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***Research Article***

# KNN ve Random Forest Algoritmalarının EMG Sinyallerini Sınıflandırmadaki Başarısının Karşılaştırılması

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**Öz**

Günümüzde artan yaş ortalamasına ve yoğun iş hayatına bağlı olarak kas rahatsızlıkları da artmaktadır. Üst uzuvda kasa bağlı rahatsızlık gündelik hayatı olumsuz etkilemektedir. Kas hastalıklarının belirlenmesinde Elektromiyagrafi (EMG) kas sensörleri kullanılmaktadır. Daha doğru sonuçlar alabilmek için EMG sensörleri ile alınan verilerin sınıflandırması gerekmektedir. Yapılan bu çalışmada kas ölçüm aracı olarak kullanılan elektromiyagrafi kas sensörleri ile üst uzuvdan veriler alınmış ve bu veriler makine öğrenmesinin sınıflandırma algoritmalarından olan ve diğer algoritmalara göre daha doğru sonuçlar veren KNN algoritması ve Random Forest algoritmaları ile karşılaştırılmıştır. Kullanıcının üst uzvuna üç adet EMG kas sensörü takılmış ve mikrodenetleyici geliştirme kartı ile 0°, 45° ve 90° açılarda veriler alınmıştır. Alınan veriler makine öğrenmesi algoritmaları ile eğitilmiş ve test edilmiştir. En yüksek doğruluk veren KNN ve Random Forest algoritmalarının doğruluk yüzdeleri bulunmuş ve sınıflandırmada kullanılacak algoritma seçilmiştir.

**Anahtar Kelimeler:** EMG, Makine Öğrenmesi, KNN, Random Forest, Mikrodenetleyici

# Comparison of KNN and Random Forest Algorithms in Classifying EMG Signals

**Abstract**

Depending on the growing average age and busy work life, muscle disorders are also increasing. Disturbing use life hurts the upper limb due to casing. Electromyography (EMG) muscle sensors are used to detect muscle diseases. To obtain more accurate results, the perception of the data received with the EMG sensors is required. This evaluation was compared with electromyography muscle sensors used as a muscle measurement tool and those taken from the upper limb and KNN explanations and Random Forest examinations, which are the predictions of machine learning in this context and give more accurate results than other effects. Three EMG muscle sensors are attached to the upper limb of the user and taken from 0°, 45° and 90° angles with the microcontroller development board. It has been read and tested with the resulting machine-learning readings. The percentages of the accuracy of the highest accuracy KNN and Random Forest locations were chosen for their assumptions and use in use.

**Keywords:** EMG, Machine Learning, KNN, Random Forest, Microcontroller

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# 1. Introduction

Muscle diseases are a heterogeneous group of diseases that are inherited, develop at birth or develop later, caused by an abnormality in the anterior horn motor cells, peripheral nerves, neuromuscular junction, or muscle. No complete and definite medical treatment option eliminates the disease in muscle diseases. For this reason, there are physiotherapy and rehabilitation applications that help protect and strengthen the muscle strength of the patients and protect or increase their daily living activities (Demirhan, 2021). In cases where human movement is restricted or not fully realized due to muscle diseases, activities of daily living are adversely affected. Electromyographic (EMG) signal analysis, which is used in the diagnosis and treatment of muscle diseases, plays a vital role, especially in the diagnosis of muscle diseases. It is based on the clinician's experience in interpreting the shape and acoustic properties of the signal. The development of new techniques to comprehensively analyze these signals for the accurate detection of these disorders is available in the literature. EMG is an electrophysiology procedure used to evaluate and diagnose the health of the muscles and nerve cells (motoneurons) that control them. They are produced by synaptic activity between nerve motor neurons and muscle fibers to induce muscle contraction. Therefore, these signals are a valuable source of information about the functioning and state of the musculoskeletal system (Torres-Castillo, 2022). An electromyography (EMG) sensor can provide information about muscle activity and is used in clinical settings for the diagnosis of neuromuscular diseases (Bawa, 2022). The use of EMG sensors is a neurological examination method based on the examination of the electrical potential of the muscles. EMG signals are used for the diagnosis of medical muscle anomalies, activation levels and analysis of biomechanical movements. EMG measurement can be done with or without electrical stimulation. In electrically stimulated measurements, the signal conduction velocity of the nerves is measured. With the electrode placed on the muscles, a low level of electrical stimulation is given to the relevant nerve. In electrical non-stimulated EMG, muscle activity is measured. Measurements can be made by immersing disposable needle electrodes into the muscle, as well as with adhesive surface electrodes (Aktan, 2017).

The EMG signal is complex and not static. Traditional signal analysis, various feature extraction and classification methods have been proposed for EMG classification in the literature (Wang, 2022, Bawa, 2022). It consists of stages such as labelling the classes for examining the EMG signals, determining the appropriate feature vectors and choosing the optimum, determining the classification models, and calculating the classification success (Akgün, 2022).

Machine learning algorithms are applied in many areas (Aydın, 2018). One of these areas is biomedical studies. Electromyography signals, which are frequently used in biomedical studies and used to measure muscle signals, do not have a definite shape and periodic repetitive forms. There are studies in which machine learning algorithms are used in the examination of such signals (Karakoyun and Hacıbeyoğlu, 2014; Bozkurt, 2007). Machine learning algorithms used in the classification of EMG signals, making decisions about similar events that may occur in the future by learning the information and experiences that the computer has acquired about an event that has occurred and results in producing solutions to the problems that will occur. Machine learning takes advantage of past data by using some methods and tries to find the most suitable model for the new data (Kutlugün, 2017). It is very difficult to manually process and analyze large amounts of data (Kurşun, 2021). The aim here is to make predictions for future situations using past data. Regardless of the application area, the importance of machine learning methods is increasing day by day, thanks to the analysis of large amounts of data, making predictions and helping decision-making (Dinçer, 2006).

When the studies in the literature are examined, many studies have been carried out on the classification and feature extraction of EMG signals. In the classification of EMG signals for hand finger movements, it has been tried to determine finger movements most accurately by using Decision Tree, Support Vector Machine, and K-Nearest Neighbors algorithms (Altan, et al., 2019). Some studies classified six different hand and finger movements, nearest neighbour (KNN), linear discrimination analysis (LDA) and support vector machine (SVM) classifiers using the features extracted in the examination of hand movements (Onay and Mert, 2020). There are also studies comparing artificial neural networks and wavelet neural networks for EMG signals (Subasi, et al., 2006). In studies on the classification of EMG signals, some of the machine learning algorithms have been presented (Yousefi, et al., 2014, Gokgoz and Subasi, 2015). Again, the deep learning method was used in some EMG signal studies (Côté-Allard, et al., 2019, Akgün, et al., 2015). In another study, there is a comparison of EMG signals with SVMand KNN algorithms.(Meena and Bansal, 2016).

In this study, three EMG muscle sensors were attached to the user's upper limb, and the data of the upper limb were taken with the help of the microcontroller development board at $0^o$, $45^o$ and $90^o$ angles from the horizontal. The received data were classified by two different machine learning algorithms, which are frequently used in classification, and the algorithm that gave the best result was determined. The study also presents a comparison of these two algorithms for the classification of real-time EMG signals in the literature. A comparison of these two algorithms and the classification of EMG signals in terms of accurate results are not available in the literature.

# 2. Material and Method

## 2.1. Acquisition of Electromyography Muscle Data

The EMG sensor, which is frequently used in many medical fields today, is a module for examining the movements of nerves and muscles in the body (Ekmekçi, 2017; Eser, 2018). Electrical signals formed in the direction of muscle movements can be read with Arduino or various microcontrollers (Aydın, 2020). EMG signals formed during muscle movements are used as source signals in the treatment of muscle and nerve disorders, in physical therapy rehabilitation applications and the development of prosthetic systems. Receiving and processing EMG signals and drawing conclusions from these signals are required for prosthetic arm studies and the detection of muscle and nerve disease treatments. Today, as a result of the development of intelligent systems, studies on EMG-based prostheses and disease detection from EMG signals have increased significantly. Measuring and recording the EMG signal, extracting features from the EMG signal and classifying these selected features form the basis of these studies (Keleş, et al., 2020 and Akgün, et al., ). In this study, data were obtained from EMG sensors for upper limb movement and these data were classified by machine learning algorithms KNN and Random Forest algorithms. EMG sensors were attached to the upper limb of the user and data were taken at three different angles 0°, 45° and 90°. The image of the EMG sensor used while receiving data from the user is shown in Figure 1.

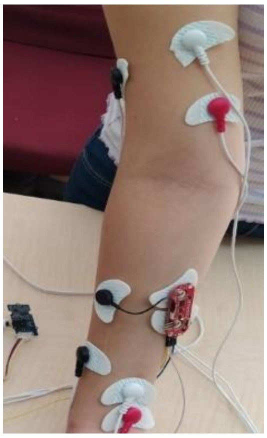

**Figure 1**. Connection of EMG Sensors on upper limb

EMG muscle sensors have three probes and pads attached to the end of the probes to receive muscle signals. Three probes (white, black and red) on the first EMG muscle sensor are attached to the inside of the wrist for wrist movement. The second EMG sensor probes are attached to the forearm, and the third EMG sensor is attached to the biceps muscle for elbow movement. Of the three probes in the EMG sensor, the black probe is the reference probe and is used for the muscle difference measured by the white and red probes. The white and red probe is placed in the center of the muscle. In the study, instant data was taken from the EMG muscle sensor with a microcontroller development board at a baud rate of 9600 and these data were converted into graphics with the microcontroller IDE software and serial plotter program. The serial plotter image of the EMG sensor data taken from the horizontal with the microcontroller at 0°, 45° and 90° angles are shown in Figures 2, 3 and 4, respectively. When the signal in the graph is examined, it is seen that the signals oscillate irregularly. For this, muscle data should be classified by classification algorithms. The blue signal in the graph shows the data from the wrist-mounted EMG sensor, the red-colored signal from the forearm-mounted EMG sensor, and the green-colored signal from the upper arm-mounted EMG sensor. The reason why the signal peaks in some areas is related to the contraction of the muscle at that moment.

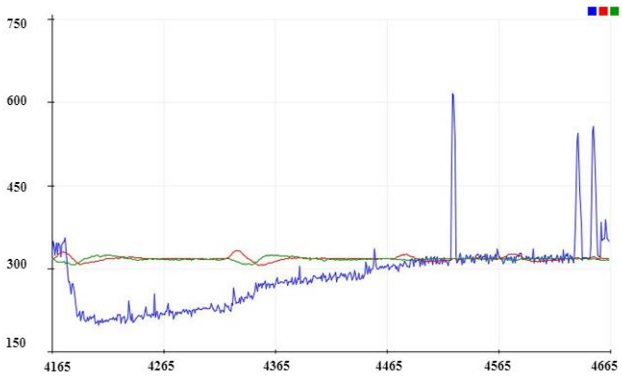


**Figure 2.** EMG signal graphs at 0° position of the upper limb

The values represented by the blue color in the graph are the values of the EMG1 sensor worn on the wrist. The red color in the graph shows the values of the EMG2 sensor mounted on the forearm. The EMG3 sensor attached to the upper arm is the graphic shown in green color. The values in the graph are the values read from the ADC (Andolog Digital Conventor) pins of the microcontroller development board. These values are shown in the graph in the y-direction. The values in the x plane show the time.

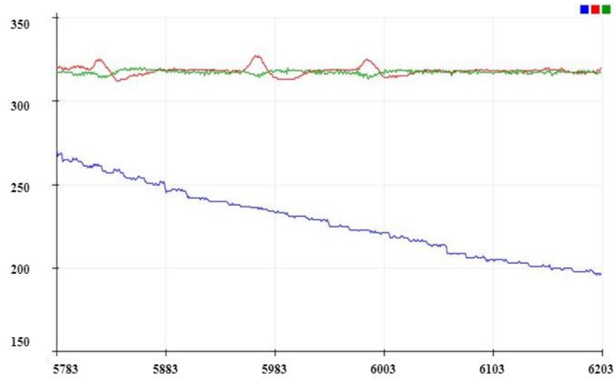


**Figure 3.** EMG signal graphs at 45º position of the upper limb

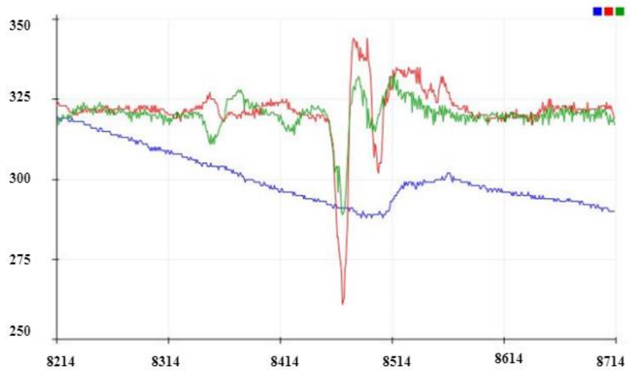


**Figure 4.** EMG signal graphs at 90º position of the upper limb

The data obtained from the microcontroller and EMG muscle sensors were analyzed in the graph and the data was then recorded and transferred to the Excel file. Then the data is imported for use with classification algorithms. Three EMG data are set as input and output at 0º, 45º and 90º angles.

## 2.2. Classification of the System with Machine Learning Algorithms

In machine learning, first of all, the dataset to be learned must be prepared by the learning method to be applied. Statistical methods are used in the learning method. Newly developed methods are also statistically based. When a new method is found, its performance is measured. In this way, comparisons are made with other methods. It is possible to analyze different applications of machine learning methods and classify them according to different expectations. Machine learning methods can be used to perform the operations explained below.

-Classification: It is the process of correctly estimating the class of a new situation by using data with a certain class.

Clustering: It is the process of determining the clusters obtained according to the similarity of the data in cases where the previous information is not known, that is, the process of belonging to a cluster.

-Curve Fitting (Regression): Problems involving continuous values rather than classes corresponding to previous data.

-Feature selection and extraction: It is the process of determining the features that determine the correspondence of the set or class of the data by making use of some features of the data.

-Relationship determination: It is the process of analyzing the relationships between the obtained classes or clusters. Machine learning techniques are divided into two supervised and unsupervised learning methods (Kutlugün, 2017).

Machine learning is an important area of Artificial Intelligence technologies. Today, thanks to this technology, machines can be successfully trained for challenging tasks in many different fields. Many algorithms such as Support Vector Machines, Random Forest, Gradient Increment, K-Nearest Neighborhood algorithms, especially ensemble learning algorithms, are used as algorithms in machine learning either alone or together (Aydın, 2018).

It uses labelled data to make predictions based on what has been learned. The data to be used in training and the classes (categories/tags) of the data are known in advance. The system learns with the data and the new data is interpreted with what has already been learned. Classification is the process of finding a set of models that allows one to identify and distinguish data classes and concepts. The applied models are based on the "training dataset" analysis.

### *2.2.1. KNN Algorithm*

The KNN algorithm, which is frequently used for classification and regression operations, is a supervised classification algorithm. The working principle of the algorithm is based on classification based on the k nearest neighbour vectors (Ecemiş, et al., 2019). The K-nearest neighbour algorithm is a frequently used method for classifying EMG data. This algorithm is a convergence method in which data is represented in space and the k-closest samples around a sample data are looked at for classification. The KNN algorithm represents each sample as a point in space and groups the samples according to their similarity to each other. For classification, the sample data to be classified must be placed in space. Then, the similarities between this sample data and other sample data are measured and the k-nearest neighbours are determined. The class of sample data is determined by a majority vote among the classes of neighbours. The KNN algorithm is a very effective classification method, especially for small-sized data sets. It also performs well on high-dimensional data such as the classification of EMG signals. However, the KNN algorithm is not suitable for large-sized datasets due to the increase in computational power and memory requirements as the number of data increases. In short, the purpose of the KNN algorithm is to classify the existing learning data when a new sample arrives. When a new sample arrives, the algorithm decides on its class by looking at its k nearest neighbours (Wang, 2010).

### *2.2.2. Random Forest Algorithm*

Random Forest model is a machine-learning method that can be used in both classification and regression problems. The working logic of the Random Forest Regression model is similar to the decision tree structure. The data set is randomly divided into small pieces and creates decision trees. In the estimation phase, the average of the estimations of the decision trees formed from the data set is taken (Arslankaya and Toprak, 2021). This algorithm is an ensemble learning method created by combining multiple decision trees. The Random Forest algorithm is a method in which each decision tree is trained using a random sample. These trees are trained using a random subset of the features. Thus, it is ensured that each tree decides independently of the other. To perform classification, test data is given to each tree and a final estimate is made by adding the class votes predicted by each tree. The Random Forest algorithm performs particularly well on high-dimensional and noisy data. It also provides fast classification, especially for large-sized data sets. This algorithm can also be used in conjunction with the variable importance measurement method, which is used to select important features for classification (Zhang, 2016).

### *2.2.3. Data Preparation – Data Preprocessing*

The most important problems encountered in data studies are deficiencies in the data, not selecting the appropriate data for the research, high correlation between the selected data, and outlier values. Data preprocessing aims to compile, correct, transform or subset the existing data into a representative set of inputs and prepare data to include information about the desired application (Aydin, 2018). With Data Cleaning, noisy and inappropriate data is cleaned. The following codes were run to process the data in the study. The independent variables in the research; It is given as EMG1, EMG2, EMG3. The dependent variables are Out (Arm position). The value 0 in the Out header is $0^o$ of the arm angle, 1 is $45^o$, and 2 is $90^o$. Some values of the dependent and independent variables are shown in Table 1.

**Table 1.** Independent variables and dependent variables

| Out | EMG1 | EMG2 | EMG3 |
|---|---|---|---|
| **0** | 38 | 309 | 320 |
| **0** | 31 | 307 | 321 |
| **0** | 28 | 306 | 321 |
| **0** | 27 | 306 | 321 |
| **0** | 26 | 305 | 321 |
| **1** | 146 | 317 | 317 |
| **1** | 155 | 316 | 318 |
| **1** | 159 | 317 | 319 |
| **1** | 148 | 318 | 318 |
| **1** | 157 | 317 | 319 |
| **2** | 273 | 314 | 320 |
| **2** | 259 | 315 | 318 |
| **2** | 258 | 315 | 318 |
| **2** | 258 | 317 | 319 |
| **2** | 251 | 319 | 318 |

To test how usable the model to be used is, the data set should be divided into training and test data. The training dataset is used by the model and establishes a correlation. The Test set is used to test how useful the model produces results. For the models to be used, the first 30% test and 70% training data were used in this study, but then these values were used as it was seen that 20% test and 80% training data provided better accuracy. The block diagram of the training and test data is shown in Figure 5.

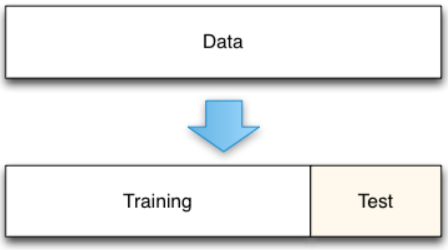


**Figure 5.** Training and testing data

# 3. Results and Discussion

The confusion matrix shows the current state of the data and the number of correct and incorrect predictions of the classification model. These numbers are used in a series of calculations to find the accuracy of the data set. Here TP - Correct detection of Positives, TN - Correct detection of Negatives, FP - False detection of Negatives and FN - False detection of Positives.). The values of the data obtained for the KNN algorithm in the confusion matrix are given in Figure 6.

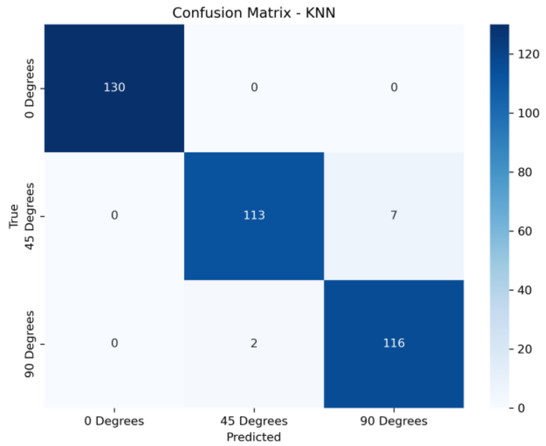


**Figure 6.** KNN Confusion Matrix

The values of the data obtained for the Random Forest algorithm in the complexity matrix are given in Figure 7.

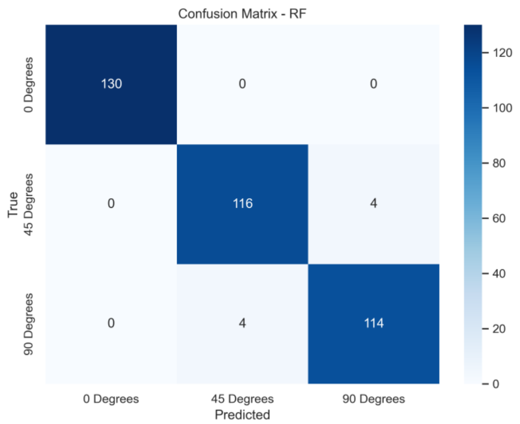


**Figure 7.** RF Confusion Matrix

True Positives (TP): These are true tables where the true value is 1 and the predicted value is 1.

True Negatives (TN): These are true tables where the true value is 0 and the predicted value is 0.

False Positives (FP): False tables where the true value is 0 and the predicted value is 1.

False Negatives (FN): False tables where the true value is 1 and the predicted value is 0.

Accuracy: Gives the correct classification rate and it is found as in equation 1.

$$Accuary = (TP + TN)/(TP + FN + FP) \quad (1)$$

Positive Predictive Value - Positive Predictive Value (PPV) - Precision : It gives the success rate in positive prediction and it is found as in equation 2.

$$Precision = PPR = TP / (TP + FP) \quad (2)$$

True Positive Rate - Sensitivity - Recall - Sensitivity: Indicates how well positive situations are predicted and it is found as in equation 3.

$$Recall = TPR = TP/(TP + FN) \quad (3)$$

F1 Score (F Score): It is a measure of the accuracy of the tested data. It is often used to compare classifiers and it is found as in equation 4.

$$F1 - score = 2 * TP/(2 * TP + FN + FP) \quad (4)$$ (Sekmenoğlu, et al., 2021).

In the study, accuracy, precision, recall and F1 score ratios were calculated using the confusion matrix. The values found were compared with other algorithms and the algorithm with the best score was selected. There may be different parameters for each algorithm in the applied algorithms. The parameter giving the best score from these parameters was selected. In addition, after the feature selection was made, the scores were recorded and the effect on accuracy was evaluated. In the study, column and line graphs showing the accuracy values of K-nn and Random Forest algorithms made with machine learning are shown in Figure 8.

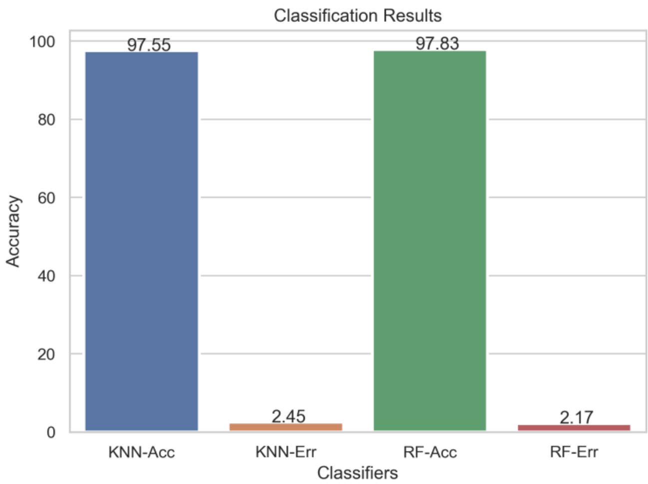


**Figure 8**. Classification results

## 4. Conclusions and Recommendations

In this study, three EMG sensors were attached to the human upper limb. The first EMG sensor is attached to the wrist for wrist movement, the second EMG sensor is attached to the front of the arm for elbow movement, and the third EMG sensor is attached to the upper arm for shoulder movement. With the three EMG sensors connected, firstly, the data was taken when the arm was in the free and straight position. Then, the data was taken with the arm at 45º from the elbow. Then, the data was taken with the arm 90º from the elbow. These data, taken with the microcontroller, were transferred to the Excel file. A total of 1840 data were obtained from three EMG sensors. Later, these data were imported and used as training and test data in the python software. K-nn and Random Forest algorithms were applied to provide information on the classification and accuracy of EMG muscle data. The accuracy rate of the KNN algorithm was 97.15% and the error rate was 2.85%. The accuracy rate of the Random forest algorithm applied to the same data was determined as 97.97% and the error rate as 2.03%. In the study, it was determined that the Random Forest algorithm gave the most accurate result according to the KNN algorithm for three EMG muscle data. This study will guide further studies in the classification of real-time upper limb EMG muscle data. It is suggested that the classification to be made should be done with the Random Forest algorithm with high accuracy. In future studies, it is recommended to compare muscle data at different angles and with different machine learning algorithms.

## 5. Acknowledge

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