International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 - 6435 (Online) Volume 14, Issue 7, July 2025)

Review of Hand Gesture Recognition Using EMG Signals

[1]Aditi Pandey, [2]Prof. Nitesh Kumar

[1]Research Scholar, [2]Assistant Professor, Department of Electronics & Communication Engineering, Sagar Institute of Research & Technology, Bhopal, India.

***Abstract*— Hand gesture recognition using electromyography (EMG) signals has emerged as a revolutionary approach to improving human-computer interaction, prosthetic control, and rehabilitation systems. EMG signals, generated by muscle activity, offer a unique medium for accurately interpreting voluntary hand movements. This review provides a comprehensive analysis of recent advancements in hand gesture recognition systems using EMG signals, focusing on signal acquisition, feature extraction, classification methods, and practical applications. The study explores the challenges associated with EMG signal variability, noise interference, and user dependency while highlighting innovative approaches employed to address these issues. Furthermore, the paper reviews the integration of advanced machine learning and deep learning algorithms, which have significantly enhanced the accuracy and reliability of gesture recognition systems. This review also emphasizes the importance of multimodal approaches and the potential role of EMG-based gesture recognition in areas such as assistive technology, virtual reality, and wearable devices. Finally, the paper discusses future research directions and the scope of EMG signal-based gesture recognition systems for advancing human-machine symbiosis.**

Keywords*— Hand, Gesture, Recognition, EMG Signals, Machine, Deep learning.

I. INTRODUCTION

Hand gesture recognition has gained substantial attention in recent years due to its potential to revolutionize human-computer interaction (HCI) and enhance assistive technologies. From controlling prosthetic limbs to enabling hands-free interaction in augmented and virtual reality environments, gesture recognition systems have become an essential aspect of various innovative applications. Among the various methods used for gesture recognition, electromyography (EMG) signals have demonstrated exceptional promise because they directly reflect muscle activity and provide a detailed understanding of voluntary movements.

EMG signals are generated by the electrical activity of muscles during contraction and relaxation. These signals, captured using electrodes placed on the skin or implanted within the muscles, carry valuable information about the underlying motor commands. The capability of EMG signals to accurately represent muscle activity has positioned them as an ideal medium for recognizing complex hand gestures. However, working with EMG signals is not without challenges. The variability of signals across users, sensitivity to noise, and dependency on proper electrode placement are some of the critical issues researchers face in developing robust gesture recognition systems.

The process of recognizing hand gestures using EMG signals typically involves several stages, starting with signal acquisition, followed by preprocessing to remove noise and artifacts. The extracted features, which represent the relevant characteristics of the signal, are then fed into machine learning or deep learning algorithms for classification. These steps collectively determine the performance and accuracy of the system. Over the years, researchers have proposed various techniques to improve each stage, resulting in increasingly reliable gesture recognition systems.

Advances in machine learning and deep learning have significantly influenced the development of EMG-based hand gesture recognition systems. Classical machine learning techniques such as support vector machines (SVM) and random forests have been widely used for gesture classification. More recently, the advent of deep learning architectures, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), has opened new possibilities for automatically extracting features and improving classification accuracy. Additionally, hybrid

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 - 6435 (Online) Volume 14, Issue 7, July 2025)

approaches combining EMG signals with other sensing modalities, such as inertial measurement units (IMUs) and computer vision, have demonstrated considerable potential in addressing the limitations of standalone EMG-based systems.

The applications of EMG-based hand gesture recognition systems are diverse and impactful. In healthcare, these systems are used to develop advanced prosthetic limbs and assistive devices for individuals with disabilities. In gaming and virtual reality, EMG signals enable more immersive and intuitive user experiences. Wearable devices leveraging EMG-based gesture recognition are also gaining traction for controlling smart devices and facilitating hands-free interactions.

This review aims to provide a comprehensive overview of the current state-of-the-art in hand gesture recognition using EMG signals. It systematically examines the challenges and advancements in signal acquisition, preprocessing, feature extraction, and classification techniques. Furthermore, it explores the integration of multimodal approaches and discusses the potential impact of these systems in various domains. By highlighting recent innovations and addressing the gaps in existing research, this review seeks to inspire further advancements in EMG-based gesture recognition and its applications. The future of EMG-based gesture recognition lies in the development of more robust, user-independent, and adaptive systems that can seamlessly integrate into everyday life, paving the way for a more inclusive and intuitive human-machine interaction.

II. LITERATURE SURVEY

N. R. et al.,[1] Hand gesture detection, which employs electromyography (EMG) signals, is a dynamic field of research with a diverse array of applications, such as human-machine interfaces and prosthetic devices. For the classification of EMG data, numerous deep-learning algorithms have been developed in recent years. This paper investigates the influence of hybrid models, which combine CNN and RNN models, on the classification of hand gestures using EMG signals. A comparative analysis is conducted to evaluate the efficacy of three hybrid models: CNN-GRU, CNN-LSTM, and CNN-BiLSTM. The Ninapro DB1 dataset is utilised to conduct the performance assessment.

P. N. Aarotale et al., [2] Electromyographic (EMG) signals are employed in EMG-based hand gesture recognition to analyse the electrical activity produced by muscle contractions in order to interpret and classify hand movements. It has a broad range of applications in the areas of rehabilitation training, prosthesis control, and human-computer interaction. The EMG sensor captures muscle signals by placing electrodes on the skin, which are then processed and filtered to reduce noise. In order to differentiate between a variety of hand gestures, a multitude of feature extraction and machine learning algorithms have been proposed for the extraction and classification of muscle signals.The objective of this paper is to evaluate the performance of EMG-based hand gesture recognition by utilising state-of-the-art machine and deep learning models in conjunction with novel feature extraction methods, including fused time-domain descriptors, temporal-spatial descriptors, and wavelet transform-based features.

A. Deb et al.,[3] demonstrates that the DPMAS-Net's accuracy is comparable to the current state-of-the-art results with privacy and exceeds them with non-privacy, despite the presence of privacy-preserving measures (Ninapro DB4 86.4% with privacy and 92.0% without privacy, Biopatrec DB2 89.3%, and the Mendeley Dataset 90.4%). Consequently, the DPMAS-Net model represents a substantial improvement in the classification of EMG signals for the recognition of hand gestures by integrating differential privacy with deep learning techniques.

P. D. Hile Bustos et al.,[4] This research endeavours to improve the accuracy of motion recognition by utilising deep learning techniques and surface electromyographic (sEMG) signals. We present a convolutional neural network (CNN) model that is specifically engineered to extract and integrate features from multichannel sEMG signals by employing a layering approach to enhance accuracy.Methodology: The proposed model was evaluated by comparing its performance to existing methodologies in a study that included ten amputees who were equipped with prosthetic hands. The results suggest that our model outperforms existing methods, potentially enabling the control of exoskeletons, prosthetic devices, wheelchairs, and virtual interactions.Results: The algorithm's superiority over conventional methods is demonstrated by its evaluation using our proprietary dataset.

W. Cao et al.,[5] Rehabilitation gesture recognition, as one of the primary methods of active rehabilitation medicine, has the potential to significantly impact stroke rehabilitation by enabling personalised interventions to meet the unique requirements of each patient and providing real-time feedback on patient progress. Noise, motion distortion, and individual differences are among the numerous obstacles that traditional gesture recognition methods encounter when analysing stroke patient data. This work suggests a novel method for the recognition of stroke patient gestures using deep learning models in order to overcome these obstacles. In order to improve the precise identification of hand movements in stroke patients, we implement a strategy that integrates a denoising autoencoder (DAE), a CNN, and a LSTM.

P. Rani et al.,[6] contrasts the conventional wavelet transform with a tempo-spatial technique that employs the wavelet multiresolution method, utilising eight machine learning algorithms. Two datasets that are publicly accessible are implemented. DB1 is characterised by ideal conditions and a variety of limb positions, whereas DB2 includes dynamic factors such as muscle fatigue and electrode shifting. The training/testing process consists of two cases: one that utilises single-position data and the other that utilises multiple positions. The results indicate that the Deep Neural Network (DNN) classifier outperforms other classifiers in terms of classification accuracy.

H. Shi, et al.,[7] The commercialisation of sEMG-based human-machine interaction (HMI) systems is impeded by the gesture classification model's heavy training burden and weak generalisation performance. In order to surmount these obstacles, eight unsupervised transfer learning (TL) algorithms that were developed on the premise of convolutional neural networks (CNNs) were investigated and contrasted on a dataset that comprised 10 gestures from 35 subjects. CORrelation Alignment (CORAL) achieves a classification accuracy of over 90%, which is 10% higher than methods that do not employ TL. In addition, the proposed model outperforms four conventional classifiers (KNN, LDA, SVM, and Random Forest) when calibrated with minimal data (two repeated trials for each gesture). The model's transfer robustness/flexibility for cross-gesture and cross-day scenarios is also demonstrated by the results. An accuracy of 87.94% was achieved using calibration gestures that are distinct from the model's training, and an accuracy of 84.26% was achieved using calibration data collected on a different day.

W. Zhong et al.,[8] Effective control of upper-limb prosthetic appendages necessitates precise hand gesture prediction. The integration of deep networks with high-density surface electromyography (HD-sEMG) arrays has garnered significant interest due to the high flexibility and multiple degrees of freedom that human hands exhibit. This integration is intended to improve the gesture recognition capabilities. Nevertheless, the specific spatial topology and temporal dependencies present in HD-sEMG data are not thoroughly exploited by many existing methods. Furthermore, these studies frequently have a restricted number of gestures and lack generalisability. Therefore, this investigation introduces a novel gesture recognition method, STGCN-GR, that utilises spatio-temporal graph convolution networks to support HD-sEMG-based human-machine interfaces.

M. Zanghieri et al.,[9] Surface electromyography (sEMG) is a State-of-the-Art (SoA) data source for natural and dexterous control in human-machine interaction for industrial, commercial, and rehabilitation-related applications. The inherent presence of numerous signal variability factors, which impede the generalisation of automated learning models, presents a significant challenge for sEMG-based control, despite its non-invasiveness and versatility. We present an unsupervised adaptation technique for sEMG classification in this work and apply it to the variability of arm posture. The method is predicated on the alignment of the Principal Components (PCs) of the new data with the PCs of the training set. The PCs are approximated online, ingesting one sample at a time without storing any data, and no classifier retraining is necessary.

S. Song et al.,[10] The surface electromyography (sEMG) signal is a physiological electrical signal that is generated by muscle contraction. The characteristics of the sEMG signal can be used to effectively identify various gestures. Because of their capacity to acquire spatial features of sEMG signals, convolutional neural networks (CNNs) are currently extensively employed in sEMG gesture recognition systems. Nevertheless, these classical CNNs are ineffective in deriving the temporal correlation that is present in the time serials of sEMG signals, a factor that is undoubtedly significant for gesture recognition. In order to address this limitation of conventional CNN-based gesture recognition methods, we suggest a multichannel hybrid deep learning model for gesture recognition that integrates multichannel

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 - 6435 (Online) Volume 14, Issue 7, July 2025)

CNNs with a gated recurrent unit (GRU). To be more precise, we employ numerous CNNs to preprocess the original multichannel EMG signals in a one-by-one fashion in order to acquire the spatial features within the current observing window.

III. CHALLENGES

Despite the significant advancements in hand gesture recognition using electromyography (EMG) signals, several challenges remain that hinder the development of robust, accurate, and user-independent systems. These challenges span across various stages of the recognition process, from signal acquisition to classification and real-world implementation. Below is a detailed discussion of the key challenges:

1. Signal Variability

- **Inter-User Variability**: EMG signals are highly user-dependent, as factors such as muscle anatomy, skin texture, and electrode placement vary significantly across individuals. This variability makes it challenging to design systems that generalize well across different users.
- **Intra-User Variability**: Even within the same user, EMG signals can vary due to changes in muscle fatigue, skin conductivity, and environmental conditions. This can affect the consistency of gesture recognition systems.

2. Noise and Artifacts

- **Electrode Noise**: EMG signals are highly susceptible to noise introduced by the electrodes, including motion artifacts, electromagnetic interference, and poor contact with the skin.
- **Cross-Talk**: Signals from adjacent muscles may overlap, making it difficult to isolate specific muscle activity related to the intended gesture.
- **Environmental Noise**: External factors, such as electromagnetic interference from nearby electronic devices, can further degrade signal quality.

3. Complexity of Hand Gestures

- Recognizing fine or complex hand gestures, such as individual finger movements or subtle variations in muscle contractions, is challenging due to the intricate nature of muscle coordination required for such gestures.
- Gestures involving simultaneous activation of multiple muscles may lead to overlapping or indistinct EMG patterns.

4. Feature Extraction and Selection

- Identifying relevant features from EMG signals is critical for accurate classification. However, the non-stationary and complex nature of EMG signals makes feature extraction a challenging task.
- Feature selection is equally important, as selecting irrelevant or redundant features can lead to decreased classification accuracy and increased computational complexity.

5. Classification Accuracy and Real-Time Performance

- Traditional machine learning models often require extensive feature engineering, which may not always generalize well to real-world conditions.
- Deep learning models, while more robust, require large datasets and high computational resources, which can be a limitation for real-time applications.
- Achieving high classification accuracy in real-time systems is particularly challenging due to processing delays and computational constraints.

6. User Dependency

- Most EMG-based systems require user-specific training and calibration, making them less practical for widespread adoption. Developing user-independent systems that adapt dynamically to new users remains a significant challenge.

8. Dataset Limitations

- Many publicly available EMG datasets are limited in size and diversity, which restricts the ability to train and validate robust models.
- The lack of standardization in gesture sets and acquisition protocols makes it difficult to compare the performance of different systems.

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 - 6435 (Online) Volume 14, Issue 7, July 2025)

IV. CONCLUSION

The hand gesture recognition using EMG signals has demonstrated immense potential for revolutionizing human-computer interaction, assistive technologies, and wearable systems. While significant advancements have been made in signal processing, feature extraction, and classification methods, challenges such as signal variability, noise interference, user dependency, and real-world implementation remain barriers to achieving robust and scalable systems. Addressing these challenges requires a multidisciplinary approach, integrating advancements in machine learning, hardware design, and multimodal sensing. By overcoming these limitations, EMG-based gesture recognition systems can pave the way for more intuitive, accessible, and impactful applications, transforming the way humans interact with technology.

REFERENCES

1. N. R and G. Titus, "Hybrid Deep Learning Models for Hand Gesture Recognition with EMG Signals," 2024 International Conference on Advances in Modern Age Technologies for Health and Engineering Science (AMATHE), Shivamogga, India, 2024, pp. 1-6, doi: 10.1109/AMATHE61652.2024.10582166.
2. P. N. Aarotale and A. Rattani, "Machine Learning-based sEMG Signal Classification for Hand Gesture Recognition," 2024 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), Lisbon, Portugal, 2024, pp. 6319-6326, doi: 10.1109/BIBM62325.2024.10822133.
3. A. Deb, R. Roy, M. S. Sadik Rian, A. Islam and C. Shahnaz, "DPMAS-Net: A Privacy-Preserving Deep Learning Model for EMG-Based Hand Gesture Recognition with Time-Frequency Domain Features," 2024 IEEE Region 10 Symposium (TENSYMP), New Delhi, India, 2024, pp. 1-6, doi: 10.1109/TENSYMP61132.2024.10752112.
4. P. D. Hile Bustos, R. R. Serrezuela, A. A. Suarez Leon, A. E. Rivera Gomez and D. M. Echeverry Suaza, "Electromyographic EMG signal recognition of hand gestures for multi-class prostheses based on DWT and CNN," 2024 IEEE VII Congreso Internacional en Inteligencia Ambiental, Ingeniería de Software y Salud Electrónica y Móvil (AmITIC), David, Panama, 2024, pp. 1-7, doi: 10.1109/AmITIC62658.2024.10747601.
5. W. Cao et al., "EMG Based Rehabilitation Gesture Recognition Using DAE-CNN-LSTM Hybrid Model," 2024 World Rehabilitation Robot Convention (WRRC), Shanghai, China, 2024, pp. 1-6, doi: 10.1109/WRRC62201.2024.10696763.
6. P. Rani, S. Pancholi, V. Shaw, M. Atzori and S. Kumar, "Enhanced EMG-Based Hand Gesture Classification in Real-World Scenarios: Mitigating Dynamic Factors With Tempo-Spatial Wavelet Transform and Deep Learning," in IEEE Transactions on Medical Robotics and Bionics, vol. 6, no. 3, pp. 1202-1211, Aug. 2024, doi: 10.1109/TMRB.2024.3408896.
7. H. Shi, X. Jiang, C. Dai and W. Chen, "EMG-based Multi-User Hand Gesture Classification via Unsupervised Transfer Learning Using Unknown Calibration Gestures," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 32, pp. 1119-1131, 2024, doi: 10.1109/TNSRE.2024.3372002.
8. W. Zhong, Y. Zhang, P. Fu, W. Xiong and M. Zhang, "A Spatio-Temporal Graph Convolutional Network for Gesture Recognition from High-Density Electromyography," 2023 29th International Conference on Mechatronics and Machine Vision in Practice (M2VIP), Queenstown, New Zealand, 2023, pp. 1-6, doi: 10.1109/M2VIP58386.2023.10413402.
9. M. Zanghieri, M. Orlandi, E. Donati, E. Gruppioni, L. Benini and S. Benatti, "Online Unsupervised Arm Posture Adaptation for sEMG-based Gesture Recognition on a Parallel Ultra-Low-Power Microcontroller," 2023 IEEE Biomedical Circuits and Systems Conference (BioCAS), Toronto, ON, Canada, 2023, pp. 1-5, doi: 10.1109/BioCAS58349.2023.10388902.
10. S. Song, A. Dong, J. Yu, Y. Han and Y. Zhou, "A Multichannel CNN-GRU Hybrid Architecture for sEMG Gesture Recognition," 2023 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), Istanbul, Turkiye, 2023, pp. 4132-4139, doi: 10.1109/BIBM58861.2023.10385891.