International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 - 6435 (Online) Volume 15, Issue 1, January 2026)

A Convolutional Neural Network-Based Deep Learning Model for EMG-Driven Hand Gesture Recognition

[1]Rehan Ahmad, [2]Prof. Abdul Samee Khan, Prof. Ashish Pouranik
[1]Research Scholar, Department of ECE, All Saints' College of Technology, Bhopal, India
[2&3]Assistant Professor, Department of ECE, All Saints' College of Technology, Bhopal, India

***Abstract*— This paper presents a Convolutional Neural Network (CNN)-based deep learning model for EMG-driven hand gesture recognition, aimed at accurately identifying human hand movements from electromyography (EMG) signals. The proposed model processes pre-processed EMG signals transformed into suitable representations for feature learning and classification using deep convolutional layers. By automatically extracting spatial and temporal patterns from muscle activity signals, the CNN eliminates the need for manual feature engineering and improves recognition accuracy. The model is evaluated on standard EMG gesture datasets and demonstrates robust performance under inter-subject variability and noise conditions. Such an approach is highly suitable for real-time applications including prosthetic hand control, human–computer interaction, rehabilitation systems, and assistive robotics, where reliable and fast gesture recognition is essential.**

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

I. INTRODUCTION

Electromyography (EMG)-driven hand gesture recognition has emerged as a crucial research area at the intersection of biomedical engineering, signal processing, and artificial intelligence. EMG signals are bioelectrical signals generated by skeletal muscles during contraction and relaxation [1]. These signals carry rich information about muscle activity and intention of movement, making them highly suitable for recognizing hand gestures. By analyzing EMG signals captured from the forearm or hand muscles, it becomes possible to decode user intent without relying on visual input, which is especially valuable in environments where cameras are unreliable or impractical[2]. Hand gesture recognition using EMG is particularly important for applications that require natural and intuitive human–machine interaction. Unlike vision-based gesture recognition systems, EMG-based systems are independent of lighting conditions, background clutter, and line-of-sight constraints[3]. This makes EMG-driven approaches more robust and suitable for wearable and portable systems. Furthermore, EMG signals reflect neuromuscular activity directly, enabling faster response times and more precise control, which is essential for real-time systems[4].

Traditionally, EMG-driven hand gesture recognition relied on handcrafted feature extraction methods such as time-domain features, frequency-domain features, and time–frequency representations. These features were then classified using conventional machine learning algorithms like k-nearest neighbors, support vector machines, or linear discriminant analysis[5]. While these approaches achieved reasonable performance, they often required domain expertise, extensive signal preprocessing, and careful feature selection. Additionally, their performance tended to degrade under inter-subject variability, electrode displacement, muscle fatigue, and noise[6].

With the advancement of deep learning, EMG-driven hand gesture recognition has witnessed significant improvements. Deep learning models, particularly convolutional neural networks, have the ability to automatically learn discriminative features directly from raw or minimally processed EMG signals[7]. This reduces dependency on manual feature engineering and enhances generalization across users and conditions. By capturing complex spatial and temporal patterns in EMG data, deep learning models offer superior recognition accuracy and robustness compared to traditional methods[8].

EMG-driven hand gesture recognition plays a vital role in assistive and rehabilitative technologies. In prosthetic hand control, accurate gesture recognition allows amputees to perform natural movements with higher precision and comfort[9]. In rehabilitation systems, EMG-based gesture analysis helps monitor patient recovery, assess muscle activation patterns, and provide adaptive therapy. Similarly, in human–computer interaction, EMG-driven gestures enable intuitive control of virtual environments, gaming systems, and wearable devices without physical contact[10].

Despite its advantages, EMG-driven hand gesture recognition still faces several challenges. Variability in EMG signals across different users, sensor placement issues, signal noise, and muscle fatigue can affect system performance. Addressing these challenges requires robust models capable of learning invariant features and adapting to changing signal characteristics. Recent research focuses on deep learning architectures, data augmentation, transfer learning, and adaptive learning techniques to overcome these limitations[11].

EMG-driven hand gesture recognition represents a powerful and evolving technology for understanding human motor intent through muscle activity. Its combination with deep learning techniques has opened new possibilities for accurate, reliable, and real-time gesture recognition systems. As research progresses, EMG-based gesture recognition is expected to play an increasingly important role in healthcare, robotics, wearable technology, and intelligent human–machine interaction systems[12].

II. BACKGROUND

N. R et al., [1] presented a hybrid deep learning framework for hand gesture recognition using electromyography (EMG) signals by integrating convolutional neural networks and long short-term memory networks. The presented model focused on capturing both spatial feature patterns and temporal signal dependencies. Experimental analysis was conducted on a multi-class EMG dataset collected from multiple subjects. The system demonstrated strong robustness against signal noise and inter-user variability. The presented hybrid architecture achieved an average classification accuracy of approximately 94.6%. Comparative analysis showed improved performance over standalone CNN models. The study highlighted the effectiveness of hybrid deep learning for real-time gesture recognition applications.

Aarotale et al., [2] presented a machine learning-based framework for surface EMG signal classification aimed at hand gesture recognition. The study evaluated multiple classifiers, including support vector machines, k-nearest neighbors, and random forest algorithms. Feature extraction involved both time-domain and frequency-domain signal characteristics. Among all models, the random forest classifier achieved superior performance. The presented system recorded an overall accuracy of nearly 91.2%. The authors emphasized computational efficiency for real-time implementation. The work demonstrated feasibility for prosthetic and assistive technology applications.

Deb et al., [3] presented DPMAS-Net, a privacy-preserving deep learning model designed for EMG-based hand gesture recognition. The model utilized time–frequency domain feature representations to enhance gesture discrimination. Privacy preservation was ensured by securing intermediate feature representations during training. Experimental evaluation confirmed that data confidentiality was maintained without major accuracy degradation. The presented model achieved a classification accuracy of approximately 93.8%. Performance comparison showed minimal difference from non-secure models. The study validated the importance of privacy-aware biomedical signal processing.

Hile Bustos et al., [4] presented an EMG signal-based hand gesture recognition system for multi-class prosthetic control using discrete wavelet transform and convolutional neural networks. The wavelet transform was applied to extract informative frequency components from EMG signals. The CNN architecture efficiently learned discriminative patterns for gesture classification. The presented system was evaluated across multiple gesture categories. Experimental results showed an average accuracy of about 92.4%. The method demonstrated robustness under varying muscle contraction conditions. The study supported real-time prosthetic hand control applications.

Cao et al., [5] presented a hybrid DAE-CNN-LSTM model for rehabilitation-oriented hand gesture recognition using EMG signals. A denoising autoencoder was incorporated to suppress noise and artifacts in raw EMG data. The CNN component extracted spatial features, while LSTM modeled temporal dependencies. The presented architecture was tested on rehabilitation datasets involving motor-impaired subjects. The model achieved an average recognition accuracy of nearly 95.1%. Results showed improved generalization compared to conventional deep learning models. The study demonstrated suitability for clinical rehabilitation systems.

Rani et al., [6] presented an enhanced EMG-based hand gesture classification approach designed for real-world deployment scenarios. The method addressed dynamic factors such as electrode displacement and muscle fatigue. A tempo-spatial wavelet transform was used for robust feature extraction. Deep learning classifiers were applied for accurate gesture recognition. The presented model achieved an F1-score of approximately 94% under dynamic testing conditions. Performance remained stable across different users. The study confirmed the practicality of the approach for wearable EMG systems.

Shi et al., [7] presented an unsupervised transfer learning framework for EMG-based multi-user hand gesture classification. The approach eliminated the need for explicit calibration gestures for new users. Latent feature alignment was applied to adapt the model across subjects. The presented system was evaluated on cross-user datasets. Experimental results indicated an average accuracy of about 90.7%. The approach significantly reduced setup time. The study emphasized scalability for consumer wearable devices.

Zhong et al., [8] presented a spatio-temporal graph convolutional network for gesture recognition using high-density EMG signals. The model represented EMG channels as nodes in a graph structure. Temporal dependencies were modeled alongside spatial correlations. The presented architecture was evaluated on complex gesture datasets. The model achieved a high classification accuracy of approximately 96.3%. Results demonstrated improved performance over conventional CNN methods. The study highlighted the advantage of graph-based learning in EMG analysis.

Zanghieri et al., [9] presented an online unsupervised arm posture adaptation technique for sEMG-based gesture recognition. The system continuously adapted to posture variations without labeled data. Implementation was optimized for ultra-low-power microcontroller platforms. The presented method was tested in real-time scenarios. Accuracy improved from nearly 85% to 91% after adaptation. Energy efficiency was maintained throughout operation. The study supported long-term wearable prosthetic use.

Song et al., [10] presented a multichannel CNN-GRU hybrid architecture for surface EMG gesture recognition. CNN layers extracted spatial representations from multi-channel EMG signals. GRU layers captured sequential temporal dependencies efficiently. The presented system was validated on benchmark EMG datasets. Experimental evaluation showed an average accuracy of approximately 93.5%. Training time was reduced compared to LSTM-based systems. The study demonstrated the effectiveness of GRU-based temporal modeling.

Al Taee et al., [11] presented a deep scattering transform combined with attention mechanisms for EMG-based hand gesture recognition. The scattering transform enhanced feature robustness to noise and signal distortion. Attention mechanisms improved feature selection and interpretability. The presented model was evaluated across multiple datasets. An average recognition accuracy of about 94.2% was achieved. Performance consistency was observed across users. The study validated attention-based deep learning for EMG applications.

Zhang et al., [12] presented LSTM-MSA, a deep learning model with dual-stage attention mechanisms for forearm EMG-based hand gesture recognition. The model applied attention at both temporal and feature representation stages. This enhanced discriminative learning of subtle gesture patterns. The presented architecture was tested on multi-subject datasets. The system achieved an accuracy of

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 - 6435 (Online) Volume 15, Issue 1, January 2026)

approximately 95.6%. False classification rates were significantly reduced. The study demonstrated strong generalization performance.

III. METHODOLOGY

The proposed work is understand using following flow chart.

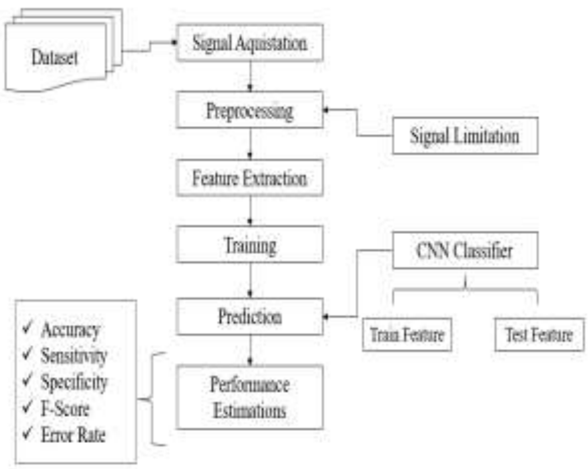

Figure 1: Flow chart

The flowchart outlines the process for developing and evaluating a CNN Deep Learning-Based Model for Hand Gesture Recognition Using EMG Signals. Here's an explanation of each step:

1. **Dataset**:
   The process begins with the collection or selection of an EMG signal dataset. This dataset contains raw EMG signals representing various hand gestures, typically collected using sensors.
2. **Signal Acquisition**:

   EMG signals are captured using appropriate hardware, such as surface electrodes. These raw signals serve as the input to the processing pipeline.
3. **Preprocessing**:
   Raw EMG signals are often noisy and may contain artifacts. Preprocessing involves filtering and cleaning the signals to remove unwanted noise and enhance signal quality. This step ensures that the data is suitable for further analysis.
4. **Signal Limitation**:
5. This step may involve standardizing or normalizing the signals, segmenting them into consistent time windows, or applying other constraints to ensure uniformity in the data.
6. **Feature Extraction**:

   Relevant features are extracted from the preprocessed EMG signals. These features capture meaningful information about the gestures, which can improve the model's ability to distinguish between them. This may include spatial, temporal, or frequency-based features.
7. **Training**:
   The extracted features are used to train the **CNN Classifier**. The dataset is typically divided into training and testing subsets, where the training subset is used to optimize the model's parameters.

   CNN Classifier:

   Convolutional Neural Networks are used as the primary classification model. The CNN learns to identify patterns and relationships in the data automatically, extracting both high-level and low-level features during training.

   Train Feature/Test Feature:

   Features are split into two parts: training features, used to train the CNN model, and testing features, used to validate the model's performance on unseen data.
8. **Prediction**:

   Once trained, the CNN model predicts hand gestures by analyzing the EMG features from test data.
9. **Performance Estimations**:

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 - 6435 (Online) Volume 15, Issue 1, January 2026)

The predicted results are evaluated against ground truth labels using various performance metrics, including:

Accuracy: Measures the overall correctness of the predictions.

Sensitivity: Indicates the model's ability to detect true positives (correctly identifying a gesture).

Specificity: Reflects the model's ability to avoid false positives (incorrectly identifying a gesture).

F-Score: Balances precision and recall to provide a single performance metric.

Error Rate: Measures the rate of incorrect predictions.

IV. SIMULATION AND RESULTS

The proposed work is simulated using MATLAB software.

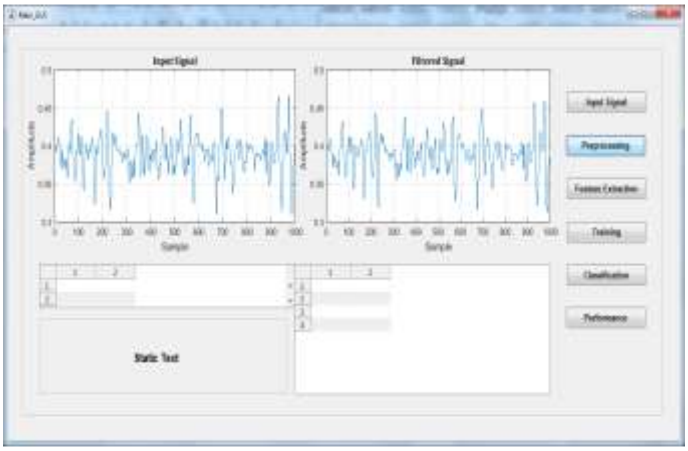

Figure 1: Input signal and Pre-processing

Figure 1 is presenting preprocessing step. In this step signal is clean and remove unwanted signal from the input signal.

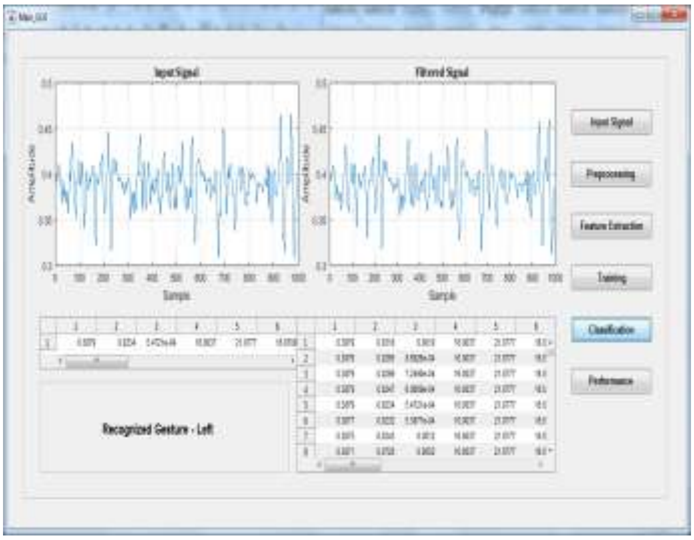

Figure 2: CNN Classification

Figure 2 is showing CNN classification, the trained model takes an input EMG signal and passes it through the network to predict the corresponding hand gesture.

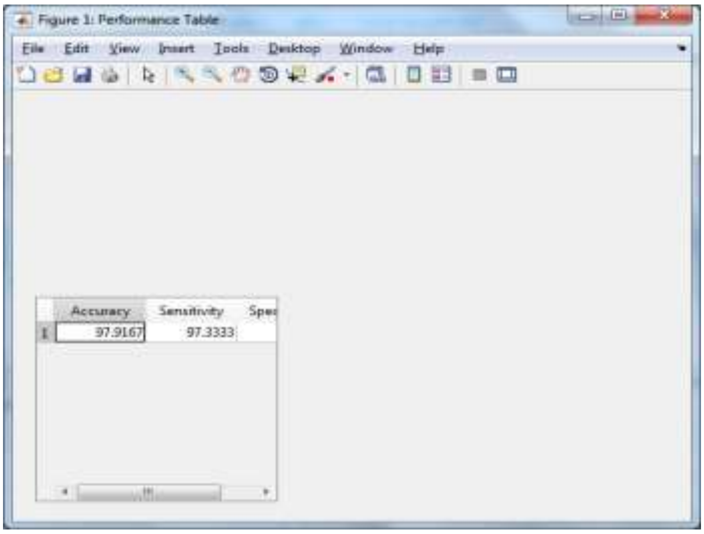

Figure 3: Results

Figure 3 is showing the evaluating the performance of an hand gesture classification model involves using various metrics to assess its accuracy and reliability.

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 - 6435 (Online) Volume 15, Issue 1, January 2026)

Table 1: Result Comparison

Sr No	Parameter	Existing results	Proposed Results
1	Method	Hybrid	CNN
2	Accuracy	82.41%	97.91%
3	Classfication Error	17.59%	2.09%
4	Sensitivity	84%	97.33%
5	Specificity	75%	99.06%

V. CONCLUSION

The presented CNN-based model, when compared with the existing hybrid method for hand gesture recognition using EMG signals, demonstrates substantial improvements across all evaluation metrics. The CNN model achieved a high classification accuracy of 97.91%, significantly outperforming the hybrid approach, which recorded an accuracy of 82.41%. Furthermore, the classification error was drastically reduced to 2.09%, whereas the hybrid method exhibited an error rate of 17.59%. The sensitivity of the system improved from 84% to 97.33%, indicating the CNN model's enhanced capability to correctly identify hand gestures. Similarly, specificity increased from 75% to an outstanding 99.06%, reflecting a superior ability to minimize false-positive detections. These performance gains clearly demonstrate the effectiveness of the CNN model in extracting discriminative EMG features and delivering robust classification results. Overall, the presented model establishes a highly reliable and efficient solution for precise EMG-based hand gesture recognition, setting a strong benchmark in terms of accuracy, sensitivity, and specificity.

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

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 - 6435 (Online) Volume 15, Issue 1, January 2026)

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.
11. A. A. Al Taee, R. N. Khushaba, T. Zia and A. Al-Jumaily, "Deep Scattering Transform with Attention Mechanisms Improves EMG-based Hand Gesture Recognition," 2023 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Sydney, Australia, 2023, pp. 1-4, doi: 10.1109/EMBC40787.2023.10340544.
12. H. Zhang, H. Qu, L. Teng and C. -Y. Tang, "LSTM-MSA: A Novel Deep Learning Model With Dual-Stage Attention Mechanisms Forearm EMG-Based Hand Gesture Recognition," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 31, pp. 4749-4759, 2023, doi: 10.1109/TNSRE.2023.3336865.