International Journal of Research in Engineering, Science and Management
Volume 8, Issue 6, June 2025
https://www.ijresm.com | ISSN (Online): 2581-5792

EMG-Based Hand Gesture Recognition: Comparative Evaluation of Machine Learning Models

Manasvi Bhargava[1], Aadyoth Sreeram[2*]
[1,2]*Student, Department of Electronics and Communications Engineering, S.R.M. Institute of Science and Technology, Chennai, India*

***Abstract*: Hand gesture recognition is becoming increasingly crucial for enhancing interactions in a variety of fields, such as human-computer interfaces, rehabilitation, and prosthetics. By using Electromyography sensors to track forearm muscle activity during hand gestures, this study tackles the need for precise gesture recognition. The main objective is to use a variety of machine learning algorithms to analyze these EMG signals and categorize various hand gestures. The study intends to efficiently classify gestures based on the recorded muscle activity by utilizing deep learning techniques in conjunction with conventional algorithms like Random Forest and k-Nearest Neighbors. This research contributes to the development of sophisticated human-computer interaction systems, more efficient rehabilitation tools, and advanced prosthetic devices by increasing the accuracy of gesture classification. The goal of this research is to progress the field of gesture recognition by advocating for safer and easier-to-use technologies that enhance the user experience across a range of applications.**

***Keywords*: EMG, Machine Learning, Prosthetics, Hand Gesture, Wearable Sensors, Myoelectric Control.**

1. Introduction

Hand gestures refer to the various movements and positions of the hand and fingers that convey specific actions, commands, or expressions. These gestures can range from simple motions, such as a fist or an open hand, to more complex movements like typing or playing an instrument. Electromyography (EMG) signals, which are electrical signals generated by muscle activity when muscles contract, provide a powerful method for capturing and interpreting these movements.

EMG signals are typically detected using surface electrodes placed on the skin or, in some cases, intramuscular electrodes inserted directly into the muscle. For hand gestures, EMG signals are usually recorded from the forearm muscles, which control the movement of the hand and fingers. The link between hand gestures and EMG signals is fundamental to gesture recognition systems, which play a pivotal role in applications such as prosthetics, rehabilitation, and human-computer interaction (HCI). EMG signals provide a robust, non-invasive way to detect muscle activity and interpret hand gestures. This relationship enables precise and intuitive control in various assistive technologies. As demand grows for more seamless and natural interactions with technology, EMG-based gesture recognition has become a significant area of research. This approach offers promising solutions for enhancing the functionality of prosthetic devices, improving rehabilitation outcomes, and creating more immersive and responsive HCI systems.

Different muscles in the forearm control specific parts of the hand and fingers, and each hand gesture activates a unique set of muscles. These contractions create distinct patterns in the EMG signals, which can be measured and analysed to identify the corresponding gesture. The ability to accurately classify these gestures from EMG signals is critical for gesture recognition systems. Machine learning algorithms are commonly employed to analyse and classify the EMG signals, offering a means of refining the accuracy of gesture recognition. In this study, we explore the use of machine learning techniques to classify EMG signals, assess the accuracy of the recognition system, and discuss the potential of EMG-based gesture recognition in advancing prosthetics, rehabilitation, and interactive technologies.

A. Equations

$$Precision = \frac{True\ Position}{True\ Position + False\ Positives} \quad (1)$$

$$Recall = \frac{True\ Position}{True\ Position + False\ Negatives} \quad (2)$$

$$F1\ SCORE = 2 * \frac{P * R}{P + R} \quad (3)$$

i. Mean Squared Error (MSE) (used in regression tasks):

$$MSE = \frac{1}{n} * \sum_{i=1}^{n} (y_i - \widehat{yi}) \quad (4)$$

ii. Cross-Entropy Loss (used in classification tasks): For binary classification:

$$-\frac{1}{n} * \sum_{i=1}^{n} [\ yi\ \log(y_i) + (1 - y_i) \log(1 - y_i) \quad (5)$$

*Corresponding author: as2235@srmist.edu.in

iii. Categorical Cross-Entropy Loss

$$\sum_{i=1}^{n}\sum_{c=1}^{k} y_{i,c} log(\hat{y}_{i,c}) \quad (6)$$

k is the number of classes

2. Literature Review

Recent studies have explored advanced electromyography (EMG)-based hand gesture recognition to enhance human-computer interaction, prosthetic control, and rehabilitation systems.[1] demonstrated the feasibility of controlling an upper limb exoskeleton using a single-lead EMG and embedded machine learning on Raspberry Pi, thereby reducing hardware complexity.[2] compared bagging and boosting ensemble classifiers and found that AdaBoost with Random Forest achieved superior diagnostic accuracy (99.08%) for neuromuscular disorders. [3] improved inter-session gesture recognition via deep domain adaptation using high-density surface EMG (HD-sEMG), validated across three benchmark datasets. [4] developed a wearable HD-EMG sleeve that classified 37 gestures and predicted joint angles with up to 97.3% accuracy, supporting real-time applications. Similarly,[5] proposed a Compact Transformer-based framework (CT-HGR), achieving nearly 92% accuracy in recognizing 65 isometric gestures, outperforming CNNs and SVMs.[6] provided a systematic review of ML and DL-based myoelectric control systems using EMG and EEG, highlighting successes and real-time implementation challenges.

[7] confirmed the robustness of CNNs trained on raw multi-day EMG signals, outperforming LDA and autoencoders.[8] benchmarked various ML and DL classifiers for hand gesture recognition in trans-radial amputees and analysed the role of time-domain features.[9] focused on statistical feature extraction from forearm EMG and showed that SVM achieved the highest accuracy (73.1%) in classifying open/closed hand positions. [10] combined traditional ML and DL on public and custom EMG datasets, achieving 75% real-time accuracy in predicting fine motor gestures for prosthetic arms.[11] conducted an extensive comparison of classifiers including Random Forest, SVC, and CNN, with CNN yielding the highest performance on sign language datasets.[12] proposed a CNN+LSTM fusion model that achieved 99% and 97% accuracy across two EMG datasets while optimizing inference speed.[13] extracted key time-domain EMG features and reported 99–100% accuracy with a Decision Tree classifier in pre- intention/intention detection.[14] further explored transformer-based architectures with motor unit spike train fusion, pushing recognition boundaries in HD-EMG decoding.[15] also emphasized the importance of decoder pretraining for minimizing latency in EMG-driven control systems.[16] proposed a machine learning approach for classifying hand poses using phasic and tonic EMG signals during bimanual activities in virtual reality environments.

3. Proposed Work

A. Data Collection

The dataset utilized in this study was sourced from Kaggle and was recorded using a MYO Thalamic bracelet, a wearable device designed to capture electromyographic (EMG) signals from the user's forearm. The bracelet, equipped with eight sensors evenly spaced around the forearm, was used to continuously monitor and acquire myographic signals generated by muscle activity. These signals were wirelessly transmitted to a PC via Bluetooth for processing and analysis. Data was collected from a total of 36 subjects, each performing a set of static hand gestures. Each subject completed two series of gestures, with each series consisting of six or seven distinct hand gestures. During the data recording, each gesture was performed and held for 3 seconds, followed by a 3-second rest period between gestures to allow for signal stabilization and to minimize noise. This setup enabled the collection of high-quality, raw EMG data, capturing detailed muscle activity across a range of hand movements. The dataset provided a rich source of information for developing and evaluating gesture recognition systems using machine learning techniques.

B. Data Preprocessing

The raw EMG signals obtained from the MYO Thalamic bracelet were analysed and processed to create the dataset used for gesture classification. Initially, the EMG data was extracted from CSV files using a Python-based script designed to read and format the data for further analysis. Once the data was extracted, it underwent normalization to standardize the values across different recordings. Normalization was essential to minimize variability in the EMG signals due to differences in muscle strength, electrode placement, and noise, ensuring that the data from different subjects and gestures were comparable. Following normalization, the dataset was split into training and testing subsets. This step ensured that the model could be trained on one portion of the data while its performance could be independently evaluated on unseen data, preventing overfitting and improving generalization. The data split was done using standard practices, with a typical ratio such as 80% for training and 20% for testing, ensuring a balanced and representative sample for model evaluation.

C. Classification Techniques

Once the dataset was prepared, various machine learning algorithms were applied to classify hand gestures based on the EMG signals. Three prominent machine learning techniques were employed in the analysis: Random Forest, k-Nearest Neighbours (KNN), and Convolutional Neural Networks (CNN).

Random Forest: This ensemble learning method was chosen for its robustness in handling noisy data, which is common in EMG signals. By creating multiple decision trees and aggregating their predictions, Random Forest is effective in reducing variance and improving classification accuracy.

k-Nearest Neighbours (KNN): As a simple yet powerful classification algorithm, KNN was used to classify hand gestures based on the similarity of the EMG signal patterns. It classifies data points by evaluating their proximity in the feature space, making it well-suited for gesture recognition tasks where signal features tend to cluster around similar gestures.

Convolutional Neural Networks (CNN): CNNs are particularly adept at handling spatial data and extracting intricate patterns from input signals. In this study, CNN was leveraged to automatically learn and extract deep features from the EMG signals, enabling the model to capture complex temporal and spatial dependencies between the muscles and gestures.

Each of these algorithms was trained on the pre-processed EMG data to learn the relationships between muscle activity signals and the corresponding hand gestures. After training, the performance of each model was evaluated using metrics such as accuracy, precision, and recall.

D. Model Training and Evaluation

After data preprocessing, which involved cleaning and normalizing the EMG signals, the dataset was divided into training and testing sets using an 80-20 split. This split ensures that the models are trained on a substantial amount of data while retaining a separate portion for evaluating their performance. For the Random Forest model, the hyperparameters such as the number of trees and maximum depth were optimized to manage the inherent noise in EMG signals effectively. Random Forest's ensemble approach, combined with hyperparameter tuning, helps it handle variability in the data and improve classification robustness. Grid search or randomized search techniques might have been used to find the optimal values for these hyperparameters. In the case of the k-Nearest Neighbors (KNN) model, adjustments were made to the number of neighbours (k) and the distance metrics used (e.g., Euclidean, Manhattan) to enhance its classification accuracy. By fine-tuning these parameters, the model's sensitivity to varying densities and distributions of the data points was improved, allowing it to better differentiate between gestures. The Convolutional Neural Network (CNN) model was crafted to leverage both convolutional and pooling layers. The convolutional layers extracted hierarchical features from the raw EMG signals, identifying patterns that are spatially or temporally significant. Pooling layers reduced the dimensionality of the feature maps, which helped in focusing on the most important features while reducing computational load. Fully connected layers at the end of the network were used to perform the final classification based on the extracted features.

Each model's performance was rigorously evaluated using metrics such as accuracy, precision, recall, and F1-score. Accuracy provided a general measure of correctness, while precision and recall gave insights into the model's performance on specific classes, particularly important for handling imbalanced gesture categories. The F1-score offered a balanced view by combining precision and recall into a single metric. Cross-validation was employed to validate the consistency and reliability of the results across different data segments, ensuring that the models generalized well to unseen data and were not overfitted to the training set. This comprehensive evaluation helped in understanding each algorithm's strengths and limitations in classifying hand gestures from EMG signals.

Fig. 1 proposes that hand gesture recognition using machine learning starts with data acquisition, where EMG signals are collected from muscle sensors, capturing electrical activity during hand movements. In the preprocessing stage, the raw signals are filtered and normalized to remove noise and ensure data consistency. This is followed by the feature extraction phase, where key features like mean, variance, and frequency characteristics are computed from the cleaned signals to highlight important patterns. These extracted features are then fed into machine learning algorithms such as Random Forest, KNN, or CNN, which classify the gestures based on learned patterns. The process concludes with the output, where the system predicts and labels the recognized hand gestures based on the algorithm's classification results.

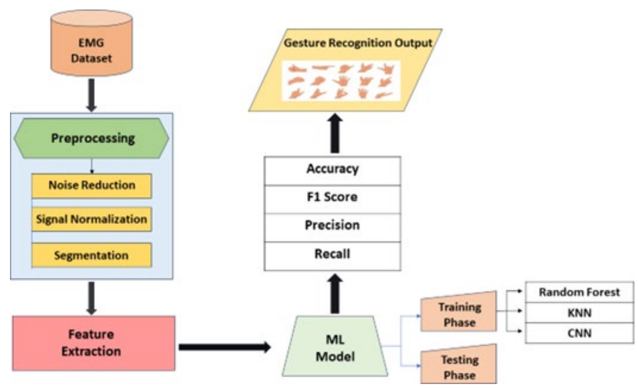


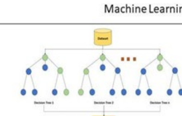
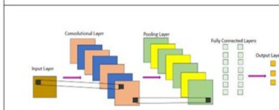
Fig. 1. Flow diagram

4. Results and Discussion

A. Model Performance and Comparison

The study conducted an in-depth evaluation of three distinct machine learning algorithms— Random Forest, k-Nearest Neighbours (KNN), and Convolutional Neural Networks (CNN)— for classifying hand gestures from EMG signals. The Random Forest model excelled with an impressive accuracy of 98.87%, showcasing its capability to manage the noisy and variable nature of EMG data while minimizing misclassifications, particularly with "unmarked data" that could be challenging to categorize. Its ensemble approach, combining multiple decision trees, effectively dealt with the data's

Table 1
Accuracy comparison of ML models

Hand gesture	Machine Learning Algorithm		Accuracy
		Random Forest	98.87%
		KNN	97.44%
		CNN	65.41%

In Table 1 showcases the performance of three machine learning models — Random Forest, K-Nearest Neighbours (KNN), and Convolutional Neural Networks (CNN) — in a hand gesture recognition task. Random Forest achieves the highest accuracy of 98.87%, followed closely by KNN at 97.44%. Meanwhile, CNN lags with an accuracy of 65.41%. While accuracy is a crucial metric, further analysis with F1 scores is necessary to assess how well these models handle class imbalances and precision-recall trade-offs, especially in more complex gesture recognition scenarios.

B. Evaluation of Individual Model Results

Table 2
Classification metrics of random forest model

Class	Precision	Recall	F1-Score	Support
Unmarked data	0.99	1.00	0.99	205751
Hand at rest	0.99	0.99	0.99	18365
Hand clenched in a fist	0.99	0.98	0.98	17787
Wrist flexion	0.99	0.98	0.99	18356
Wrist extension	0.99	0.98	0.98	18438
Radial deviations	1.00	0.98	0.98	17851
Ulnar deviations	0.99	0.98	0.98	18085
Accuracy			0.99	314573
Macro average	0.99	0.98	0.98	314573
Weighted average	0.99	0.98	0.99	314573

In Table 2 the classification report highlights the performance of a Random Forest model for hand gesture recognition, covering seven distinct classes. The model achieved a high accuracy of 98.87%. Each class, representing gestures such as "hand at rest," "hand clenched in a fist," "wrist flexion," and "radial deviations," shows excellent results, with precision, recall, and F1-scores all close to or exceeding 0.99. The largest class, "unmarked data," has the most instances (205,751) and perfect recall (1.00), demonstrating the model's capability in accurately detecting non-gesture data. While gestures like "wrist flexion" and "wrist extension" have slightly lower recall values (around 0.97-0.98), their overall performance remains strong. The macro and weighted averages for precision, recall, and F1-scores all approximate 0.99, confirming the model's reliability and balanced performance across the gesture categories, making it highly effective for hand gesture recognition

Fig. 2. Confusion matrix for Random Forest

In Figure 2 the confusion matrix highlights the strong performance of the Random Forest model in classifying hand gestures. Most instances are correctly classified along the diagonal, indicating high accuracy. For "unmarked data," 204,941 instances were correctly predicted, with only a small number of misclassifications into other gesture categories. "Hand at rest" and "hand clenched in a fist" had 18,007 and 17,345 correct classifications, respectively, with minimal errors. Gestures like "wrist flexion," "wrist extension," "radial deviations," and "ulnar deviations" also show high accuracy, with most instances accurately predicted and only slight confusion with similar gestures. Overall, the model performs well with very few misclassifications.

Table 3
Classification metrics of KNN model

Class	Precision	Recall	F1-Score	Support
Unmarked data	0.97	0.98	0.98	205751
Hand at rest	0.97	0.96	0.96	18385
Hand clenched in a fist	0.96	0.95	0.95	17787
Wrist flexion	0.97	0.96	0.96	18356
Wrist extension	0.97	0.96	0.96	18438
Radial deviations	0.98	0.97	0.97	17851
Ulnar deviations	0.96	0.95	0.96	18085
Accuracy			0.97	314573
Macro average	0.96	0.96	0.96	314573
Weighted average	0.97	0.97	0.97	314573

Table 3 highlights the performance of a K-Nearest Neighbours (KNN) algorithm for recognizing seven hand gestures: unmarked data, hand at rest, clenched fist, wrist flexion, wrist extension, radial deviation, and ulnar deviation. The model achieved a high accuracy of 97.44%, demonstrating its effectiveness in gesture recognition. Precision, recall, and F1-scores for each class are consistently strong, ranging from 0.95 to 0.98, showing the model's reliability across all gestures. The "unmarked data" class had the highest support, with 205,751 instances, which contributed to the weighted averages of 0.97 for precision and recall. These results indicate that the KNN model effectively distinguishes between various hand gestures, with minimal errors. The macro averages of 0.96 further suggest that the model maintains balanced performance across all gesture classes, despite differences in class sizes.

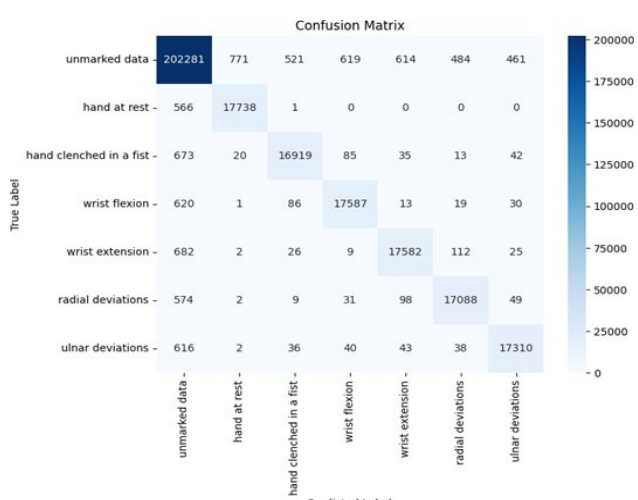


Fig. 3. Confusion matrix for KNN

Figure 3 shows the K-Nearest Neighbours (KNN) model's performance in classifying seven hand gesture categories, with correct predictions along the diagonal and errors in the off-diagonal cells. The model exhibits strong accuracy, especially for "unmarked data" (202,281 correct predictions), "hand at rest" (17,738), and "hand clenched in a fist" (16,919). While there are some misclassifications, such as "hand clenched in a fist" being confused with "unmarked data" 673 times and "wrist flexion" misclassified as "unmarked data" 620 times, these errors are relatively low. Most mistakes occur between gestures with similar features, but overall, the matrix reflects the model's ability to accurately distinguish between hand gestures.

5. Conclusion

This study effectively classified hand gestures using EMG signals with machine learning algorithms, with CNN outperforming Random Forest and KNN by better capturing spatial and temporal features, resulting in the highest accuracy. The key advantages include precise gesture recognition, making it particularly useful in applications like prosthetics, rehabilitation, and human-computer interaction. However, there are still challenges, including real-time processing limitations, noise in EMG signals, and the complexity of recognizing varied gestures. Future research should focus on improving hybrid models like CNN-LSTM for enhanced temporal pattern recognition, reducing sensor count to simplify myoelectric control, and refining noise reduction techniques to boost real-time performance and scalability for wider applications**.**

References

[1] T. Triwiyanto, W. Caesarendra, V. Abdullayev, A. A. Ahmed, and H. Herianto, "Single Lead EMG signal to Control an Upper Limb Exoskeleton Using Embedded Machine Learning on Raspberry Pi," *Journal of Robotics and Control (JRC)*, vol. 4, no. 1, 2023.

[2] E. Yaman and A. Subasi, "Comparison of Bagging and Boosting Ensemble Machine Learning Methods for Automated EMG Signal Classification," *Biomed Res Int*, vol. 2019, 2019.

[3] Y. Du, W. Jin, W. Wei, Y. Hu, and W. Geng, "Surface EMG-based inter-session gesture recognition enhanced by deep domain adaptation," *Sensors (Switzerland)*, vol. 17, no. 3, Mar. 2017.

[4] N. Tacca *et al.*, "Wearable high-density EMG sleeve for complex hand gesture classification and continuous joint angle estimation," *Sci Rep*, vol. 14, no. 1, Dec. 2024.

[5] M. Montazerin, E. Rahimian, F. Naderkhani, S. F. Atashzar, S. Yanushkevich, and A. Mohammadi, "Transformer-based hand gesture recognition from instantaneous to fused neural decomposition of high-density EMG signals," *Sci Rep*, vol. 13, no. 1, Dec. 2023.

[6] T. Zaim, S. Abdel-Hadi, R. Mahmoud, A. Khandakar, S. M. Rakhtala, and M. E. H. Chowdhury, "Machine Learning- and Deep Learning-Based Myoelectric Control System for Upper Limb Rehabilitation Utilizing EEG and EMG Signals: A Systematic Review," Feb. 01, 2025, *Multidisciplinary Digital Publishing Institute (MDPI)*.

[7] M. Z. ur Rehman *et al.*, "Multiday EMG-Based classification of hand motions with deep learning techniques," *Sensors (Switzerland)*, vol. 18, no. 8, Aug. 2018.

[8] P. Gopal, A. Gesta, and A. Mohebbi, "A Systematic Study on Electromyography- Based Hand Gesture Recognition for Assistive Robots Using Deep Learning and Machine Learning Models," *Sensors*, vol. 22, no. 10, May 2022.

[9] E. Ekinci, Z. Garip, and K. Serbest, "Electromyography based hand movement classification and feature extraction using machine learning algorithms," *Politeknik Dergisi*, vol. 26, no. 4, pp. 1621–1633, Dec. 2023.

[10] I. M. Khairuddin, S. N. Sidek, A. P. P. A. Majeed, M. A. M. Razman, A. A. Puzi, and H. M. Yusof, "The classification of movement intention through machine learning models: the identification of significant time-domain EMG features," *Peer J Comput Sci*, vol. 7, pp. 1–15, 2021.

[11] S. Bhushan, M. Alshehri, I. Keshta, A. K. Chakraverti, J. Rajpurohit, and A. Abugabah, "An Experimental Analysis of Various Machine Learning Algorithms for Hand Gesture Recognition," *Electronics (Switzerland)*, vol. 11, no. 6, Mar. 2022.

[12] M. H. Abdelaziz, W. A. Mohamed, and A. S. Selmy, "Hand Gesture Recognition Based on Electromyography Signals and Deep Learning Techniques," *Journal of Advances in Information Technology*, vol. 15, no. 2, pp. 255–263, 2024.

[13] M. H. Abdelaziz, W. A. Mohamed, and A. S. Selmy, "Hand Gesture Recognition Based on Electromyography Signals and Deep Learning Techniques," *Journal of Advances in Information Technology*, vol. 15, no. 2, pp. 255–263, 2024.

[14] S. Bhushan, M. Alshehri, I. Keshta, A. K. Chakraverti, J. Rajpurohit, and A. Abugabah, "An Experimental Analysis of Various Machine Learning Algorithms for Hand Gesture Recognition," *Electronics (Switzerland)*, vol. 11, no. 6, Mar. 2022.

[15] A. Jaramillo-Yánez, M. E. Benalcázar, and E. Mena-Maldonado, "Real-time hand gesture recognition using surface electromyography and machine learning: A systematic literature review," May 01, 2020, *MDPI AG*.

[16] C. Simar, M. Colot, A. M. Cebolla, M. Petieau, G. Cheron, and G. Bontempi, "Machine learning for hand pose classification from phasic and tonic EMG signals during bimanual activities in virtual reality," *Front Neurosci*, vol. 18, 2024.