2. MAIN PART

### 2.1. Statement of the problem

The aim of the work is to develop a test device for collecting EMG data and classifying muscle activity in real time through an adaptive ADAM algorithm used to optimize the weights of a two-layer feed-forward neural network using the gradients of neuronal activation functions. This study aims to develop a compact system that would provide:

1. Collecting EMG signals using a low-cost and energy-efficient microcontroller-based device.
2. Primary processing and filtering of signals taking account the noise and movement artefacts.
3. Real-time classification of muscle states.
4. Ensuring the stability and accuracy of classification is suitable for further implementation in practical medical-rehabilitation or sports systems.

The research task includes not only the development of a hardware-software complex but also testing its ability to accurately classify the main states of muscle activity (rest, abduction, adduction) based on a single-person collected EMG dataset. Particular attention should be paid to ensuring the stable operation of the classifier under conditions of limited resources and potential use in mobile or portable devices.

### 2.2. Hardware part of the development

The following components were used in developing the test device for collecting and analyzing EMG data (Fig. 1):

1. The ESP32C6 microcontroller providing wireless data transmission such as Wi-Fi and Bluetooth and supporting numerous sensors, due to which it is often used in Internet of Things (IoT) technology [13–15].

2. The integrated AD8232 chip designed for reading electrophysiological signals, suitable for use in portable devices, health monitors and telemedicine systems.

3. Ag/AgCl electrodes used for reading electrical activity; they contact the skin and transmit electrophysiological signals to the sensor module.

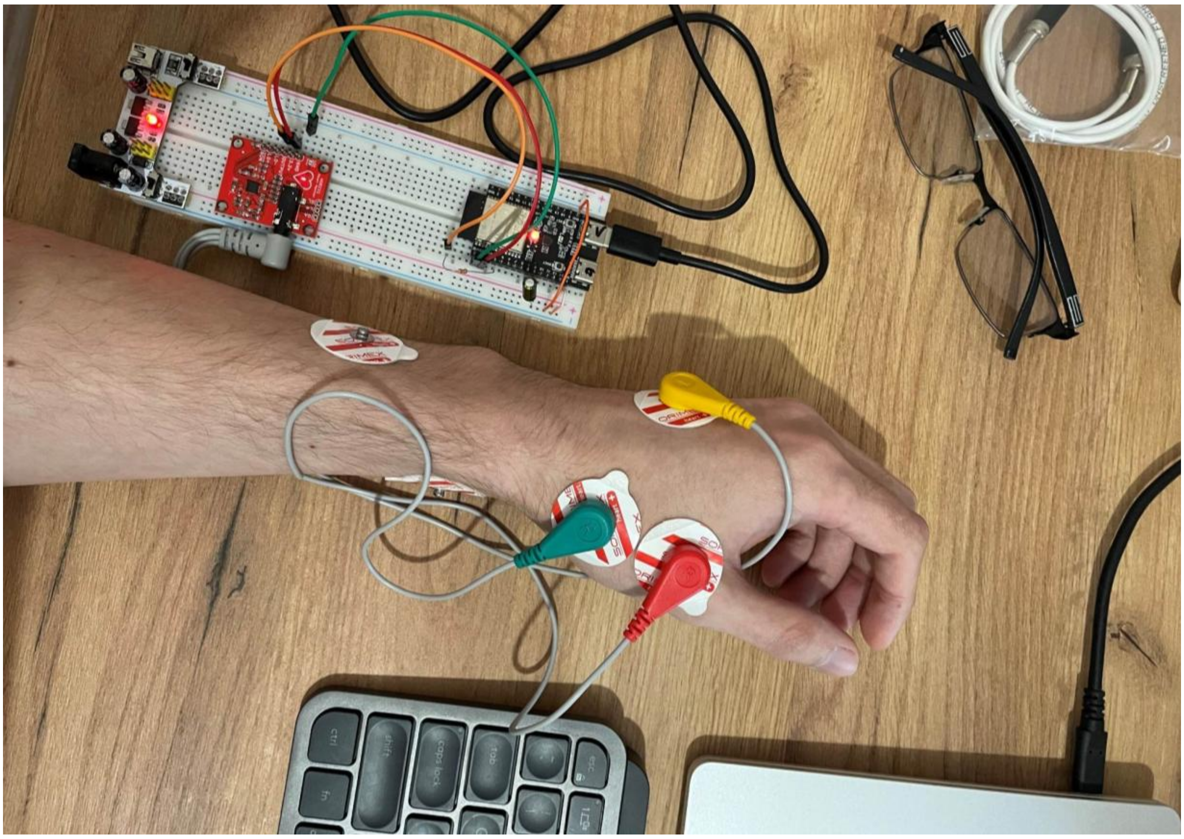

**Figure 1.** Test device for collecting EMG data

### 2.3. Data collection and processing

For EMG data collection, Ag/AgCl electrodes are preliminarily placed on antagonist muscles of the hand. Analogue-to-digital conversion (ADC) converts analogue electrophysiological signals into a digital format for further processing. An ADC with a high sampling frequency of 1 kHz ensures accurate reproduction of muscle activity, preserving high-frequency components necessary for correct reconstruction of contraction amplitude. The AD8232 module acts as a differential amplifier/filter, allowing digital filtering at 10–450 Hz. Once the signal enters the ESP32C6 microcontroller, it undergoes normalization, which brings the signal values to the standard range [0, 1], thereby facilitating further processing and avoiding the influence of absolute amplitudes. All these steps reduce noise and artefacts that may arise due to electrode movement or electrical interference. The microcontroller transmits the already aggregated data to the computer via wireless communication (Fig. 2). The Wi-Fi 6 (802.11ax) communication standard is used, offering improved bandwidth and speed in congested networks in the 2.4 GHz range, providing greater range and signal stability even through interference, which is important for continuous transmission of electrophysiological signals.

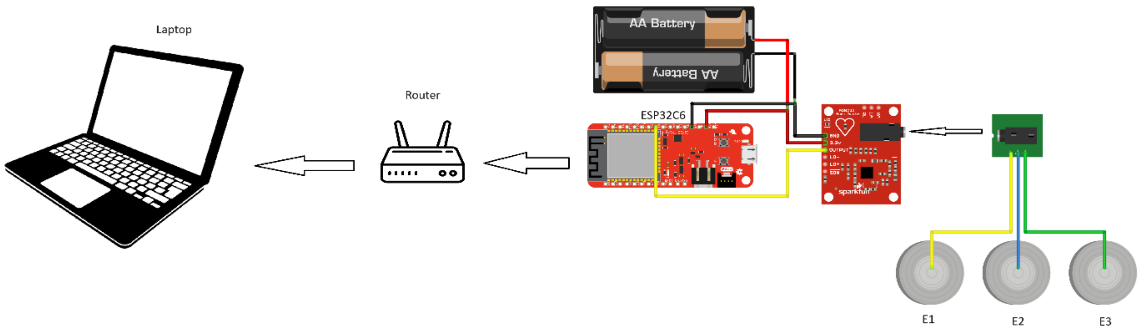


**Figure 2.** The working principle of the test device for collecting and analyzing EMG data

### 2.4. Data classification

A model based on a two-layer feed-forward neural network (FFNN) is used for EMG-signal classification. The network learns to recognize different muscle states/actions. The model training process includes data preparation: EMG data are split into training and test sets. The model is trained for 50 epochs; the size of the hidden layer in the model is set to 64 neurons. During training the ADAM (Adaptive Moment Estimation) algorithm is used, combining gradient descent with adaptive learning-rate correction. This is a key element in training the model because these gradients indicate the direction in which the weights need to be adjusted to reduce the loss, allowing greater accuracy and stable and fast convergence even for large and complex datasets. To update the parameters $\theta_t$ the ADAM algorithm uses the following equations:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t,$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2,$$

$$m_t^\wedge = \frac{m_t}{1-\beta_1^t}, v_t^\wedge = \frac{v_t}{1-\beta_2^t},$$

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{v_t^\wedge + \epsilon}} m_t^\wedge, \tag{1}$$

where $g_t$ are the gradients, $m_t$ is the exponentially weighted moving average of the gradients and $v_t$ is the exponentially weighted moving average of the squared gradients. The default values for $\beta_1$ and $\beta_2$, which are exponential decay rates for moment estimation, are 0.9 and 0.99 respectively. $m_t^\wedge$ and $v_t^\wedge$ are the bias-corrected estimates of $m_t$ and $v_t$; $\epsilon = 1e\text{-}8$ is a parameter to avoid division by zero; $\eta$ is the learning rate.

After training, the model is evaluated on the test set; accuracy is calculated as the proportion of correctly predicted classes, which is an important indicator of its effectiveness. To reduce the impact of random fluctuations in the predicted values, a function is used that «activates» a neuron if the input value is greater than zero and returns zero if the input value is equal to or less than zero. This smooths the data, allowing more stable results. The model saves the learned weights, allowing them to be used further without retraining. During the prediction of new data, the model returns not only the predicted classes but also probabilities, which helps to assess the degree of confidence in each prediction.

### 2.5. Testing of the developed device

During the experiment, a dataset of EMG signals collected with the developed test device was gathered consisting of 4 000 consecutive time series representing the variability of electrode signals. The collected set was used to test the developed EMG-data classifier based on the ADAM algorithm used to optimize the two-layer feed-forward neural-network model (80 % for training and 20 % for testing). Figure 3 visualizes the classification results of EMG data obtained from the test device in real time. The graphs demonstrate the processing and recognition of muscle activity in three states: rest (1), abduction (0) and adduction of the thumb (2):

– EMG_HAND (top graph) displays the normalized EMG signal read from the antagonist muscles. Clear amplitude fluctuations corresponding to muscle activity during motor actions can be observed;

– state displays the real (reference) muscle-activity states recorded during the experiment;

– predicted shows the predicted classes generated by the model. With a predominant majority of correctly classified states, the results correspond to the reference values;

– smoothed_predicted is the model’s prediction smoothed by a moving average (reducing fluctuations between state transitions, increasing the model’s resistance to noise and short bursts);

– probabilities illustrate the prediction probabilities for each class: the orange line corresponds to the model’s confidence in the rest state; the green line the confidence in thumb adduction; and the blue line the confidence in thumb abduction.

The last metric is used to convert the raw model outputs into probability distributions, interpreting each result as belonging to the corresponding pattern. Clear dominance of one of the lines in each segment of the signal indicates a high degree of differentiation between states.

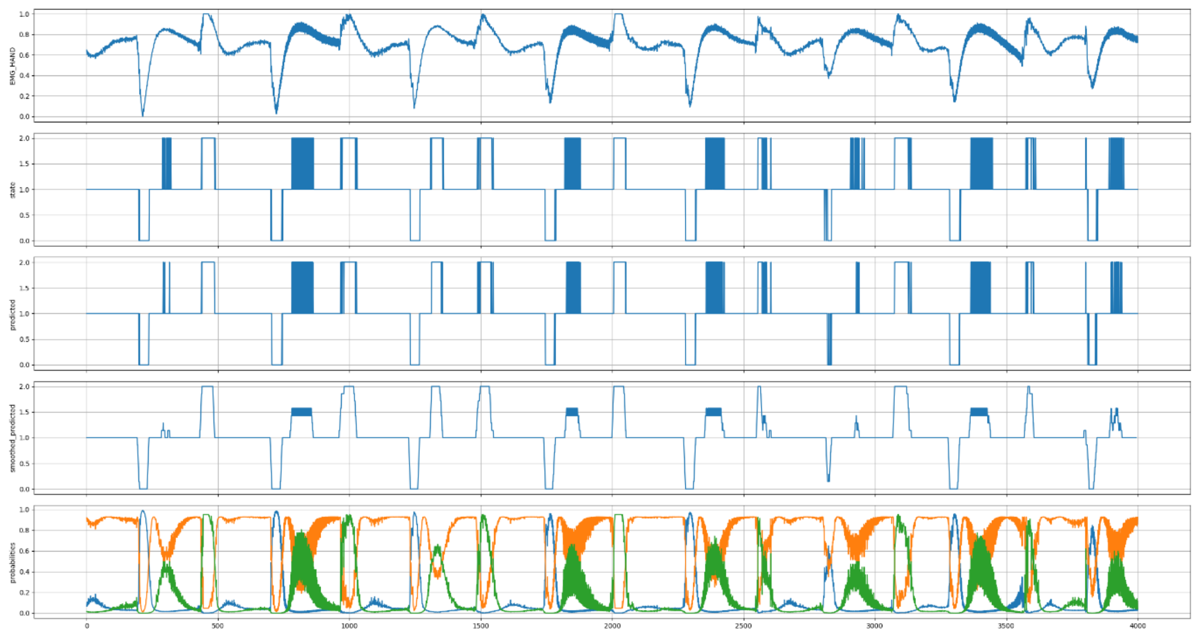

**Figure 3.** EMG data classification results

The test results for the participant’s dataset achieved a classification accuracy of 94% in real time. Based on the visualization of the EMG-signal classification results, we can conclude that the developed model shows high accuracy in recognizing thumb states in real time. The model’s predictions closely match the reference values, indicating correct training and adaptation of the model to the signal characteristics. The probability distributions confirm the confidence of the classifier: only one of the curves clearly dominates in each time window, indicating effective differentiation between classes. The applied smoothing further improves the stability of predictions, reducing the impact of single errors or noise in the signal. Thus, the presented classifier demonstrates significant potential for use in biomedical diagnostic and rehabilitation technologies that require accurate and rapid identification of muscle states/actions.

## 3. CONCLUSION

During the study, a test device for collecting and classifying EMG data was developed, designed to determine the states of hand muscles. Its principle of operation ensures the acquisition of EMG signals, their primary processing and wireless transmission of data via Wi-Fi for further analysis on a computer. The proposed classification model uses the ADAM algorithm to optimize the weights of a two-layer feed-forward neural network using the gradients of neuronal activation functions, enabling efficient determination of functional muscle states/actions with high accuracy, namely 94 % based on the test dataset of the experiment participant. Among the strengths of the proposed approach are the compactness of the device, stable data transmission via Wi-Fi and the adaptive operation of the neural network. Well-implemented stages of filtering, normalization and signal processing contribute to improving classification quality. At the same time, a limitation of this study is the use of data from only one participant, which does not allow the model’s generalized capability to be tested on other users. Other neural-network architectures or alternative optimizers were not tested for comparison with Adam. In future work it is planned to expand the experiment to a larger number of participants, use multichannel EMG recording and test the model under dynamic conditions, for example during movement or sporting loads. It would also be advisable to create an interface for visual feedback or integrate it into a neuroprosthesis or rehabilitation trainer.

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# РОЗПІЗНАВАННЯ ЕМГ-ПАТЕРНІВ СТАНІВ М'ЯЗІВ ВЕЛИКОГО ПАЛЬЦЯ З ВИКОРИСТАННЯМ НОСИМИХ СЕНСОРІВ І АДАПТИВНОЇ НЕЙРОННОЇ МЕРЕЖІ

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***Резюме.*** *Точна класифікація електрофізіологічних сигналів, зокрема електроміографічних (ЕМГ), є важливою для розроблення сучасних систем у спортивній медицині, біомеханічних протезах та нейрокомп'ютерних інтерфейсах. Однак такі проблеми, як шум сигналу, портативність пристроїв та обмеження опрацювання в реальному часі обмежують практичне впровадження інтерфейсів на основі ЕМГ. У статті представлено спеціалізований носимий пристрій для збирання даних ЕМГ та класифікації м'язевої активності в режимі реального часу. Пристрій інтегрує мікроконтролер ESP32C6 для бездротового передавання даних, аналоговий сенсорний модуль AD8232 для захоплення електрофізіологічних сигналів та електроди Ag/AgCl, розміщені на м'язах-антагоністах кисті руки. Сигнали ЕМГ дискретизуються з частотою 1000 Гц, попередньо опрацьовуються шляхом нормалізації та фільтрації, а потім класифікуються за допомогою двошарової нейронної мережі прямого розповсюдження, навченої за допомогою алгоритму оптимізації ADAM. Набір даних містить 4000 послідовних часових рядів, які відображають динаміку сигналів ЕМГ у трьох станах рухів великого пальця: спокої, відведення та приведення. Нейронна мережа досягла точності класифікації 94% в режимі реального часу з високою стабільністю та мінімальним затриманням, демонструючи надійне виявлення патернів м'язевої активності. Інтеграція недорогого обладнання з адаптивним нейронним класифікатором дозволяє ефективно інтерпретувати сигнали ЕМГ у реального часу. Використання оптимізації ADAM забезпечує стабільну конвергенцію та стійкість до варіабельності сигналу. Ця робота пропонує компактне та ефективне рішення для класифікації ЕМГ у режимі реальному часі, що відкриває шлях для його застосування в носимих реабілітаційних системах, нейрокерованих протезах та інтелектуальних інтерфейсах людина–машина.*

***Ключові слова:*** *аналіз даних, електрофізіологічні сигнали, ЕМГ, носимі датчики, класифікація, нейронна мережа, оптимізаційний алгоритм, патерн.*

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