Classification of Electromyography Signal with Machine Learning

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Abstract—The problem of classifying electromyography signals in each gesture occurs due to the use of a constant level of signal amplitude. This research presents an efficiency enhancement of electromyography signal classification in each gesture with machine learning. The performance efficiency of 5 models: SVM, RF, MLP, KNN, and Deep Leaning was compared. The signals were recorded by a low-cost signal sensor. Fist clenching and hand opening gestures were alternately performed every 5 second for 5 times each. Therefore, the total was 4,767 records divided into 3,274 records of hand opening gesture, 1,492 records of fist clenching gesture and 4,833 records of wrist rotating gesture. The results showed that the MLP model was found to have the highest accuracy at 81.45% for fist clenching and hand opening gestures. The Deep Learning model was found to have the highest accuracy at 89.03% for wrist rotating and hand opening gestures.

Keywords—signal classification, electromyography signal

1 Introduction

Electromyography, known as EMG, takes place when the nervous system sends signals to skeletal muscles to stimulate movement. The signals consist of many frequency components [1]. The brain of the handicapped with damaged forearm is still able to send nerve impulses to stimulate the muscles in the forearm [2]. The muscle strength is directly proportional to the level of electromyography signals [3] and the placement of the electrodes has the effect on the signal strength level and interference [4]. In addition, there are several variables that affect signal clarity. Highly efficient signal measuring devices are costly. Thus, the use of an inexpensive sensor combined with an ESP8266 microcontroller to record electromyography signals for the most performed gestures including fist clenching, wrist rotating, hand opening as well as machine learning to classify the recorded gestures were applied. Machine learning is applied to gesture classification to enhance gesture recognition which is different from using signal amplitude to define gesture constants.

2 Theories and related research

2.1 Electromyography

The degree of muscle tension is caused by intense stimulation. Muscles are made up of millions of thread-like muscle fibers. Contracted muscle fibers are caused by the action of mechanical neurons that transmit nerve impulses to such muscle fibers. At any time, a few relaxing muscle fibers appear to be contracting under a normal condition. The stimulation that occurs in the muscles is stimulated until the total response or some of the muscle responses are achieved [5], [6]. The whole muscle is responded, and it can show the transmission of mechanical nerve impulses in the spine to the muscles that need to move as shown in Figure 1.

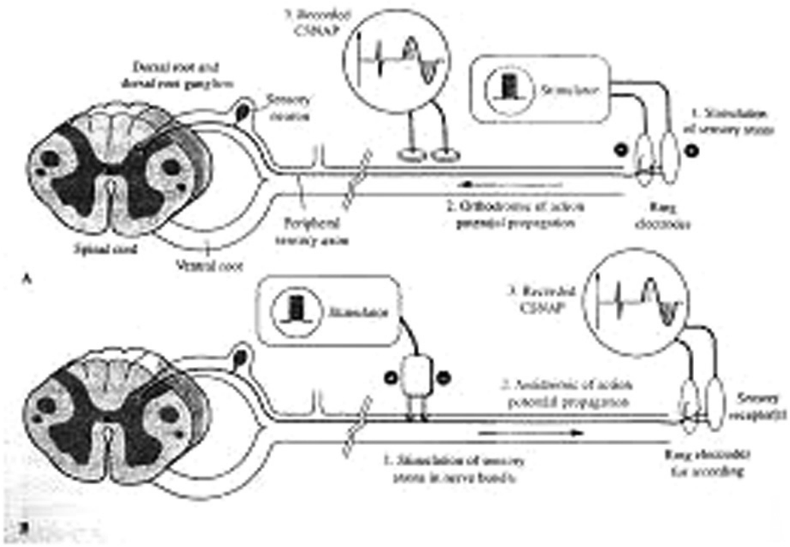

Fig. 1. A process of electromyography signal transmission

2.2 Devices used

Sensor for measuring electromyography signals. The sensors used to measure electromyography signals are several ranging from 1 channel to 8 channels. The techniques used to process the signals differ. The types of electrodes used to measure the signals include The Myo Armband [7], MyoWare Muscle Sensor [18] and EMG Muscle Sensor Module. In this research, a basic and low-cost sensor was used. Therefore, the EMG Muscle Sensor Module [8] was selected. It is a sensor composed of an internal electronic circuit that measures original electromyography signals. It has an AC to DC conversion circuit and is optimized for analog-to-digital reading by a microcontroller [16]. An external power source is used for electromyography signal measurement. A non-high quality adhesive electrode is employed. The sensor has a micro-sensing metal that can be combined with ECG measurement and is suitable for electromyography signals with low-quality reception that does not require multiple gesture recognition. There is also a signal wire connecting the electrode [9] to the sensor as shown in Figure 2.

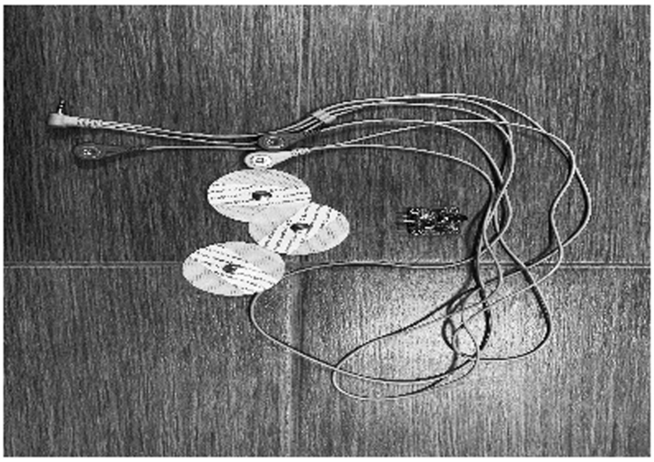

Fig. 2. EMG muscle sensor module

ESP8266 microcontroller. It is a compact microcontroller with processing features based on Tensilica L106 32-bit processor. The operating voltage is 2.5–3.6 V and the operating current is 80 mA. There is a port to connect to the GPIO for digital control operation to assign bit 0 or 1 to control all Internet of Things devices. It also supports analog-to-digital signal conversion with the resolution of 10 bits ADC. It has a port for generating a continuous signal 1 or 0 bit. The amplitude depends on a given period called PWM [10] which affects the control of a servo motor used to control arms. In addition, there is an antenna that supports Wi-Fi connectivity according to the IEEE 802.11 b/g/n standard as shown in Figure 3.

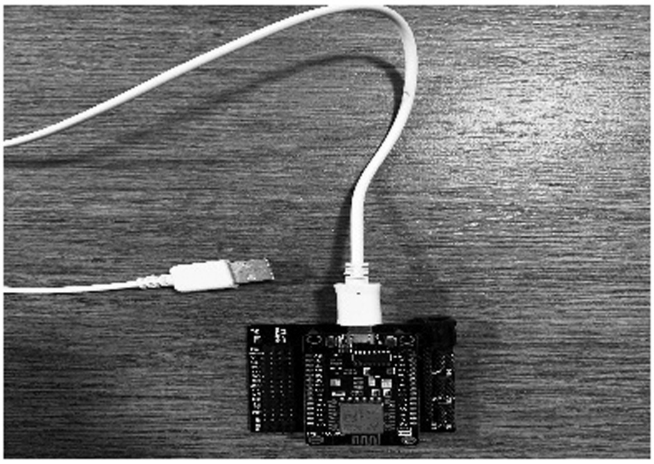

Fig. 3. An ESP8266 microcontroller

2.3 Supervised learning

The emphasis is on learning from previous data to create a model for predicting what will happen in the future. This can be divided into data Classification and data Regression. The two techniques are different in terms of answers to be predicted. That is, Classification predicts data with nominal values such as genders: male, female, or non-numeric values while Regression is used for numerical values only.

2.4 Machine learning by classification

This research applied Supervised Learning for data classification to classify gestures. The 5 models were used as follows.

1. Support Vector Machine (SVM)
   This is a Supervised Learning method used for solving problems of classification and regression analysis which is similar to Logistic Regression (LR). The Support Vector Machine technique aims for data classification by dividing class of data apart. It can be used with both linear and non-linear equations. The advantages of SVM are follows. This model is efficient for classifying large dimensional data. Kernel function is used to convert data to higher dimensions, and it can classify ambiguous data effectively [11]. The principle is to find the linear with the largest margin that can divide the data into 2 classes in 2 dimensions to minimize prediction error and maximize the distance between the two groups as shown in Equation 1.

   $$(xi, yi), \ldots, (xn, yn) \text{ when } x \ \varepsilon \ Rm, y \ \varepsilon \ \{+1, -1\} \quad (1)$$

   When
   (xi, yi), … , (xn, yn) are supervised samples.
   n is the amount of sample data
   m is the amount of input dimensions
   y is the result equal to +1 or −1
2. Random Forest (RF)
   This is a technique developed from the Decision Tree technique for regression analysis and classification. Random Forest Classification creates a prediction model in the form of Bootstrapping Ensemble of Decision Trees to assist prediction results. The correlation values between each Decision Tree are independent. Bootstrap learning data sets are randomly selected from the existing learning data sets. The randomly selected datasets might probably be re-selected to balance the amount of data between classes. Each Decision Tree randomly selects a dataset of features used in the prediction, making each tree unique according to the process of constructing a family tree consisting of Entropy and Gini. Then, the Majority Vote is used to assist the determination of the prediction results. The prediction results with the highest votes will be selected.
3. K Nearest Neighbor (KNN)
   This is a classification for categorizing data. It compares the considered data with other data to see how similar they are. If the considered data is closest to the data,

the system will respond as the closest data [12]. For determining K, the sample is defined to determine the distance by the number of K values as shown in Equation 2. Defining K is to determine the sample data used for consideration through comparing the distance based on the amount of K [17] as shown in Equation 2.

$$dist = \sqrt{\sum_{k=1}^{n} (p_k - q_k)^2} \tag{2}$$

When
n is the amount of K or the amount of sample data,
p_k is the value of sample data at K
p_k is the value of data that the distance is measured.

4. Multi-Layer Perceptron (MLP)
   This is a model developed from Neural Networks that supports the learning of non-linear and highly complex data that can have multiple hidden layers, depending on the data complexity [13]. Electromyography signals are complex, so it requires this model. The structure of the model is illustrated as in Figure 4.

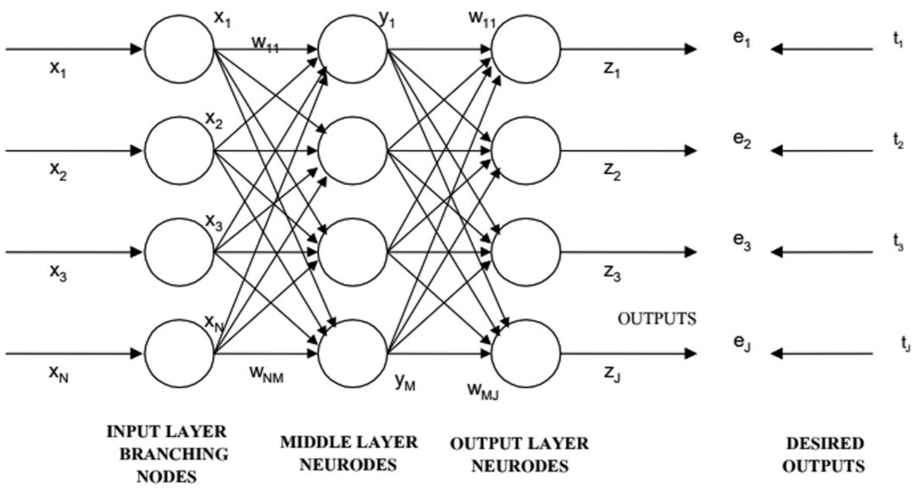

Fig. 4. Shows operation process of MLP

When
X_n is input node when n contains N nodes
y_m is output node of hidden layer after adjusting nodes when m contains M nodes
z_j is adjusted output of output node layer when j contains J nodes
t_j is desired output that output node layer when j contains J nodes
w_{nm} is weight of linked linear between input layer and hidden layer
w_{mj} is weigh of linked linear between hidden layer and output layer
$e^{(q)}$ is error of sample data

5. Deep Learning: Convolutional Neural Network (CNN)
   This is a model developed from Neural Networks where the weight is multiplied by the input from input layer, and all paths are connected and compared. However, CNN is a complex calculation. The convolution is combined with classification of electromyography signals. In-depth analysis is provided to extract key features within the model including 1D convolution, scaling, and data selection [14]. Details of structures of each model are shown in Figure 5.

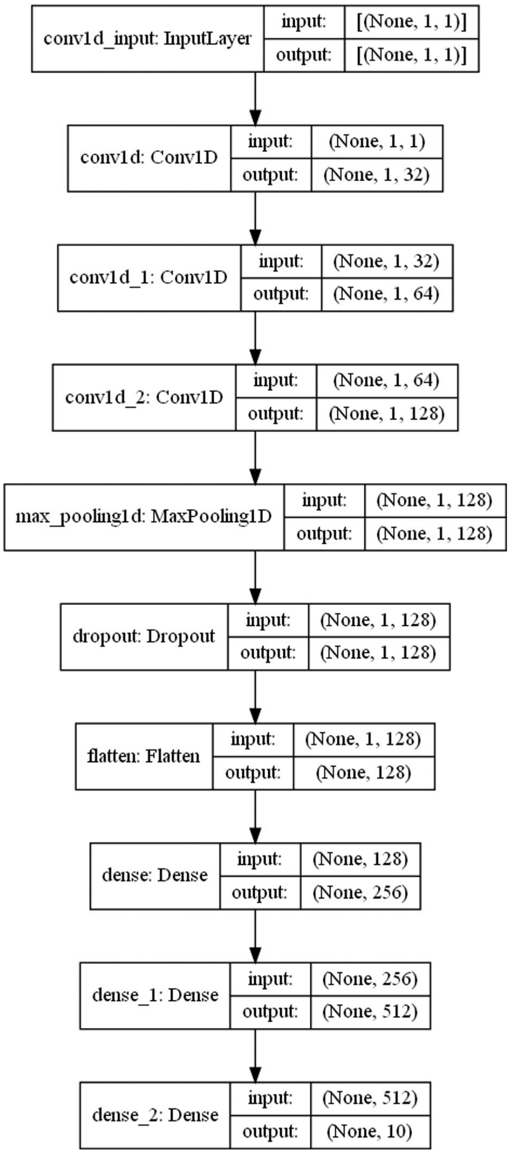

Fig. 5. Structure of deep learning

2.5 Performance measurement of data classification models

Performance efficiency of data classification models [15] can be measured as follows.

1. Accuracy
   A measurement of the overall system accuracy between the actual and the predicted value. If the Accuracy is high, it means that the prediction is correct and is close to the actual value as in Equation 3.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

   When
   TP is the predicted value that is predicted to be true which corresponds to the actual value.
   TN is the predicted value that is predicted to be false that corresponds to the actual value.
   FP is the predicted value that is predicted to be false that does not correspond to the actual value.
   FN is the predicted value that is predicted to be true that does not correspond to the actual value
2. Recall
   A measurement of completeness. This means that the ratio of the predicted value corresponds to the actual value from the total number of actual values. If the Recall value is high, that means the predicted value can be fully predicted and is close to the actual value as in Equation 4.

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

3. Precision
   A measurement of accuracy that is measured by the repeatability of the predicted values that correspond to the actual value. If the Precision is high, it means that the predicted value is accurate and is close to the true value as in Equation 5.

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

4. F1-Score
   The harmonic mean between Precision and Recall, when F1 is shown in Equation 6.

$$F1 = \frac{2 \times \left(\frac{Precision \times Recall}{Precision + Recall} \right)}{N} \tag{6}$$

3 Research methodology

This research aimed to record electromyography signals by using the sensor and to classify gestures by using Machine Learning technique. The 5 models were compared according to the operation process as follows.

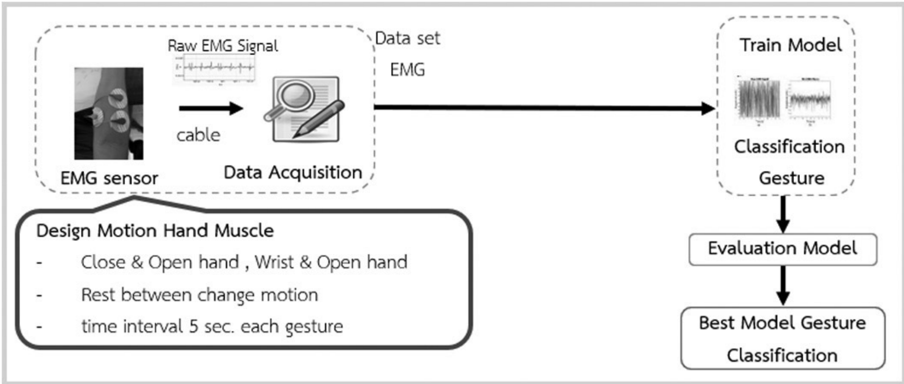

Fig. 6. Operation process

3.1 Electromyography signal recording

Basic gestures including fist clenching and hand opening, wrist rotating, and hand opening gestures were defined. Fist clenching and hand opening gestures were alternately performed every 5 second for 5 times each. The device used to record the electromyography signals was an electromyography signal sensor with low-cost adhesive electrode type, connected to 2 batteries of 9V external power supplies. It was operated with an ESP8266 microcontroller and was connected to a computer. The communication was performed via URAT (Universal Asynchronous Receiver-Transmitter) protocol.

3.2 Machine learning and evaluation

The recorded signals were divided into teaching and testing parts. Cross-validation was performed for 10 times and was used to classify gestures of each signal from each model including 1. Support Vector Machine (SVM) 2. Random Forest Classifier (RF) 3. K-Nearest Neighbors (KNN) 4. Multi-Layer Perceptron (MLP) and 5. Deep Learning: Convolutional Neural Network (CNN). Hyperparameter tuning was performed in each model for the highest classification efficiency. The results of comparing classification efficiency of each model that gave the highest classification efficiency were achieved. The performance efficiency was measured thorough the prediction performance indicators such as Accuracy, Recall, Precision and F1-Score.

4 Results

The research recorded electromyography signals through the sensor. According to the tests, 4,767 records of fist clenching and hand opening gestures were recorded divided into 1,492 records of fist clenching and 3,274 records of hand opening gestures. In addition, 4,833 records of wrist rotating, and hand opening gestures were recorded divided into 1,479 records of wrist rotating and 3,353 records of hand opening as shown in Figures 7 and 8 respectively.

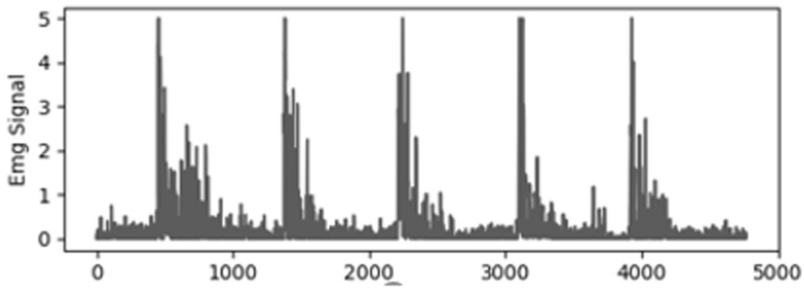

Fig. 7. Fist clenching and hand opening gestures

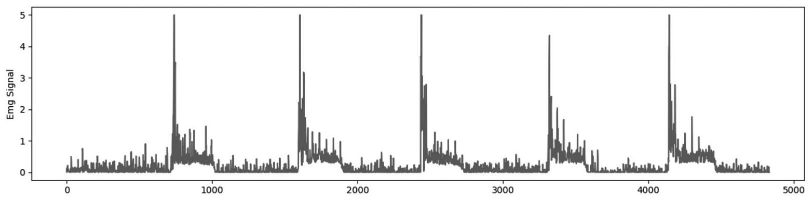

Fig. 8. Wrist rotating and hand opening gestures

The records were classified by Machine Learning using the 5 models. The results were compared, and the efficiency of the models were measured as shown in Tables 1 and 2 respectively

Table 1. Comparison of classification efficiency of original electromyography signals for fist clenching and hand opening gestures

Original Electromyography Signal				
Model :Parameter Tunning	Accuracy	Precision	Recall	F1-score
Random Forest Classifier	80.92%	81.06%	80.92%	79.31%
Support Vector Machine	80.82%	82.08%	80.82%	78.58%
K-Nearest Neighbors	80.71%	80.74%	80.71%	79.12%
Multi-layer Perceptron	**81.45%**	**82.27%**	**81.45%**	**79.58%**
Deep learning	81.03%	83.21%	71.20%	73.64%

According to the table, it was found that the Accuracy, the Precision, the Recall, and the F1-Score of original electromyography signals classified by the MLP model were the highest which were 81.45 %, 82.27%, 81.45%, 79.58% respectively.

Table 2. Comparison of classification efficiency of original electromyography signals for wrist rotating and hand opening gestures

Original Electromyography Signal				
Model :Parameter Tunning	Accuracy	Precision	Recall	F1-score
Random Forest Classifier	88.71%	89.67%	88.71%	89.05%
Support Vector Machine	88.58%	89.19%	88.58%	88.83%
K-Nearest Neighbors	88.52%	89.72%	88.52%	88.93%
Multi-layer Perceptron	88.58%	89.19%	88.58%	88.83%
Deep learning	**89.03%**	**81.62%**	**88.82%**	**84.34%**

According to the table, it was found that the Accuracy, the Precision, the Recall, and the F1-Score of original electromyography signals classified by the Deep Learning model were the highest which were 89.03 %, 81.62%, 88.82%, 84.34% respectively.

5 Conclusion

The study found that the Machine Learning efficiency of electromyography signal classification for fist clenching and hand opening gestures in overall was less effective than that of electromyography signal classification for wrist rotating and hand opening gestures by about 8%. This was because each record of fist clenching gesture had higher external noise than that of wrist rotating and hand opening gestures. This can be seen in Figures 7 and 8. To eliminate noise as much as possible in the future, a signal processing study is proposed to reduce noise [19] and optimize classification efficiency by feature extraction [20]. Long-term problems can be solved by selecting more effective sensors to measure electromyography signals.

6 References

[1] Gianluca De Luca. "Fundamental Concepts in EMG Signal Acquisition," March 2003.
[2] Ali H. Al-Timemy, Guido Bugmann, Javier Escudero, and Nicholas Outram. "Classification of Finger Movements for the Dexterous Hand Prosthesis Control with Surface Electromyography." IEEE Journal of Biomedical and Health Informatics 17, no. 3 (May 2013): 608–18. https://doi.org/10.1109/JBHI.2013.2249590
[3] Suphattra Saenthaweesuk, Matchima. "Electrical Signal Analysis of Muscle Strength." Burapha University, 2018.

[4] Yasir Hassan Jaffar and Dr. Ali Hussein Ali Al-Timemy. "Investigation of Pattern Recognition System Based On Electromyography Signals for Optimal Electrodes' Number and Positions." Association of Arab Universities Journal of Engineering Sciences 25, no. 2 (2018).
[5] Assoc. Prof. Dr. Somchai Rattanathongkham. "Electrical Neuromuscular Examination," 2012.
[6] Yousef, Jamileh, and Andrew Hamilton-Wright. "Characterizing EMG Data Using Machine-Learning Tools." Elsevier Ltd., 2014, 0010–4825. https://doi.org/10.1016/j.compbiomed.2014.04.018
[7] Bisi, Stefano, Luca De Luca, Bikash Shrestha, Zhijun Yang, and Vaibhav Gandhi. "Development of an EMG-Controlled Mobile Robot." Robotics 2018, July 5, 2018. https://doi.org/10.3390/robotics7030036
[8] Sadikoglu, Fahreddin, Cemal Kavalcioglu, and Berk Dagman. "Electromyogram (EMG) Signal Detection, Classification of EMG Signals and Diagnosis of Neuropathy Muscle Disease," 422–29. Budapest, Hungary: Procedia Computer Science 120 (2017), 2017. https://doi.org/10.1016/j.procs.2017.11.259
[9] Miftachul Ulum, Fatkur Rozi, and Achmad Fiqhi Ibadillah. "Signal Classification and Electromyography (EMG) Instrumentation Design as Basic Electronic Control System." Indonesia: IOP, 2019. https://doi.org/10.1088/1742-6596/1569/3/032081
[10] Vishnu Vardhan Battu, Randy Joy Magno Ventayen, A. Firos, and Ruchi Yadav. "Unmanned Six-Wheels Bogie Rover with Robotic Arm for Surveillance and Fixing Objects." Turkish Journal of Computer and Mathematics Education 12, no. 10 (2021): 2066–75.
[11] Yousef, Jamileh, and Andrew Hamilton-Wright. "Characterizing EMG Data Using Machine-Learning Tools." Elsevier Ltd., 2014, 0010–4825. https://doi.org/10.1016/j.compbiomed.2014.04.018
[12] Attika Puspitasari, Achmad Rizal, and Husneni Mukhtar. "Prosthetic Finger Movement Controller Based on EMG Signals Using Statistical Feature and K-Nearest Neighbors." International Journal of Scientific & Technology Research 9, no. 03 (March 2020): 1472–75.
[13] Mohd Azlan Abu, Syazwani Rosleesham, Mohd Zubir Suboh, Mohd Syazwan Md Yid, Zainudin Kornain, and Nurul Fauzani Jamaluddin. "Classification of EMG Signal for Multiple Hand Gestures Based on Neural Network." Indonesian Journal of Electrical Engineering and Computer Science 17, no. 1 (January 2020): 256–63. https://doi.org/10.11591/ijeecs.v17.i1.pp256-263
[14] Jawad Ahmad, Ammar Mohsin Butt, Mohsin Hussain, Muhammad Azeem Akbar, and Waheed Ur Rehman. "The Deep Neural Network Based Classification of Fingers Pattern Using Electromyography," 455–61. IEEE Xplore: Cornell University, 2020.
[15] Widyo Laksono, Pringgo, Widyo Laksono Widyo Laksono, Joseph Muguro, Matsushita Kojiro, Minoru Sasaki, and Muhammad Syaiful Amri bin Suhaimi. "Minimum Mapping from EMG Signals at Human Elbow and Shoulder Movements into Two DoF Upper-Limb Robot with Machine Learning." MDPI, March 5, 2021. https://doi.org/10.3390/machines9030056
[16] Hadeel K. Aljobouri. "A Virtual EMG Signal Control and Analysis for Optimal Hardware Design." International Journal of Online and Biomedical Engineering (IJOE) 18, no. 02 (February 16, 2022): 154–66. https://doi.org/10.3991/ijoe.v18i02.27047
[17] Bagus Priambodo, Azlina Ahmad, and Rabiah Abdul Kadir. "Prediction of Average Speed Based on Relationships Between Neighbouring Roads Using K-NN and Neural Network." International Journal of Online and Biomedical Engineering (IJOE) 16, no. 1 (January 21, 2020): 18–33. https://doi.org/10.3991/ijoe.v16i01.11671

[18] Endro Yulianto, Tri Bowo Indrato, Bima Triwahyu Mega Nugraha, and Suharyati Suharyati. "Wheelchair for Quadriplegic Patient with Electromyography Signal Control Wireless." International Journal of Online and Biomedical Engineering (IJOE) 16, no. 12 (October 19, 2020): 94–115. https://doi.org/10.3991/ijoe.v16i12.15721
[19] Mounaim Aqil, Atman Jbari, and Abdennasser Bourouhou. "ECG Signal Denoising by Discrete Wavelet Transform." International Journal of Online and Biomedical Engineering (IJOE) 13, no. 09 (September 22, 2017): 51–68. https://doi.org/10.3991/ijoe.v13i09.7159
[20] Achmad Rizal, Wahmisari Priharti, and Sugondo Hadiyoso. "Seizure Detection in Epileptic EEG Using Short-Time Fourier Transform and Support Vector Machine." International Journal of Online and Biomedical Engineering (IJOE) 17, no. 14 (December 14, 2021): 65–78. https://doi.org/10.3991/ijoe.v17i14.25889

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