

# Arm Muscle Activation Performance Analysis Using Machine Learning Algorithm in the Assembly System

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**Abstract** Human activity recognition has been broadly evaluated in the industry due to ergonomics and optimization purposes. This recognition can provide a human evaluation for several purposes such as motion characteristics, fatigue, and performance analysis. There are some challenges in recognizing the indicators that are used to evaluate the characteristics of motion. The automatic system needs to understand what kind of human activity is in the production system. This article uses motion classification to estimate human motion characteristics. It is known that humans dominantly use their hands in the assembly process. To support it, the electromyography (EMG) sensor was used to detect Biceps Brachii and Flexor Digitorum muscle activity. This article uses basic motion classification to estimate human activity. Four motions were classified using a machine learning algorithm. The result informs that the accuracy reached 89.5%. The evaluation using 2-channel EMG provides good performance in classifying the human motions. It indicates that muscle activity could be used as information for the system to recognize human activity status in the assembly system. This evaluation can also reduce the number of sensors that are used in human activity recognition. This will be useful input for human performance evaluation and prediction in the smart manufacturing system.

**Keywords** Muscle Activation, Human Recognition, Smart System, Motion, Electromyography, Machine Learning

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## 1. Introduction

Human activity recognition become one of concern during the growth of Industry 4.0. Technological advancement increasingly foresees the usage of low-cost sensors in recognizing human status in the various application areas of smart manufacturing systems. The use of the sensor for human activity will provide a meaningful data foundation for automation systems to improve their productivity. These advantages will result from a good human activity analysis using wearable technology during task execution. However, it requires some proper indicators to build evaluation. The indicator is used to inform the system about human status, and the system will adjust the production parameter based on the human status. The production parameter adjustment will have an impact on human safety and productivity. In our case here, the assembly system was chosen as the scenario for the human recognition system due to high repeatability, and during the execution, it potentially impacts fatigue.

Naturally, when humans do any kind of activity, muscle activation can be depicted by non-stationary signal characteristics. This has potential applications for muscle signal evaluation captured by EMG devices. Using EMG, the captured signal can be classified and used to control any kind of device, such as prosthetic hands, rehabilitation, human-machine interaction, and many more [1]–[6]. This

informs that EMG signals are already widely used and applied for various human activity identification purposes. Although dominantly EMG is used in the prosthetic hand and rehabilitation practice, EMG signal can still be used as an indicator for other applications such as human recognition systems in smart manufacturing. However, there is still a complex computational problem for data analysis captured from wearable sensors. For example, in building human recognition, a lot of features and channels need to be considered in the analysis.

Minimizing the number of channels used in the evaluation requires carefully selecting the muscle to capture the activity in the assembly system. Based on preliminary analysis of the GPU assembly, it was found that there are four motions used dominantly in the activities. The MTM-based evaluation was used to evaluate the activities, resulting in four motions that are dominant in the activities: grasp, move, hold, and reach. These four motions can be categorized as hand activity motions. Biceps brachii and Flexor muscles identified dominate in these four motions. Flexor muscles are activated when humans tend to use their finger for flexion movement [7]. Lee et al. [8] used flexor muscle evaluation to classify six target tasks consisting of hand open, key grip, pinch grip, cylinder grip, spherical grip, and grip that uses three fingers with an accuracy of up to 71%. Another muscle considered is biceps brachii that is activated during forearm motions [9], [10]. To minimize the use of sensors, these two muscles will evaluate based on accuracy to evaluate the type of motions performed by the human.

Machine learning can analyze and evaluate complex datasets to make any classification and prediction. This ability makes this approach receive much attention from any practitioner to solve their classification and prediction problem in their area. Especially for an expert who focuses on human behavior study. Human behavior information can be recognized from physiological data such as muscular activity. Several machine learning algorithms such as Random forest (RF), Naïve Bayes, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Decision trees have already been used to analyze human physiological feedback [11]. The performance of each algorithm in analyzing the dataset will depend on the suitability of the dataset's characteristics. Especially for predicting human motion intention, several types of research have already been conducted to evaluate muscle activity. KNN for gesture recognition for single-channel EMG [12]. The research conducted by Wu et al. (2018) classifies five human gestures captured from flexor muscle and reaches an accuracy of 75.8%. Another study also compared several machine learning algorithms such as Quadratic discriminant analysis, Support vector machine, random forest, gradient boosted bagged tree, and subspace KNN to classify the hand movement [13]. The non-linear time series characteristics from muscle activity signal patterns are also used to classify human hand motion [14].

The random forest has superior performance compared with other algorithms like SVM, Neural network, and KNN. At least, it is essential to note that all previous studies used machine learning to solve complex, non-linear, and time series physiological data. It seems that data from the EMG will result in good performance using a minimum channel sensor. This indicates that there are possibilities to evaluate the muscle activation classification performance using a machine learning method for motion evaluation in the assembly system.

Classification of information from human activity recognition is essential for improving the capabilities of the system. Therefore, the EMG signal acquired from their muscles can be used to differentiate human motion while executing assembly tasks. The EMG signals relating to each motion like reach, grasp, move, and hold can be considered indicators to recognize the human activity status in the smart system. Using these indicators, the system will easily adjust the automation parameters system such as speed, safety, and performance prediction. Also, human motion status from EMG signal can be used to estimate fatigue, execution time, and performance assessment during certain times. Therefore, this study aims to evaluate muscle activation performance based on four types of motions in the assembly system.

## 2. Materials and Methods

### 2.1. Data Acquisition

This study aims to classify the four human hands' motions in executing assembly tasks based on their EMG signals. The 2-Channel Noraxon EMG is used as a device to capture muscle activation. Machine learning is one of the algorithms in artificial intelligence used to classify the EMG signal, which consists of a training stage where the model is trained with signals from sEMG. The corresponding features and a subsequent will be selected in a testing stage where the knowledge was acquired by the model in the previous step. There are a total of 313.110 collected, with 78.275 for each basic motion. The dataset collection for experiments was performed by each subject with the dominant hand to execute the assembly task. The signals were recorded using Noraxon EMG electrodes with signals acquired and preprocessed by the Noraxon preprocessing system. Figure 1 shows the Noraxon EMG sensor and path used to capture the muscle activity during the experiment. The sampling rate was 1500Hz. The signal cutoff was done to remove irrelevant conditions.

For all experiments (Figure 2), the myoelectric activations of 2 muscles from the upper arm and forearm were recorded. More precisely, for the upper arm at the biceps brachii, 1 electrode was placed at the back of the arm as ground and two electrodes at the biceps brachii area. On the forearm, 2 electrodes were placed at the flexor digitorum area and 1 at the wrist as the ground area. The

muscles' selection and electrode placement were based on the directions provided in [7] or the flexor digitorum and the [9] for biceps brachii.

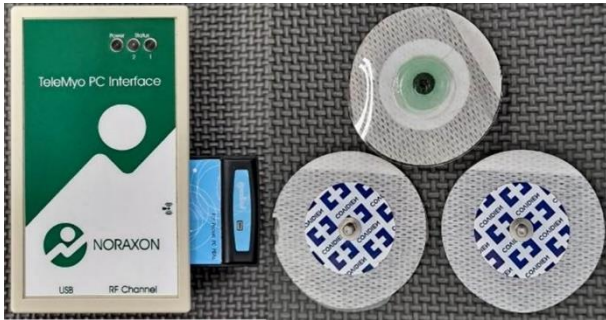


Figure 1. Noraxon EMG sensor and path

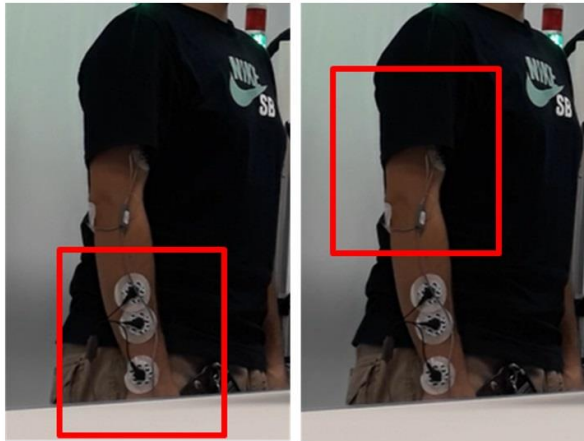


Figure 2. Sensor placement for detecting muscle activity

## 2.2. Data Preprocessing and Features Extraction

EMG signals indicate electrical activity produced by muscular action during the activation phase. The captured EMG signals from muscle activation contain a lot of noise because of the electronics equipment, electromagnetic radiation, motion artifact, instability of signals, cardiovascular activity, electrode, skin contract, transducer,

and baseline shift [15]. Consequently, minimizing the noise in the raw signals is necessary to provide quality data for the classification. In this study, the dataset is preprocessed with smoothing and noise reduction using the Noraxon preprocessing system. The preprocessing considers root-mean-squared (RMS) and the average rectified because these methods are appropriate and can provide valuable information on the signal amplitude.

### 1. Rectification

The EMG signal processing only looks at positive values. All negative data is eliminated during half-wave rectification, whereas only positive data is retained [16]. In order to determine the overall strength of the neural drive to the muscle, an appropriate processing step is EMG rectification, which is connected with the force of muscular contraction and its output [17].

### 2. Root Mean Square (RMS) for smoothing

The basic RMS processor was built as a single-channel unwhitened amplitude processor. The EMG RMS value ( $\hat{S}_1(t)$ ) was formed if the EMG waveform at sample  $t$  is represented by  $m(t)$  and  $N$  is the smoothing window length.

$$\hat{S}_1(t) = \left[ \frac{1}{N} \sum_{i=t-N+1}^t m^2(i) \right]^{1/2} \quad (1)$$

### 3. Cut off

The cut off was designed to remove irrelevant signals that didn't represent the motion. This can be evaluated based on the plot of the signal in the graph.

### 4. Integrated EMG (IEMG)

IEMG is generally easily calculated from captured signals from sensors or muscle activity. IEMG informs the area under the EMG signal curve [18]. IEMG can be simplified and expressed as equation 2.

$$IEMG = \frac{1}{N} \sum_{i=0}^{N-1} |X_i| \quad (2)$$

$X_i$  is the signal value that is recorded and collected by the sensors and  $N$  is the value number involved.

Figure 3 shows the result of preprocessing and feature extraction for the EMG signal.

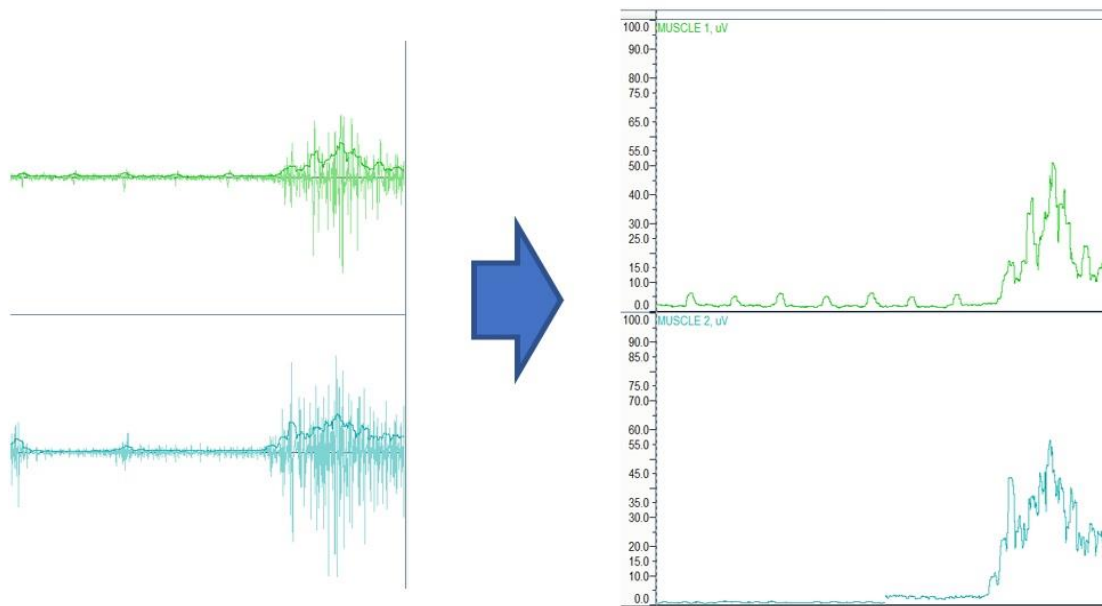


Figure 3. Preprocessing result from raw EMG signal2.4. Classification

### 2.3. Classification

The important process in evaluating the performance of muscles in the activity is to train and test data using a machine learning algorithm. Then the algorithm will classify the input signal to specific motion intention based on any input signals. Machine learning algorithm was one effective method for analyzing complex data for classification and prediction cases. The artificial neural network is the most effective data classification and system training method.

Table 1. Motion classification from dataset

No	Motion	Class
1	Reach	1
2	Grasp	2
3	Move	3
4	Hold	4

This analysis was intended to classify the signal from the flexor digitorum and biceps brachii muscle activation while performing four types of motions. Table 1 shows the class information for four types of motions. From the database, a total of 313,110 EMG signals were collected for training and testing. The database was separated for training and testing with 70% and 30%, respectively. The algorithms in the supervised machine learning used in this analysis were the Random forest and Decision tree.

### 2.4. Confusion Matrix

A confusion matrix with a classifier of size  $n \times n$

displays the expected and actual classification, where  $n$  is the classes total number[19]. The confusion matrix includes information which consists of:

- The prediction of correct negative (TN)
- The prediction of incorrect positive (FP)
- The prediction of incorrect negative (FN)
- The prediction of correct positive (TP)

These all predictions tell the accuracy of actual and predicted classifications. Table 2 shows the matrix to evaluate the muscle classification.

Table 2. Confusion matrix for muscle classification

	Positive prediction	Negative prediction
Actual positive	TP	FN
Actual negative	FP	TN

## 3. Result

EMG signals dataset recorded at 1000 Hz for two muscle activations consisting of the Biceps Brachii and the Flexor Digitorum. Then, preprocessing was done to filter and smooth the data from noise. The classification using a machine learning algorithm was done to compare the muscle performance to depict the human motions in the collaboration. In this section, explain the result of the algorithm comparison and muscle performance comparison in the section below.

### 3.1. Algorithm Comparison

This section compares the performance of the algorithm

used to classify the motion based on the input from the dataset. Here, two algorithms which consist of a random forest and a decision tree, are used to classify four basic motions. Figure 2 shows the performance comparison between random forest and decision tree based on four parameters consisting of accuracy, f1\_score, recall, and precision.

This performance evaluation considers biceps brachii and flexor digitorum muscle to classify four types of motion. Based on Figure 4, all indicators show that the random forest performs better than the decision tree. The accuracy for random forest reaches up to 89.5% for the testing.

### 3.2. Classification Result for Each Muscle

After evaluating the algorithm performance, the muscle activation between the biceps brachii and the flexor digitorum was compared. Figure 6 and 7 illustrates the performance comparison between the biceps brachii and the flexor digitorum for each parameter. Comparing these two muscles resulted in the two muscles having similar performance. The performance difference between these two muscles was not too significant, below 1%. Figure 8 also describes the confusion matrix for each muscle. The performance shows that for the classification task, the algorithm can reach an accuracy of up to 84% for first-class (reach). The second class has the lowest performance for these two muscles which reach around 60%. This is similar to the release motion in the fourth class. The other motion is move can get an accuracy of 71%.

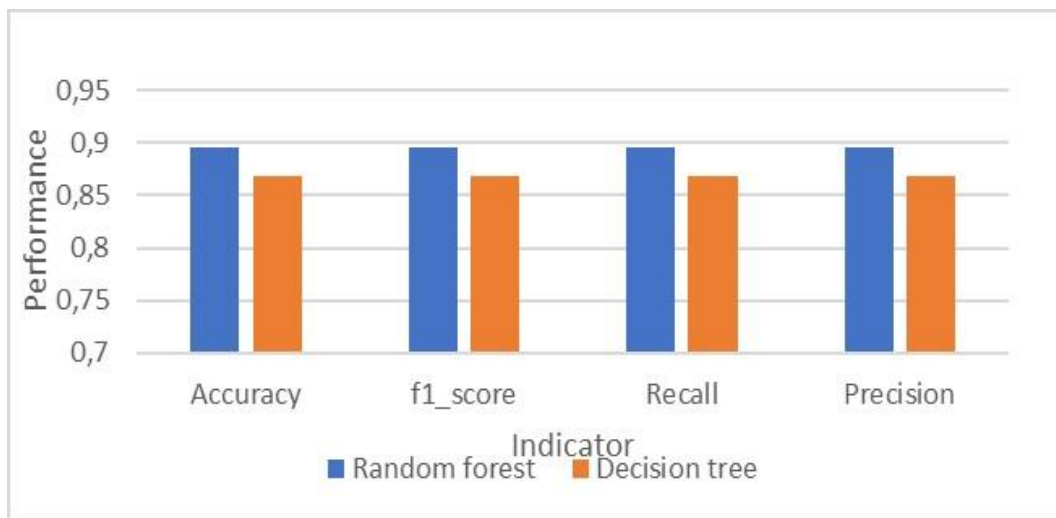


Figure 4. Performance comparison between random forest and decision tree for the dataset

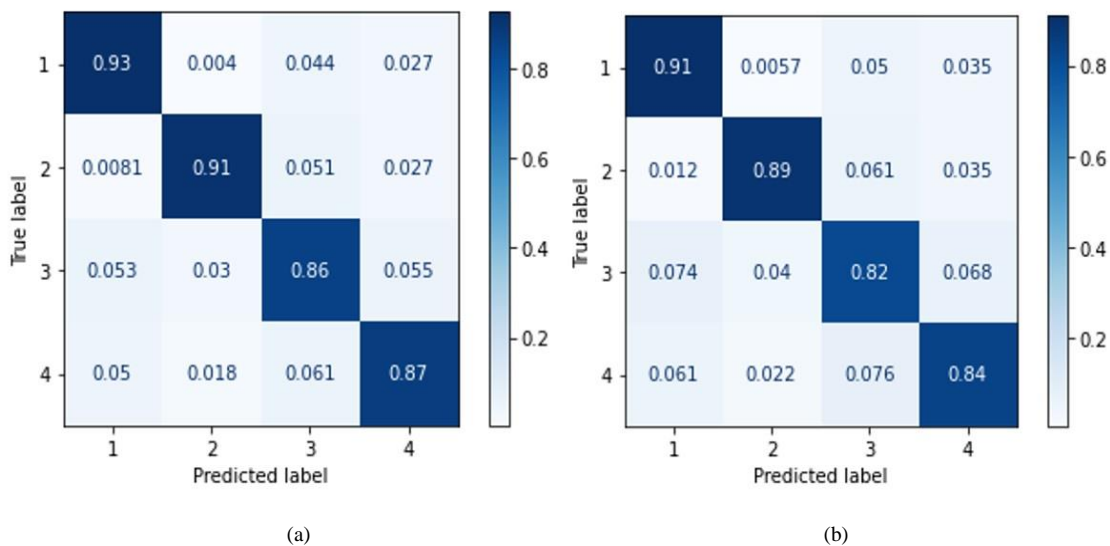


Figure 5. Confusion matrix for performance comparison for Random forest (a) and decision tree (b)

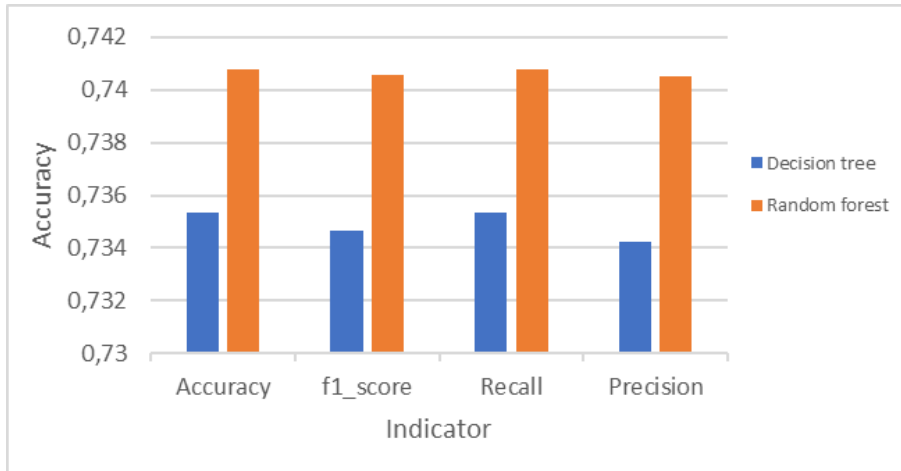


Figure 6. Biceps brachii muscles activation performance comparison

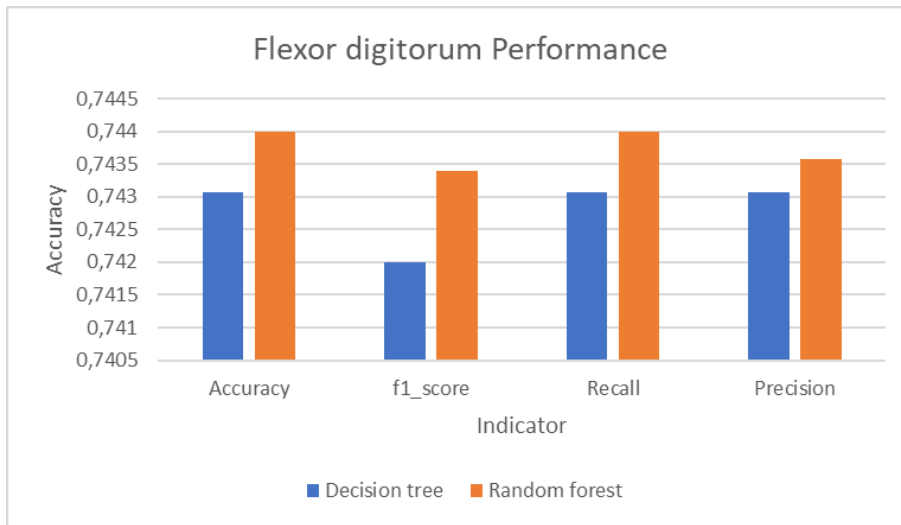
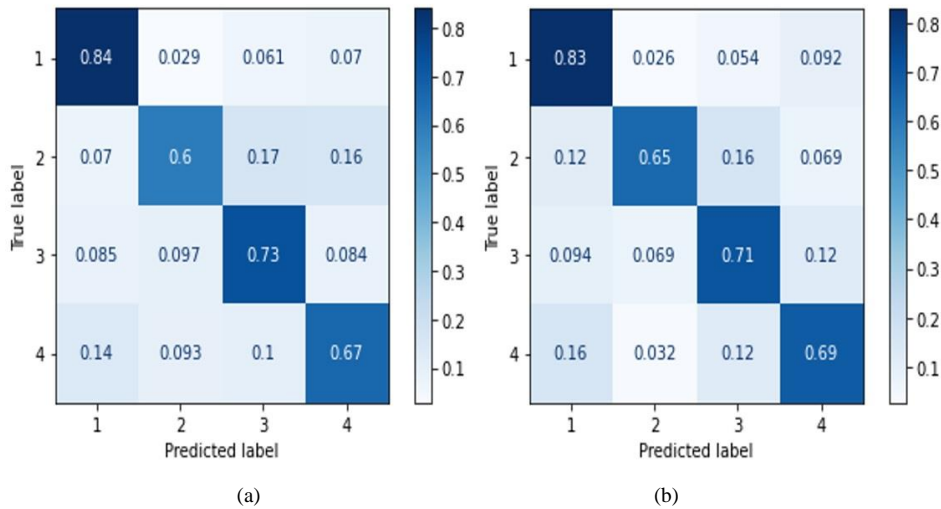
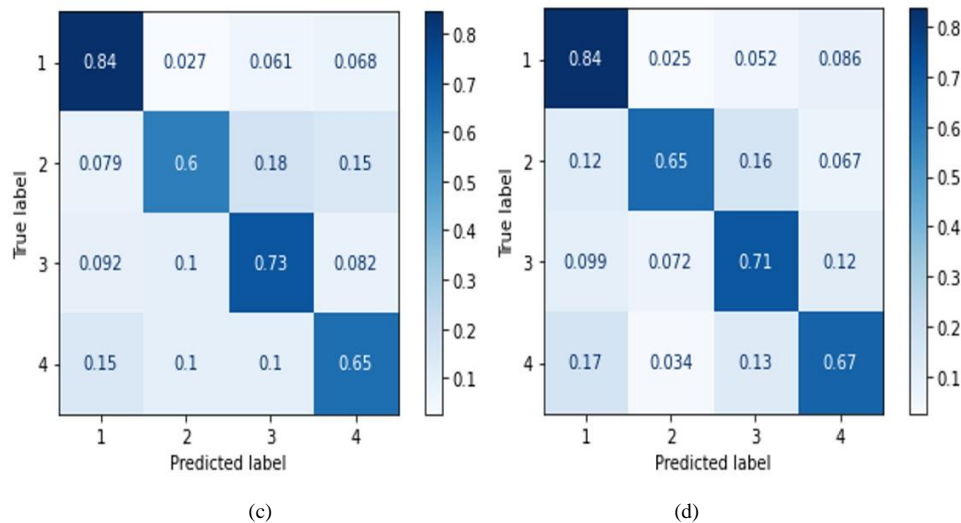


Figure 7. Flexor digitorum muscles activation performance comparison





**Figure 8.** Confusion matrix for performance comparison (a) Biceps brachii with random forest, (b) flexor digitorum with random forest, (c) Biceps brachii with decision tree, (d) Biceps brachii with decision tree

## 4. Discussion

This study aimed to evaluate human motion based on muscle activation while performing four types of motion. For this objective, EMG was used to capture the muscle activity signals. There are two muscles selected based on the observation of the GPU assembly execution by the operator. Two muscles were selected, which consist of the biceps brachii and the flexor digitorum. The results in section 3 show that by using random forest, the accuracy of testing classification is up to 89.5%. The confusion matrix in Figure 5 shows that the random forest can reach up to 93% for each motion, 91% for grasp motion, 86% for move motion, and 87% for hold. This analysis only uses one of the features (IEMG) from two-channel of EMG signals.

The flexor digitorum muscle can be used as a reference if the evaluation only needs a single channel. Figure 6 shows that the flexor digitorum muscle performs better in classifying four motions than the biceps brachii. The accuracy, which is only 74%, may not be good as an indicator in the smart system. These results are still comparable with single-channel EMG classification, which consider a single feature for diagnosing the neuromuscular issue [20]. Another research that considers a single channel to recognize human hand gestures considers 14 features [21]. Using single features and a single channel will reduce computational processing complexity for EMG signal evaluation. This will provide a good evaluation for the type of motion in the assembly system. Using a single channel will improve human comfort while attaching the sensor to the task execution.

The EMG signal classification will result in the human motion status in the assembly system. In our evaluation, human motion status is classified into four types: grasp, reach, move, and hold. Moreover, the time duration also can be recorded while EMG informs the human motion status. This will be used as input to the smart system for two objectives. First, human activity status information

will be used to adjust the production parameters such as speed, safety system, and environmental parameters. Second, to provide input in the human performance evaluation database systems. The database will be used as input to predict human fatigue and execution time. Next, this will be another approach as a quantitative physiological-based human performance assessment system.

## 5. Conclusions

In this paper, we presented muscle activity evaluation in GPU assembly for a smart system. The muscle evaluation using the random forest algorithm provides a good result with accuracy, which reaches up to 89.5%. This result was achieved by using single features from the EMG signal. Moreover, a single-channel EMG evaluation was also done to propose a minimum sensor attached in the collaboration scenario. Using single channel and features, the accuracy reached up to 74% for the flexor digitorum muscle. The single-channel flexor digitorum muscle can be used in the collaboration scenario. This result will provide computationally inexpensive and efficient features for the smart system evaluation. The evaluation system will be able to seamlessly adjust the automation parameters system such as speed, safety, and performance prediction in the system. Furthermore, from a human factor perspective, human motion status classification from EMG signal can be used to estimate fatigue, execution time, and performance assessment during a specific time period.

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