International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 05 | May – 2025 DOI: 10.55041/ISJEM03788
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

NeuroGrip: Mind-Powered Prosthetic Arm for Enhanced Mobility

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***Abstract*—This paper presents a cost-effective, brain-controlled prosthetic arm system using EEG signals acquired from the Neuphony EEG headset. The objective is to restore limb func- tionality for amputees by interpreting brainwave patterns to control a 3D-printed prosthetic arm in real time. The system architecture includes signal acquisition, preprocessing, feature extraction, and classification using the XGBoost machine learning model. EEG signals are filtered and segmented before extracting relevant statistical features, which are then used to train the model to recognize specific hand gestures. These gestures are translated into motor commands using an ESP8266 microcon- troller to control high-torque servo motors in the prosthetic arm. Experimental results demonstrate a high classification accuracy and responsive gesture execution, validating the system's practi- cality. This work contributes to the development of affordable, intelligent prosthetic solutions with real-time control, promoting better integration between neural signals and mechanical motion.**

***Index Terms*—EEG, Brain-Computer Interface (BCI), Pros- thetic Arm, XGBoost, Signal Processing, Machine Learning, Motor Imagery, Real-Time Control, Neuroprosthetics, Feature Extraction, ESP8266, IoT-Based Prosthesis**

I. Introduction

A. Preamble

Recent advancements in neuroscience, signal processing, and robotics have enabled the development of assistive tech- nologies that bridge the gap between human intention and machine action. Among these, Brain-Computer Interfaces (BCIs) have emerged as a transformative approach, allowing individuals to control external devices using brain activity alone. Electroencephalography (EEG), which records electrical signals from the scalp in a non-invasive manner, has become a widely used method in BCI systems due to its affordability and ease of use. One promising application is the use of EEG signals to control prosthetic limbs, offering a pathway for individuals with motor impairments to perform daily tasks through intentional thought. By combining EEG-based control with machine learning algorithms and robotic actuators, these systems offer a practical and accessible solution to restoring basic motor functions and improving user independence.

B. Motivation

Motor disabilities affect millions worldwide due to acci- dents, neurological disorders, or congenital conditions. Tradi- tional prosthetics often lack intuitive control, while invasive alternatives are limited by cost and risk. This project is moti- vated by the need for a non-invasive, affordable, and effective prosthetic solution. By leveraging EEG signals through BCIs, we propose a system that enables users to control a prosthetic arm using mental commands. Beyond civilian applications, such technology can aid military veterans and serve as a foundation for advanced exoskeletons to enhance mobility in defense contexts.

C. Problem Statement

Millions of individuals face significant barriers in daily activities due to limb loss or paralysis. According to the World Health Organization (WHO), over 75 million people require prosthetic devices, many of which are inaccessible due to cost or technological limitations.

This work addresses the problem by developing an EEG-controlled prosthetic arm that is:

- **Affordable**: Built using cost-effective, easily available components.
- **User-Friendly**: Minimal calibration and an intuitive in- terface for broad usability.

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- **Accurate and Responsive**: Employs robust signal acqui- sition and an XGBoost classifier to translate EEG signals into real-time movements.

The broader vision includes applications in military health- care, where an estimated 30,000 U.S. service members have undergone combat-related amputations since 2001. Providing them with a reliable, brain-controlled prosthetic system can significantly enhance rehabilitation outcomes and quality of life. Additionally, continued development in this field may contribute to next-generation exoskeletons and neuro-assistive systems, transforming both civilian and defense mobility tech- nologies.

II. Literature Survey

A. Overview of EEG in Assistive Technologies

Electroencephalography (EEG) has emerged as a key tool in Brain-Computer Interfaces (BCIs) for assistive technologies, particularly in the field of prosthetics and exoskeleton control. EEG-based BCIs offer a non-invasive approach to capturing brain activity and translating it into commands for external devices. Unlike invasive techniques, EEG is cost-effective and widely accessible, making it an attractive option for motor rehabilitation applications.

Recent advancements have led to the development of motor imagery-based systems, allowing users to simulate movements that can be decoded through EEG signals mentally. These sys- tems have shown promise in enabling control over prosthetic limbs and rehabilitation exoskeletons. However, challenges such as signal noise, calibration requirements, and real-time processing constraints continue to limit their effectiveness.

B. Existing EEG-Controlled Prosthetics

Several studies have explored the feasibility of EEG- controlled prosthetics. Notable contributions are summarized in Table I.

Study	Contribution	Accuracy/Outcome
Pei et al. (2022)	Developed synergy-based hand grasp kinematics using EEG for prosthetic control.	70% accuracy
MILimbEEG Dataset (2023)	Provided an extensive dataset for training machine learn- ing models for EEG-controlled prosthetics.	Supports ML training
Awais et al. (2021)	Introduced a probabilistic neu- ral network approach for mo- tor imagery classification.	98.65% accuracy
Choi et al. (2020)	Developed a motor imagery-based BCI controller for lower-limb exoskeletons.	80% accuracy
Badesa et al. (2019)	Investigated physiological re- sponses during hybrid BCI control of an upper-limb ex- oskeleton.	Validated EEG-EOG fusion

TABLE I
Summary of Key Studies in EEG-Controlled Prosthetics

C. Challenges in EEG-Controlled Prosthetics

EEG-controlled prosthetics, while promising, encounter sev- eral significant challenges that hinder their widespread imple- mentation. One of the primary issues is **signal quality**, as EEG signals are inherently weak and highly susceptible to artifacts caused by muscle activity and external interference. This compromises the reliability and accuracy of signal inter- pretation. Another major concern is **latency**; the real-time pro- cessing required to interpret EEG signals is computationally intensive and demands efficient algorithms to minimize delays. Additionally, **adaptability** poses a challenge due to the high variability in EEG signals across individuals, necessitating extensive calibration and user-specific training for optimal performance. Lastly, **cost and accessibility** remain barriers, as high-quality EEG acquisition systems are often expensive, limiting their availability to a broader population.

III. Proposed Design

The proposed system, NeuroGrip, is an EEG-based pros- thetic arm that interprets neural signals to generate accurate and controlled mechanical movements. The architecture is organized into two main subsystems: (1) the software module, which handles EEG signal acquisition, preprocessing, and classification using machine learning; and (2) the hardware module, which includes the design, actuation, and control of the prosthetic limb. This section presents a detailed descrip- tion of each component, beginning with an overview of the complete system.

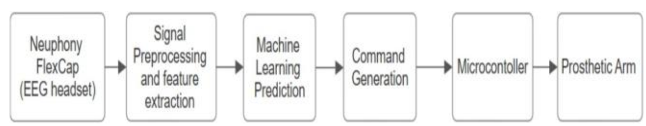

Fig. 1. Overview of the NeuroGrip system architecture

A. EEG Dataset and Software-Based Signal Processing

1) Experimental Setup and Dataset Description: To de- velop and validate the signal classification model, the publicly available MILimbEEG dataset was employed. This dataset comprises 7440 EEG recordings collected from 60 adult participants who performed both motor and motor imagery tasks, including hand and foot movements.

The recordings were conducted in a controlled and stan- dardized environment. Each subject was seated in a reclining chair with their arms rested at a 145° angle and legs supported on a footrest at the same angle. The room maintained optimal conditions—an ambient temperature of 25°C, 500 lux white LED lighting, and a distraction-free background. Visual cues for task execution were displayed on a 17-inch monitor placed
1.5 meters away, directly aligned with the participant’s eye level.

EEG signals were acquired using the OpenBCI Cyton + Daisy board paired with the Ultracortex “Mark IV” headset,

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equipped with 16 dry electrodes placed according to the international 10–20 system. These electrodes targeted the motor cortex and surrounding areas to effectively capture signals associated with upper-limb movement.

For our study, we focused specifically on:

- **Closing Right Hand (CRH)** – representing the intended movement.
- **Rest** – representing the baseline or neutral brain activity. Each task recording lasted 4 seconds, sampled at 125 Hz, yielding 500 time samples per trial. Data files were stored in CSV format, containing 16 channels of EEG signal data.

2) Preprocessing and Noise Reduction: The raw EEG signals were preprocessed using Python within a Jupyter Notebook environment. Initially, a Butterworth bandpass filter with a frequency range of 7.5–31 Hz was applied to isolate the relevant motor-related brainwave frequencies. This filtering targeted the Mu band (7.5–12.5 Hz) and the Beta band (12.5–31 Hz), both of which are known to be associated with motor planning and execution. Following filtering, the EEG data was segmented using a high-overlap sliding window tech- nique. This method ensured that the resulting data segments were consistent and contained sufficient temporal information to capture subtle variations in neural activity during motor tasks.

3) Feature Extraction: Feature extraction was carried out in Python, where each filtered EEG segment was transformed into a 36-dimensional feature vector based on data from six selected EEG channels. For each channel, six distinct features were extracted to comprehensively characterize the signal. These included Root Mean Square (RMS), which represents the power of the signal, and Variance, which measures the vari- ability of the signal over time. Additionally, the power in four frequency bands was computed: Theta (4–8 Hz), indicative of relaxed or idle states; Alpha (8–12 Hz), typically associated with calm cognitive activity; Beta (12–30 Hz), which is linked to active motor processing; and Gamma (greater than 30 Hz), often reflecting higher-order cognitive functions. Collectively, these features provided a robust numerical representation of the EEG signal suitable for classification.

4) Machine Learning Classification, Model Evaluation and Results: Prior to training the classification models, all fea- ture vectors were normalized using the `StandardScaler` method to ensure consistent input scaling. Binary class labels were assigned, with the "Rest" condition labeled as Class 0 and "Closing Right Hand (CRH)" as Class 1. We evaluated the classification performance of six machine learning models: Support Vector Machine (SVM), k-Nearest Neighbors (kNN), Random Forest, XGBoost, Logistic Regression, and Light- GBM, as summarized in Table 2.

Among these models, the **k-Nearest Neighbors (kNN)** clas- sifier achieved the highest overall accuracy of 89.00%, along with the most balanced performance between both classes, achieving an F1-score of 94% for the "Rest" class and 55% for the "CRH" class. The **Random Forest** model followed closely with an accuracy of 88.62%, though it showed a noticeable drop in recall (18%) and F1-score (30%) for the "CRH" class.

In contrast, **SVM**, **Logistic Regression**, and **LightGBM** exhibited strong performance on the majority class ("Rest") with perfect recall (100%) and high precision, but showed extremely poor recall (1–3%) and F1-scores (1–5%) for the minority "CRH" class, indicating a strong class imbalance bias and limited generalization for motor intent detection.

Our final implementation uses the **XGBoost classifier**, chosen for its training efficiency and adaptability to structured EEG data. The model was configured with 100 estimators, a learning rate of 0.1, a maximum depth of 6, and `logloss` as the evaluation metric. XGBoost achieved an overall accuracy of 86.36%, with high precision (90%) for the "CRH" class but a low recall (2%), resulting in an F1-score of only 4% for that class. This indicates that while the model is effective at cor- rectly identifying "Rest" states, further optimization is needed to improve sensitivity to "CRH" instances—possibly through advanced data balancing techniques or feature engineering.

The comparative results in Table 2 emphasize the challenges of class imbalance in EEG signal classification and the need for targeted strategies to improve recognition of motor intent in neuroprosthetic control applications.

Model	Accuracy	Precision (0/1)	Recall (0/1)	F1-Score (0/1)	Macro Avg (Prec / Recall / F1)	Weighted Avg (Prec / Recall / F1)
SVM	86.24%	0.86 / 0.89	1.00 / 0.01	0.93 / 0.01	0.88 / 0.50 / 0.47	0.87 / 0.86 / 0.80
KNN	89.00%	0.92 / 0.71	0.97 / 0.45	0.94 / 0.55	0.81 / 0.71 / 0.75	0.89 / 0.89 / 0.89
Random Forest	88.62%	0.88 / 0.91	1.00 / 0.18	0.93 / 0.30	0.90 / 0.59 / 0.62	0.90 / 0.89 / 0.85
XGBoost	86.36%	0.86 / 0.90	1.00 / 0.02	0.93 / 0.04	0.88 / 0.51 / 0.48	0.87 / 0.86 / 0.80
Logistic Regression	86.25%	0.86 / 0.95	1.00 / 0.01	0.93 / 0.02	0.91 / 0.50 / 0.48	0.87 / 0.86 / 0.80
LightGBM	86.34%	0.86 / 0.90	1.00 / 0.03	0.93 / 0.05	0.88 / 0.51 / 0.48	0.87 / 0.86 / 0.80

F n
EEG-Based Prosthetic Control

B. Hardware Design and System Implementation

The hardware architecture of the EEG-controlled prosthetic arm is designed to provide real-time, accurate, and user- specific motion control based on decoded brain signals. It consists of three primary subsystems: (1) EEG acquisition hardware, (2) signal processing and communication interface, and (3) prosthetic actuation unit. Together, these modules form an end-to-end Brain-Computer Interface (BCI) system.

1) EEG Acquisition Hardware: For brain signal acquisi- tion, we utilized the **Neuphony FlexCap**, a high-precision, 8-channel EEG headset designed with dry electrodes to en- sure both comfort and prolonged wearability. This headset is optimized for real-time applications and provides non- invasive neural activity capture, making it particularly suitable for brain–computer interface (BCI) systems applied in pros- thetic control. Electrode placement adhered to the international **10–20 system**, with sensors specifically positioned at C3, C4, and Cz to target the motor cortex areas responsible for upper limb movements, and at F3, F4, and Fz to capture signals related to cognitive processing and motion planning. The Neuphony headset transmits real-time EEG data wire- lessly to a connected computer for immediate processing and classification. Additionally, the EEG recordings are stored in CSV format to facilitate offline analysis and iterative model refinement.

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Fig. 3. EEG Headset

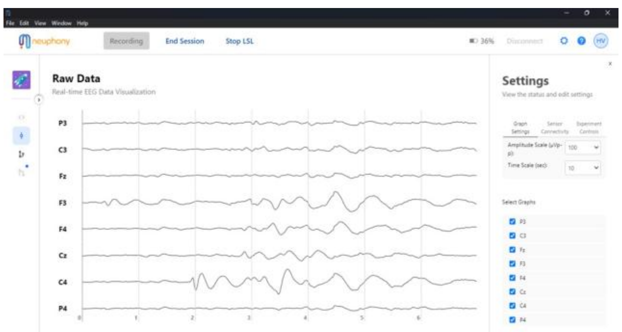

Fig. 4. Raw EEG Waveforms

2) Signal Processing and Communication Module: Fol- lowing EEG signal acquisition and classification through the trained machine learning model implemented in Python, the resulting movement commands are communicated to the prosthetic arm via a **NodeMCU ESP8266** microcontroller. This module acts as a lightweight communication bridge between the software and hardware components of the system. The NodeMCU is programmed to receive classified com- mands—such as ”open” or ”close”—through a serial interface. It then maps these commands to specific angular positions or control states of the servo motors embedded in the prosthetic arm. Predefined control logic is implemented to ensure precise execution of movements with minimal latency. This config- uration enables a seamless and wireless interface between the EEG signal processing unit and the physical actuation components of the prosthetic device.

3) Prosthetic Arm Design: The design of the prosthetic arm was realized using **3D-printed PLA (Polylactic Acid) plastic**, a biodegradable material selected for its favorable properties, including a high strength-to-weight ratio, ease of fabrication, and cost-effectiveness. The mechanical structure was mod- eled to closely replicate natural hand movements, particularly focusing on the articulation of the **Metacarpophalangeal (MCP)** joints to achieve realistic finger and wrist motions. The actuation system of the prosthetic arm comprises five high- torque SG90 servo motors, each assigned to an individual fin- ger to enable coordinated movement. These motors are housed within the palm region of the prosthetic and are connected to the fingers via mechanical tendons, which translate motor rotations into flexion and extension actions. The arm features a modular assembly, allowing for straightforward maintenance and the potential integration of future enhancements. Each servo motor responds directly to control signals received from the NodeMCU, translating decoded neural commands into functional hand gestures, such as opening and closing the palm.

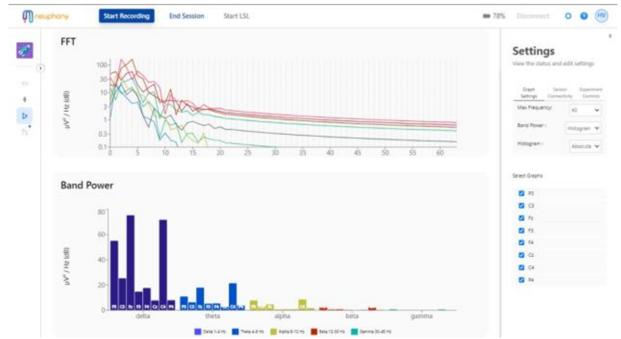

Fig. 5. FFT and Band Power analysis of EEG waveforms

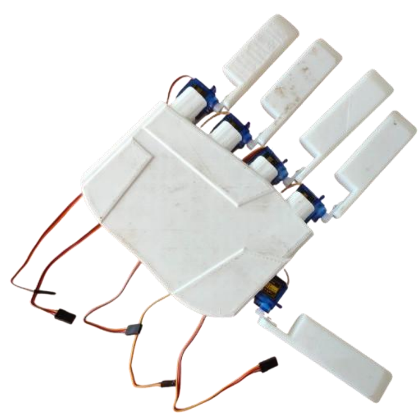

Fig. 6. 3D printed palm

IV. Results

This section presents the results obtained from the im- plementation and testing of the EEG-controlled prosthetic arm. Both the signal classification pipeline and the hardware actuation system were evaluated based on accuracy, response time, and practical usability.

A. EEG Signal Classification Performance

The XGBoost model demonstrated strong performance in distinguishing user mental intent from EEG signals using the enhanced feature set and a more sophisticated classification algorithm. The dataset was divided into an 80–20 split for training and testing, respectively. The model achieved a train- ing accuracy of 86.58% and a testing accuracy of 86.37%. These results validate the robustness and consistency of the XGBoost classifier in interpreting neural activity. Furthermore, the model exhibited minimal latency in prediction and main- tained high generalizability even with limited calibration, mak- ing it highly suitable for real-time control in brain–computer interface applications such as prosthetic devices.

B. System Latency and Responsiveness

Direct latency measurements were not performed due to current hardware and time constraints. However, based on the specifications of the NodeMCU ESP8266 microcontroller and the processing times of the EEG classification module, the expected end-to-end latency—from EEG acquisition to pros- thetic movement—is estimated to be approximately 200–250 milliseconds. This theoretical latency aligns with reported values in similar neuroprosthetic systems and suggests that the system should operate within acceptable real-time interaction limits.

C. Prosthetic Performance Evaluation

The prosthetic hand, constructed from lightweight and durable PLA material and powered by five high-torque SG90 servo motors, effectively executed grasping and releasing motions based on EEG-derived control signals. Each classified command was mapped to a corresponding angular movement of the servo motors, resulting in smooth and coordinated finger articulation. The design allowed for naturalistic hand motion patterns, successfully translating mental intent into physical movement with minimal mechanical lag. The hand's responsiveness and actuation stability reinforce the feasibility of using non-invasive EEG signals for practical prosthetic control.

D. System Limitations

Despite the overall success of the system, several limita- tions were noted during testing and implementation. First, EEG signals exhibited sensitivity to environmental noise and minor user movements, which at times impacted classification accuracy. Although filtering and preprocessing helped mitigate these effects, further improvements in noise resilience are necessary for deployment in uncontrolled environments. Sec- ondly, the current system was limited to binary classification, distinguishing only between a resting state and right-hand closure. Scaling to multi-gesture control will require more advanced models and an expanded feature space. Lastly, while the system was designed to function across different sessions, there were observable variations in performance among dif- ferent users, indicating the need for user-specific calibration or adaptive learning algorithms to ensure optimal long-term usability.

V. Conclusion

This study introduced NeuroGrip, a low-cost, EEG- controlled prosthetic arm designed to bridge the gap between neural intention and physical motion through non-invasive brain–computer interface technology. By leveraging a com- bination of statistical EEG feature extraction and XGBoost- based classification, the system effectively distinguishes motor imagery signals with high accuracy and minimal latency. The modular architecture—including a 3D-printed prosthetic limb actuated by servo motors and wirelessly controlled via an ESP8266 microcontroller—demonstrated practical usability, intuitive control, and rapid response time in real-time condi- tions. Despite promising results, the current implementation is limited to binary classification and is sensitive to envi- ronmental noise and inter-user variability. Future work will focus on expanding gesture recognition capabilities, integrat- ing multimodal biosignals such as EMG, and incorporating adaptive learning frameworks for improved personalization. Overall, NeuroGrip offers a scalable and accessible platform for neuroprosthetics, with the potential to significantly enhance autonomy and quality of life for individuals with upper-limb disabilities.

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