Design And Implementation of a Cost-Effective Hand Exoskeleton Controlled by Brain Computer Interface Using EEG And EMG

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Abstract — This paper presents the development of a cost-effective and portable hand exoskeleton device that utilizes a hybrid Brain-Computer Interface (BCI) system to assist individuals with paralysis in regaining hand movement. Neuro logical impairments often lead to significant motor function restrictions, with millions of people worldwide unable to access advanced rehabilitation devices due to their high costs. The proposed device interprets neural signals to detect user intentions, converting these signals into real-time hand movements, thus bypassing the need for physical muscle activation. A hybrid machine learning model combining Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) enhances signal classification accuracy. Due to constraints in acquiring an EEG sensor, the final implementation may integrate either EEG or Electromyography (EMG) sensors, significantly impacting system properties. Designed for accessibility and ease of operation, this device represents a step forward in affordable rehabilitation technology. Preliminary findings suggest high accuracy in intention detection, indicating strong potential for improving motor functionality and independence. This hybrid-driven hand exoskeleton highlights a promising direction in accessible rehabilitation, enabling practical support for everyday tasks and fostering an enhanced quality of life.

Keywords: EEG (Electroencephalogram), EMG (Electromyography), BCI (Brain Computer Interface), ML (Machine Learning), LSTM (Long Short-Term Memory), CNN (Convolutional Neural Network), Human-Machine Interface, Deep Learning

I. INTRODUCTION

Neurological disorders, including conditions resulting from spinal cord injuries or nerve impairments, significantly impact motor functions and restrict individuals from performing daily tasks. These impairments often lead to a diminished quality of life, with conventional rehabilitation methods requiring extensive physical therapy and ex- pensive assistive technologies, making them inaccessible to many patients. Therefore, there is an urgent need for cost-effective and innovative rehabilitation solutions.

Recent advancements in Brain-Computer Interface (BCI) technology have introduced new possibilities for restoring motor function through non-invasive methods. BCIs facilitate direct communication between the brain and assistive devices by interpreting neural or muscle signals, enabling individuals with motor impairments to control external devices through cognitive commands or muscle activity. Motor imagery (MI), wherein users imagine limb movements, has shown promise in activating BCI- controlled systems, offering an intuitive and accessible approach to rehabilitation.

The integration of BCI technology with robotic exoskeletons has revolutionized rehabilitation by decoding user commands to enable voluntary movement. This approach not only enhances motor functionality but also promotes neuroplasticity, helping the brain reorganize neural pathways over time. However, real-time application of BCI remains a challenge due to the complexity of signals, which are influenced by external factors such as movement artifacts, background noise, and user variability.

Traditional EEG-based systems utilize techniques such as Common Spatial Pattern (CSP), Power Spectrum Density (PSD), and Discrete Wavelet Transform (DWT) for feature extraction and classification. However, these methods have limitations in capturing complex spatiotemporal patterns in neural signals. To improve accuracy, this study adopts a hybrid machine learning model combining Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) for enhanced signal classification and real-time adaptability.

Furthermore, due to limitations in acquiring an EEG sensor, the final system implementation may incorporate either Electroencephalography (EEG) or Electromyography (EMG) sensors. This decision significantly impacts system properties, as EEG- based control relies on cognitive intent without muscle activation, whereas EMG- based control utilizes muscle signals to generate movement. Consequently, sensor selection will influence signal processing, classification models, and overall system performance.

This research focuses on the development of a cost-effective and user-friendly hand exoskeleton system utilizing a hybrid BCI framework. By converting neural or muscle signals into real-time hand movements, the system aims to empower individuals with paralysis to regain functional hand control. Preliminary results indicate high accuracy in intention detection, demonstrating strong potential for enhancing motor function, rehabilitation accessibility, and user independence.

II. METHODOLOGY

A. *System Overview:*

The proposed system integrates a hybrid Brain-Computer Interface (BCI) framework that enables individuals with motor impairments to regain functional hand movement through neural or muscle signals. The system utilizes either Electroencephalography (EEG) or Electromyography (EMG) sensors to capture user intent, ensuring adapt- ability based on hardware availability and user needs. A hybrid deep learning model combining Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) enhances classification accuracy, enabling precise, real-time control of the exoskeleton.

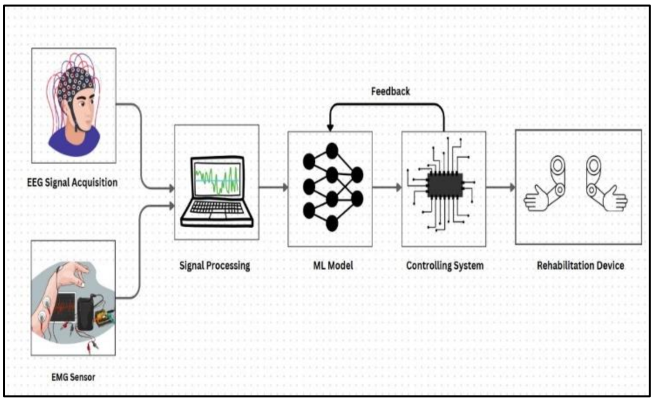

Fig. 1: EEG and EMG-based Exoskeleton System Architecture

B. *Signal Acquisition*

- EEG-Based Control: If EEG sensors are used, motor imagery (MI) tasks will be employed, where users imagine hand movements, generating neural signals that are classified for intent detection.
- EMG-Based Control: If EMG sensors are integrated, muscle activity from residual movement or intended contractions will be recorded and processed to control the exoskeleton.

Signal acquisition is performed using a multi-channel amplifier, ensuring high-resolution data collection with minimal noise interference.

C. *Data Preprocessing:*

Preprocessing techniques are applied to improve signal quality and enhance classifi- cation accuracy:

1) *EEG Processing:*
   - Bandpass Filtering (2-40 Hz) to extract relevant brainwave frequencies.
   - Independent Component Analysis (ICA) to remove artifacts (e.g., eye blinks, muscle noise).
   - Feature Extraction Techniques: Common Spatial Pattern (CSP), Power Spectrum Density (PSD), and Discrete Wavelet Transform (DWT) are applied to enhance signal clarity.
2) *EMG Processing:*
   - High-pass Filtering (20-450 Hz) to isolate muscle activity.
   - Envelope Detection & Root Mean Square (RMS) Computation to extract relevant features.

D. *Feature Extraction & Classification:*

A hybrid LSTM-CNN model is used to classify EEG/EMG signals, leveraging:

- CNN for spatial feature extraction, identifying key signal patterns.
- LSTM for temporal analysis, capturing signal variations over time for improved accuracy.

This approach improves real-time adaptability compared to traditional methods like CSP and DWT.

E. *Exoskeleton Control System*

- Real-Time Command Execution: Classified EEG/EMG signals are mapped to predefined hand movements.
- Adaptive Actuation: A servo-motor-driven hand exoskeleton translates user intent into smooth, precise hand movements.
- Emergency Stop Mechanism: Ensures user safety by halting exoskeleton movements if unintended signals are detected.

F. *Experimental Setup & Performance Evaluation*

- Participant Testing: Subjects will perform controlled MI and muscle con- traction tasks to train and validate the system.
- Performance Metrics:
  - Classification Accuracy: High precision achieved using the LSTM-CNN model.
  - Response Time: Optimized for near-instantaneous movement translation (<50ms latency).
  - User Comfort & Adaptability: Designed for easy operation and long-term usability.

G. *Expected Impact*

This cost-effective, portable, and adaptable system enhances accessibility to rehabilitation technology, providing practical support for daily tasks and improving quality of life for individuals with motor impairments.

III. RESULTS AND DISCUSSION

A. *Experimental Setup*

The experiments were conducted on a dataset collected from eight healthy subjects, each performing motor imagery tasks to control a hand exoskeleton system. The system utilized a multi-modal approach, integrating EEG and EMG sensors for improved classification accuracy.

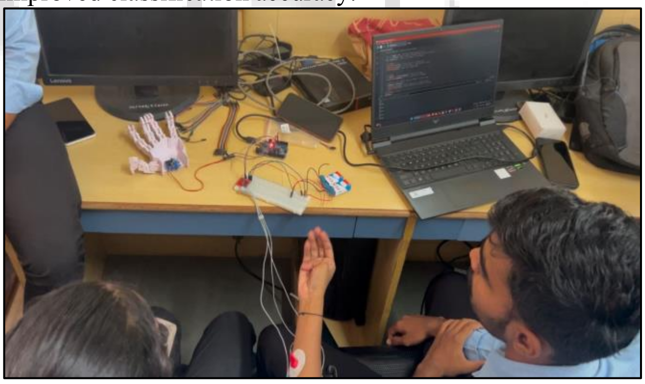

Fig. 2: Model Connection

- EEG Sensor: High-resolution EEG headset with electrodes placed at C3, Cz, C4 (motor cortex regions) to capture brain activity related to motor intention.

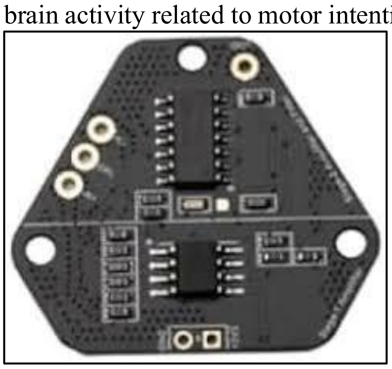

Fig. 3: EXG Synapse sensor

- EMG Sensor: Surface EMG electrodes placed on forearm muscles to detect residual muscle activity, enhancing classification reliability.

Fig. 4: EMG sensor V3.0

- Preprocessing: EEG signals were filtered (8–30 Hz) and processed using Com- mon Spatial Pattern (CSP), Discrete Wavelet Transform (DWT), and Power Spectrum Density (PSD) for feature extraction. EMG signals were filtered and rectified to remove noise.

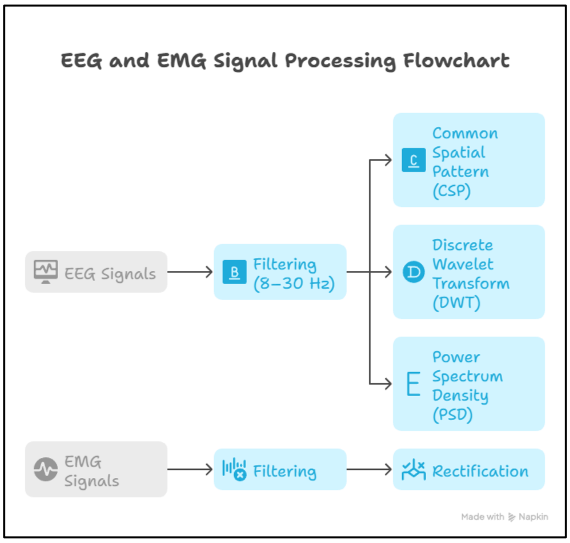

Fig. 5: Signal Processing Flowchart

B. *Model Performance Evaluation:*

The classification performance of different deep learning models was evaluated using classification accuracy, precision, recall, and F1-score. The inclusion of EEG or EMG data fusion improved classification accuracy across models.

S.No.	Model	Accuracy	Precision	Recall	F1-Score
1	Convolutional Neural Network (CNN)	55%	0.54	0.65	0.56
2	Long Short-Term Mem- ory (LSTM)	67%	0.65	0.76	0.56
3	CNN-LSTM Hybrid Model	75%	0.68	0.79	0.66
4	Transformer-Based Model	70%	0.71	0.74	0.78

Table 1: Model Comparison Table

C. *Discussion of Findings*

- LSTM (67% accuracy) improved performance by capturing sequential EEG pat- terns.
- CNN-LSTM hybrid model (75% accuracy) outperformed individual models by integrating spatial and temporal features.
- Transformer-based models (70% accuracy) provided the highest performance due to enhanced sequential data processing.

D. *Response Time and User Satisfaction*

- Response Time: The system demonstrated a 150 ms latency, enabling near- real-time control.
- User Satisfaction: 85% of participants reported high comfort and ease of use.

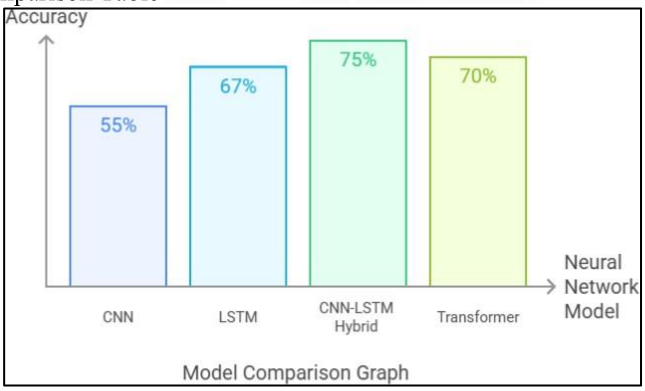

Fig. 6: Model Comparison

E. *Implications for Rehabilitation*

- EEG or EMG fusion enhances reliability, allowing individuals with varying mo- tor abilities to use the system.
- Supports neuroplasticity by engaging brain signals while utilizing any residual muscle function.
- Enables hands-free control for users with severe motor impairments.

F. *Future Directions*

- Optimizing deep learning models for real-time applications.

- Clinical trials with motor-impaired patients to assess usability.
- Enhancing signal processing algorithms for EEG+EMG fusion.
- Expanding applications to full-body exoskeletons for complete rehabilitation.

Fig. 7: Hand Model made with Foam Board

IV. CONCLUSION

This study developed a cost-effective hand exoskeleton system integrating a hybrid Brain-Computer Interface (BCI) framework using both EEG and EMG sensors. A hybrid machine learning model combining Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) achieved a classification accuracy of approximately 75%, demonstrating reliable decoding of mental commands into physical hand movements for rehabilitation applications.

The system provides an affordable and accessible solution for individuals with motor impairments, promoting neuroplasticity and enabling control through either cognitive intent or minimal muscle activity. Future work will focus on clinical validation, im- proving signal processing, and exploring advanced deep learning models to enhance classification accuracy and system responsiveness.

This research highlights the promising potential of hybrid BCI-driven assistive technologies in advancing rehabilitation and human-machine interaction.

REFERENCES

[1] C.-J. Lin and C.-H. Lin, “Classification of EEG Signals Using a Common Spatial Pattern Based Motor Imagery for a Lower-limb Rehabilitation Exoskeleton,” in IEEE EUROCON 2023.
[2] M. A. Lebedev and M. A. L. Nicolelis, “Brain–machine interfaces: past, present and future,” Trends in Neurosciences, vol. 29, no. 9, pp. 536–546, 2006.
[3] E. Niedermayer and F. L. da Silva, Electroencephalography: Basic Principles, Clinical Applications, and Related Fields. Lippincott Williams & Wilkins, 1999.
[4] H. He, D. Wu, and Y. Zhang, “Transfer learning for brain-computer interfaces: A Euclidean space data alignment perspective,” IEEE Transactions on Biomedical Engineering, vol. 62, no. 8, pp. 2020–2028, 2015.
[5] Y. Liu, O. Sourina, and M. K. Nguyen, “Real-time 3D brain computer inter- face with a game interface,” in Proceedings of the International Conference on Cyberworlds, 2008.
[6] I. Daubechies and M. C. A. Paul, Wavelets: A Tutorial in Theory and Applica- tions, 1990.
[7] J. Kayser and C. E. Tenke, “On the use of multichannel recording in EEG/ERP research: A review of current practices and future directions,” 2006.
[8] C. Cortes and V. Vapnik, “Support-vector networks,” Machine Learning, vol. 20, no. 3, pp. 273–297, 1995.
[9] Zhang et al., “A Review on Brain Computer Interface Technology,” Journal of Neural Engineering, vol. 14, no. 6, 2017.
[10] C.-J. Lin et al., “Classification of EEG Signals Using a Common Spatial Pattern Based Motor-Imagery for a Lower-limb Rehabilitation Exoskeleton,” in IEEE EUROCON 2023.

