Recognition of Finger Movement Disability Level of Post-Stroke Patient Based on Fugl-Meyer Assessment Using Surface EMG

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Abstract: Regaining finger movement function is thought to be more challenging during rehabilitation because its muscle complexity. Thus, Fugl-Meyer Assessment (FMA) is employed by a doctor to evaluate manually the disability level of the finger movement. This will lead to subjectivity and risk of mistake during assessment. Thus, a system capable of predicting the disability level is required to aid the doctor in making more accurate judgement. This study aims to recognize the finger movement disability level based on Fugl-Meyer Assessment. The EMG recorded from 4 patients when they performed 7 movements based on FMA and extracting the time domain feature values. SVM and Random Forest were employed in classifying the disability level of each movement. SVM classifier could obtain better output in movement 4 which was 91.67% of accuracy and 0.78 of f1 score.

Keywords: disability level, finger movement, post-stroke patients, recognition

1. Introduction

Muscle dysfunction is the most common type of disability after stroke. Muscle dysfunction leads to the risk of hand paralysis following hemiplegic stroke which usually associated with greater impairment, worse function, and lower health-related quality of life. The increase of unused muscle fiber as a consequence of muscle dysfunction leads to abnormal patterns of muscle activation, such as spastic co-contraction, which mostly contribute to the disabled condition [1], [2]. In the case of finger, disability condition is an important factor in the performance of muscle motor unit, because finger is used for many daily activities, especially the finger of dominant hand. People who suffer stroke on their dominant hand may affect their ability to perform daily tasks [3].

In order to restore the function of fiber muscle after stroke, rehabilitation process as the common procedure of regaining the muscle function should be performed [2], [4]. Rehabilitation is defined as the utilization of combined and coordinated use of medical, social, educational, and vocational measures for retraining a person to the highest possible level of functional ability [4]. Fugl-Meyer Assessment of Upper Extremity (FMA-UE) is a common method to measure motor recovery of post-stroke subjects during rehabilitation process especially in the upper limb part, including hand evaluation. The process of FMA-UE assessment was performed by a doctor or physiotherapist by examining directly from the patients' finger movement. This process raises the possibility of subjectivity and and risk of mistake during assessment. Another fact stated that studies in the field of clinical rehabilitation is believed to be difficult due to multiple variables that affect selection and outcome. Some of the problem limits the comparability of the rehabilitation value, which was caused by a descriptive studies and a lot of studies have inadequately matched or ill-defined control group [4]. This implies that the assessment of rehabilitation, including FMA-UE, needs to be conducted by a professionally trained physiotherapy or specialized doctor since the outcome of the assessment might be different.

According to the problem, this research proposes a recognition method for post-stroke patients' finger movement disability level based on Fugl-Meyer Assessment (FMA) using surface EMG. The proposed method aimed at assisting the doctor or physiotherapist in making more accurate judgment of the current patient's condition.

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2. Related Research

2.1 Automation of Fugl-Meyer Assessment

The difficulty on the rehabilitation process assessment had raised issues to the solution to overcome the problem. There are

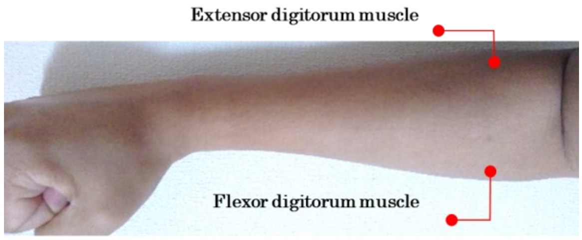

Figure 1. Location of Extensor Digitorum and Flexor Digitorum Muscle

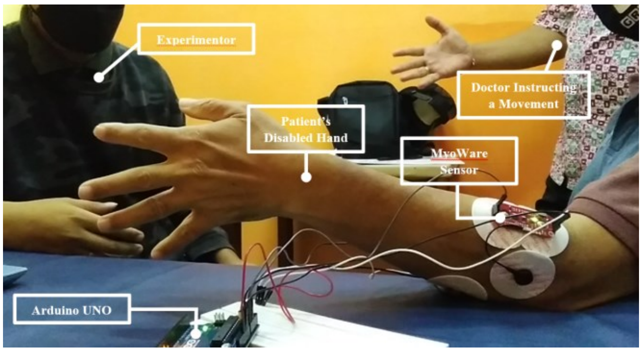

Figure 2. Data Collection Environment

several studies aimed to overcome the subjectivity and inflexible condition of this problem. One of the research was conducted in 2014 from 24 inpatients with varying degrees of upper extremity hemiparesis following stroke [5]. The researchers employed accelerometer sensor on measuring the change of acceleration of the Shoulder-Elbow movement based on FMA. The patients were ordered to perform 4 tasks related the movement of Shoulder-Elbow. The first task is shoulder flexion through the full available Range of Motion (ROM), elbow at 0°, forearm in mid-position. Second task is shoulder abduction through the full available ROM, elbow at 0°, and forearm in mid position. Third task is elbow at 90°, shoulder at 0°, pronation or supination of forearm was performed. The fourth task is the movement of hand to lumbar spine.

Support Vector Regression (SVR) was implemented to predict the feature values which were extracted from the accelerometer signal. Two kernels were applied which are RBF and polykernel to predict 14 selected features. The result showed that a comprehensive model, which was a leave-one-subject-out cross validation, output the best result of 2.1273 Root Mean Square Error (RMSE) score with 2.1594 standard deviation.

Another research proposed an automated data acquisition system specifically for pinch assessment based on FMA protocol. They used Force Sensing Resistor (FSR) and Displacement sensor for Pinch and Grip Assessment [6]. The participants were 50 right-handed healthy male students who has no prior history of upper limb injury and passed the health status questionnaire (SF-36). The paper stated that the subjectivity of the measurement could be removed by replacing the gentle pull from therapist with a linear actuator sub-system exerting a consistent amount of pulling force. However, the final judgment of the proposed system was on the therapist decision since a further study was needed to be conducted to investigate the slip onset and pinch-pulling force of the stroke patients.

2.2 Utilization of Muscle Sensor on Fugl-Meyer Assessment

An automated FMA assessing system for upper extremity motor function of post-stroke was conducted in 2019 [7]. They employed both kinematic information and myographic data from mechanomyography (MMG) sensor to build and learn the arm motor function using Support Vector Machine (SVM). Twenty-eight subjects with acute stroke were recruited and instructed to perform the movement task based on FMA-UE. The result for non-hand function showed that the combination of kinematic and myographic data achieved lower mean classification accuracy by 50.5% compared to 62.0% achieved from kinematic data only. The result of hand function tasks showed higher classification accuracy of 62.4% using myographic data only.

This result implies that kinematic sensors give better result on classifying the movement of non-hand tasks for Fugl-Meyer Assessment. However, for hand function task, the information of the muscle which was obtained from muscle sensor such as MMG is very important factor on improving the quality of the classification. Thus, in our study, we employed the Electromyography (EMG) sensors which measure the electric activity of the muscle to develop a recognition system to classify the disability level of hand function task that is post-stroke patients' finger movements.

3. Methodology

3.1 Participants

EMG data were collected from four subjects of stroke survivor. The subject consisted of three males and one female in their 50s years. All subjects were partially disabled of one of their hands. Three subjects were disabled on their left hand and one subject on the right hand. The experiment was conducted with an assistance of a Doctor of Physical Medicine and Rehabilitation in the Dr. Soetomo General Hospital and followed the relevant guidelines. The environment of data collection experiment is shown in Figure 2. All experiment procedure was approved by the Ethical Committee of Dr. Soetomo General Hospital, Surabaya, Indonesia (No. 0776/116/3/VI/2021).

3.2 Instruments

EMG signal was collected using Two Myoware Muscle sensors (SparkFun Electronics, Niwot, CO, USA) which was attached at flexor digitorum muscle and extensor digitorum muscle as shown

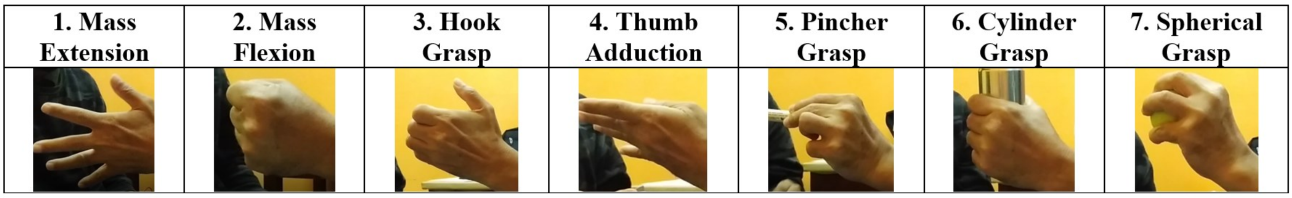

Figure 3. Seven Finger Movements Based on Fugl-Meyer Assessment.

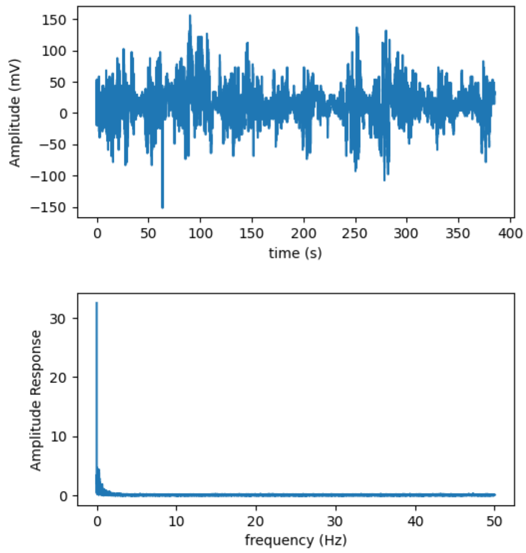

Figure 4. EMG Signal and The Amplitude Response of Subject 1 Before Filter.

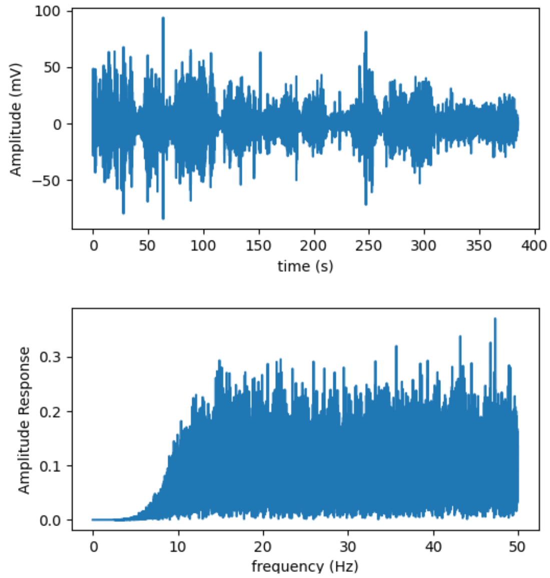

Figure 5. EMG Signal and The Amplitude Response of Subject 1 After Filter.

in Figure 1. This EMG sensor was powered with a minimum of 3.1V supply voltage and supported with differential amplifier adjustable gain of $201R_{gain}/1$ kΩ via potentiometer [8]. Myoware has two EMG modes that is EMG Envelope and Raw EMG. For Raw EMG mode, the gain is not adjustable. Since Enveloped EMG was focused on amplitude analysis of muscular activation [9], this research implemented Raw EMG signal to analyze both time-domain and frequency-domain EMG signal. Raw EMG signal from MyoWare was simply a signal with 201 times amplification without filter. Thus, signal filtering is needed to obtain clean Raw EMG signal.

Arduino UNO was used to receive the EMG signal from two Myoware sensors. Arduino Uno also provided the supply voltage for two Myoware sensors. Analog to Digital Converter (ADC) was implemented within Arduino UNO. In this study, a delay of 10 ms was implemented during ADC process of EMG signal in order to avoid ADC overload. The EMG data was transferred directly to PC and saved into .csv file using PyCharm. PyCharm is an open-source Integrated Development Environment (IDE) for Python programming which was developed by JetBrains company. All data process and machine learning modelling were performed in Python environment.

Fugl-Meyer Assessment of Upper Extremity (FMA-UE) table for hand evaluation was employed to assess the condition of the of the subject's finger movement. FMA is an assessment tools for clinical examination method that has been tested widely in the stroke subject population [1], [2] . The FMA-UE for hand evaluation assessed the condition of the subject's finger movement into Full, Partial, and None [10]. The movements consisted of : 1) Mass Extension (ME), 2) Mass Flexion (MF), 3) Hook Grasp (HG), 4) Thumb Adduction (TA), 5) Pincher Grasp (PG), 6) Cylinder Grasp (CG), and 7) Spherical Grasp (SG) as shown in Figure 3.

3.3 Data Collection

Two MyoWare EMG sensors were attached at the extensor digitorum muscle and flexor digitorum muscle, which control the fingers' extension and flexion movement. Then sensor attached at extensor digitorum muscle was assigned as Channel 1 (Ch1) of EMG and sensor at flexor digitorum muscle as Channel 2 (Ch2). The EMG signal was recorded when the subjects performed 7 types of movement based on FMA-UE for hand evaluation. In this study, the fatigue condition of the muscle was avoided by implementing the rest condition after the movement. The doctor will assess the disability level of each movement using FMA-UE. The assessment from the doctor was used as a ground-truth in modelling the machine learning. During the experiment of 4 subjects, there was no condition of None disability level obtained from all movements. The subjects only had Full and Partial

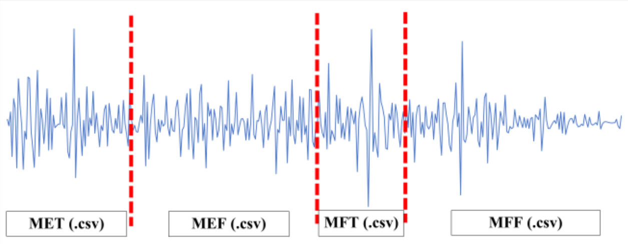

Figure 6. Process of Event Exporting into Different Files. (MET: Mass Extension Transition; MEF: Mass Extension Full; MFT: Mass Flexion Transition; MFF: Mass Flexion Full)

disability level which also varied from each movement. In this study, we adopted the transition phase of the muscle contraction as a target class to be classified. The transition phase corresponds to a muscle fiber recruitment process which leads to the contraction phase of the muscle. Eventhough the transition phase is not correlated to the Fugl-Meyer Assessment output, this phase was also one factor that shows the contraction quality of the muscle [11].

As a consequence of 10ms delay in Arduino UNO, the obtained sampling rate from the sensor was 100Hz. This low frequency of sampling produces an EMG signal with a maximum frequency of 50Hz. Eventhough the obtained EMG signal has low frequency, this frequency is still included in the range of a common EMG signal which showed an ideal power with frequency range of 20-150 Hz [12].

3.4 Preprocessing

The EMG data from each subject was then analyzed in the frequency spectrum to see whether the EMG data contaminated with the noise. The most common EMG signal contamination was caused by motion artifact, baseline, and powerline interference [13], [14]. In this study, powerline interference was ignored since the maximum frequency was 50 Hz. The range of baseline and motion noise ranged between 0-20 Hz. Thus, High Pass Filter (HPF) was performed to remove the existed noise.

3.4.1 High Pass Filter (HPF)

The process of HPF for EMG data was implemented using the Python tools from the Scipy module. The Butterworth High Pass Filter was chosen with 5 filter order and 10 Hz of cut-off frequency. Figure 4 showed the EMG signal of the first Subject and its amplitude response and frequency. From the amplitude response, it is shown that the EMG signal was contaminated with a baseline noise which make the frequency below 1 Hz had a very high magnitude. However, after Butterworth HPF was performed, the noise was eliminated which was shown in the Figure 5. After filtering process, the EMG signal baseline was centered at 0 mV and the amplitude response showed no abnormal magnitude of the frequency. The filtered EMG data

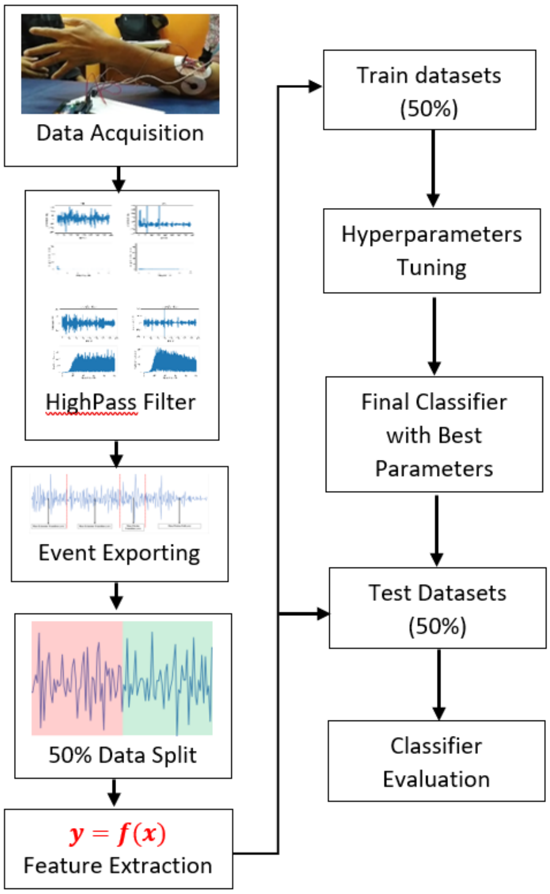

Figure 7. Data Processing Steps.

from all subjects were combined into one file with an order from the first subject, second subject, third subject, and fourth subject respectively.

3.4.2 Data Split

In order to perform a proper data splitting of each movement and the corresponding disability level event, EMG data exporting based on the event was conducted to save each event into different file as shown in Figure 6. After the exporting process finished, data splitting was conducted into each file to split the data for classification process. Sklearn module of Python was employed to perform data splitting. The data was split into 50% or data train and 50% for data test. The splitting size was chosen in order to tolerate the small number of EMG data for transition class. The data splitting process was conducted without performing data shuffling, so that the EMG data was not decomposed into random and meaningless EMG data.

3.4.3 Feature Extraction

In this study, time-domain and frequency-domain features were employed to obtain important feature value from EMG data. A total of nine time-domain (TD) features and one frequency-domain (FD) feature were extracted from 100 ms window size with 10ms window slide size. The features are mean absolute value (MAV), variance (VAR), root mean square (RMS),

Table 1. Best Parameters of SVM and RF for Each Movement

Method	Parameter	Movement						
		1	**2**	**3**	**4**	**5**	**6**	**7**
SVM	Kernel	Linear	Linear	RBF	Poly	Poly	Poly	Poly
	C	1000	10	10	10	1000	10	1
	Gamma	0.001	1	0.1	1	1	1	1
	Degree	0	0	0	3	2	2	3
RF	Criterion	Gini	Gini	Entropy	Gini	Gini	Entropy	Gini
	Number of Trees	700	00	100	100	500	1000	700

Table 2. Classifier Accuracies for Each Movement and Machine Learning Method

Method	Movement						
	1 (%)	**2 (%)**	**3 (%)**	**4 (%)**	**5 (%)**	**6 (%)**	**7 (%)**
SVM	67.38	45.21	48.40	91.67	69.92	80.10	66.82
RF	61.19	41.00	44.40	90.13	76.96	80.78	57.59

waveform length (WL), Slope Sign Change (SSC), zero crossing (ZC), willison amplitude (WAMP), and Mean Power Frequency (MNF) [15]–[18]. These features were widely used to extract important values from EMG and improve the output of classification. After feature values was extracted, the data was standardized using Standard Scaler and concatenated into one train file and one test file.

3.4.4 Classification

In this study, the classification was conducted by comparing the performance of two machine learning algorithms. Support Vector Machine (SVM) and Random Forest (RF) were employed to classify the disability level of the Subjects' finger movement. SVM classifier was widely known of its ability to recognize complex pattern [19], [20]. As an ensemble machine learning, RF was the most popular classifer which also believed to be an efficient classifier and has a good performance in the field of EMG signal classification [21], [22].

In order to make the final output of each classifier focused on the disability level, we made a machine learning model based of each movement. However, the amount of data for each target class was unbalance which leads to a bad performance of the machine learning model. In order to overcome this problem, Smote filtering was performed to produce synthesis data so that the same amount of data is generated for each target class. On deciding the hyperparameters for SVM and RF, we followed the suggested parameters in [15] and tuned the parameters using ten-fold cross-validation randomized search process in the training dataset as shown in the Figure 7. The best parameter was chosen based on the f1 micro score. For SVM classifier, we adjusted the kernel (linear, polykernel, and rbf), polykernel degrees (1, 2, and 3), C value (1, 10, 100, and 1000), and gamma value (1, 0.1, 0.01, 0.001). For RF classifier, we adjusted the criterion parameters (gini and entropy) and number of trees (100, 300, 500, 700, 1000).

Table 3. F1 Score for Each Movement and Machine Learning Method

Method	Movement	Target Class				mean	std
		Full	Partial	None	Transition		
SVM	1	0.60	0.58	0.00	0.99	0.72	0.23
	2	0.32	0.54	0.00	0.53	0.46	0.12
	3	0.54	0.52	0.00	0.18	0.41	0.20
	4	0.98	0.83	0.00	0.53	0.78	0.23
	5	0.85	0.20	0.00	0.00	0.35	0.44
	6	0.88	0.58	0.00	0.42	0.63	0.23
	7	0.76	0.74	0.00	0.19	0.56	0.32
RF	1	0.57	0.41	0.00	1.00	0.66	0.31
	2	0.29	0.45	0.00	0.88	0.54	0.31
	3	0.38	0.61	0.00	0.19	0.39	0.21
	4	0.99	0.70	0.00	0.57	0.75	0.22
	5	0.90	0.40	0.00	0.00	0.43	0.45
	6	0.89	0.60	0.00	0.59	0.69	0.17
	7	0.70	0.49	0.00	0.11	0.43	0.30

4. Results

We developed the machine learning-based classifier to recognize the disability level of the Subjects' finger movements using SVM and RF. In this study the target classes which was learned and recognized by the employed machine learning model were Full, Partial, and Transition. Since FMA-UE for hand evaluation has None condition, we included the None class in the confusion matrix with zero value. The calculation of all performance metrics was conducted only for Full, Partial, and Transition class.

4.1 Classifier Parameters

The established machine learning model was optimized by the best parameters which were determined using randomized search process based on the f1 micro score as shown in Table 1. The maximum value of C parameter for SVM classifier was 1000, meanwhile the gamma parameter varied in the set range from 1 until 0.001. Degree parameter only worked for polykernel parameters, thereby only SVM model for movement 4, 5, 6, and 7 output the degree parameter which was 2 and 3.

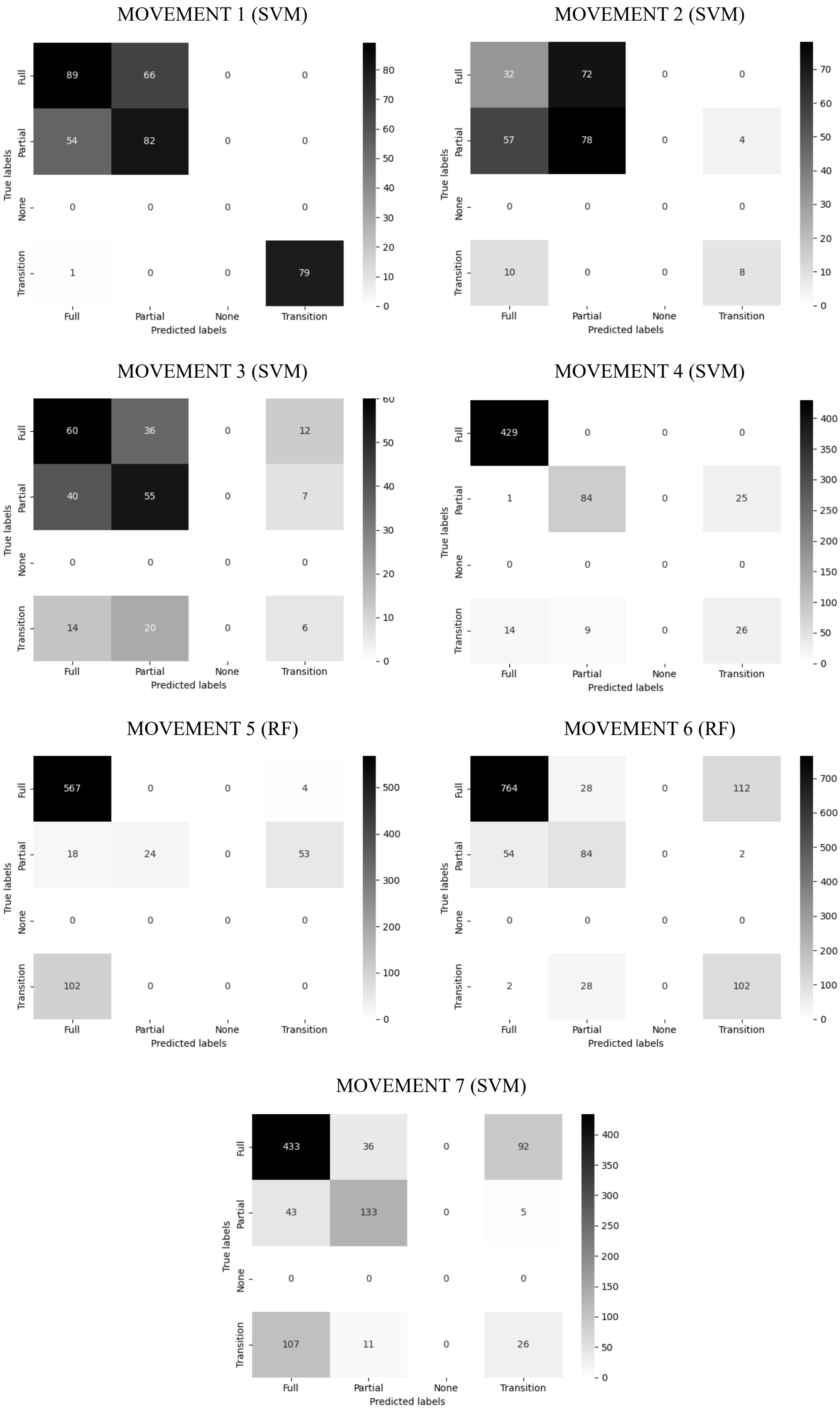

Figure 8. Confusion Matrix for 7 Movements Based on Highest Accuracy from Each Classifier

In the RF parameters, the maximum number of trees was 1000 which is obtained by movement 6. Entropy was the best criterion parameter of movements 3 and 6. Meanwhile, gini criterion was the best parameter for movement 1, 2, 4, 5, and 7.

4.2 Classifier Performance

Based on Table 2, the highest accuracy of 91.67% was obtained in movement 4 for SVM classifier and the lowest accuracy of 41.00% was obtained in movement 2 for RF. Correspond to the accuracy result, both machine learning models showed best performance on recognizing the disability level in movement 4, while poor performance occurred in movement 2 and 3 with low accuracy score below 50%. In order to observe more regarding the performance of the machine learning model, the score of f1 is needed.

Table 3 shows f1 score of each disability level on each movement. Based on the mean of f1 score, SVM and RF classifier obtained the best f1 score in movement 4 which was complementing the accuracy score. Random Forest classifier showed better performance on classifying the disability level in movement 5 and 6. In movement 5, the accuracy of RF was 7.04 higher than SVM, while the f1 score was 0.08 higher. In movement 6, the accuracy of RF was slightly higher than SVM which is 0.68, and the f1 score of RF was 0.03 higher than the SVM.

5. Discussion

In this study, we developed a recognition method to recognize the disability level of post-stroke patients' finger movement. Two machine learning method were implemented to classify three target classes for each movement. The SVM method achieved the highest accuracy and f1 score in the fourth movement (Thumb Adduction) of 91.67% and 0.78 respectively. This result implies that recognizing the disability level from post-stroke subjects' finger movement is applicable.

The proposed method with low sampling rate of 100Hz with 4 post-stroke patients was able to recognize each disability level of finger movements. In this study, the amount of data for each target class and each movement is unbalance especially for Partial and Transition. The transition class is a changing phase from rest condition to a contraction condition, called recruitment of motor unit process. The duration of transition phase of healthy person is very small, ranged from 80ms until 150ms [23].

Since the employed sampling rate in this study only able to capture 1 EMG data every 10ms, then only 8-15 EMG data correlated with transition phase will be captured. However, in the case of disabled muscle condition, the transition phase has the possibility to occur longer than normal muscle. In this paper, various f1 score for Transition target class was obtained. RF classifier could achieve the highest f1 score in classifying the Transition class of the first movement by 1.00. SVM was also able to achieve high f1 score in Transition class in the first movement by 0.99. However, a lot of transition class for other movements were poorly classified. Figure 8 showed that Transition class of SVM method for movement 2, 4, and 7 were biased mostly to the Full class. Similar condition happened for Transition class in RF classifier as shown in Figure 8. In movement 5, the transition class was misclassified as Full class, while in movement. Both SVM and RF classifier showed 0.00 f1 score of Transition class as shown in Table 3. The similar condition occurred with Partial target class. Eventhough some of the predicted classes were misclassified as Full or Transition class, due to higher amount of data on the Partial class compared with Transition class, the result for f1 score is better than Transition class. Both SVM and RF classifier showed biased result of Partial class that varied to rather Full or Transition class.

In order to compensate the unbalance number of EMG data, especially for Transition target class, 50% data splitting was performed. The condition leads to small number of features learned by the employed machine learning model. Based on another study, the classifier was preferred to learn more features in order to output a good machine learning model by performing data splitting with 90% for train dataset and 10% test dataset [15]. The expected condition also requires the system to obtain more EMG data by increasing the sampling rate. Eventhough the sampling rate which was employed in this research is still included in the Nyquist frequency range of EMG [12], higher sampling rate is needed to collect more EMG data within 1s.

6. Conclusion and Future Work

This research proposed a recognition method to recognize the disability level of the post-stroke patients' finger movement based on Fugl-Meyer Assessment. In this research the SVM and RF classifier could detect all target classes which was Full, Partial, and Transition condition. The employed classifiers were optimized with the best parameters which was chosen by 10-folds cross validation (CV) of randomized search method. The SVM classifier achieved the highest accuracy and mean of f1 score on detecting the disability level of movement 4 (Thumb Adduction) by 91.67% and 0.78 respectively. RF classifer also achieved the highest accuracy on recognizing the disability level in movement 4 with 90.13% accuracy score and 0.75 mean of f1 score. Collecting more EMG data from the post-stroke patients, especially patient with None disability level condition and employing higher sampling rate will be conducted for the next research.

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