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BioSync Arm: Synchronization between Biological Signals and a Prosthetic Arm

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ABSTRACT: Millions of people worldwide suffer from limb loss due to accidents, congenital conditions, or medical issues, making daily activities difficult. Traditional prosthetic arms often have limited adaptability, control, and sensory feedback. This paper presents an AI-based smart prosthetic arm designed to improve independence and quality of life. The system uses a modular 3D-printed structure for affordability and customization and bending sensors to monitor muscle activity and environmental conditions. The collected EMG signals are amplified, filtered, and processed to identify muscle activity patterns. A machine learning model deployed on a Raspberry Pi interprets these signals to predict hand movements, adjust grip strength, and provide haptic feedback for safer object handling. The system aims to address the limitations of conventional prosthetics through intelligent control and real-time processing. It can support rehabilitation and assist people with disabilities in performing daily activities independently.

KEYWORDS: Prosthetic Arm, AI, Electromyography (EMG), 3D Printing, Gesture Recognition.

I. INTRODUCTION

The loss of an upper limb due to accidents, congenital disorders, neurological diseases, or amputation significantly affects an individual's independence and quality of life. Prosthetic arms are designed to restore lost functionality and help users perform daily activities such as picking up objects, holding a glass of water, lifting a pencil, and typing on a keyboard. However, conventional prosthetic systems often have limitations in adaptability, intelligent control, real-time feedback, and sensory interaction. The high cost of advanced prosthetic devices also restricts their accessibility, particularly in low- and middle-income regions.[7]

Electromyography (EMG) is one of the widely used methods for controlling prosthetic limbs. It involves detecting electrical signals generated by muscle contractions through electrodes placed on the skin. These signals provide information about the user's intended movements and can be processed to control the opening, closing, and gripping actions of a prosthetic hand. Research has demonstrated that EMG signals, combined with machine learning and neural networks, can improve movement recognition, object grasping, and releasing capabilities. However, conventional muscle-based control may not be suitable for individuals with high-level amputations or neuromuscular impairments. Therefore, Electroencephalography (EEG), a non-invasive brain-machine interface technology, has gained attention for enabling prosthetic control through brain activity, motor imagery, and movement intention without depending on residual muscle activity.

Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), the Internet of Things (IoT), and 3D printing have created new opportunities for developing intelligent, affordable, and customizable prosthetic arms. AI and machine learning algorithms can analyze biological signals, recognize user intentions, and translate them into appropriate movements.[4] Furthermore, intelligent systems can adapt to individual users' movements and preferences and support tasks such as picking up, holding, and manipulating objects. Three-dimensional printing also enables the development of customized prosthetic structures that are cost-effective and suitable for individual requirements.

Despite these advancements, several challenges remain in prosthetic development, including improving movement recognition accuracy, reducing computational complexity, and integrating actuators, sensors, and electronic components within the size and weight limitations of a natural limb. Additional challenges arise in designing

prosthetics for children, whose rapid growth and specific ergonomic and functional requirements demand frequent adjustments and customized solutions.

To address these challenges, the development of intelligent prosthetic arms integrating advanced sensing technologies and AI-based control methods offers a promising approach. By combining biological signal processing, machine learning, and customizable mechanical design, future prosthetic systems can provide improved responsiveness, adaptability, and ease of use. These advancements have the potential to enhance the functional capabilities of prosthetic limbs, support users in performing everyday activities, and improve their overall quality of life.

II. LITERATURE REVIEW

1. Satya Sree et al. (2021)

Satya Sree et al. proposed an ensemble machine learning model combining Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) algorithms for hand gesture recognition using surface Electromyography (sEMG) signals. The SVM classifier was used for dimensionality reduction and initial gesture classification, while KNN refined the predictions. The model achieved an accuracy of 82.3% to 91.2%, depending on the sensor aperture area. However, the study identified limitations in generalization across different users and the possibility of increased computational cost and processing delays.

2. Avilés-Mendoza et al. (2023)

Avilés-Mendoza et al. developed an AI-based prosthetic arm using a five-layer Multilayer Perceptron (MLP) neural network optimized for deployment on a microchip using TensorFlow Lite. The model achieved 78.67% accuracy, with 80.21% precision and 75.67% recall. The study demonstrated the potential of neural networks for prosthetic control. However, the model was not tested across a wide range of users, and improvements in generalization and preprocessing speed were identified as important areas for future research.

3. Sattar, Kausar, and Usama (2021)

Sattar, Kausar, and Usama developed a machine learning-based control system for transhumeral prosthetic arms using EMG signals collected from the biceps and triceps. The system classified movements such as elbow flexion, extension, wrist pronation, and supination using features including Root Mean Square (RMS), Mean Absolute Value (MAV), and waveform length. Four classifiers—LDA, SVM, QDA, and KNN—were evaluated. KNN achieved the highest accuracy of 95.8% for healthy subjects and 68.1% for amputees during offline testing. Real-time experiments demonstrated control of two degrees of freedom using a 3D-printed prosthetic arm. However, variations in signal quality and classification accuracy among amputees remained significant challenges.

4. Unanyan and Belov (2021)

Unanyan and Belov developed a low-cost prosthetic hand controlled by EMG signals using an Arduino Nano microcontroller. The prosthetic hand was manufactured using 3D-printed ABS plastic and supported real-time multi-finger control. Experimental results demonstrated a response time of approximately 200 milliseconds and grip strength ranging from 8 to 12 kg. The design focused on affordability and accessibility while providing functional grasping movements. However, further improvements were needed to maintain performance while reducing costs. The researchers proposed adding vibration-based tactile feedback to improve the user's sense of touch and control.

5. Amira J. Zalyaa et al. (2024)

Amira J. Zalyaa et al. investigated an AI-driven prosthetic arm that uses neural networks to recognize EMG signals and customize hand gestures according to individual user requirements. The system focused on improving responsiveness, gesture recognition, and personalized control. Adaptive AI algorithms were used to interpret muscle signals and translate them into appropriate prosthetic movements. The study highlighted the potential of neural networks to improve the natural operation of prosthetic arms. However, high computational requirements and processing latency remained challenges, indicating the need for more efficient algorithms and training methods.

6. Ke Xu et al. (2016)

Ke Xu et al. presented an EMG-based prosthetic arm using pattern recognition algorithms implemented on a portable embedded system. The system processed muscle signals to enable dexterous hand manipulation and stable control of complex movements. Lightweight materials and advanced signal processing were incorporated to improve portability

and everyday usability. The research demonstrated the importance of embedded processing in developing practical prosthetic devices. However, variations in EMG signal quality and processing delays affected performance. Future improvements focused on increasing computational efficiency and expanding the number of recognizable hand gestures.

7. Jimmy Lu et al. (2022)

Jimmy Lu et al. developed a convolutional neural network (CNN)-based system for real-time bionic arm control using EMG signals. The model processed muscle signals directly on an embedded device, reducing dependence on external computing systems and improving portability. This approach demonstrated the potential of deep learning for intelligent prosthetic control. However, limited computational resources and energy efficiency were identified as major challenges for embedded platforms. Further optimization was considered necessary to improve performance and support wider practical applications.

8. Fuentes-Gonzalez et al. (2021)

Fuentes-Gonzalez et al. explored the use of artificial intelligence to control a 3D-printed prosthetic hand using EMG sensor data. The study focused on improving the adaptability and functionality of prosthetic devices through AI-based control. The proposed approach demonstrated the potential for scalable prosthetic designs that could accommodate different users. However, the requirement for large training datasets and improvements in real-time adaptability remained important challenges. Future research focused on expanding gesture recognition capabilities and improving system performance.

9. Raval et al.

Raval et al. proposed an AI-enhanced bio-prosthetic arm integrating EMG signal processing, tactile sensors, real-time feedback, and adaptive machine learning. Neural networks were used to learn the user's muscle patterns and generate appropriate movements, while tactile sensors supported natural gripping and sensory feedback. The study also highlighted the role of 3D printing in developing affordable and customized prosthetic arms. However, ethical considerations, including data privacy and equitable access to advanced prosthetic technologies, were identified as important concerns.

III. METHODOLOGY

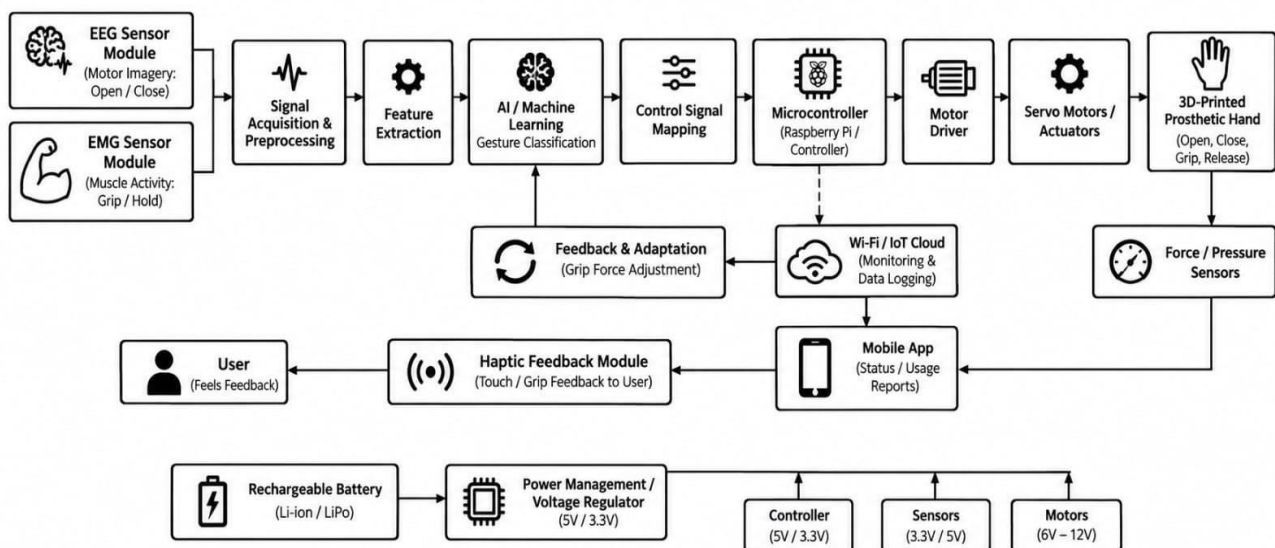


Fig. 1. Block Diagram of AI-Based Prosthetic Arm Methodology

The proposed study focuses on developing an AI-integrated prosthetic arm using EMG and EEG signals to improve movement control, adaptability, and functionality. The methodology consists of the following steps:

1. EMG and EEG Signal Acquisition

EMG sensors are used to capture electrical signals generated by muscle activity, while EEG electrodes placed on the scalp record electrical activity of the brain. These signals are collected to identify the user's intended hand movements. Proper signal acquisition and optical isolation of monitoring devices help reduce interference and improve signal quality.

2. Signal Preprocessing

The collected EMG and EEG signals may contain noise and unwanted disturbances. Therefore, preprocessing techniques such as amplification, filtering, noise reduction, normalization, and artifact removal are applied to improve signal quality. For EEG signals, bandpass filtering is used to isolate the mu (8–12 Hz) and beta (13–30 Hz) frequency bands associated with motor control.

3. Feature Extraction

Relevant features are extracted from the processed signals to identify different movement intentions. EMG features include amplitude, frequency, and Root Mean Square (RMS), while wavelet analysis is used to examine signal characteristics in both time and frequency domains. EEG features include event-related desynchronization and synchronization (ERD/ERS), spatial patterns, temporal patterns, and frequency-band characteristics.

4. AI and Machine Learning Model Development

Machine learning algorithms, including Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Convolutional Neural Network (CNN), are used to classify the extracted features and recognize intended movements. For EEG-based control, Artificial Neural Networks (ANN) can also be used to classify brain activity patterns. The models are trained using labelled signal data corresponding to specific prosthetic arm movements.

5. CNN-Based Signal Classification

The CNN model is used to extract features and identify patterns from the acquired signals. Two-dimensional representations of signal frequency variations over time are created and used as training data. The model employs convolutional and max-pooling layers to identify relevant patterns. Hyperparameters are optimized using grid search, and Stochastic Gradient Descent with Momentum (SGDM) is used for training. A dropout layer is included to reduce overfitting.

6. Prosthetic Arm Design and Fabrication

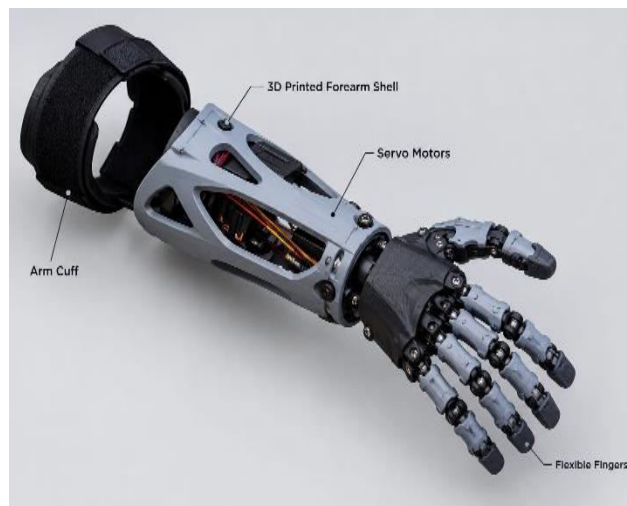


Fig2: Prosthetic Arm Design

A lightweight prosthetic forearm is designed using computer-aided design (CAD) and fabricated using 3D printing. The mechanical structure is assembled with servo motors, sensors, and a suitable power supply. The design aims to provide a cost-effective and functional prosthetic arm capable of performing basic hand movements.

7. Integration of the Control System

The trained machine learning model is integrated with a microcontroller-based control system. Real-time EMG and EEG signals are processed and classified to identify the user's intended movements. The microcontroller then generates appropriate commands to activate the servo motors, enabling actions such as opening and closing the hand, grasping objects, and pointing.

8. Real-Time Movement Control and Feedback

The classified signal patterns are mapped to corresponding prosthetic movements. The system processes incoming signals continuously to provide responsive control and adapt to changes in the user's signal patterns. A feedback mechanism helps inform the user about the status of the prosthetic arm and the execution of intended movements.

9. Experimental Setup and Testing

The experimental study was conducted on one 45-year-old male participant with a congenital upper-limb disability and absence of the forearm below the elbow. A lightweight 3D-printed prosthetic forearm equipped with two servo motors was used. Two EMG electrodes were placed on the upper-arm muscles, and the collected signals were processed using noise removal, normalization, and wavelet-based feature extraction. SVM, CNN, and KNN classifiers were trained using prerecorded gesture data. An Arduino microcontroller connected to a laptop processed the classified signals and activated the motors.

10. Performance Evaluation

The participant performed four tasks: opening the hand, closing the hand, grasping and lifting a light object, and pointing. Each task was repeated ten times. The performance of CNN, SVM, and KNN was evaluated using classification accuracy and response time.

The CNN achieved the highest accuracy, ranging from 90% to 95% across the four tasks, with response times ranging from 0.7 to 1.2 seconds. The observations indicated that EMG signals supported gross motor control, while EEG signals provided additional information for fine gesture recognition.

11. Limitations

The experiment was limited to a single participant, which restricts the generalizability of the results. EEG accuracy was affected by minor head movements and required periodic recalibration. Additionally, fatigue during repeated gestures slightly affected EMG signal quality. Further testing with more participants is required to evaluate the system's reliability and adaptability.

IV. FLOW CHART

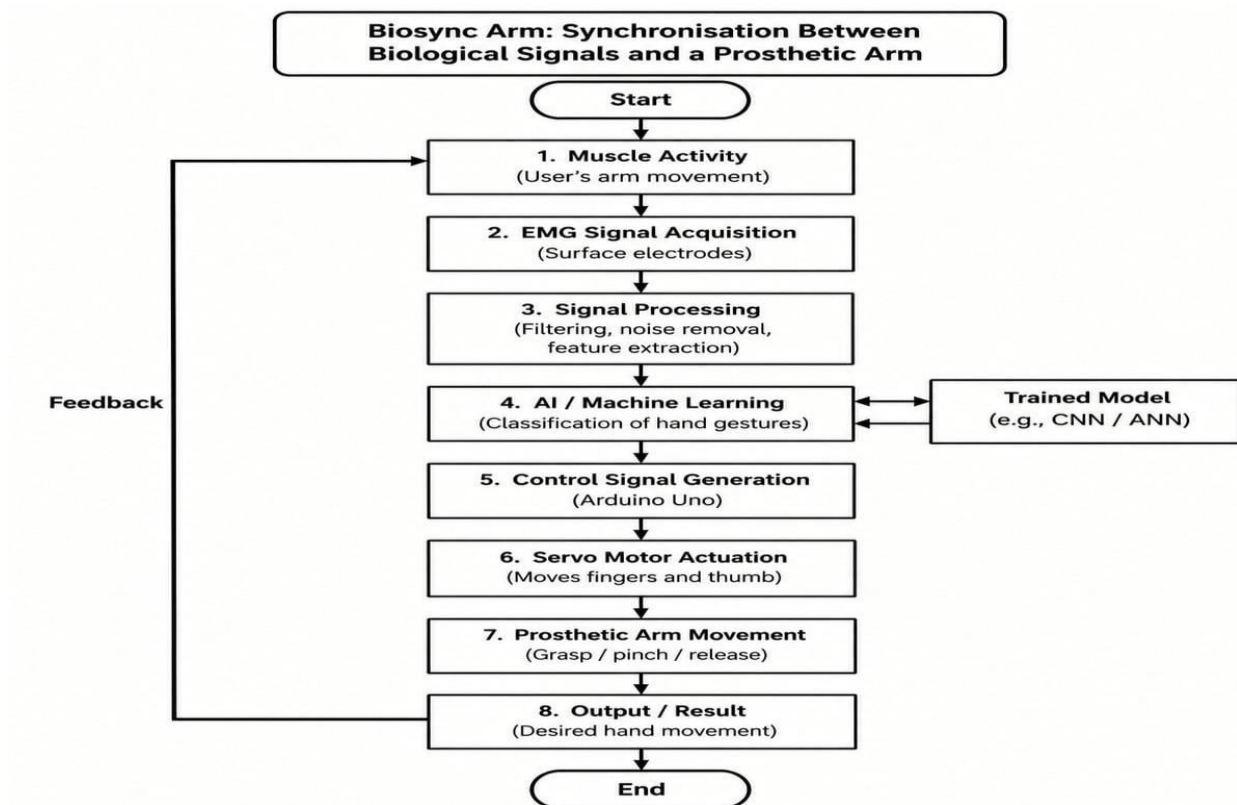


Fig 3 .Flow Chart

V. DISCUSSION

The discussion of the AI-based prosthetic arm focuses on the use of artificial intelligence, EMG and EEG signals, and 3D printing to improve prosthetic arm functionality.

EMG signals detect electrical activity produced by muscles, while EEG signals help identify brain activity related to movement. Before classification, these signals require preprocessing to remove noise and unwanted artifacts. Features such as Root Mean Square (RMS), Mean Absolute Value (MAV), Zero Crossing Rate (ZCR), and frequency-based features are extracted to improve gesture recognition.

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Machine learning algorithms, including Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Convolutional Neural Networks (CNN), can classify signals and control the movement of the prosthetic arm. The reported results indicate that CNN provides better gesture recognition accuracy than SVM and KNN in the evaluated tasks.

The 3D-printed structure helps create a lightweight and customizable design, while servo motors enable hand and finger movements. However, challenges such as signal variations, classification errors, muscle fatigue, EEG interference, and response delays can affect performance.

Overall, integrating AI, biological signals, and 3D printing offers a promising approach to developing more adaptable and affordable prosthetic arms, although further testing with more participants is required to evaluate reliability and practical usability.

VI. CONCLUSION

This review paper highlights the potential of Artificial Intelligence (AI), Electroencephalography (EEG), Electromyography (EMG), and 3D printing in the development of smart prosthetic arms. EEG signals enable control based on brain activity, while EMG signals detect muscle activity to support hand movements and gripping tasks. Machine learning algorithms help improve gesture recognition and control accuracy. The integration of these technologies can make prosthetic arms more adaptable, lightweight, and user-friendly. The reviewed findings report classification accuracy of up to 94% for a combined EEG-EMG control system, demonstrating the potential of using both signals together. However, challenges such as signal interference, classification errors, calibration requirements, muscle fatigue, and limited testing remain. Overall, AI-based prosthetic arms offer a promising solution for improving the independence and quality of life of individuals with upper-limb disabilities. Further research and practical testing are required to improve their accuracy, reliability, affordability, and everyday usability.

VII. FUTURE SCOPE

1. Improved Accuracy: Develop advanced AI algorithms to improve gesture recognition and reduce classification errors.
2. Better Movement Control: Enable smoother and more precise finger movements for performing daily activities.
3. Sensor Integration: Integrate EEG, EMG, tactile, and pressure sensors for better control and feedback.
4. Automatic Calibration: Develop automatic calibration techniques to improve reliability and reduce manual adjustments.
5. Lightweight Design: Use 3D printing to develop lightweight, comfortable, and customizable prosthetic arms.
6. Reduced Cost: Use affordable components and manufacturing techniques to make prosthetic arms accessible to more people.
7. Adaptive Learning: Develop AI systems that learn individual users' movement patterns and adapt to their needs.
8. Extended Testing: Test the system with more users and different daily activities to evaluate its accuracy, comfort, safety, and long-term performance.

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