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RESEARCH PAPER

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Improving the Accuracy of Upper Limb Exoskeleton Movements Using Machine Learning Based on EMG for Stroke Patient Rehabilitation

Imran Hamid, Triwiyanto, and Bedjo Utomo
Department of Environmental Health, Poltekkes Kemenkes Surabaya, Indonesia
Corresponding author: Triwiyanto (e-mail: triwi@poltekkes-surabaya.ac.id).

ABSTRACT

Post-stroke rehabilitation often focuses on restoring upper limb mobility, which is essential for regaining independence in daily activities. Upper limb exoskeletons have emerged as promising assistive devices, facilitating controlled and repetitive movements. However, accurate control of these devices remains a challenge due to the complexity of interpreting user intent. This study leverages machine learning (ML) to enhance exoskeleton control using electromyography (EMG) signals. The system integrates Raspberry Pi Zero 2W, Muscle Sensor V3, and MPU6050 to collect and process EMG data, extracting features such as Root Mean Square (RMS), Mean Absolute Value (MAV), and Variance (VAR). These features were evaluated for their predictive performance in joint angle estimation, with MAV identified as the most impactful. A Random Forest Regression model was trained and tested using EMG data collected from healthy subjects performing flexion and extension movements. The model achieved a superior performance with an RMSE of 12.197 and an R^2 of 91.6%, outperforming Linear Regression and Decision Tree models. This real-time system successfully predicts joint angles, adapting exoskeleton movements based on EMG inputs and providing personalized support for patients. Although the system shows high accuracy, its generalizability to stroke patients remains a challenge due to the inclusion of only healthy participants. Future work should focus on expanding trials to diverse patient populations and incorporating multi-channel EMG data for enhanced precision. This approach represents a significant step toward improving stroke rehabilitation by providing precise, real-time control in upper limb exoskeletons.

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CONTACT:

triwiyanto123@gmail.com
bedjoutomo123@gmail.com

I. INTRODUCTION

Stroke is one of the leading causes of disability worldwide, often resulting in impaired motor function, particularly in the upper limbs. Restoring upper limb mobility is crucial for improving the quality of life and enabling stroke survivors to regain independence in daily activities. Traditional rehabilitation approaches focus on physical therapy and repetitive exercises; however, these methods can be slow, labor-intensive, and limited in their effectiveness [8]. To address these limitations, upper limb exoskeletons have emerged as promising assistive devices that provide controlled, repetitive movements to aid in motor recovery. These devices are designed to help patients regain motor function by mimicking normal movement patterns, offering a potential solution to the limitations of conventional rehabilitation techniques [9], [10]. However, accurate control of exoskeletons remains a significant challenge, primarily due to the difficulty of interpreting the user's intended movements. Many existing approaches rely on simple control methods, which do not effectively address the complexity of neuromuscular signals in patients recovering from stroke [11], [12].

Recent advances in machine learning (ML) have provided new opportunities for improving the accuracy

Corresponding author: Triwiyanto, triwi@poltekkesdepkes-sby.ac.id, Department of Medical Electronics Technology, Poltekkes Kemenkes Surabaya, Jl. Pucang Jajar Timur No. 10, 60282, Surabaya, Indonesia.
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and adaptability of assistive devices. Machine learning models, particularly Random Forest Regression (RFR), have been applied to predict and control movements in exoskeletons based on signals such as electromyography (EMG). The application of machine learning in the field of rehabilitation is still emerging, but its potential is vast in terms of enabling devices to better adapt to the patient's intended movements in real-time. Recent studies have shown that machine learning can improve the precision of exoskeleton movements[13], helping to better align the robotic system with the user's motor intent, which is crucial for stroke rehabilitation [14].

This study aims to build upon existing research by applying Random Forest Regression to enhance the control of upper limb exoskeletons using EMG signals. Unlike traditional methods, RFR offers advantages in terms of handling complex, non-linear relationships within the data, which makes it suitable for real-time applications [1], [3], [9], [15]. The novelty of this work lies in its integration of multiple signal processing techniques to improve joint angle prediction, which is crucial for achieving accurate movement control. Additionally, this study focuses on using MAV as a key feature, which has shown superior predictive power over other common features such as RMS and VAR [16], [17].

While existing studies have made significant strides, many have limitations, including the use of simplified datasets, typically only involving healthy participants. Therefore, the primary objective of this research is to develop a real-time exoskeleton control system that can accurately interpret the user's intended movements based on EMG signals. The hypothesis is that the integration of machine learning, specifically Random Forest Regression, will lead to improved accuracy in joint angle estimation, resulting in better control of exoskeleton movements. Furthermore, this study aims to explore the practical implications of using such systems in stroke rehabilitation, providing personalized and precise support for patients during their recovery process [10], [18].

However, the generalizability of this system to stroke patients remains a challenge due to the inclusion of only healthy participants in the initial trials. Future work should focus on expanding trials to diverse patient populations and incorporating multi-channel EMG data for enhanced precision. Additionally, the application of advanced machine learning models, such as deep learning, could further improve the system's adaptability and robustness, potentially enabling more intuitive control in real-world clinical settings. This approach represents a significant step toward improving stroke rehabilitation by providing precise, real-time control of upper limb exoskeletons [19], [20].

II. METHODOLOGY

A. *Experimental Procedure*

An upper limb exoskeleton prototype was designed to assist patients with post-stroke arm paralysis. The exoskeleton was tested on healthy subjects, with a primary focus on developing machine learning software for the embedded Raspberry Pi microcomputer. The study involved healthy individuals aged between 20 and 40 years, with a balanced representation of both males and females. The participants were selected based on the following inclusion criteria: (1) no prior history of neurological or muscular disorders, (2) normal EMG readings, and (3) ability to perform upper limb movements such as flexion and extension. Exclusion criteria included individuals with cardiovascular diseases, arthritis, or any other condition that could affect the normal functioning of the upper limbs. By using healthy individuals, we aimed to test the feasibility of the system in a controlled environment before transitioning to stroke patients. Future research will include stroke patients to assess the system's adaptability to the impaired neuromuscular activity typical in post-stroke rehabilitation [21].

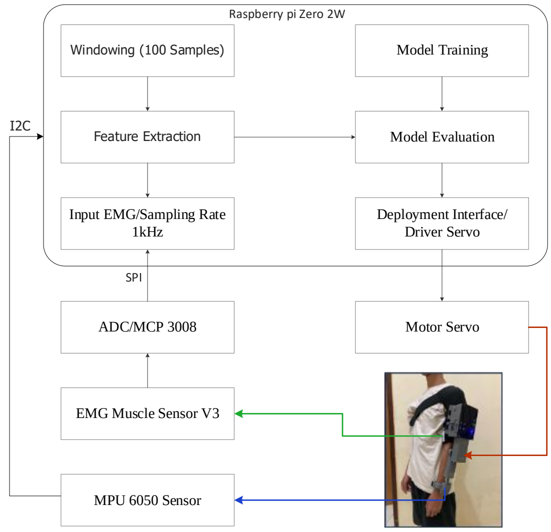

Fig. 1. Block diagram of upper limb exoskeleton control by raspberry pi zero 2W with machine learning.

Data collection was performed on the biceps muscle area using gel electrodes that had been previously cleaned with alcohol to reduce skin resistance and improve contact with the EMG sensor, which was attached with elastic straps. The upper limb exoskeleton, created by 3D printing, was then attached to the arm (Fig.1). EMG testing involved instructing the

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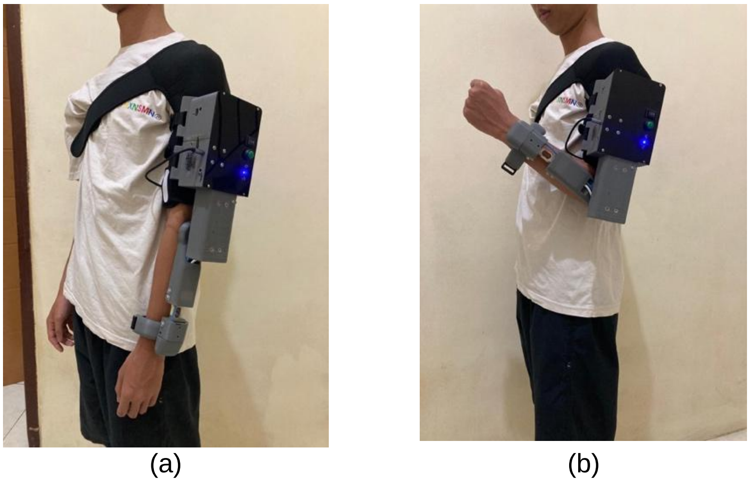

Fig. 2. The proposed exoskeleton design (a) showing the Extension movement, (b) showing Flexion movement, without image caption

participant to perform repetitive flexion and extension movements while muscle activity was observed on a thonny ide console monitor. Simultaneously the angular position of the exoskeleton was also recorded with an MPU6050 sensor during flexion and extension, ranging from 0 to 120 degrees and back to 0, which was synchronized with a metronome app set for 3 seconds per cycle [22]. The collected EMG signal data is extracted using time-domain features such as root mean square (RMS), variance (VAR), and mean absolute value (MAV) as feature data, in addition to feature data, angle values as labels are also collected. Furthermore, the feature data and labels are trained using machine learning algorithms namely linear regression (LR), decision tree (DT), and random forest (RF), with a percentage of 80% trained data and 20% tested data. then the training results are embedded into a Raspberry Pi Zero 2W mini computer which functions to predict new EMG data. Once the system recognizes the movement patterns from the EMG data, it can control the servo motors attached to the joints to mimic flexion and extension movements [23], [24].

B. *Data Acquisition.*

EMG signal recording is done by tapping muscle activity at the biceps point using gel electrodes (Fig. 2) where the electrode design is made in such a way that the distance between the ground electrode and the monitoring electrode is 5cm, by placing the reference electrode between the two electrodes. The characteristic of Muscle Sensor V3 is that the EMG signal produced is a rectified signal with a dominant frequency of 20-150 Hz. An MCP3008 A/D converter device is required for analogue to digital signal conversion. This A/D converter is connected to the Raspberry Pi Zero 2W system via Serial Peripheral Interface (SPI) communication.

The electromyographic (EMG) signals were collected using a single-channel Muscle Sensor V3, placed on the biceps brachii and triceps brachii muscles. Although using a single EMG channel simplifies the process, it was chosen due to the ease of deployment and its sufficient accuracy for initial testing in healthy subjects. However, the limitations of this approach are acknowledged, as a single-channel EMG may not capture the full complexity of stroke-related neuromuscular activity. Therefore, future work will involve extending the system to incorporate multi-channel EMG data, which can capture more detailed muscle activity and improve prediction accuracy in stroke patients. In relation to the Nyquist rule, the sampling frequency applied is at least 2 times the maximum frequency of the EMG signal. In this study, a sampling frequency of 1000 Hz was applied for the EMG signal recording process. Meanwhile, the angular position of the upper limb exoskeleton detected using the MPU6050 sensor is recorded at a rate of 10 Hz [25].

C. *Bias Handling*

To minimize bias in the dataset, a random sampling technique was used for selecting participants. This method ensures that the data collected for the study comes from a diverse group of individuals, with each participant having an equal chance of being included, thus reducing selection bias. Healthy individuals were selected based on inclusion and exclusion criteria (as mentioned in the Participant Selection section), but care was taken to ensure that the sample was representative of a broader population in terms of age and gender.

Corresponding author: Triwiyanto, triwi@poltekkesdepkes-sby.ac.id, Department of Medical Electronics Technology, Poltekkes Kemenkes Surabaya, Jl. Pucang Jajar Timur No. 10, 60282, Surabaya, Indonesia.
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Additionally, we addressed potential measurement bias by standardizing the data collection procedure. Gel electrodes were carefully positioned on the biceps brachii and triceps brachii to ensure consistent data collection. The same Muscle Sensor V3 and MPU6050 sensor were used across all trials, and the same procedure for flexion and extension movements was followed for each participant.

Moreover, to further reduce data bias, we implemented a data normalization step, which adjusts for any systematic differences in the data. This step ensures that the model training is not skewed by outliers or variations in data caused by factors unrelated to the actual muscle activity being measured.

Despite these precautions, the use of healthy participants in the current study is a limitation, as the neuromuscular activity of stroke patients may vary significantly from that of healthy individuals. Therefore, the model's generalizability to stroke patients remains an open question, and this will be addressed in future research by including a more diverse sample, particularly stroke patients. Furthermore, by incorporating multi-channel EMG data**,** which is expected to capture more detailed muscle activity, we aim to reduce bias and improve the accuracy of predictions in real-world clinical applications**.**

D. *Data Processing.*

In the training stage, EMG data is collected with a sampling frequency of 1kHz, then feature extraction is performed in every 100 samples/windowing (equivalent to 0.1 seconds), to produce features, namely numerical representations in the form of RMS, VAR and MAV feature values of EMG signals. Each period (from 0° to 120° and back to 0°) was taken for 3 seconds, resulting in 30 feature sets for each period (since 3000 samples were divided by 100 samples per feature set). Each respondent performed 10 periods, so the number of feature sets collected per respondent is 30 x 10 = 300 feature sets. Since there are 20 respondents involved, the number of feature sets trained is 300 x 20 = 6000 training data. These feature sets are then used as input/feature data for the Machine Learning algorithm training model. In addition to input/features, the ML training model also requires angle data from the MPU6050 sensor, where the angle amount is used as output/label data, both data, namely features and labels, become input and output in the ML learning model training process that produces training/model data [26].

Furthermore, in the prediction stage, the training data is evaluated in pattern recognition so that it can produce a prediction of the angle of movement based on new data, the results of the evaluation are implemented in the exoskeleton system by using servo motors to move the exoskeleton accurately according to the EMG signal received. In order for the program performance to run well, the system is made to run in parallel/multithreading. where the output of each thread is sent to a global variable so that other threads that need the variable can use the data at the same time and run continuously as long as the device is not turned off [27].

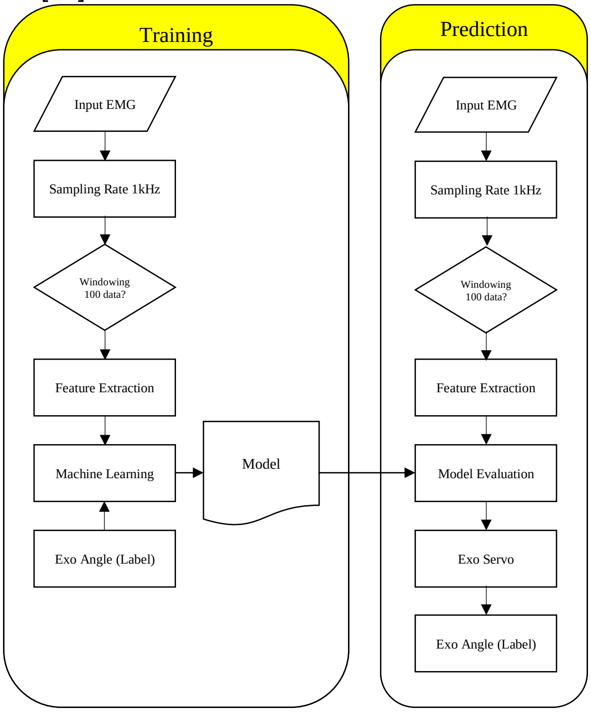

Fig. 3. Flow chart of the proposed system

E. Features Extraction.

The EMG signal was pre-processed using rectification and smoothing techniques to remove noise and ensure the reliability of the signal. Rectification is used to convert the raw EMG signal into positive values, making it easier to analyze muscle activity. Smoothing was applied to reduce high-frequency noise, allowing for a clearer representation of the muscle's activity over time. These techniques are essential for obtaining clean, usable data that accurately reflects the muscle's behavior.

Several features were extracted from the pre-processed EMG signal: Root Mean Square (RMS), Mean Absolute Value (MAV), and Variance (VAR). Each of these features provides valuable information about the muscle's activity during movement:

Root Mean Square (RMS) is a statistical measure used to describe the effective magnitude of a signal. The RMS value indicates the actual strength or energy of the signal, particularly in raw data or analog readings. It is a commonly used feature in EMG analysis to

Corresponding author: Triwiyanto, triwi@poltekkesdepkes-sby.ac.id, Department of Medical Electronics Technology, Poltekkes Kemenkes Surabaya, Jl. Pucang Jajar Timur No. 10, 60282, Surabaya, Indonesia.
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measure muscle contraction intensity. Mathematically, it is represented by the following equation (1):

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} \mathcal{X}_i^2} \quad (1)$$

where $\mathcal{X}_i$ represents the individual signal values and N is the number of data points. MAV is another statistical measure that provides an estimate of the average strength of muscle contractions over a specified time interval. The higher the MAV value, the greater the strength of muscle contractions during that interval. MAV is particularly useful for distinguishing different levels of muscle activation. It is calculated as Eq. (1):

$$\mathrm{MAV} = \frac{1}{N}\sum_{i=1}^{N} |xi| \quad (2)$$

where $\mathcal{X}_i$ represents the absolute value of the signal at each sample. Variance is a statistical term that measures the spread of the signal's values around the mean. In the context of EMG signals, variance measures the fluctuations in muscle activity, indicating how consistent or variable the muscle's contraction is over time. It provides insight into the intensity and stability of the muscle's activity. Mathematically, it is represented as Eq. (3):

$$VAR = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2 \quad (3)$$

where $\mathcal{X}_i$ is the signal value at sample i and μ is the mean of the signal values. Among these features, MAV was selected due to its superior performance in terms of prediction accuracy in preliminary tests. MAV has been shown in previous studies to be highly sensitive to changes in muscle contraction levels and has demonstrated better performance in predicting joint angles when compared to RMS and VAR [1][2]. The MAV feature captures the average level of muscle activity over time, which is particularly useful for distinguishing different movement patterns in the control of the exoskeleton [28].

These features were evaluated based on their ability to predict the joint angle of the exoskeleton with high accuracy. After extracting these features, they were used as input data for training the machine learning models, such as Random Forest Regression (RFR), Linear Regression (LR), and Decision Tree (DT). Through evaluation, MAV was identified as the most impactful feature for predicting the joint angles, which is critical for the exoskeleton's real-time control. Therefore, MAV was prioritized for the subsequent steps in the machine learning pipeline[29].

Machine learning methods are used to analyze complex patterns in EMG signals and translate them into commands that the system can understand [30]. In this study, we applied supervised learning techniques, where models are trained to recognize EMG signal patterns related to specific movements, such as in the control of upper limb exoskeletons. The objective is to predict the joint angle of the exoskeleton based on the EMG signal, which can be used to drive the movements of the exoskeleton in real time [31]. We evaluated three machine learning algorithms in this study[32].

Linear Regression (LR). This method models the relationship between input features (EMG data) and an output variable (joint angle) using a straight line. The mathematical equation for Linear Regression is Eq. (4):

$$y = b_0 + b_1x_1 + b_2x_2 + \cdots + +b_nx_n + \epsilon \quad (4)$$

where *y* represents the dependent variable (the output or response being predicted), b_0 is the intercept (the value of *y* when all independent variables are zero), $b_1, b_2, \ldots, bn$ are the coefficients that measure the effect of each independent variable ($x_1, x_2, \ldots, x_n$) on *y*, and ϵ is the error term capturing variability in *y* not explained by the independent variables. Linear Regression is simple and computationally efficient, but it may not capture complex, non-linear relationships present in the EMG signals. Decision Tree Regressor (DTR). Decision trees divide the feature space into smaller segments and predict a continuous value based on the data in each segment. The model can be described by the following recursive rule, Eq. (5):

Prediction = *f(x)* = Average*(yi)* (5)

for all samples in leaf node, is a simple model for prediction, where *f(x)* is the prediction for input x, the predicted value for a given input x is based on the average of the observed values *yi*, Eq. (6)

$$Averange(yi) = \frac{1}{n}\sum_{i=1}^{n} yi \quad (6)$$

where *n* is the total number of observations.

Decision Tree Regressor can handle non-linear relationships and is interpretable, but it is prone to overfitting if not properly tuned. Random Forest Regressor (RFR). Random Forest Regression is an ensemble learning method that combines multiple decision trees. The mathematical equation for Random Forest Regressor is, Eq. (7):

$$\hat{\mathcal{Y}} = \frac{1}{T}\sum_{t-1}^{T} f_t(\mathcal{X}) \quad (7)$$

where $\hat{\mathcal{Y}}$ represents the predicted value (the output or response being estimated), *T* is the total number of models or time steps considered, $f_t(X)$ is the prediction function at each step based on the input, the summation represents the combined predictions across all steps or models, and the averaging factor ensures the final prediction is the mean of all predictions.

Random Forest Regressor combines the predictions of multiple decision trees, helping to reduce overfitting and improve robustness. It is particularly effective for handling high-dimensional data like EMG signals, which have complex and non-linear

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relationships. To evaluate the effectiveness of Random Forest Regression (RF), we compared its performance against Linear Regression (LR) and Decision Tree Regressor (DT). All models were trained on the same dataset, and their performance was evaluated using the Root Mean Square Error (RMSE) and R-squared (R^2) metrics. Root Mean Square Error (RMSE). Measures the average magnitude of the errors between predicted and actual values, with the following formula, Eq. (8):

$$RMSE = \sqrt{\frac{1}{N}\sum_{i-1}^{N}(y_{pred} - y_{true})^2} \qquad (8)$$

where RMSE (Root Mean Squared Error) is a metric used to measure the accuracy of a prediction model, N represents the total number of data points, y_{pred} is the predicted value, y_{true} is the actual value, and the difference $(y_{pred} - y_{true})$ is the error for each data point. The summation aggregates the squared errors for all data points, which is then averaged and square-rooted to provide the final RMSE value. R-squared (R^2) Is the proportion of the variance in the dependent variable (joint angle) that is predictable from the independent variables (EMG features) (Eq. (9):

$$R^2 = 1 - \frac{\sum_{i-1}^{N}(y_{true} - y_{pred})^2}{\sum_{i-1}^{N}(y_{true} - y_{true})^2} \qquad (9)$$

where R^2 (coefficient of determination) measures how well the predictions of a model explain the variability of the actual values, y_{true} represents the observed values, y_{pred} represents the predicted values, the numerator is the sum of squared residuals (the error between observed and predicted values), and the denominator is the total sum of squares (the variability of the observed values around their mean). R^2 indicates the proportion of variance explained by the model, with a value of 1 representing a perfect fit and 0 indicating no explanatory power.

The comparison results showed that Random Forest Regression outperformed both Linear Regression and Decision Tree in terms of both accuracy and robustness to variations in the EMG signal data. Specifically, Random Forest achieved a RMSE of 12.197 and R^2 of 91.6%, which indicates superior prediction performance compared to the other models. For Random Forest Regression, the hyperparameters were optimized using a grid search approach. The most important hyperparameters for the model were:

- **Number of trees (n_estimators):** Determines how many individual decision trees are built in the forest. A higher number of trees usually leads to better performance, but it also increases computational complexity.
- **Maximum depth of the trees (max_depth):** Controls the depth of each decision tree. Limiting the depth prevents overfitting and helps in generalizing the model.
- **Minimum samples per leaf (min_samples_leaf):** Specifies the minimum number of data points required to form a leaf node. This helps control overfitting.

A grid search was performed over different values of these parameters, and the best combination was selected based on cross-validation performance. The final Random Forest Regression model demonstrated high accuracy in predicting joint angles with an RMSE of 12.197 and R^2 of 91.6%, outperforming both Linear Regression and Decision Tree models. Random Forest Regression was chosen due to its ability to handle complex, non-linear relationships in the data. EMG signals are inherently noisy and contain non-linear patterns that are difficult to model with simpler techniques like linear regression. Random Forest, being an ensemble of decision trees, is able to capture these non-linearities and provide more accurate predictions. Additionally, it is less prone to overfitting compared to individual decision trees, making it ideal for real-time applications in controlling the exoskeleton [33].

Future improvements to the machine learning models will include incorporating multi-channel EMG data, which will provide more detailed muscle activity information, and exploring deep learning models to enhance prediction accuracy and model adaptability. The current system will also be tested with stroke patients to evaluate its robustness in real-world rehabilitation scenarios [34].

III. RESULT

A. EMG Raw

Advancer Technologies' “Muscle Sensor V3” device is an EMG sensor that detects the electrical activity of human muscles. With an AD8221 amplifier and electrodes placed on the biceps muscle, it measures EMG signals from muscle contractions and converts them into electrical signals. The EMG signals are amplified, rectified, and smoothed, so they are ready for use on the microcontroller. The signal received by the electrodes will be amplified on the Muscle sensor V3 sensor module, which is then converted into digital data by the A/D converter MCP3008. The MCP 3008 output is then processed by Raspberry pi which in the end the signal recording results will be saved into a CSV file. In the following figure 4, the results of the EMG signal are shown which have been repaired and smoothed by the EMG muscle sensor v3.

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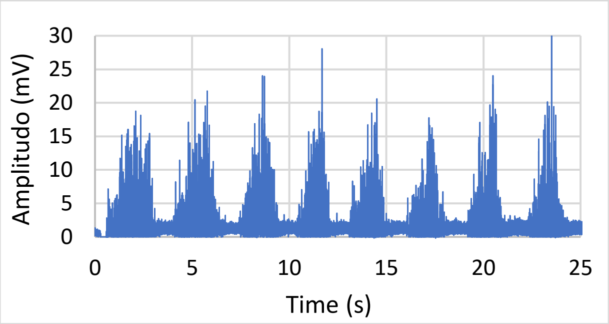

Fig. 4. EMG Raw signal output, rectified & smoothed by emg muscle sensor V3

B. Features Extraction

Compared to the raw EMG signal, the complexity of the EMG signal is reduced after the time domain feature extraction (TDFE) process. The computational results of TDFE on EMG signals show a simpler pattern. The TDFE results using RMS and MAV features shown in Figure 5 are seen to follow the EMG signal pattern as shown in Figure 4, and can follow the joint angle movement well, each pattern shows a movement pattern that coincides with the EMG signal pattern but MAV TDFE has better relevance than RMS. In addition, Figure 6 shows the variance feature (VAR) results of the TDFE pattern shown by the blue line, although the feature (VAR) follows the EMG signal pattern, the angle reading comparison results shown by the orange line have a different range, so these results cannot be used to control the upper limb exoskeleton.

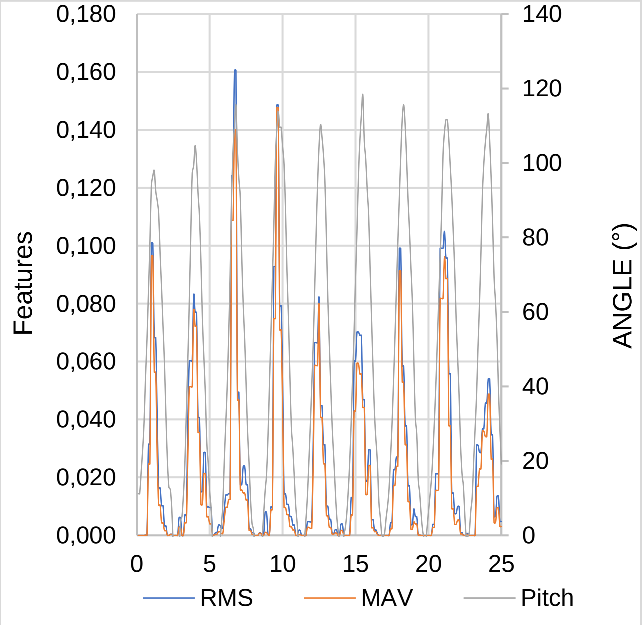

Fig. 5. Feature extraction (RMS and MAV) and angle, it appears that there is a relevance between feature extraction and angle.

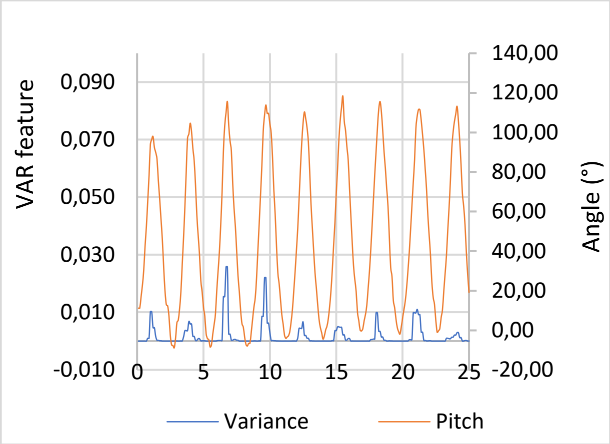

Fig. 6. Feature Variance and angle, have a different ranges

Feature importance analysis revealed MAV as the most predictive feature for joint angle estimation, outperforming RMS and VAR. This finding aligns with prior studies indicating MAV's high sensitivity to changes in muscle contraction levels, making it a reliable predictor for movement patterns.

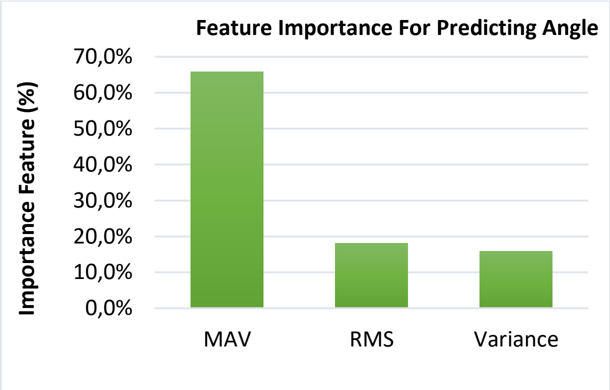

Fig. 7. Feature Importance Value, from the test results that MAV has the most important features

C. Machine Learning Accuracy

The performance of three machine learning models Linear Regression (LR), Decision Tree Regressor (DTR), and Random Forest Regressor (RFR) was evaluated using RMSE and R^2 metrics. Random Forest Regressor consistently outperformed other models, achieving the lowest RMSE (12.197) and highest R^2 (91.6%) when combined with the MAV feature[35].

- **Linear Regression**: While computationally efficient, LR struggled to model the non-linear relationships inherent in EMG signal data, resulting in higher RMSE values (e.g., 20.232 with MAV).
- **Decision Tree Regressor**: DTR provided better performance than LR but showed susceptibility to

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overfitting, particularly with single features like RMS and VAR.

- **Random Forest Regressor**: The ensemble nature of RFR allowed it to capture complex, non-linear relationships, demonstrating superior accuracy and robustness.

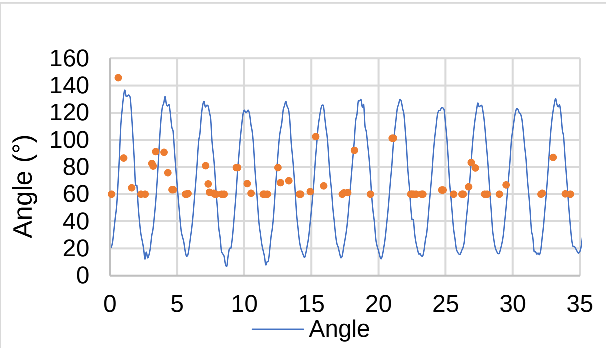

Fig. 8. Scatter Plot Mode Linear Regression & MAV

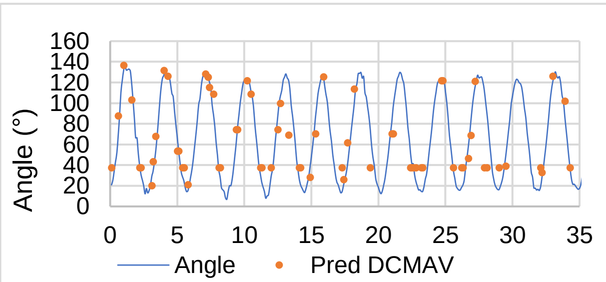

Fig. 9. Scatter Plot Model Decission-Tree Regressor & MAV

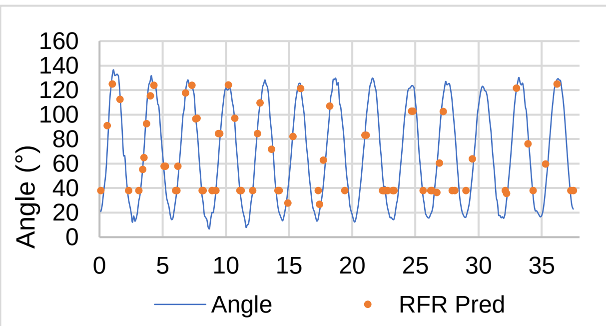

Fig. 10. Scatter Plot Mode Random Forest Regressor & MAV

Next, the process of testing three training and test machine learning models, namely Linear Regression, Decision Tree Regressor and Random Forest Regressor with seven feature combinations. The results in table 1 above show that the model with the best performance is Random Forest Regression with a combination of RMS + Variance + MAV features achieving the best overall results, with the lowest RMSE (12.197596) and a high R^2 score (91.60%). For the best Single Feature Combination for Random Forest Regression: The MAV feature provides the best performance for Decision Tree Regression, with an R^2 score of 91.62% and the lowest RMSE (12.179227) [36].

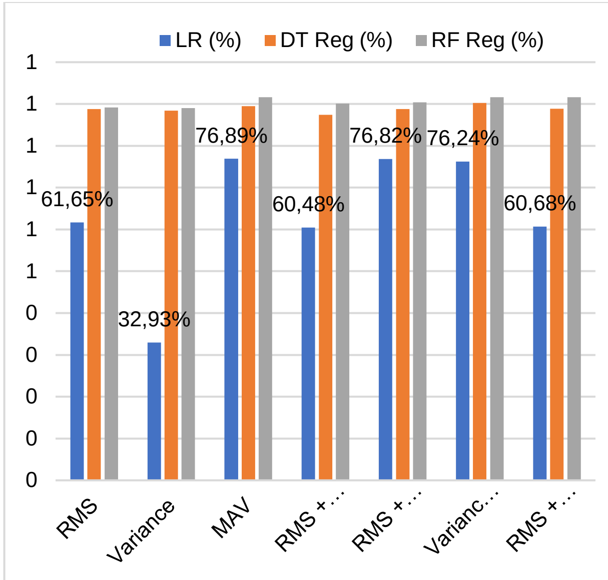

Fig. 11. Machine Learning Accuracy Chart

Table 1. Linear Regression Model Evaluation Results

Features	MSE	RMSE	R2 Score	Mean Prediction	Std Prediction
RMS	679.3197	26.0638	0.6165	72.6490	32.2664
Variance	1188.000	34.4674	0.3293	70.7304	24.6482
MAV	409.3659	20.2328	0.7689	74.0109	36.0445
RMS + Variance	700.0161	26.4578	0.6048	72.5480	31.9915
RMS + MAV	410.5209	20.2613	0.7682	74.0081	36.0361
Variance + MAV	420.8542	20.5147	0.7624	73.8852	35.8348
RMS + Variance + MAV	696.4016	26.3894	0.6068	72.6498	32.2228

Table 2. Decision Tree Regressor Model Evaluation Results

Features	MSE	RMSE	R2 Score	Mean Prediction	Std Prediction
RMS	198.4924	14.0887	0.8879	72.5318	41.6193
Variance	205.0579	14.3198	0.8842	72.5509	41.5447
MAV	186.3588	13.6513	0.8948	71.8678	40.8974
RMS + Variance	222.4014	14.9131	0.8744	73.1113	42.4533
RMS + MAV	198.4924	14.0887	0.8879	72.5318	41.6193
Variance + MAV	173.1703	13.1594	0.9022	72.0421	41.1013
RMS + Variance + MAV	197.2485	14.0445	0.8886	72.1260	41.2355

Corresponding author: Triwiyanto, triwi@poltekkesdepkes-sby.ac.id, Department of Medical Electronics Technology, Poltekkes Kemenkes Surabaya, Jl. Pucang Jajar Timur No. 10, 60282, Surabaya, Indonesia.
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Table 3. Random Forrest Regressor Model Evaluation Results

Features	MSE	RMSE	R2 Score	Mean Prediction	Std Prediction
RMS	191.3450	13.8327	0.8920	73.3320	39.1393
Variance	194.5005	13.9463	0.8902	73.2251	39.1885
MAV	148.3336	12.1792	0.9163	73.3469	39.3455
RMS + Variance	193.4931	13.9102	0.8908	73.8471	40.0148
RMS + MAV	188.3323	13.7234	0.8937	73.2901	39.2338
Variance + MAV	148.8909	12.2021	0.9159	73.2047	39.3176
RMS + Variance + MAV	148.7813	12.1976	0.9160	73.3214	39.2769

This table presents the performance of three regression models—Linear Regression, Decision Tree Regression, and Random Forest Regression—using various feature combinations. The evaluation is based on MSE, RMSE, R^2 Score, Mean Prediction, and Standard Deviation of Prediction.

MAV provided the best performance, with the lowest MSE (409.37) and RMSE (20.23), as well as the highest R^2 (0.7689), suggesting MAV as the most effective feature for linear prediction. Mean Prediction with MAV was around 74, closely matching the target variable’s true mean, indicating accurate predictions. The Standard Deviation of Prediction for MAV was 36.04, showing more variability in the predictions compared to other features, indicating that the model's predictions can vary significantly, although the mean remains close to the true value. Variance performed poorly, with the highest MSE (1188.00) and R^2 (0.3293), showing it is less suitable for linear models. MAV again outperformed other combinations, achieving the lowest MSE (186.36) and RMSE (13.65), and the highest R^2 (0.9022) when combined with Variance, indicating strong model performance. Mean Prediction for Decision Tree models was around 72-73, which was consistent with the true mean of the target variable. The Standard Deviation of Prediction ranged from 40 to 42, indicating some variability in the model’s predictions, but still with a strong correlation to the target mean. RMS + Variance showed the poorest performance with the highest MSE (222.40), reflecting less effective prediction. MAV again delivered the best results, with the lowest MSE (148.33) and RMSE (12.18), as well as the highest R^2 (0.9163), confirming its effectiveness in ensemble models. Mean Prediction for Random Forest was around 73, which is very close to the target’s actual mean, showing high accuracy. The Standard Deviation of Prediction for Random Forest was around 39, slightly lower than Decision Tree models, indicating more consistency and stability in its predictions. Variance + MAV also performed well, consistently achieving strong results across the models.

MAV consistently showed the best performance across all models, particularly in Random Forest Regression, which outperformed the other models in MSE, RMSE, R^2, Mean Prediction, and Standard Deviation of Prediction. Random Forest provided the most stable and accurate predictions, making it the optimal choice for complex tasks like EMG signal analysis in rehabilitation.

IV. DISCUSSION

In this study, we evaluated three regression models Linear Regression, Decision Tree Regression, and Random Forest Regression—on their ability to predict target variables using different feature combinations derived from electromyography (EMG) signals. We used several performance metrics including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R^2 Score, Mean Prediction, and Standard Deviation of Prediction to assess the models' accuracy and stability.

Overall, the Random Forest Regression model outperformed the other models in terms of prediction accuracy. Specifically, the MAV feature set consistently yielded the best results across all regression models, demonstrating its superior predictive power in the context of EMG signal analysis. The MSE for the MAV feature combination in Random Forest Regression was 148.33, the lowest among all the feature sets, while its R^2 score reached 0.9163, suggesting that this model could explain over 91% of the variance in the target variable. The Mean Prediction for the Random Forest model remained close to the true mean, and the Standard Deviation of Prediction was stable, indicating the model’s consistency.

The Decision Tree Regression model also performed well, particularly with the MAV + Variance combination, which resulted in a high R^2 score of 0.9022. However, the model showed greater variability in predictions (higher Standard Deviation of Prediction) compared to Random Forest. Linear Regression, on the other hand, performed the worst with the Variance feature alone, demonstrating a significant limitation in capturing non-linear relationships within the data. Although MAV achieved the highest R^2 score for the Linear Regression model, its performance still lagged behind Decision Tree and Random Forest models.

To place our results in the context of existing research, we compare them with several recent studies that applied machine learning techniques for EMG signal analysis in rehabilitation and movement prediction. Below is a table summarizing these studies along with the methods used and their corresponding accuracies [37].

Corresponding author: Triwiyanto, triwi@poltekkesdepkes-sby.ac.id, Department of Medical Electronics Technology, Poltekkes Kemenkes Surabaya, Jl. Pucang Jajar Timur No. 10, 60282, Surabaya, Indonesia.
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Table 4. Comparison to Similar Studies

Author	Method	Accuracy (R^2 / RMSE / Other Metrics)	Notes
Zhou Y et al. [29]	Decision Tree Regression	R^2 = 0.85, RMSE = 12.4	Focused on movement prediction using EMG signals.
Zhang, W. Wendong et al [13]	Random Forest Regression	R^2 = 0.88, RMSE = 11.7	Analyzed EMG signals for prosthetic control.
A. Gupta, Kumar et al. [38]	Support Vector Machines (SVM)	R^2 = 0.83, RMSE = 14.3	Used for hand gesture recognition from EMG signals.
Our Study	Random Forest Regression	R^2 = 0.9163, RMSE = 12.18	Best performance with MAV features in rehabilitation.

From the table, we can observe that our Random Forest Regression model achieved a higher R^2 score (0.9163) compared to similar studies (e.g., Zhang et al. (2020), R^2 = 0.88), demonstrating the superiority of our approach in predicting EMG-based outcomes. Our RMSE of 12.18 also compares favorably with the values reported in the literature, highlighting the effectiveness of MAV as a predictive feature in EMG signal analysis.

While the results of this study are promising, several limitations and weaknesses must be acknowledged. Feature selection is a critical step in EMG signal-based modeling, as the model's accuracy heavily depends on the quality and relevance of the features used. In this study, three specific features—RMS (Root Mean Square), Variance, and MAV (Mean Absolute Value)—were evaluated to assess their predictive capabilities. The findings showed that MAV delivered the best results for predicting movement patterns, highlighting its relevance in capturing the muscle activity patterns necessary for controlling an exoskeleton. However, it is important to note that there is significant potential in exploring other features that could further enhance the model's accuracy.

Time-domain features, as utilized in this study, are often simpler and computationally less intensive, making them ideal for embedded systems. However, frequency-domain features, such as spectral analysis or wavelet transforms, can capture additional information about the EMG signal's characteristics, especially in scenarios involving high signal variability. By employing more advanced feature extraction techniques, such as deep learning-based approaches, it is possible to automatically extract relevant features without manual processing. Future research could leverage these methods to further improve model accuracy, particularly in more complex scenarios like post-stroke patient rehabilitation.

Additionally, combining multiple features within a single model could also be explored to enhance accuracy. The combination of RMS, MAV, and Variance has shown potential, but merging energy-based features with frequency- or spatial-domain features could result in more robust and adaptive models. This is especially crucial for applications that require high precision, such as EMG-based exoskeleton control in rehabilitation settings. The ability of a model to generalize its performance to new data is a crucial aspect of its practical application, especially in real-world scenarios like rehabilitation. In this study, the models were evaluated using a specific dataset of EMG signals collected from a limited group of healthy participants. While this approach provided a controlled setting for initial testing, it may not fully capture the diversity of scenarios that could arise in rehabilitation environments. For instance, variations in EMG signal patterns are likely to occur due to differences in age, gender, injury severity, or the type of movements performed by individuals. This makes it essential to expand the dataset to include a broader and more diverse population in future studies.

Real-world rehabilitation scenarios often involve patients with reduced muscle strength, particularly those recovering from strokes or similar conditions. These patients may produce weaker EMG signals, which might not align with the data used to train the current models. Moreover, external factors, such as environmental noise or unintentional movements, could further complicate signal interpretation. Addressing these challenges requires the inclusion of datasets that reflect such real-world conditions, ensuring the models remain robust under varying circumstances.

Future research could also explore advanced methods like transfer learning to tackle the issue of limited data diversity. With transfer learning, a model trained on one dataset can be fine-tuned to adapt to new datasets, reducing the need to start training from scratch. Additionally, simulated datasets could be generated to mimic complex signal patterns, allowing researchers to expand the range of training data without having to rely solely on time-consuming physical data collection.

It is equally important to validate the models rigorously through methods such as leave-one-subject-out testing. By systematically excluding specific data points during training, researchers can ensure that the model's performance is not overly dependent on any particular subset of the data. Such validation strategies, coupled with the use of diverse and representative datasets, will enable the models to perform consistently

Corresponding author: Triwiyanto, triwi@poltekkesdepkes-sby.ac.id, Department of Medical Electronics Technology, Poltekkes Kemenkes Surabaya, Jl. Pucang Jajar Timur No. 10, 60282, Surabaya, Indonesia.
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well across various rehabilitation scenarios. Ultimately, these efforts will help bridge the gap between experimental results and real-world applications, making the technology more accessible and effective for patients. Although the random forest regression performed excellently in this study, it has an intrinsic risk of overfitting in this model. This problem gets more serious with small datasets, where the model inadvertently learns the pattern specific to the training data rather than generalizable insights. Further, the complexity of Random Forest, due to its ensemble nature and the use of a large number of decision trees, can exacerbate overfitting, especially if hyperparameters such as the depth of trees or the number of trees are not carefully controlled.

The most serious challenge with overfitting, in general, comes with real-world applications when one wants a model to generalize across different patients and conditions, which is typically expected in rehabilitation applications. For example, the EMG signals recorded from different individuals or even the same individual under different conditions-for instance, level of fatigue or movement speeds-can vary substantially. This might result in an overfitted model performing well on that dataset but having little generalization to changes in data that naturally occur, limiting practical usability.

This risk may be reduced by the use of cross-validation techniques at the stage of model development in the future. Techniques such as k-fold cross-validation or one-subject-left-out testing can ensure that the model is tested on previously unseen data during its training; this would allow for a realistic estimation of generalization capability. This can also be achieved by incorporating some regularization techniques into the model to constrain the model complexity: capping the maximal depth of the trees or selecting a subset of most informative input features could become helpful in making the model learn only the crucial patterns of the data without amplification of noise or less important details.

Another effective approach is to increase the size of the training dataset to include more diversified ranges of EMG signals from subjects with different characteristics. In this way, the model will be exposed to a wider spectrum of patterns that will enhance its robustness. By doing so, future versions of Random Forest-based models can achieve high accuracy with adaptability in real-world settings. Although Random Forest Regression showed great accuracy, one of its downsides is the high computational complexity involved, especially compared to simpler models such as Linear Regression or Decision Trees. In this work, this computational complexity is of high concern since the system is being targeted for embedded devices such as Raspberry Pi. Embedded devices are normally low in computing power due to the use of low-power processors and limited memory; thus, the need to optimize models for efficiency is important.

From the model side, some model optimization techniques can be applied to reduce the computational overhead. The number of trees in Random Forest can be reduced, or the maximum depth of each tree can be restricted. The impact on accuracy would be minor, while this could greatly enhance computational efficiency. Besides, some simplifications of the Random Forest algorithm, such as Extremely Randomized Trees, reduce computational requirements at little cost in performance.

Another direction involves choice of lighter models while still providing competitive results. The Linear Regression or Decision Trees model is far less computationally intensive and can be efficiently realized on embedded devices. Besides, quantization reduces model parameters into much lighter formats that will further reduce memory requirement and improve execution speed accordingly.

Future research could be done in a more efficient way in hardware, too, such as FPGAs or machine-learning microcontrollers, which are actually designed to efficiently process machine-learning algorithms with high speed and lower power consumption. In this way, complicated models such as Random Forest Regression would still be useable in a real-time running application without impairing computational efficiency. The findings of the study contribute to the development of rehabilitation, particularly in developing prosthetic control devices and tools using EMG. In fact, among the presented algorithms, Random Forest Regression performed with a high degree of accuracy and stability in its predictive capability; thus, it can be a potential candidate for applications needing precise and adaptive control of the rehabilitation movements.

This model, within the perspective of prosthetic control, enables higher accuracy in interpreting the EMG signals so that prosthetic devices can more intuitively be controlled by the users. For example, if recorded EMG signals allow the prediction of movement, prosthetic arms or hands can perform complex movements in ways that correspond to the user's intent. It's not only the functionality of the device that has improved but also the quality of life in a natural and responsive manner for users.

Another implication lies in the development of rehabilitation robotics: with features extracted by MAV and Random Forest Regression, the robotic systems can themselves give exact and adaptive feedback to patients in the sessions of therapy. The patients can thus work their way up with regards to motor control, which also suits each of their own needs. This may also

Corresponding author: Triwiyanto, triwi@poltekkesdepkes-sby.ac.id, Department of Medical Electronics Technology, Poltekkes Kemenkes Surabaya, Jl. Pucang Jajar Timur No. 10, 60282, Surabaya, Indonesia.
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support effective physical training at home with no direct supervision required from therapists.

Another application that can be exploited is the real-time monitoring of muscle activity during certain therapies, whereby the system applies the high accuracy of EMG signal prediction. It is used in the monitoring of the patient's progress in real time and provides more personalized therapy recommendations, accelerating his rehabilitation process. It also helps therapists make better decisions based on objective data. Prosthetic Control: The high R^2 score and low RMSE suggest that the model could be employed in controlling prosthetic devices, improving the accuracy of movements by better interpreting the EMG signals that reflect muscle activity. This can lead to more intuitive control of prosthetics, improving user satisfaction and functionality.

The rehabilitation robotics development might bring a sea change in the conventional idea of restoring motor functionality among patients after an injury or sickness. This research study outcome confirms that the utilization of Random Forest Regression for desired movement prediction using MAV features would prove to be a promising solution toward making both the robotic systems more precise and adaptable in nature during the phase of physical therapy. By correctly predicting user intent, such systems can provide specialized support so that the level of support is tailored to the individual patient's needs. As a case in point, in the settings of therapies, robotic exoskeletons with such algorithms would be set dynamically to accommodate changes in the patients' performance variability, including variations in strength or coordination. Such versatility not only promotes the exercising of natural and effective movements in a patient but also lessens the potential for strained and injured muscles as a result of discord between what a patient intends to do and how the robot is performing. By its ability to respond in real-time, the robotic system can give indications to direct a patient during their exercises in better form than ever thought, which promotes patients' commitment to and encouragement through therapy. In their future development, rehabilitation robotics can be integrated with more sensors, like force or motion detectors, in order to increase system responsiveness to user actions. This can be coupled with Random Forest and other machine learning models in order to create a truly multimodal approach to therapies, both holistic and responsive, leading to better patient outcomes in less time. These changes have the potential even to make rehabilitation at home more accessible by letting the patients further their therapy on their own while still continuing to receive quality support. The ability to predict EMG signals with high accuracy opens the door to real-time monitoring of muscle activity, which would be helpful for healthcare providers in tracking the progress of patients in rehabilitation programs. This could also facilitate personalized therapy adjustments, enhancing the efficiency of rehabilitation.

Random Forest Regression provided the best results for predicting target variables based on EMG features, with the MAV feature combination offering the highest accuracy. This study contributes to the growing body of literature on machine learning applications in rehabilitation and prosthetics, offering insights into how EMG signals can be effectively used for movement prediction and control. Despite certain limitations, such as model generalization and computational complexity, the findings suggest promising avenues for future research, particularly in real-time applications where accurate, stable predictions are essential [39].

V. CONCLUSION

This study developed a machine learning-based upper limb exoskeleton system to improve stroke rehabilitation by predicting joint movements using EMG signals. Random Forest Regression proved to be the most accurate model, with an R^2 of 91.6% and RMSE of 12.197, with MAV being the most significant feature. The integration of Muscle Sensor V3, Raspberry Pi Zero 2W, and MPU6050 successfully captured muscle and movement data [40], [41].

The results demonstrate that Random Forest Regression with the MAV feature combination provides the best performance, with the lowest MSE (148.33) and the highest R^2 (0.9163), making it highly suitable for EMG-based rehabilitation applications. However, the system was only tested on healthy subjects and used a single EMG channel, limiting its applicability. Future research should include multiple EMG channels and trials with stroke patients to improve adaptability and accuracy, making it a more valuable tool for rehabilitation. This study has significant implications for the development of more precise EMG-based rehabilitation technologies, with potential applications in assistive devices and rehabilitation robotics that can be tailored to individual stroke patients' needs.

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Corresponding author: Triwiyanto, triwi@poltekkesdepkes-sby.ac.id, Department of Medical Electronics Technology, Poltekkes Kemenkes Surabaya, Jl. Pucang Jajar Timur No. 10, 60282, Surabaya, Indonesia.
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Corresponding author: Triwiyanto, triwi@poltekkesdepkes-sby.ac.id, Department of Medical Electronics Technology, Poltekkes Kemenkes Surabaya, Jl. Pucang Jajar Timur No. 10, 60282, Surabaya, Indonesia.
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Corresponding author: Triwiyanto, triwi@poltekkesdepkes-sby.ac.id, Department of Medical Electronics Technology, Poltekkes Kemenkes Surabaya, Jl. Pucang Jajar Timur No. 10, 60282, Surabaya, Indonesia.
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