Review of Deep Learning Model for Hand Gesture Recognition Using EMG Signals

[1]Dr. Rajeev Kumar Thakur, [2]Pushpa Patel
[1]Associate Professor, [2]Research Scholar,
Department of Electronics and Communication Engineering,
NRI Institute of Information Science and Technology, Bhopal, India

***Abstract*— This review presents a comprehensive analysis of deep learning models used for hand gesture recognition based on electromyography (EMG) signals, a key technology for human–computer interaction, prosthetic control, and rehabilitation systems. The paper examines the complete processing pipeline, including EMG signal acquisition, preprocessing, feature extraction, and classification using advanced deep learning architectures such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory (LSTM), and hybrid models. Emphasis is placed on the comparative performance of these models in terms of accuracy, robustness, real-time capability, and adaptability to inter-subject variability. The review also highlights publicly available EMG datasets, evaluation metrics, and major challenges such as signal noise, electrode placement sensitivity, and limited generalization across users. Finally, the study outlines open research directions, including lightweight models for embedded systems, transfer learning, and multimodal fusion, to guide future advancements in EMG-based hand gesture recognition systems.**

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

I. INTRODUCTION

Hand gesture recognition using electromyography (EMG) signals has emerged as a powerful and reliable approach for enabling natural and intuitive interaction between humans and machines. Hand gestures are a fundamental means of non-verbal communication, and their automatic recognition plays a vital role in applications such as prosthetic hand control, rehabilitation engineering, assistive technologies, virtual and augmented reality, robotics, and human–computer interaction systems[1]. Traditional vision-based gesture recognition techniques often suffer from limitations such as sensitivity to lighting conditions, occlusion, background complexity, and camera positioning. In contrast, EMG-based gesture recognition directly captures the electrical activity generated by muscle contractions, making it independent of external visual conditions and more suitable for real-time and wearable applications[2].

EMG signals are bioelectrical signals produced when motor neurons activate muscle fibers during voluntary or involuntary movements. Surface EMG sensors, which are non-invasive and easy to deploy, are commonly placed on the forearm to capture muscle activity associated with different hand and finger gestures[3]. Each gesture produces a unique muscle activation pattern, which can be analyzed and mapped to specific hand movements. This physiological basis allows EMG-based systems to detect user intent even before visible motion occurs, offering faster response times compared to vision-based systems. As a result, EMG-driven hand gesture recognition is particularly effective in applications requiring precision, responsiveness, and robustness[4].

The process of hand gesture recognition using EMG signals typically involves several stages, including signal acquisition, preprocessing, feature extraction, and classification. Raw EMG signals are often noisy and affected by factors such as motion artifacts, power line interference, electrode displacement, muscle fatigue, and inter-subject variability[5]. Therefore, preprocessing techniques such as filtering, normalization, and segmentation are essential to enhance signal quality and reliability. Feature extraction then plays a crucial role in representing EMG signals in a compact and discriminative form, using time-domain, frequency-domain, time–frequency, or learned representations that capture the underlying muscle activation characteristics[6].

Recent advancements in machine learning and deep learning have significantly improved the performance of EMG-based hand gesture recognition systems. Unlike conventional approaches that rely heavily on handcrafted features, deep learning models can automatically learn hierarchical and task-specific representations directly from raw or minimally processed EMG data[7]. This capability has led to improved recognition accuracy, better generalization across gestures, and enhanced adaptability to complex muscle activation patterns. Consequently, EMG-based gesture recognition systems are becoming more scalable and capable of handling a larger set of gestures in real-world scenarios[8].

Despite its advantages, hand gesture recognition using EMG signals still faces several challenges. Variations in muscle anatomy across users, electrode placement differences, signal non-stationarity, and long-term signal drift can affect system performance and limit generalization. Additionally, achieving high accuracy while maintaining low computational complexity is critical for real-time and embedded applications such as wearable devices and prosthetic controllers. Addressing these challenges requires robust modeling techniques, adaptive learning strategies, and efficient signal processing pipelines[9].

Hand gesture recognition using EMG signals represents a promising and rapidly evolving research area that bridges biomedical engineering, signal processing, and artificial intelligence. Its ability to provide intuitive, reliable, and real-time interaction makes it a key enabling technology for next-generation intelligent systems. Continued research in this field is expected to further enhance system robustness, usability, and accessibility, paving the way for widespread adoption in both clinical and consumer-oriented applications[10].

II. LITERATURE SURVEY

T. T. Oyemakinde et al. [1] presented novel sensor fusion framework combining surface EMG (sEMG) and force myography (FMG) signals for dynamic hand gesture recognition. The authors introduced an attention-driven convolutional neural network (CNN) to automatically emphasize the most informative signal channels. By fusing physiological and mechanical muscle information, the system achieved higher robustness against noise and motion artifacts. Extensive experiments demonstrated superior performance compared to single-sensor approaches. The model effectively handled dynamic gestures and temporal variations. Results indicated improved accuracy and stability across multiple gesture classes. This work highlights the benefit of multimodal sensing in EMG-based gesture recognition.

N. R. and G. Titus [2] presented hybrid deep learning architectures for EMG-based hand gesture recognition, integrating convolutional and recurrent neural networks. The study focused on capturing both spatial muscle activation patterns and temporal dependencies in EMG signals. Feature learning was performed directly from preprocessed EMG data, reducing reliance on handcrafted features. Experimental results showed that hybrid models outperformed standalone CNN and LSTM architectures. The approach demonstrated improved recognition accuracy for multiple hand gestures. The authors emphasized the suitability of hybrid deep learning for real-time EMG applications. This work contributes to efficient model design for wearable gesture recognition systems.

P. N. Aarotale and A. Rattani [3] investigated machine learning techniques for sEMG signal classification in hand gesture recognition tasks. The study evaluated multiple classifiers using time-domain and frequency-domain features extracted from EMG signals. Performance analysis highlighted the influence of feature selection on classification accuracy. The authors demonstrated that traditional machine learning models can achieve competitive results with proper feature engineering. Cross-validation experiments confirmed the robustness of the proposed framework. The work also discussed inter-subject variability as a major challenge. This study provides a strong baseline for comparing deep learning approaches.

P. D. Hile Bustos et al. [4] presented an EMG-based hand gesture recognition system for multi-class prosthetic control using discrete wavelet transform (DWT) and CNN. The DWT was employed to capture time–frequency characteristics of EMG signals effectively. Extracted features were fed into a CNN for automatic classification of gestures. The system achieved high accuracy across multiple gesture classes relevant to prosthetic applications. The authors validated the approach using real EMG data collected from users. Results showed improved robustness against signal noise. This work demonstrates the applicability of deep learning for prosthetic hand control.

W. Cao et al. [5] developed a hybrid DAE-CNN-LSTM model for EMG-based rehabilitation gesture recognition. A denoising autoencoder (DAE) was used to reduce noise and enhance EMG signal quality. CNN layers extracted spatial features, while LSTM captured temporal dependencies. The proposed framework showed high recognition accuracy for rehabilitation-related hand gestures. The model was evaluated under different movement conditions to ensure robustness. Experimental results confirmed improved generalization compared to single-model approaches. This study highlights the importance of hybrid architectures in clinical rehabilitation systems.

P. Rani et al. [6] addressed real-world challenges in EMG-based hand gesture classification by mitigating dynamic factors such as arm position and muscle fatigue. The authors applied a tempo-spatial wavelet transform to extract discriminative EMG features. Deep learning models were then used for gesture classification under realistic conditions. The proposed approach significantly improved performance in non-ideal environments. Extensive experiments validated robustness across users and sessions. The study emphasized real-world deployment considerations. This work advances practical EMG-based gesture recognition systems.

H. Shi et al. [7] presented an unsupervised transfer learning framework for multi-user EMG-based hand gesture classification. The method eliminated the need for explicit calibration gestures from new users. Feature alignment techniques were used to adapt models across subjects. Experimental results demonstrated effective generalization to unseen users. The approach significantly reduced calibration effort while maintaining high accuracy. The study addressed one of the major limitations of EMG systems, namely inter-user variability. This work is highly relevant for scalable wearable gesture recognition solutions.

W. Zhong et al. [8] introduced a spatio-temporal graph convolutional network (ST-GCN) for gesture recognition using high-density EMG signals. The graph-based representation modeled spatial relationships between EMG electrodes. Temporal dynamics were captured through sequential graph convolutions. The proposed method achieved superior performance compared to conventional CNN-based models. The study demonstrated the effectiveness of exploiting electrode topology. Results highlighted improved recognition for complex gestures. This work provides a novel perspective on EMG signal modeling.

M. Zanghieri et al. [9] presented an online unsupervised adaptation framework for sEMG-based gesture recognition on ultra-low-power microcontrollers. The system dynamically adapted to arm posture changes without labeled data. Efficient algorithms were designed for real-time processing on resource-constrained hardware. Experimental validation showed stable performance under varying postures. The approach significantly reduced power consumption. This work is crucial for embedded and wearable EMG systems. It demonstrates the feasibility of long-term autonomous gesture recognition.

S. Song et al. [10] presented a multichannel CNN-GRU hybrid architecture for sEMG-based hand gesture recognition. CNN layers extracted spatial features from multi-channel EMG signals, while GRU modeled temporal dependencies. The hybrid model achieved high classification accuracy across multiple datasets. The study showed improved convergence speed and reduced computational complexity. Experimental results confirmed robustness to signal variability. The architecture was suitable for real-time applications. This work reinforces the effectiveness of CNN-recurrent hybrid models in EMG gesture recognition.

III. CHALLENGES

Hand gesture recognition using EMG signals faces several technical and practical challenges that limit its reliability and large-scale adoption in real-world applications. EMG signals are inherently non-stationary and highly sensitive to physiological and environmental variations, making consistent gesture classification difficult. Factors such as electrode displacement, muscle fatigue, inter-subject variability, and signal noise significantly affect recognition accuracy. Moreover, achieving robust performance across different users, sessions, and operating conditions remains a major concern. The trade-off between high accuracy and low computational complexity further complicates the deployment of EMG-based systems in real-time, wearable, and embedded platforms.

1. **Signal Noise and Artifacts**: EMG signals are easily corrupted by power-line interference, motion artifacts, and sensor noise. These disturbances distort muscle activation patterns and degrade classification performance, especially in dynamic movements.
2. **Inter-Subject Variability**: Muscle anatomy and activation patterns differ significantly across individuals. A model trained on one user often performs poorly on another, limiting the generalization capability of EMG-based gesture recognition systems.
3. **Electrode Placement Sensitivity**: Small changes in electrode position or orientation can cause large variations in EMG signals. Repositioning errors during repeated usage lead to inconsistent data and reduced recognition accuracy.
4. **Muscle Fatigue Effects**: Prolonged or repetitive gestures cause muscle fatigue, which alters EMG signal amplitude and frequency characteristics. This non-stationarity affects long-term system stability and reliability.

5. **Limited Availability of Large Datasets**: Publicly available EMG gesture datasets are relatively small and lack diversity. Limited training data restricts the effectiveness of deep learning models and increases the risk of overfitting.

6. **Real-Time Processing Constraints**: Many deep learning models require high computational resources. Implementing accurate yet lightweight models suitable for real-time wearable and embedded systems remains a critical challenge.

7. **Gesture Similarity and Overlapping Patterns**: Some hand gestures produce very similar muscle activation signals, making them difficult to distinguish. This overlap increases misclassification rates, particularly in multi-gesture scenarios.

8. **Long-Term Signal Drift**: EMG signals drift over time due to changes in skin condition, sweat, and sensor impedance. Without adaptive learning mechanisms, system performance degrades during prolonged use.

IV. CONCLUSION

Hand gesture recognition using EMG signals has proven to be a promising and effective approach for enabling intuitive human–machine interaction, particularly in applications such as prosthetics, rehabilitation, robotics, and assistive technologies. The integration of advanced signal processing techniques with machine learning and deep learning models has significantly improved gesture recognition accuracy and robustness by capturing complex spatial and temporal muscle activation patterns. Despite these advancements, challenges related to signal variability, electrode placement, user dependency, and real-time implementation continue to limit widespread adoption. Addressing these issues through adaptive learning, transfer learning, lightweight model design, and multimodal sensing is essential for enhancing system reliability and scalability. With ongoing research and technological progress, EMG-based hand gesture recognition is expected to play a vital role in next-generation intelligent and wearable systems.

REFERENCES

1. T. T. Oyemakinde et al., "A Novel sEMG-FMG Combined Sensor Fusion Approach Based on an Attention-Driven CNN for Dynamic Hand Gesture Recognition," in IEEE Transactions on Instrumentation and Measurement, vol. 74, pp. 1-13, 2025, Art no. 2533413, doi: 10.1109/TIM.2025.3552811.
2. 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.
3. 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.
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.