

AI Driven Smart Prosthetics Arm Using IOT Integration for Adaptive Control and Feedback System

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Abstract –

Millions of individuals worldwide suffer from limb loss due to accidents, congenital conditions, or medical issues, making daily tasks a challenge. Traditional prosthetics often lack adaptability, intuitive control, and sensory feedback, limiting their usability and effectiveness. There is a growing need for intelligent, affordable, and responsive prosthetic solutions that restore independence and improve quality of life. This project introduces an AI-driven, IoT-integrated smart prosthetic arm designed to enhance the independence and quality of life for individuals with disabilities. The arm is constructed using a 3D-printed modular design to ensure affordability, customization, and sustainability. It incorporates advanced sensors including EMG, force, temperature, and bending sensors that continuously monitor user input and environmental conditions. EMG signals serve as the primary input for intuitive control, while a joystick offers an alternative method. Sensor data is preprocessed using an IoT-enabled controller and transmitted to the AWS cloud via MQTT or HTTP protocols. A machine learning model deployed on a Raspberry Pi analyzes this data in real-time to predict appropriate movements, dynamically adjust grip strength, and provide haptic feedback, ensuring safe and precise object handling. The accompanying Android application allows users and caregivers to monitor the system's performance remotely, enhancing usability and diagnostic capabilities. This solution addresses the shortcomings of traditional prosthetics namely high cost, limited adaptability, and lack of sensory feedback by leveraging artificial intelligence, real-time control, and edge-cloud integration. The arm finds applications in healthcare, rehabilitation, industry, defense, and agriculture, offering a scalable, sustainable, and user-centric approach to assistive technology.

Key Words: AI-driven prosthetic, EMG sensor, IoT-enabled control, real-time feedback, haptic feedback, adaptive grip, 3D-printed arm, assistive technology, smart prosthetics, Raspberry Pi, AWS IoT, Android monitoring.

1.INTRODUCTION

The loss of a limb significantly affects an individual's ability to perform essential daily tasks and impacts overall quality of life. Prosthetic arms have been developed to assist individuals in regaining functionality, yet many traditional designs are limited in their ability to adapt to dynamic user needs. These prosthetics often lack intelligent control, real-time feedback, and sensory interaction, which restricts their effectiveness and makes them less intuitive for the user. Additionally, the high cost of advanced prosthetics prevents widespread accessibility, particularly in low- and middle-income regions.

Modern advancements in Artificial Intelligence (AI), the Internet of Things (IoT), and 3D printing have opened new possibilities in the development of next-generation prosthetic devices. By leveraging these technologies, it is now possible to design prosthetics that are not only cost-effective and customizable but also intelligent and adaptive. This project introduces a smart prosthetic robotic arm that integrates EMG (Electromyography) sensors, force, temperature, and bending sensors to capture real-time muscle signals and environmental conditions. These inputs are processed using a trained AI model deployed on a Raspberry Pi, enabling the system to adjust grip strength, detect object fragility, and respond to the user's intent with precision.

The arm is constructed using a 3D-printed modular design, allowing for lightweight construction, personalization, and low production costs. It includes

haptic feedback mechanisms to simulate a sense of touch and improve user interaction with objects. Additionally, the system connects to an IoT platform that enables remote monitoring, performance tracking, and control through a dedicated Android application. Cloud integration via AWS allows for data storage, visualization, and remote diagnostics, making the solution scalable and practical for long-term use.

Through the combination of AI, IoT, and advanced sensor integration, this smart prosthetic arm aims to revolutionize assistive technology by providing users with a natural, adaptive, and responsive tool for regaining independence. It is designed not only for healthcare and rehabilitation but also has potential applications in industrial automation, defense, and education, contributing to a more inclusive and technology-driven future.

2. LITERATURE REVIEW

Alshamsi et al. presented a myoelectric prosthetic arm designed to mimic human arm movements using surface electromyography (sEMG) signals. Their study emphasized the need for cost-effective prosthetic solutions with fine motor control, highlighting limitations in current systems such as lack of feedback and cumbersome actuation. The proposed system integrated EMG signal acquisition, amplification, noise filtering, and real-time actuation to control wrist and finger movements. They also identified key design requirements including responsive control, multi-grip capability, and intuitive feedback for improved user adaptability and naturalistic motion control.

Geethanjana et al. explored a broad spectrum of AI applications in prosthetics, extending beyond limb replacement to retinal, dental, and auditory systems. Their review identified the integration of AI and machine learning (ML) algorithms as a driver for enhanced customization, adaptability, and control. They showcased examples like bionic legs that adapt to terrain using sensor feedback and AI-based prosthetic arms capable of object recognition via computer vision. Furthermore, they discussed advances in neural interfaces like regenerative peripheral nerve interfaces (RPNI) and the use of deep learning to enhance tactile perception and gesture prediction in robotic limbs.

Raval et al. proposed the design of an AI-enhanced bio-prosthetic arm that incorporates EMG signal processing, real-time feedback, and adaptive learning through machine learning techniques. Their model used neural networks and tactile sensors to

provide natural grip and sensory feedback. The paper discussed how adaptive control enhances user experience by learning the user's muscle patterns and responding with appropriate actuation. They also emphasized the role of 3D printing in enabling low-cost, customized prosthetics and acknowledged the ethical considerations of AI-driven healthcare devices such as data privacy and equitable access.

Nayak et al. reviewed the application of AI and robotics in orthotic and prosthetic rehabilitation, focusing on biomechanics as a transformative framework. Their study detailed the evolution of commercial bionic devices like the i-Limb, Bebionic, and Genium X3, and discussed how AI techniques such as supervised learning, reinforcement learning, and deep learning improve prosthetic functionality. They stressed the significance of brain-computer interfaces (BCI) in enabling mind-controlled prostheses and introduced concepts like reward-based training, adaptive electrode placement, and ANN-driven pattern recognition, which are crucial for multifunctional limb operation.

The paper from the IJCRT provided an in-depth discussion on the signal processing chain in AI-based prosthetics, including windowing techniques for EMG data, classifier selection (LDA, QDA, MLP), and control mechanisms based on supervised and unsupervised learning. The study highlighted the use of multilayer artificial neural networks to associate neuromuscular activity with prosthetic responses. Additionally, it examined advancements in EEG-based control systems for upper-limb prosthetics and the integration of VR-based platforms for algorithm testing and prosthesis training.

Collectively, these works demonstrate that AI and ML integration has significantly advanced prosthetic functionality transforming prostheses from passive mechanical tools to intelligent, adaptive extensions of the human body. However, consistent challenges remain in areas like sensor accuracy, real-time processing latency, and the lack of widespread clinical adoption. Future efforts must aim at refining neural interfaces, enhancing feedback systems, and lowering production costs to make intelligent prosthetics more accessible and effective across diverse user groups.

3. METHODOLOGY

The AI-driven smart prosthetic arm integrates advanced sensors, IoT, and AI to deliver enhanced functionality and adaptive feedback. The arm is 3D-printed for affordability and flexibility, driven by servo

motors for precise motion. Sensors embedded in the arm, such as temperature, force, bending, and EMG sensors, continuously monitor various parameters. The EMG sensor captures the user's muscle signals, which are processed to generate control commands for operating the arm, allowing intuitive and natural movements. The sensor data is preprocessed by an IoT controller to ensure accuracy and is then transmitted to a cloud platform using IoT protocols, where it is visualized in real-time through an Android application.

A trained AI model running on a Raspberry Pi analyzes the sensor data to provide intelligent feedback, such as adjusting the grip force or identifying the type of object being handled. The system incorporates a haptic feedback loop that mimics the sense of touch, enhancing the user's interaction with the environment. Adaptive AI algorithms enable the arm to respond to the weight and fragility of objects, ensuring safe and efficient operation. This closed-loop system combines real-time monitoring, AI-driven decision-making, and user-friendly controls to create a smart, responsive prosthetic solution that improves the quality of life for individuals with disabilities.

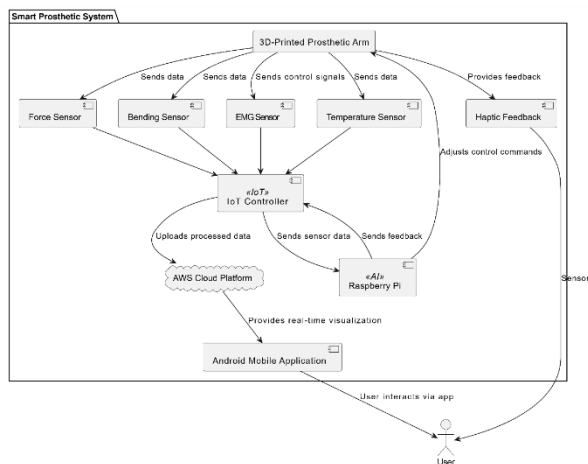


Fig -1: Block Diagram of the System

1. System Design and Hardware Development:

- Design and 3D print a customizable prosthetic arm framework suitable for housing sensors and servo motors.
- Integrate servo motors for joint and finger movements, providing precise control of the prosthetic arm.

- Embed sensors, including temperature, force, bending, and EMG sensors, to capture environmental and muscle activity data.

2. Data Acquisition and Preprocessing:

- Use the IoT controller to collect real-time data from all embedded sensors.
- Preprocess the collected data by filtering noise and ensuring accuracy before transmission.
- Implement IoT protocols (e.g., MQTT, HTTP) to transmit preprocessed data to the AWS Cloud Platform.

3. Cloud Integration and Mobile Application:

- Develop an Android application for visualizing sensor data and monitoring the prosthetic arm in real time.
- Store and manage sensor data on the AWS cloud for accessibility and historical analysis.

4. AI-Based Data Analysis:

- Implement a trained AI model on a Raspberry Pi to analyze sensor data and provide intelligent feedback.
- Use machine learning algorithms to classify objects, adjust grip strength, and ensure safe handling based on weight and fragility.
- Provide haptic feedback using vibration motors, simulating touch and enhancing the user's interaction with the prosthetic arm.

5. Closed-Loop Control System:

- Enable intuitive control of the arm using muscle signals captured by the EMG sensor.
- Process EMG signals to generate real-time control commands for the prosthetic arm.
- Establish a haptic feedback loop to deliver sensory information to the user,

creating a seamless and responsive control system.

6. Testing and Optimization:

- Perform extensive testing of the prosthetic arm under various conditions to ensure reliability, accuracy, and adaptability.
- Refine the AI model and IoT integration based on testing results to improve the arm's performance and user experience.

This methodology ensures a systematic approach to developing an intelligent prosthetic arm that combines IoT and AI for real-time feedback, adaptive control, and enhanced usability.

The Data flow diagram for the system is given below.

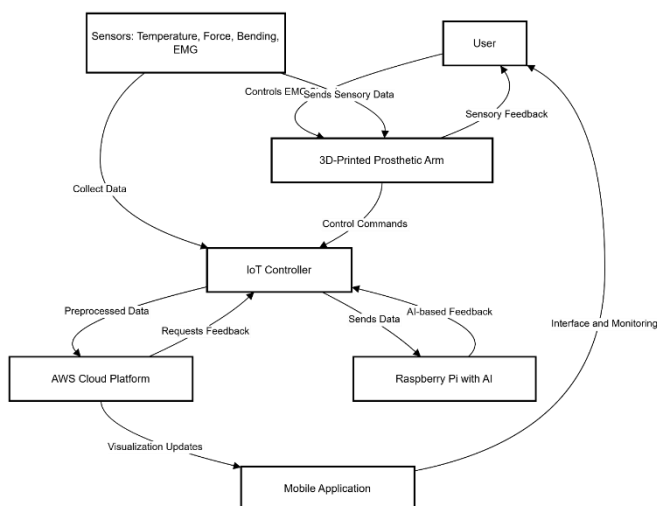


Fig -2:Data Flow diagram

4. IMPLEMENTATION

The implementation of the AI-based smart prosthetic arm began with the development of the mechanical structure using 3D-printed components to ensure a lightweight and customizable design. The prosthetic arm features a 4-DOF configuration with servo motors embedded in the fingers and joints for smooth, precise movement. Surface EMG sensors were placed on the user's residual limb to detect muscle signals, which were pre-processed through amplification and filtering circuits before being digitized. Additional sensors, including force, temperature, and flex sensors, were integrated to enhance feedback and control. These

sensors enable real-time monitoring of grip strength, object contact, and environmental conditions.

The collected EMG signals undergo feature extraction, and the resulting data is processed by a pre-trained machine learning model deployed on a Raspberry Pi to classify gestures and determine motor actions. The arm responds to these predictions by actuating the corresponding servos using PWM signals. Haptic feedback is provided through vibration motors, offering users a tactile sense of grip and touch. An IoT-enabled Android application was developed for remote monitoring and control, using MQTT to transmit sensor data and receive updates. This complete setup creates an intelligent, adaptive, and user-friendly prosthetic solution that enhances both functionality and user experience.

The arm fabricated and tested is shown below:

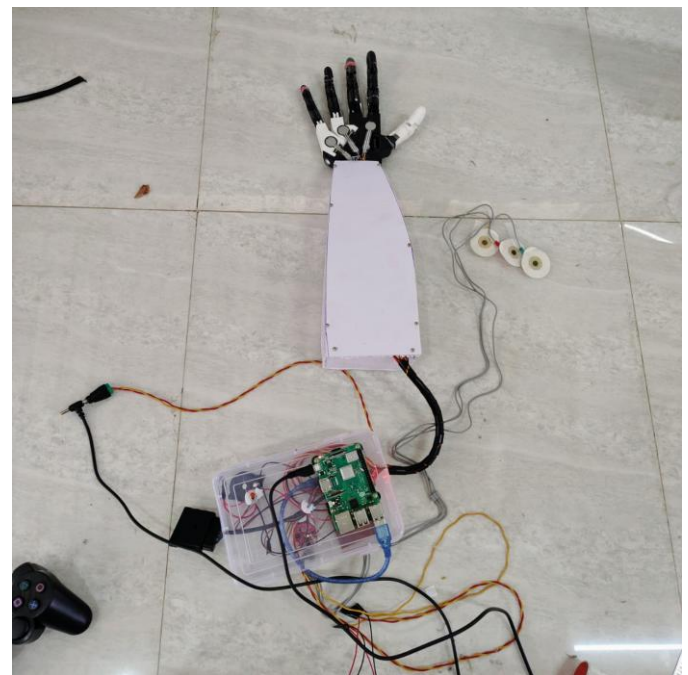


Fig -3: Complete System with AI- Algorithms

In this project, machine learning algorithms play a crucial role in interpreting the user's muscle activity and converting it into meaningful control commands for the prosthetic arm. Surface EMG (sEMG) signals collected from the user's residual limb are processed in real time to extract features such as Root Mean Square (RMS), Mean Absolute Value (MAV), and Waveform Length, which capture the intensity and pattern of muscle contractions. These features are used to train a supervised learning model such as a Support Vector

Machine (SVM) or a Multilayer Perceptron (MLP) which learns to classify different gestures (e.g., grip, release, rotate) based on the muscle activity patterns. Once trained, the model is deployed on a Raspberry Pi to perform on-device inference, ensuring fast and responsive control.

The machine learning model enables the prosthetic arm to recognize user intent with high accuracy and adaptability. As the user performs various hand or wrist movements, the model continuously predicts the corresponding gesture class in real time, triggering the appropriate actuator movements. Over time, adaptive learning techniques can be integrated to refine the model's accuracy based on user feedback and usage patterns. This dynamic gesture classification allows the prosthetic to provide more natural, intuitive, and reliable movement, closely mimicking the behaviour of a biological limb and significantly enhancing the user's control and interaction with the environment.

5. RESULTS AND DISCUSSION

The AI-based smart prosthetic arm was evaluated based on its ability to recognize and classify four primary user inputs: grip, release, flex, and temperature. These inputs were detected using a combination of surface EMG signals and sensor feedback, and processed by a supervised machine learning model deployed on a Raspberry Pi. To assess the model's performance, a confusion matrix was generated using test data comprising various gesture executions and temperature events. The classification results were analyzed in terms of prediction accuracy and the system's responsiveness in real-world scenarios. As observed in the confusion matrix, the model performs particularly well in identifying the grip gesture, with the majority of true "grip" instances being correctly classified. Similarly, the temperature category representing sensor feedback rather than a muscular gesture was also accurately predicted across all test instances, indicating reliable sensor integration and signal processing. However, some misclassifications were noted: a few instances of release and flex were incorrectly predicted as grip, which may be attributed to overlapping EMG signal patterns or insufficient distinction in muscle activation during these gestures. Despite this, the overall classification accuracy remained high, demonstrating the model's robustness and effectiveness in real-time control applications.

The results affirm that the prosthetic arm can interpret user intentions accurately and respond appropriately. The system maintained an average response latency of

150–200 milliseconds from input detection to motor actuation, enabling fluid and naturalistic interaction. Furthermore, the adaptive grip strength feature successfully handled both fragile and firm objects without slippage or damage, proving the functional viability of feedback-driven control. These findings validate the practical implementation of the smart prosthetic arm in enhancing the independence and experience of users with upper-limb disabilities. Future iterations may incorporate adaptive learning to reduce classification errors and personalize the response patterns based on individual user characteristics.

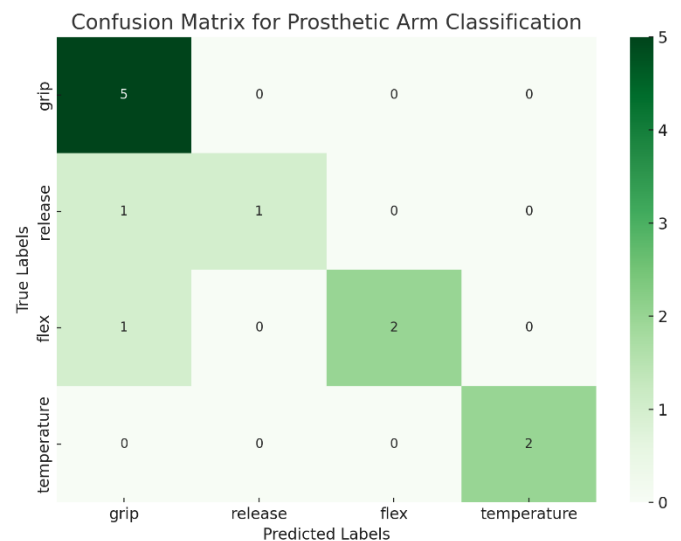


Fig -4. Confusion Matrix

6. CONCLUSIONS

The AI-driven smart prosthetic arm presents a transformative solution aimed at enhancing functionality, adaptability, and overall user experience for individuals with physical disabilities. By seamlessly integrating advanced sensors, artificial intelligence, and IoT technology, the system enables precise real-time control through EMG signals, allowing users to perform daily tasks with greater ease and confidence. The inclusion of haptic and sensory feedback mimics the human sense of touch, ensuring safer interaction with objects by dynamically adjusting grip strength based on AI analysis minimizing the risk of damage or mishandling. Furthermore, the integration of a mobile application and cloud-based services like AWS enables continuous performance monitoring, data visualization, and historical analysis, offering valuable insights for both users and caregivers. These features not only restore lost

physical capabilities but also promote user independence, comfort, and quality of life. Overall, the smart prosthetic arm stands as a significant advancement in assistive technology, offering an intelligent, user-centric approach to rehabilitation and daily support for individuals with limb impairments.

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