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Comprehensive Analysis of an EMG Based Human-Robot Interface Using Various Machine Learning Techniques

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Electromyography (EMG) signals hold critical significance in biomedical research, capturing muscle electrical activity during rest and contraction in the upper limb. Their versatility in applications, particularly in human-assisting robotic tools, drives ongoing exploration and research. This paper presents an original study focusing on leveraging machine learning techniques to classify EMG datasets and efficiently control a robotic arm based on predicted gestures. Data acquisition involves strategically placing an EMG muscle sensor on the forearm to ensure precise measurement of signals associated with hand gestures and movements. Diverse classifiers including random forest, support vector machine (SVM), K-nearest neighbors (KNN), Gaussian naïve Bayes, gated recurrent unit (GRU), long short-term memory (LSTM), artificial neural network (ANN), recurrent neural network (RNN), convolutional neural network (CNN), and vision transformer (ViT) are employed. Performance results are meticulously analyzed and presented in tabular format, showcasing the ViT classifier as the most successful, achieving an impressive 97.7% accuracy in robotic arm control. Notably, ANN, RNN, and CNN also exhibit high accuracy exceeding 90%. Furthermore, this work is comprehensively compared with existing literature, laying the groundwork for future advancements in human-robot interaction and cutting-edge assistive technologies that markedly enhance the quality of life for individuals with motor impairments or disabilities. The findings carry significant implications for designing and implementing intuitive, responsive robotic systems based on EMG signals.

Keywords: electromyography (EMG), EMG muscle sensor, human-robot interface, machine learning algorithms, robotic arm

INTRODUCTION

Robotics represents a realm of sophisticated and intelligent systems designed to assist and support humans. Presently, the focus of robotic system design revolves around creating products that mimic human behavior, enabling seamless collaboration and integration of human capabilities in performing physical tasks. Human-robot interaction (HRI) plays a pivotal role in this framework, aiming to establish an intuitive interface between humans and robots achieved through the utilization of electromyography (EMG) signals derived from muscles to control manipulators or robotic arms. EMG sensors capture the electrical activity produced by muscle movements in humans. The primary objective of a muscle sensor-driven system is to control external devices through intuitive gestures and commands. Surface electrodes yield accurate EMG signals that convey essential information about human hand motion. Additionally, the modulation of grasp strength is crucial in accomplishing various grasping tasks. Moreover, in the literature, researchers explore the application of low-rank

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approximate nonnegative matrix factorization algorithms in the domains of text mining and spectral data analysis. The focus lies on leveraging these algorithms for feature extraction and identification purposes. Moreover, the findings of Meng *et al.* (2016) highlight the potential of non-invasive brain-computer interface technology for enabling individuals to operate prosthetic limbs with great success.

Thobbi and Sheng (2010) introduced an innovative platform designed for the implementation and assessment of a learning-by-imitation framework. The primary objective is to empower humanoid robots to acquire hand gestures from human users through a systematic learning process. Benalcázar *et al.* (2017) introduced a model that utilizes surface EMG data acquired from a Myo armband, a commercially available sensor placed on the forearm. Also, this model relies on the Λ-nearest neighbor and dynamic time-warping algorithms. Tepe *et al.* (2020) classified the data acquired from the Myo armband for human arm control. Various strategies of gesture control and recognition were discussed by Benatti *et al.* (2017), Benalcázar *et al.* (2020), Colli Alfaro *et al.* (2019), and Colli Alfaro and Trejos (2022). Support vector machine (SVM) based gesture recognition was followed by Chang and Lin (2011) and Wu *et al.* (2013).

The findings from the literature indicated a strong correlation between kinematic and EMG variability. The data from both EMG measurements and trajectory analysis revealed that practice led to improved central nervous system control over various aspects of movement. The results of Burdet *et al.* (2014) show that the taken simulations support the notion that their controller closely resembles how humans adapt and control their movements in similar circumstances. Ficuciello *et al.* (2011) and Scheme and Englehart (2011) provide detailed descriptions and analyses of human motor control and various aspects related to hand control. They delve into the intricacies of how the human brain and nervous system manage and coordinate movements, particularly in the context of hand gestures and actions.

Machine learning plays a crucial role in machine learning and can be utilized in the human-robot interface to enable robots to understand and interpret human gestures, commands, and behavior. By training machine learning models on large datasets of human interactions, robots can learn to recognize patterns and respond appropriately to human inputs. Quantum machine learning can enhance sensor fusion and perception in HRI scenarios (Liu *et al.* 2022; Zidan *et al.* 2021, 2022). Quantum algorithms (Zidan *et al.* 2023) can process and integrate data from multiple sensors, enabling robots to have a more comprehensive understanding of their environment and human presence, leading to safer and more efficient interactions (Zidan 2020; Panda *et al.* 2022). Gesture classification based on various machine learning algorithms such as CNN, CRNN (convolutional recurrent neural network), LSTM (long short-term memory), ANN, KNN, and ViT were discussed by Samadani (2018), Zhang *et al.* (2019), Jo and Oh (2020), Li and Langari (2022), Zhang and Kan (2022), and Kim *et al.* (2023).

Machine learning algorithms are employed for hand posture classification and pattern identification. Notably, Garate *et al.* (2018) measured human finger stiffness using force torque sensors, directly relating it to the posture of the robotic arm. Similarly, Meattini *et al.* (2018) utilized differential EMG sensor data, trained with the SVM algorithm, achieving over 90% accuracy in correlating the algorithmic output with corresponding hand postures in the robotic manipulator.

Previous studies have explored forearm muscle EMG signals for controlling robotic arms, employing various approaches involving two EMG channels placed on antagonistic muscle pairs. These methods often require the user to switch between functions through the coactivation of muscles, after which the arm actuates based on the EMG channel's threshold (Oskouei *et al.* 2013). To manage different configurations of the human hand during grasping tasks, researchers have proposed ideas based on machine learning techniques to interpret EMG signals and predict corresponding hand postures (Allard *et al.* 2016).

Our approach involves using an EMG muscle sensor, which remains unaffected by changes in light, hand alignment, and position. Moreover, we identified hand postures using multiclass SVM, KNN, and naïve Bayes classifiers for five gesture categories. Pre-processing was initially performed using a low pass filter to eliminate noise and smoothen the signals. Subsequently, we conducted machine learning-based classification and compared the performance of the algorithms. The rest of the paper is organized as follows: system design, robotic arm interfacing, experimental results, and conclusion.

SYSTEM DESIGN

Figure 1 illustrates the complete workflow of the implemented system. In the first step, the EMG muscle sensor dataset is acquired, as described in the following section. The data collected includes EMG signals from the forearm muscles. Subsequently, the obtained dataset is subjected to classification using diverse machine-learning techniques, as further explained in the upcoming section. This process involves analyzing and processing the EMG signals to identify specific hand gestures and patterns. Inverse kinematics in robotics involves determining the

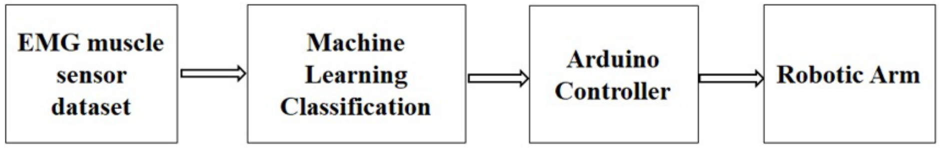

Table 1. Hand gestures and their corresponding label.

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Class label	Hand gestures
0	Unmarked data
1	Hand at rest
2	Hand clenched in fist
3	Wrist flexion
4	Wrist extensions
5	Radial deviations
6	Ulnar deviations

joint angles and positions necessary to achieve a desired end-effector position and orientation. Machine learning models for solving inverse kinematics in robotic arms typically involve training a neural network. The network is fed with end-effector positions and orientations as input and trained to predict the corresponding joint angles. The training data comprises pairs of desired end-effector positions and the associated joint angles achieved by the robot arm. The neural network learns the complex mapping between the end-effector space and joint space during training. Once trained, the model can take a desired end-effector position and orientation as input, providing the necessary joint angles for the robotic arm to achieve the desired pose. Integration of this model into the robotic arm's control system enables efficient and accurate movement based on desired end-effector positions.

The classification results are then utilized in conjunction with Arduino, an open-source hardware and software platform, to control the robotic arm. The Arduino platform acts as an interface between the machine learning-based classification outcomes and the robotic arm, facilitating seamless communication and control.

DATASET DESCRIPTION

The EMG signal dataset used in this study was obtained from the University of California Irvine's machine learning library website (UCI n/d). To collect the data, a personal computer with a myoelectric bracelet placed on the user's forearm was used, along with Bluetooth for logging purposes. The forearm was equipped with eight myographic sensors evenly distributed. These sensors recorded the signals, which were then transmitted to the computer through a Bluetooth interface. The dataset comprises raw EMG data from 36 subjects, each performing a series of static hand movements. Each subject executed two series of gestures, with each series containing a sequence of six The dataset files are structured with ten columns. The first column represents time in ms, whereas the 10th column indicates the label corresponding to various hand gestures. The remaining columns (2–9) represent the eight EMG channels of the myoelectric bracelet. Table 1 provides details of the different hand postures considered in the study along with their corresponding labels. Imbalanced data refers to a situation where the classes in a dataset are significantly skewed, with one or a few classes having substantially more instances than others. This disparity can distort the learning process of machine learning models, causing them to favor the majority class and neglect the minority class. Consequently, the model's predictive performance becomes biased, and evaluation metrics like accuracy may be misleading, giving a false sense of success. Addressing this imbalance is crucial to ensure that the model learns from all classes effectively, especially when the minority class holds significant importance such as in rare events or critical outcomes. Various strategies like resampling techniques and algorithm-level modifications are employed to mitigate the effects of this imbalance and enable the model to make informed and balanced predictions.

MACHINE LEARNING BASED CLASSIFICATION

In this study, raw data such as EMG signals were collected using sensors and stored in a designated repository. Data preprocessing involved cleaning, normalization, feature extraction, and encoding. The model selection involved training these models on preprocessed data with appropriate validation and test sets to ensure accuracy and robustness. Relevant hyperparameters for each model were identified such as learning rate, batch size, activation functions, number of layers, *etc.* Hyperparameters were fine-tuned to optimize model performance. Techniques like grid search and random search were employed to search through the hyperparameter space effectively and the best set of hyperparameters, resulting in the highest model performance, were chosen for the final model deployment. Model performance was evaluated using appropriate metrics such as accuracy, precision, recall, and F1-score and then validated to ensure it met the desired criteria. Cross-validation and stratified sampling were used to prevent bias.

In the field of machine learning, several types of classification algorithms are available, such as SVM, KNN, Perceptron's, naïve Bayes, decision trees, and neural networks. These classifiers have the capability of performing binary classification, as well as single-class and multi-class grouping. For the current research, 10 specific algorithms were selectively chosen due to their proven accuracy and superiority in the existing literature. The chosen algorithms are random forest, SVM, KNN, Gaussian naïve Bayes, GRU, LSTM, ANN, RNN, CNN, and ViT. By leveraging these classifiers, the implemented system can accurately interpret and classify the EMG data, enabling intuitive control of the robotic arm based on the recognized hand gestures and movements.

ROBOTIC ARM INTERFACING

Figure 2 illustrates the robotic arm equipped with a two-fingered gripper, which serves as the basis for evaluating the entire process. This robotic arm is equipped with a set of three joints, all of which are responsive to controller signals for precise manipulation. The Arduino controller facilitates the interface between the system components. Specifically, the Arduino Nano controller is responsible for governing the movements of the robotic arm. These movements are determined by analyzing the predicted hand gestures obtained through the classification process discussed in the previous section. Given the diverse nature

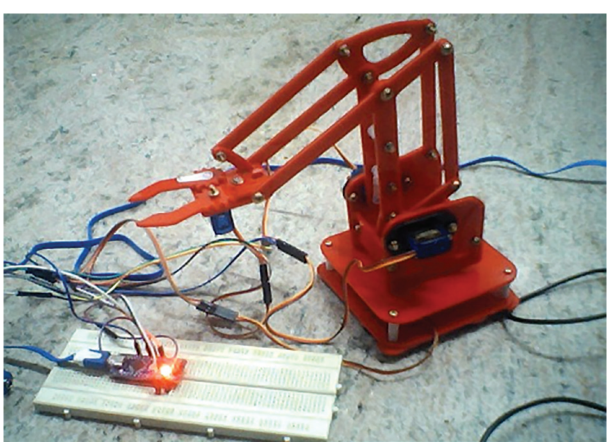


Figure 2. Robotic arm.

of hand gestures, the data from the EMG sensor varies accordingly. Consequently, for each specific feature, a corresponding pulse width modulated (PWM) signal is generated using the Arduino controller. These PWM signals are then transmitted to the four servo motors controlling the robotic arm – namely, the bottom, right, left, and claw servos. As the Arduino produces various signals based on the EMG sensor values, the robotic hand adapts its position accordingly. For this setup, an AD8226-based EMG sensor is used, as shown in Figure 3.

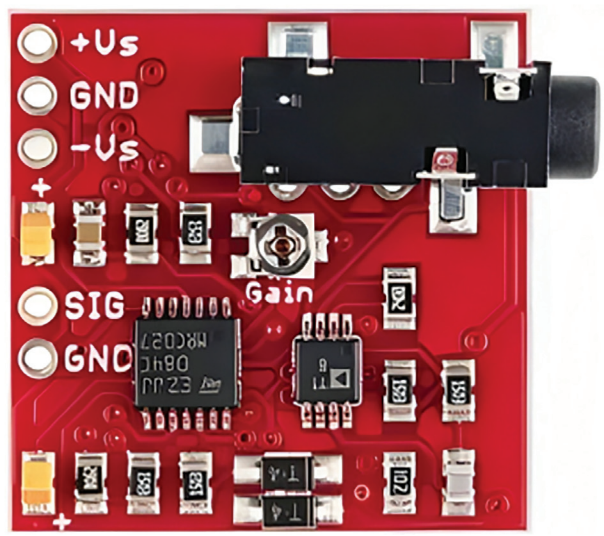


Figure 3. AD8226-based EMG sensor.

EXPERIMENTAL RESULTS AND DISCUSSION

Firstly, the training phase involves using various machine learning algorithms to train the system on the provided dataset. The objective is to enable the system to recognize and classify different hand gestures accurately. The trained algorithms learn to associate specific hand gestures with corresponding movements or orientations of the robotic arm. After the training phase, the system proceeds to the calibration stage. During calibration, the robotic arm's orientation is configured based on the corresponding data obtained from the training process. In Table 2, the different hand gestures are listed along with their respective configurations or orientations of the robotic arm. Essentially, the calibration step ensures that the robotic arm is programmed to respond appropriately to each recognized hand gesture, allowing it to move and adjust its position accordingly. By associating the trained gestures with predefined configurations in Table 2, the system achieves accurate and synchronized movements between the user's hand gestures and the robotic arm's orientation.

Table 2. Hand gesture and its corresponding robotic arm orientation.

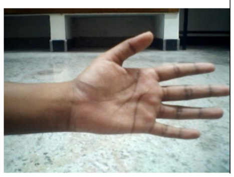
Hand gesture	Robotic arm movement
Hand at rest 	
Hand clenched in fist 	
Wrist flexion 	
Wrist extension 	
Radial deviation 	
Ulnar deviation 	

Table 3 provides performance metrics of various algorithms used in a certain task. Accuracy is the ratio of correctly predicted instances to the total number of instances in the dataset and is calculated as follows:

$$\text{Accuracy} = \frac{\textit{Number of correct predictions}}{\textit{Total number of predictions}} \; x\, 100\% \qquad (1)$$

Higher accuracy generally indicates better performance. Efficiency refers to the computational requirements of the algorithm, indicating how quickly it can process data and make predictions. High efficiency means the algorithm is computationally less demanding, whereas low efficiency suggests that it requires more computational resources. The F1 score is the harmonic mean of precision and recall, providing a balance between the two metrics. It is particularly useful when there is an uneven class distribution.

$$F1 \text{ score} = \frac{2 \times Precision \times Recall}{Precision + Recall} \qquad (2)$$

$$Precision = \frac{True\ positives}{True\ positives + False\ positives} \qquad (3)$$

$$Recall = \frac{True\ positives}{True\ positives + False\ negatives} \qquad (4)$$

These metrics were calculated using the model's predictions on a holdout or validation dataset, ensuring an unbiased evaluation. The process involved comparing the model's predictions with the actual ground truth labels, determining true positives, true negatives, false positives, and false negatives. These values were then used to compute accuracy, AUC-ROC, and F1 score. The AUC-ROC measures the area under the curve of the receiver operating characteristic. It quantifies the model's ability to distinguish between the positive and negative classes. A higher AUC-ROC indicates better classification performance.

In Table 3, the performance of various classifiers on the robotic arm interface, considering metrics such as accuracy, efficiency, precision, recall, F1 score, and AUC-ROC are provided. Among the classifiers, the ViT demonstrated exceptional performance, achieving an accuracy of 97.70% and high scores across all metrics, including a notable AUC-ROC of 0.97. The RNN also performed impressively with a balanced precision, recall, and F1 score of 0.94 and an AUC-ROC of 0.97. Conversely, Gaussian naïve Bayes displayed lower scores across all metrics, underscoring its limitations for this task, particularly evident in its AUC-ROC of 0.53. Generally, models with higher efficiency levels tend to perform

Table 3. Algorithms considered and their performance metrics.

Chosen classifier	Accuracy	Efficiency	Precision	Recall	F1 score	AUC-ROC
Random forest	74.30%	High	0.82	0.93	0.88	0.83
Support vector machine (SVM)	75.60%	High	0.87	0.87	0.87	0.75
K-nearest neighbors (KNN)	86.40%	Low-medium	0.89	0.94	0.91	0.64
Gaussian naïve Bayes	70.40%	Low	0.76	0.87	0.81	0.53
Gated recurrent unit (GRU)	86.33%	Medium	0.88	0.88	0.88	0.61
Long short-term memory (LSTM)	86.66%	Medium	0.89	0.94	0.91	0.64
Artificial neural network (ANN)	91.30%	Medium	0.94	0.94	0.94	0.72
Recurrent neural network (RNN)	90.30%	Medium	0.89	0.94	0.92	0.97
Convolutional neural network (CNN)	94.60%	Medium-high	0.94	0.94	0.94	0.87
Vision transformer (ViT)	97.70%	Medium-high	0.95	0.95	0.95	0.97

better, indicating the importance of efficient classification in achieving superior accuracy and overall model effectiveness. These findings shed light on the strengths and weaknesses of different classifiers, providing valuable insights for selecting the most appropriate model for similar tasks.

Table 4 presents a comprehensive comparison between our research findings and those from prior studies, focusing on various aspects such as the type of classifiers, gestures count, and performance evaluation. It is worth noting that all these studies utilized EMG signals as input. Notably, our achieved performance surpassed all the previous studies such as those of Allard *et al.* (2016), Jo and Oh (2020), Benalcázar *et al.* (2017, 2020), (Samadani 2018), Tepe *et al.* (2020), Colli Alfaro and Trejos (2022), Li and Langari (2022), Colli Alfaro *et al.* (2019), (Zhang and Kan 2022), and Kim *et al.* (2023) except (Zhang *et al.* 2019).

Comparatively, previous works incorporated various deep learning models and EMG data for hand gesture classification, testing the generalizability of their models by evaluating the accuracy of data collected from separate subjects. In these studies, the reported test accuracies were either lower or similar to the accuracies achieved in our research.

Table 4. Comparison of the proposed work with the previous studies.

Various methods	Classifier	Gesture count	Accuracy
Allard *et al.* (2016)	CNN	7	93.14%
Jo and Oh (2020)	CRNN	6	92.5%
Benalcázar *et al.* (2017)	K-NN	6	86.0%
Benalcázar *et al.* (2020)	FNN	6	96.87%
Zhang *et al.* (2019)	ANN	6	98.7%
Samadani (2018)	RNN	17	86.7%
Tepe *et al.* (2020)	SKNN	6	95.83%
Colli Alfaro and Trejos (2022)	Adaptive LS-SVM	7	92.9%
Li and Langari (2022)	CRNN	5	84.2%
Colli Alfaro *et al.* (2019)	MLP	10	78.94%
Zhang and Kan (2022)	ViT	23	97%
Kim *et al.* (2023)	CRNN	10	96.04%
Proposed work	ViT	6	97.70%

CONCLUSION AND FUTURE WORK

The research presents an original study focusing on the use of EMG signals and machine learning to control a robotic arm. This has applications in robotic tools designed to assist humans in various tasks. The findings suggest that the research can lead to the development of cutting-edge assistive technologies. These technologies could significantly improve the quality of life for individuals with motor impairments or disabilities by enabling intuitive control of robotic systems using EMG signals. In this study, we successfully developed a gesture recognition system for controlling a robotic arm using various machine learning algorithms. The training phase involved training the algorithms on a provided dataset to accurately recognize and classify different hand gestures. The calibrated robotic arm demonstrated synchronized movements based on the recognized gestures, allowing it to respond appropriately to user commands. The achieved accuracy and efficiency metrics demonstrated the effectiveness of the system, with the ViT standing out as the top performer, achieving an accuracy of 97.70%. The ANN and CNN also performed well with high accuracies of 91.30 and 94.60%, respectively. The choice of algorithm would depend on specific requirements, computational resources, and the desired balance between accuracy and efficiency.

Additionally, expanding the dataset and involving a more diverse group of participants could lead to a more robust and universally applicable gesture recognition system. Integration of more sensors or input modalities such as IMU data could potentially improve the system's performance and enable more complex gestures. Furthermore, investigating real-time edge AI implementations to reduce latency and improve responsiveness would be beneficial for practical applications. Overall, continued research and development in this area will contribute to the advancement of gesture recognition systems for various robotic control and human-computer interaction applications.

CONFLICT OF INTEREST

All authors declare that they have no conflicts of interest.

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