SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V12I3P112

Volume 12 Issue 3, 114-127, March 2025

Original Article

Development of an Adaptive AI-Enhanced Prosthetic Arm for Physically Impaired Children

Manal Al Khaldi[1], Tariq Al Balushi[2], Amin Al Maqbali[3], Amuthakkannan Rajakannu[4]*

[1,2,3]*Department of Mechanical and Industrial Engineering, College of Engineering, National University of Science and Technology, Muscat, Oman.*
[4]*Associate Professor, Department of Mechanical and Industrial Engineering, College of Engineering, National University of Science and Technology, Muscat, Oman.*

[*] *Corresponding Author : amuthakkannan@nu.edu.om*

Received: 17 January 2025 Revised: 10 March 2025 Accepted: 20 March 2025 Published: 31 March 2025

Abstract - *This research addresses the critical gap in pediatric prosthetics for children by developing an adaptive prosthetic arm tailored to children aged 7 to 14, a demographic often overlooked in prosthetic innovation. Rapid physical growth during this age requires frequent adjustment and more medical care. Because of the requirement for frequent adjustment, pediatric prosthetics are more complex than adult models. Existing solutions have disadvantages, such as difficulty adapting adult designs and lack of the ergonomic, functional, and psychological considerations required for children. This work introduces a novel prosthetic arm that integrates Artificial Intelligence (AI) and Deep Learning (DL) to enhance adaptability, control, and user experience. In the initial phase of the work, the existing models and their disadvantages were considered. Then, the new design is developed, which leverages biosensors and electromyographic (EMG) signals for intuitive gesture recognition, enabling tasks such as gripping, pinching, and twisting. After developing the design, a 3D printer was used to create the arm. The arm was tested in real-time, and the AI developed with the prosthetic arm showed a promising overall accuracy of 91%. This shows the design and other components' accuracy and that the proposed arm design can be implemented for pediatric prosthetics.*

Keywords *- Prosthetics, Artificial Intelligence, Machine Learning, Pediatric healthcare, AI algorithms, Oman vision 2040*

1. Introduction

Children between the ages of 7 and 14 with physical impairments often face unique challenges when using prosthetic limbs. Children's rapid growth requires frequent adjustments, making prosthetics more complex than those designed for adults. Children's prosthetics, however, lack specialised designs that meet their physical and psychological needs due to a lack of research and development. This research aims to address that gap by introducing a prosthetic arm specifically designed to meet the needs and requirements of people in this age group.

Despite the advances in prosthetic technology, these innovations have primarily focused on adult users, with little focus on the unique needs of children. Due to a lack of modern medical technology in Oman, many families seek solutions abroad. As Oman advances toward its Vision 2040, which emphasises innovation and accessibility in healthcare, addressing this gap is critical. This project integrates Artificial Intelligence and Machine Learning to develop a prosthetic arm that meets the unmet needs of pediatric users. The lack of adequate research and development in pediatric prosthetics has led to a scarcity of prosthetic solutions specifically designed for children. Most available prosthetic arms are adaptations of adult models, which fail to address young users' unique ergonomic, functional, and psychological needs, especially for long-term usage. This gap in research and design results in poor functionality, limited comfort, and reduced satisfaction. This project focuses on designing, fabricating, and testing an AI-enhanced prosthetic arm for children. Moreover, the research explores integrating advanced technologies, such as biosensors and AI algorithms, to improve prosthetic arms' functionality, adaptability, and user experience. Testing will ensure that the prototype meets high durability, comfort, and practicality standards for pediatric users.

This work addresses the lack of research in pediatric prosthetics by designing a prosthetic arm that enhances children's mobility, adaptability, and comfort.

The key objectives include:

- To Investigate the specific needs and challenges of pediatric prosthetic users.
- To Develop a lightweight and durable prosthetic arm that meets functional requirements.

- To Integrate AI and ML technologies for improved control and adaptability.
- To Validate the prototype through simulated and real-world testing.

This project encounters challenges such as ensuring reliable biosensor signal detection, minimising response time and achieving cost-effective prosthetic arms. The project introduces innovations in pediatric prosthetics by incorporating AI and Deep learning technologies to enhance absolute time control.

The design addresses ergonomic and functional gaps in existing prosthetics, offering a tailored solution for children's needs. Environmentally, using 3D printing and recyclable materials minimises waste and promotes sustainability. Societally, the project fills a critical gap in healthcare by improving the quality of life for children with disabilities and reducing the financial burden on families in Oman by providing a cost-effective solution. This research aims to develop a novel AI-based prosthetic arm with deep learning techniques to improve adaptability, control, and ease of adoption by children. The block diagram of the proposed methodology is given in Figure 1.

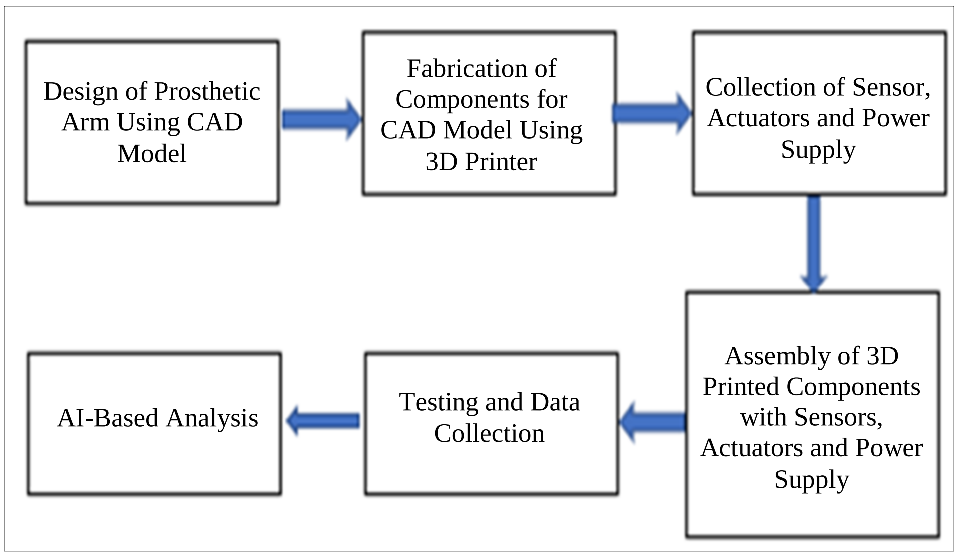

Fig. 1 Block diagram of the proposed methodology

2. Literature Review

In the study conducted by Satya Sree et al. (2021), an ensemble model combining Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) algorithms was proposed to classify hand gestures using data from surface Electromyography (sEMG) sensors. The SVM classifier served dual roles: reducing the high-dimensional space of the dataset and performing primary gesture classification. Subsequently, the KNN algorithm was employed to refine and enhance the SVM predictions. The model demonstrated accuracy levels between 82.3% and 91.2%, contingent upon the varying aperture areas of the sensors. This ensemble model outperformed the standalone SVM and KNN algorithms in gesture recognition accuracy, underscoring the efficacy of combining multiple classifiers to improve robustness.

However, a notable gap in this study is the limited exploration of generalisation across different demographic groups, a factor essential for broad clinical application. Additionally, the ensemble approach, while effective, may introduce latency and computational costs that could challenge real-time usability, an area unaddressed in the paper [1]. In the study by Avilés-Mendoza et al. (2023), the authors developed a prosthetic arm based on a five-layer Multilayer Perceptron (MLP) architecture, optimised for deployment on a microchip using TensorFlow Lite. This model achieved an accuracy of 78.67%, with a precision of 80.21% and a recall of 75.67%. Despite the promising metrics, the model exhibited limited generalizability, as it was not tested across varied test subjects, leading to questions about its effectiveness in broader, real-world applications. The authors acknowledged this limitation and proposed that future research explore Deep Neural Networks (DNNs) for better generalisation. Additionally, they highlighted the need for faster preprocessing times to facilitate real-time control.

Therefore, the gap in this study centres on the model's adaptability to various user groups and environments and the lack of optimisation for processing efficiency, which is crucial for real-time prosthetic applications [2]. Sattar, Kausar, and Usama (2021) investigate the development of an EMG-based control system for transhumeral prostheses using machine learning algorithms. By employing EMG signals from the biceps and triceps, the study classifies arm motions such as elbow flexion, extension, wrist pronation, and supination through advanced feature extraction methods like RMS, MAV, and waveform length. Four machine learning classifiers-LDA, SVM, QDA, and KNN-were evaluated, with KNN achieving the highest accuracy (95.8% for healthy subjects and 68.1% for amputees) in offline testing. A Myo armband was utilised for signal acquisition, offering a non-invasive and wearable solution. Real-time performance was tested on a 3D-printed prosthetic arm, demonstrating reliable control of two degrees of freedom. The study identifies challenges in accuracy variability among amputees, noise sensitivity, and limitations in real-time classification. Future work emphasises integrating additional gestures, enhancing algorithm robustness, and incorporating Brain-Computer Interface (BCI) technologies for more intuitive prosthetic control [3].

In a recent study by Jethro Odeyemi et al. (2024), a simulated environment was designed to evaluate the performance of different reinforcement learning policies in controlling a prosthetic hand to detect and grasp nearby objects autonomously. The authors implemented three distinct policies, Soft Actor-Critic (SAC), Deep Q-Network (DQN), and Proximal Policy Optimization (PPO), which were trained over 1,000,000 timesteps in the simulation. The results indicated that the SAC algorithm significantly outperformed the other two, achieving a high success rate of 99.03% in approximately 200,000 timesteps. DQN and PPO yielded mean success rates of 60.21% and 82.14%, respectively [4].

The study by Unanyan and Belov (2021) details developing a low-cost prosthetic hand controlled by electromyography (EMG) signals to assist individuals with arm amputations or musculoskeletal disabilities. The prosthetic hand uses an Arduino Nano microprocessor to interpret EMG signals, enabling real-time multi-finger control. Designed with 3D-printed ABS plastic for durability, the hand mimics natural grasping actions and delivers grip strength between 8 to 12 kg, comparable to a healthy hand, with minimal delays of 200 milliseconds. Experimental results demonstrated precise movements and superior force efficiency, outperforming traditional prosthetics using elastic materials. Priced at $150 lower than comparable devices, the design focuses on accessibility for people in developing regions. However, challenges remain in maintaining performance while reducing costs. Future enhancements will incorporate vibration-based tactile feedback, using sensors to simulate a sense of touch for improved functionality and user control [5].

Amira J. Zalyaa et al. (2024) discuss the development of an AI-driven prosthetic arm that utilises neural networks to customise gestures based on electromyography (EMG) sensor inputs, focusing on creating a highly responsive system capable of mimicking natural hand functions. The study highlights using adaptive AI algorithms to accurately interpret EMG signals, allowing the prosthesis to adjust to user-specific needs in real time. Key advancements include seamless gesture recognition and the integration of responsive control mechanisms to improve user satisfaction. Despite its successes, the system faces challenges such as high computational demands and the need for efficient training to reduce latency. Future research addresses these limitations by refining the algorithms for real-time adaptability and minimising the overall computational load. This work underscores the potential of neural network-based prosthetics in advancing personalised and functional solutions for upper-limb amputees [6].

Ke Xu et al. (2016) introduce a prosthetic arm employing EMG pattern recognition algorithms implemented on a portable embedded system to achieve dexterous hand manipulation and stable control. The research focuses on overcoming user acceptance and functionality challenges, achieving significant improvements in real-time control of complex hand movements. The portable design incorporates lightweight materials and advanced signal processing to interpret EMG data effectively, making it more practical for everyday use. The study acknowledges limitations such as variability in EMG signal quality and processing delays, proposing future work to optimise algorithmic efficiency and expand the library of gestures the system can interpret. This research represents a significant leap in making EMG-controlled prosthetics more accessible and functional for users [7].

Jimmy Lu et al. (2022) present a convolutional neural network system for real-time bionic arm control to process EMG signals directly on an embedded device. The study emphasises the benefits of an on-device processing framework, which eliminates dependence on external computational systems, ensuring greater portability and user convenience. However, the system encounters challenges such as energy efficiency and computational constraints within embedded platforms, prompting future efforts to optimise performance for broader applicability [8].

Murugan et al. (2024) describe the development of an innovative prosthetic arm controlled by non-invasive surface EMG signals, employing deep learning techniques to achieve precise and intuitive hand movements. The system significantly improves user experience by incorporating advanced signal processing algorithms that enhance accuracy and responsiveness while maintaining a lightweight and portable design. Despite the advancements in the research, challenges exist, such as variability in signal consistency across users and the need for recalibration to maintain performance. Future research directions suggest developing more robust algorithms to handle signal variability and enhancing the system's ability to perform complex tasks. This work demonstrates the transformative potential of EMG-based prosthetics in improving the quality of life for individuals with upper-limb amputations [9]. Fuentes-Gonzalez et al. (2021) explore the application of artificial intelligence in controlling a 3D-printed prosthetic hand through EMG sensor data, focusing on enhancing adaptability and functionality. Key contributions include successfully implementing AI-driven controls and the system's scalability for diverse users. Challenges such as the need for large training datasets and improving real-time adaptability are addressed, with future research aimed at expanding gesture recognition capabilities and refining system performance. This research highlights the synergy between artificial intelligence and additive manufacturing in revolutionising prosthetic technologies [10].

Rialto Júnior et al. (2023) present a forearm prosthesis controlled by a Fiber Bragg Grating (FBG) sensor, which detects finger-induced deformations on the forearm. The system comprises a 3D-modeled prosthesis, MG995 servo motors, and a Raspberry Pi 3B+ microprocessor, using MATLAB for signal processing and Node-RED for control. FBG sensors enable wrist rotation and finger movements by mapping deformation signals to motor actions through linear equations. Experimental validation demonstrated a latency of 140 milliseconds in response time, ensuring real-time functionality. Despite its promising outcomes, challenges include integrating computational hardware with optical interrogators. Future advancements aim to enhance FBG signal processing with advanced pattern recognition techniques, improving prosthetic responsiveness and adaptability to individual user needs [11].

Gopal, Gesta, and Mohebbi (2022) provide a comprehensive study on EMG-based hand gesture recognition for assistive robots, benchmarking various machine learning and deep learning models. Utilising the NinaPro dataset, the study evaluates classifiers like KNN, SVM, LDA, Ensemble, ANN, and CNN on their ability to process EMG signals into gesture classifications. Results show that ensemble models and CNNs outperform others, achieving high accuracy and F1 scores. Key findings include the influence of sliding window sizes on performance and the importance of time-domain features like Root Mean Square (RMS). Challenges include noisy EMG signals, variability in muscle activity, and generalisation across subjects. Future research will enhance real-time classification reliability and improve preprocessing for better generalisation [12].

Zandigohar et al. (2024) explore the fusion of EMG and vision data for prosthetic hand control. Using Bayesian evidence fusion, the system combines eye-view video, gaze data, and dynamic EMG signals to enhance gesture recognition accuracy. Neural network-based classifiers for both EMG and vision were integrated, with the fusion model achieving superior robustness and precision during critical phases like reaching and grasping. Experiments demonstrated enhanced classification accuracy by combining modalities, outperforming individual classifiers. Challenges include reliance on sensor data, robustness limitations, and poor performance during occlusions. Future advancements will focus on refining classification algorithms and improving fusion techniques for dynamic environments [13].

Odeyemi, Ogbeyemi, Wong, and Zhang (2024) delve into developing intelligent prosthetic hands capable of autonomous object grasping, addressing persistent challenges in user training and control precision. Their study employs reinforcement learning algorithms such as Soft Actor-Critic (SAC), Deep Q-Network (DQN), and Proximal Policy Optimization (PPO) to enable automated gripping actions. Among these, SAC demonstrates superior performance with a 99% success rate within 200,000 timesteps, outperforming its counterparts in handling high-dimensional action spaces and sparse rewards. The research further emphasises the influence of object properties-like shapes and textures on grasping success. Challenges such as achieving optimal grip force and preventing object slippage or damage are tackled through advanced simulation environments and tailored reward functions. The study underscores the potential of combining computer vision and machine learning techniques in prosthetic development, paving the way for more efficient and accessible solutions in the biomedical engineering domain [4].

Jiang et al. (2022) review wearable interfaces and algorithms for hand gesture recognition. Sensing modalities such as surface EMG, electrical impedance tomography (EIT), and inertial measurement units (IMUs) are evaluated for their applications in gesture recognition. Both classical machine learning and deep learning methods are discussed, with examples of CNN and LSTM architectures achieving high accuracy rates. Challenges include robustness against subject-specific variations and scaling gesture sets. Future research is directed toward soft systems like e-skin and e-tattoos, offering more comfortable and accurate interfaces [14].

Uptasarma and Kennedy (2024) introduce the Prosthetic Arm Control Testbed (ProACT), an augmented reality platform to evaluate intelligent control methods for prosthetic arms. Integrating movement-based intent estimation with low-level robotic autonomy enhances user satisfaction and task success rates. The study demonstrates that intent estimation methods improve performance in virtual myoelectric prosthetic arm tasks, marking a pioneering effort in semi-autonomous control for complex whole-arm prostheses [15].

Guo et al. (2024) systematically review bionic prosthetic hands, focusing on control mechanisms, sensory feedback integration, and mechanical design innovations. The review emphasises the utilisation of bioelectrical signals, such as electromyography (EMG), for prosthetic control and discusses the application of machine learning algorithms to enhance gesture recognition accuracy. Advancements in sensory feedback technologies, including tactile, visual, and auditory modalities, are explored to improve user interaction. The authors identify key areas for future development, aiming to refine the utility and accessibility of prosthetic hands for amputees [16].

Sarker et al. (2024) present a sensorized, vision-enabled prosthetic hand to replicate natural hand performance and functionality. The design incorporates a camera and embedded processors to perform tasks, with pressure sensors ensuring safe object grasping and accelerometers detecting gestures for object release. Unlike current EMG-based designs, this prosthetic does not require personalised training, offering a user-friendly interface [17].

Nazari and Zheng (2024) introduce ProRuka, a novel low-cost prosthetic hand with six degrees of freedom, controlled using sonography (SMG). By monitoring forearm muscle activity through ultrasonic imaging, the system employs machine learning algorithms to classify different hand gestures accurately. Real-time experiments with amputees demonstrate ProRuka's effectiveness in assisting with daily activities, highlighting SMG's potential as an alternative control system to electromyography [18].

3. Design and development of prosthetic arm

3.1. Design of Arm Using CAD model

In Fusion 360, a prosthetic arm was designed with a focus on achieving a balance between usability, aesthetics, and manufacturing feasibility. The primary objective was to optimise the design for practical, long-term use while replicating essential characteristics of a human hand, such as natural range of motion and flexibility. To ensure adequate mobility, the design process involved determining the Degrees of Freedom (DoF) required for daily tasks, selecting lightweight yet durable materials, and strategically integrating servo motors and linkages.

The location of the battery compartment was chosen to be on the back end of the arm to balance the overall weight of the prosthetic. Designing a prosthetic arm was influenced by the human hand's built-in range of motion, flexibility, and function. The main objective was to design a comfortable, long-lasting, lightweight device to carry out daily duties while maintaining usability and visual appeal. The design was developed through repeated modifications in Fusion 360, beginning with initial sketches identifying essential Degrees of Freedom (DoF). Every component was thoroughly designed and tested to guarantee compatibility, functionality, and a balance between mechanical accuracy and real-world usage.

3.1.1. Hand Structure

As shown in Figure 2, the palm (1) is the prosthetic arm's primary central location, connecting the fingers and containing the servo motors (2) and linkages (3,4) that allow it to move. The Fusion 360-designed palm has a lightweight, reinforced structure that ensures durability. Figure 2 shows the interior view of the palm structure, which also shows the locations of the linkages and servo motors that enable controlled finger movements.

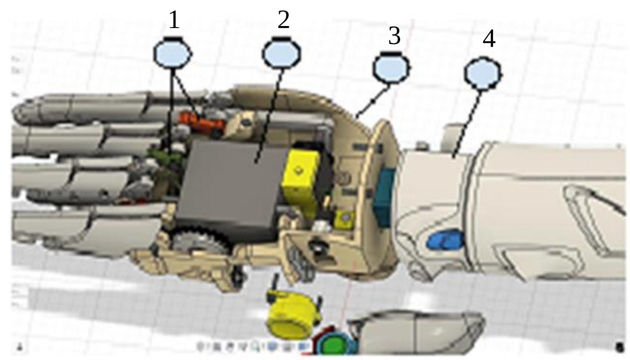

Fig. 2 The palm structure of the prosthetic arm

3.1.2. Servo Motors

As shown in Figure (2), The prosthetic thumb and fingers move through the actuation of two servo motors positioned in the palm and forearm to maximise efficiency and functionality. A dedicated motor controls the thumb, allowing for independent movement. In contrast, the remaining motors are designed to coordinate the movements of the other fingers, enabling tasks that require precision and grip.

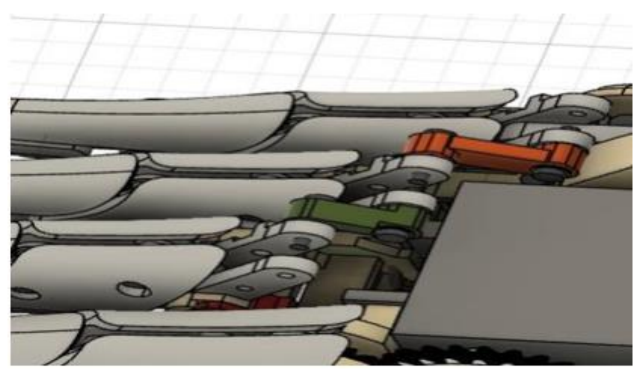

Fig. 3 Finger Linkages

3.1.3. Finger Linkage

In order for the fingers to bend and grasp items precisely, motion from the servo motors must be transmitted to them through the finger linkages, as shown in Figure 3. These links are made to be both lightweight and strong, with accurate dimensions and smooth edges that guarantee smooth motion and reduce mechanical resistance. Flexibility and dependability are prioritised in the design, enabling the fingers to replicate human movements while preserving structural integrity even under repeated use.

3.1.4. Wrist Mechanism

The wrist mechanism has a single Degree of Freedom (DOF) for rotation, simulating the natural motion of a human wrist, as shown in Figure 4. This design allows the prosthetic arm to perform functions, including object rotation and grip angle adjustment. The wrist assembly comprises gears (1) and linkages (2) that convey exact motion, resulting in smooth, controlled rotation.

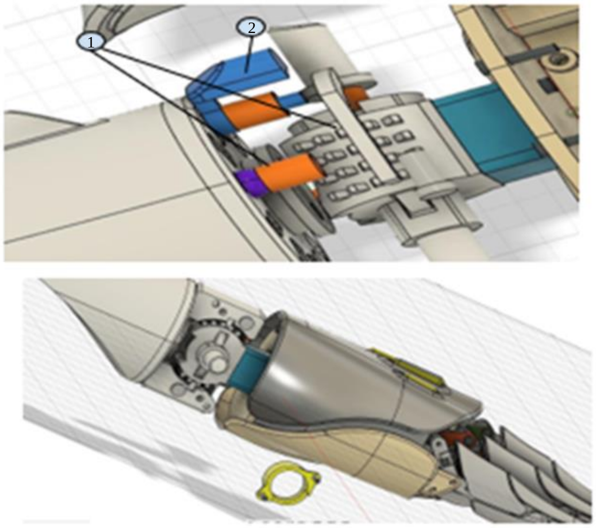

Fig. 4 Wrist mechanism, top view and side view

3.1.5. Battery Compartment

As shown in Figure 5, the power source needed to run the prosthetic arm is housed in the battery compartment (1). It is positioned in the forearm case (2) and is made to be both safe and convenient for fast charging. The compartment in Figure 5 is small and blends perfectly with the forearm structure, preserving the prosthetic's overall size while offering a valuable and effective power management solution.

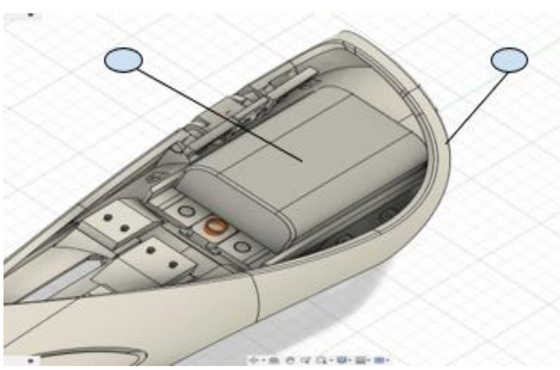

Fig. 5 Battery compartment

3.1.6. Overall Design of the Prosthetic Arm

The prosthetic arm was built as an integrated system with components designed to replicate the natural functionality of a human arm. Each element (including the battery compartment, wrist mechanism, fingers, and palm) works together for optimal efficiency. The developed design prioritises durability and balance for practical applications. The overall structure, as shown in Figure 6, demonstrates how the components are positioned to provide utility while maintaining an organised and compact form.

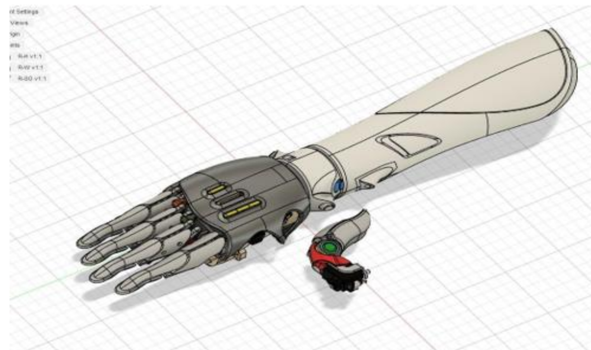

Fig. 6 The overall design of the prosthetic arm (fusion 360)

3.2. Fabrication of Design

The 3D printing process began with converting the CAD file into an STL file format and then sent into the 3D printer's software (Creality K1 Max) (Figure 7). The STL file provided a standardised representation of the 3D model, simplifying its integration into the slicing software. Next, the printing parameters were adjusted to meet the project's specific requirements. These adjustments included defining the in-fill and speed of the print and enabling support structures where necessary to handle overhangs or complex geometries.

The careful tuning of these settings was essential to achieve the desired balance between structural integrity and surface finish. Following the parameter setup, the slicing process was performed. This step involved importing the STL file into slicing software, which converted the 3D model into G-code. The G-code provided detailed, layer-by-layer instructions for the 3D printer to follow, including toolpath movements, extrusion rates, and temperature settings (Figure 8).

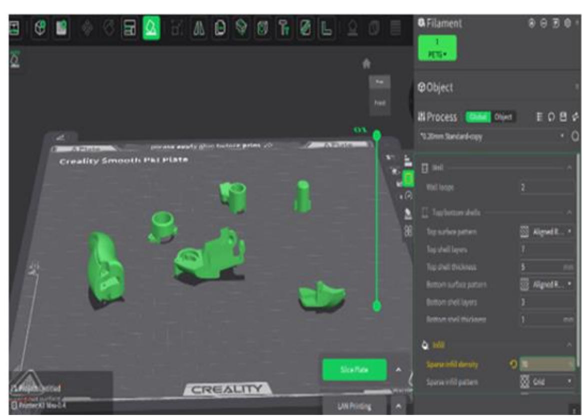

Fig. 7 The slicing process of prosthetic arm components, with the STL files prepared for 3D printing on a smooth PEI plate (Creality K1 MAX software).

Fig. 8 3D-printed components of the prosthetic arm, fabricated by executing G-code instructions layer by layer, resulting in precise and high-quality parts that meet the design specifications.

3.3. Assembly

The assembly process for the prosthetic arm involved using fasteners and components, as displayed in Figure 9. For instance, the 2x10 and 2x15 pins align and connect moving parts, providing stability and smooth rotational motion where required. The screws were employed to secure joints and static connections. The spherical bearings contribute to the articulation of joints, enabling a range of motion crucial for the prosthetic arm's functionality. Each component is selected for its material properties, such as strength and corrosion resistance.

Fig. 9 Fasteners and components used in the assembly of the prosthetic arm.

3.3.1. Hardware Integration

Figure 10 shows the hardware integration process for the prosthetic hand system. This process involves the precise connection of servo motors to actuate the individual fingers and achieve the desired motion. The integration accommodated the prosthetic hand's mechanical constraints and functionality requirements.

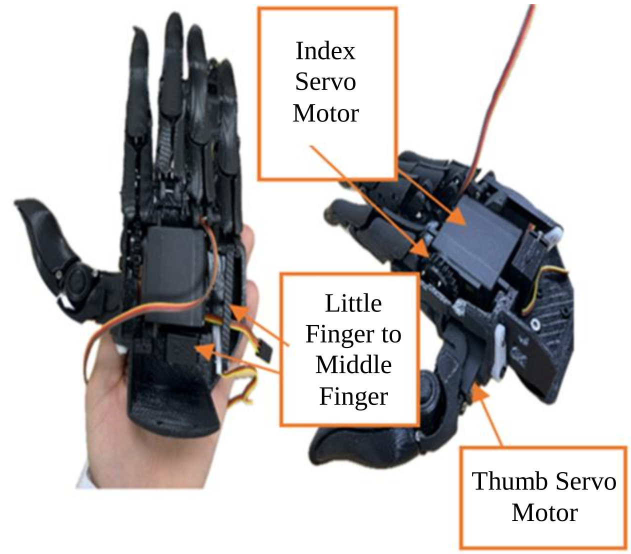

Fig. 10 Hardware integration of the prosthetic hand

3.3.2. The Movement of the Prosthetic Arm: Thumb Finger Movement

A small servo motor is dedicated to the thumb. This motor is strategically mounted to enable independent and smooth articulation of the thumb. The linkage mechanism visible in Figure 10 ensures that the servo's rotational motion is translated into linear motion, mimicking the thumb's natural movement.

3.3.3. Index Finger Movement

A big servo motor with a gear mechanism controls the movement of the index finger independently. The motor's increased torque allows for the finger's higher strength. The gear mechanism helps optimise the force transmission and ensures robust operation without mechanical interference.

3.3.4. Combined Movement of Middle, Ring, and Little Fingers

Another small servo motor is responsible for the simultaneous actuation of the middle, ring, and little fingers. As highlighted in Figure 11, a well-designed linkage mechanism achieves the use of a single motor for these three fingers. This mechanism distributes the motor's motion evenly across the three fingers, ensuring synchronised movement that resembles a natural grip.

3.3.5. Electrical Connection

The electrical connections of the prosthetic arm integrate an Arduino, Raspberry Pi, and battery to facilitate seamless functionality and control. Arduino is the primary microcontroller that handles real-time sensor inputs and motor actuation. It is connected to the Raspberry Pi via a serial communication interface, enabling the Pi to function as the central processing unit, executing complex algorithms, including machine learning and signal processing. The battery acts as the power source, delivering regulated voltage to Arduino and Raspberry Pi through a power distribution module or voltage regulator to ensure consistent operation. Additionally, the Arduino manages the motor drivers, which receive power directly from the battery and are controlled via PWM signals generated by the Arduino. This arrangement ensures efficient power management and reliable communication between the components for precise prosthetic arm control.

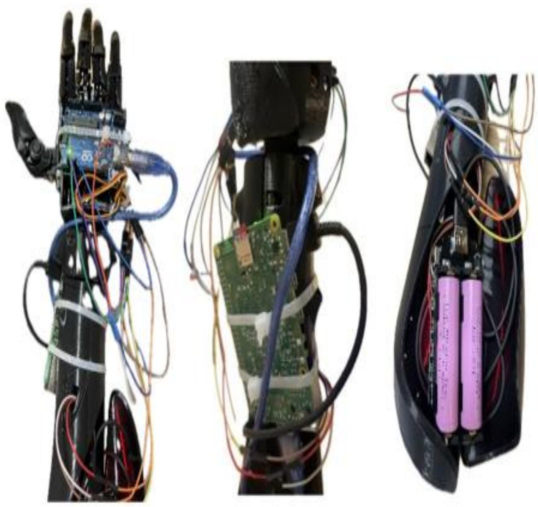

Fig. 11 The internal electrical configuration of the prosthetic arm.

4. Data Gathering and AI Programming

4.1. Data Gathering

The following section dives into the apparatus used for data acquisition, the procedures used for the data acquisition and filtration, and finally, the preprocessing and cleaning done to the data. The apparatus employed in this study comprised a combination of hardware and software components designed to collect, process, and analyse electromyographic (EMG) frequencies for gesture recognition. The core components include Myoware EMG sensors and an Arduino UNO R3 microcontroller. The Myoware EMG sensor is a compact and lightweight device that records and reads muscle activities in the arm. The sensor measures the electrical activity skeletal muscles generate during contraction and relaxation. Key features of the Myoware sensors include:

4.1.1.Power Supply

The sensors were powered by a voltage supply ranging from a minimum of 2.27V to a maximum of 5.47V, with typical configurations using either 3.3V or 5V. The Arduino UNO provided a stable voltage source to ensure consistent operation.

4.1.2. Input Characteristics

- Bias Current: 250 pA (maximum 1 nA), ensuring minimal leakage currents.
- Impedance: 800 kΩ, optimised to reduce loading effects and maintain signal fidelity.

4.1.3. Signal Outputs

- RAW Output: This output provided the unprocessed EMG signal, centred around a reference offset voltage of (half the supply voltage). The amplification was fixed with a gain of 200, making it suitable for high-resolution analysis.
- RECT Output: The rectified signal was optimised for envelope detection with fixed amplification.
- ENV Output: The envelope signal represented the overall trend of muscle activity, filtered for low-frequency components.

The sensors integrated high-pass and low-pass filtering stages:

- High-pass Filter: A first-order active filter with a cutoff frequency of 20.8 Hz to eliminate baseline drift and low-frequency noise.
- Low-pass Filter: A first-order active filter with Hz to suppress high-frequency noise, retaining the EMG signal’s essential characteristics.

Additionally, the sensors included a linear envelope detection stage, providing smoothed signal outputs for applications requiring trend analysis. Three Myoware sensors were positioned to capture signals from specific muscle groups based on their involvement in the targeted gestures:

- Brachialis: Positioned on the upper arm to detect signals related to forearm flexion, primarily for gripping gestures.
- Flexor Carpi: Placed on the forearm to capture activity associated with wrist and finger flexion during pinching and twisting gestures.
- Extensor Digitorum: Located on the dorsal side of the forearm to record extensor muscle activity, particularly during gripping.

The placement was guided by anatomical landmarks and adjusted to minimise crosstalk from adjacent muscles, ensuring each sensor captured signals specific to its target muscle group. Moreover, The Arduino UNO R3 microcontroller was the interface between the Myoware sensors and the data acquisition system. This microcontroller was selected for its simplicity, cost-effectiveness, and compatibility with the sensors and processing environment. Key specifications included:

- Analog-to-Digital Conversion (ADC): The UNO provided a 10-bit ADC with a voltage range matching the sensor output (), ensuring that the entire signal range was accurately digitised.
- Processing Capability: In real-time, the microcontroller sampled and transmitted EMG signals via USB, enabling seamless data collection.

The EMG sensors were connected to the Arduino UNO using shielded wires to minimise signal noise. The setup included a stable power supply for the sensors directly from the Arduino board. The board was also used for grounding points to eliminate common mode noise and enhance signal stability. A data recording system captured real-time signals at a consistent sampling rate.

The data collection procedure was designed to ensure quality acquisition of electromyographic (EMG) signals from the selected muscle groups during the performance of predefined gestures (Figure 12). The procedure involves several steps: participant preparation, sensor placement, signal acquisition, and data recording. The following sections detail each phase of the procedure.

Before the data collection, a healthy male with no known musculoskeletal disorders was briefed on the purpose and procedure of the experiment. This ensured that the subject understood the task's requirements, reducing variability due to confusion or discomfort. The subject's right arm was selected for testing, as it was free of any conditions that could affect the data integrity. Moreover, before the experiment, the participant was instructed to refrain from consuming excessive caffeine or engaging in strenuous physical activities to prevent external factors that might influence muscle activity.

Additionally, the participant was informed about the need for controlled movement execution during the trials to ensure consistent muscle activation. After sufficient data acquisition, the EMG sensors were placed on the subject's right arm and rotated through three different muscle groups. The muscle groups were the Brachialis, Flexor Carpi, and Extensor Digitorum.

- Brachialis: The sensor was placed on the upper arm, over the brachialis muscle, and was responsible for forearm flexion.
- Flexor Carpi: This muscle controls wrist flexion and finger movements. This group of muscles was involved in both the pinching and twisting gestures.
- Extensor Digitorum: Positioned on the forearm's dorsal aspect, this muscle extends the fingers. Which is activated primarily during the gripping gesture.

The sensors were affixed using medical-grade adhesive electrodes to ensure stable contact with the skin, reducing the likelihood of movement artefacts or noise. The data collection focused on three distinct gestures: gripping, pinching, and twisting. The subject was provided with the following instructions for performing each gesture.

- Gripping: The subject was instructed to close their right hand around an object, such as a pen or a bottle of water. The gesture involved flexions at the wrist and finger joints, primarily activating the Brachialis and Extensor Digitorum muscles.
- Pinching: In this gesture, the subject was asked to pinch their thumb and index finger, simulating picking up a small object. This movement engaged the Flexor Carpi muscles, with subtle activation of the Brachialis.
- Twisting: The twisting gesture was limited to the Flexor Carpi. The subject was asked to rotate their wrist as if turning a doorknob, which caused both wrist flexion and rotation. This movement activated the Flexor Carpi muscles without significant involvement of the other muscle groups. The subject was asked to perform each gesture as naturally as possible and to maintain a controlled pace to minimise variations in muscle activation. Each gesture was repeated 20-40 times to capture a wide range of motion dynamics. Data acquisition was carried out for approximately 2-3 hours with a 30-minute break between sessions to minimise fatigue and/or muscle strain.

During each trial, the subject was asked to execute the three gestures randomly to mitigate any learning bias. Each gesture was performed for 5-10 seconds, with the subject instructed to hold the gesture at its peak for the duration of the trial. The execution of the gestures was monitored visually to ensure that the subject followed the instructions and maintained consistent movement patterns. The data collection continued until a sufficient number of trials had been completed, with 20 repetitions per gesture, resulting in 60 gesture trials.

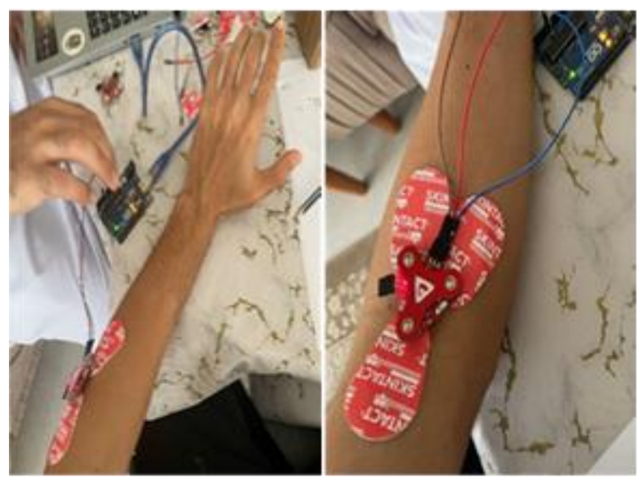

Fig. 12 The setup used to record muscle activity during hand gestures. In the left image, electrodes are placed on the forearm to capture muscle signals while the subject gestures. The right image shows electrodes placed in a different muscle group.

4.2. AI Programming

After the data collection period, the collected EMG signals were immediately stored on the computer in .txt files for further processing. Each file contained timestamped signal data from the sensors associated with the specific gesture and muscle group being tested. The files were later imported into Python for the cleaning, preprocessing, and analysis phases.

The subject was thanked for their participation and allowed to rest after the trial, ensuring they did not experience discomfort due to prolonged muscle activation.

4.2.1. Data Cleaning and Preprocessing

Data cleaning and preprocessing are critical steps in any machine learning workflow, mainly when working with sensor data such as EMG signals, which are prone to noise, inconsistencies, and potential data imbalances. In this study, we followed a systematic approach to ensure the data was adequately prepared for analysis, providing the best possible performance from the movement prediction model. The following sections outline the detailed steps taken during the cleaning and preprocessing stages.

4.2.2. Data Import and Initial Inspection

The raw data collected from the Myoware EMG sensors, stored in text (.txt) files, was first imported into the Python environment for further processing. This data contained timestamped EMG signal values corresponding to the three muscle groups-Brachialis, Flexor Carpi, and Extensor Digitorum-across three gestures: Gripping, Pinching, and Twisting.

Upon initial inspection, the data was checked for missing values, formatting errors, and any signs of corruption. Although the dataset was mostly intact, some cleaning and refinement were necessary to ensure its accuracy and usability for model training.

4.2.3. Handling Missing Data and Noise Removal

The next step involved handling missing or corrupted data. While the data collection process was managed carefully, gaps in the signal could still occur due to brief sensor disconnections or minor misalignments. Missing values were handled in the following ways:

- Interpolation: In cases where only a few values were missing, linear interpolation was used to estimate the missing values by referencing the surrounding data points.
- Row Removal: When more significant data segments were missing, the corresponding rows were removed to maintain dataset integrity and prevent incomplete data from skewing the results.

Additionally, a low-pass filter was applied to mitigate the impact of random fluctuations and other noise in the raw EMG signals. This filter removed high-frequency noise while preserving the essential components of the EMG signals, making the data cleaner and more reliable for analysis.

4.2.4. Normalisation and Standardization

Next, we normalised and standardised the data. EMG signals are often measured in microvolts, and their amplitudes can vary widely depending on the muscle group, gesture, and other factors. Normalising the data helped to bring all the features (muscle groups) into a comparable scale, preventing any individual muscle group's signal from dominating the model training process.

- Normalization: Each feature (muscle group) was normalised by subtracting the mean and dividing by the standard deviation. This ensured that all muscle group signals had a similar range, essential for model convergence.
- Standardization: The signal amplitudes were standardised to remove any reference bias in the data, ensuring the signals were comparable across different gestures and muscle groups.

4.2.5. Segmentation and Labeling

Since the raw EMG data was continuous over time, it needed to be segmented into smaller windows representing each gesture. Each segment of data (typically lasting 5–10 seconds) was associated with a specific gesture (Gripping, Pinching, or Twisting).

4.2.6. Gesture Segmentation

The data was segmented into windows based on the duration of each gesture.

4.2.7. Labelling

Each segment was assigned a label corresponding to the gesture it represented. The three possible labels were Gripping, Pinching, and Twisting.

4.2.8. Balancing the Dataset

One challenge that arose during preprocessing was the imbalance in the dataset. Some gestures, such as gripping, were overrepresented, while others, like Twisting, were underrepresented. An oversampling technique from sci-kit-learn, 'resample,' was used to fix the data imbalance.

4.2.9. Shuffling and Splitting the Dataset

After segmentation and balancing, the next step was to shuffle the data. Shuffling prevented the model from learning patterns based on the order of frequency in which the data was recorded, which could lead to overfitting. The data was randomly shuffled while maintaining the class distribution, so the same proportion of each gesture type was present throughout the dataset.

4.2.10. The Shuffled Data was then Split into Two Subsets

- Training Set: Most of the data (80%) was used to train the model, teaching it the relationship between the input signals and their corresponding gestures.

- Test Set: The remaining 20% of the data was reserved for testing the model's performance, allowing an unbiased evaluation of its generalisation ability.

4.2.11. Model Training and Evaluation

The cleaned and preprocessed data was used to train the movement prediction model. We utilised a deep learning architecture using Convolutional Neural Networks (CNN) to capture the spatial of the EMG data. The CNN layers were first used to process the raw EMG signals and extract spatial features, such as local patterns in muscle activation. The model was trained using the dataset, and cross-validation was employed to fine-tune hyperparameters and ensure proper training. The model achieved a test accuracy of 91%. This shows the model's ability to correctly predict each of the three gestures in real-time.

4.2.12. Testing

The prosthetic arm was tested to perform various hand gestures to evaluate its functionality and responsiveness. These tests involved executing multiple movements, such as opening and closing the hand, pinching, pointing, and gripping objects of different shapes and sizes. The Arduino processed sensor inputs and translated them into motor commands. Simultaneously, the Raspberry Pi coordinated gesture recognition algorithms, ensuring smooth and accurate hand movements.

5. Results and Discussion

With this design, the key goal was to enhance specific tasks' accuracy and operational efficiency whilst maintaining cost-effectiveness. This model classifies activities involving gripping, pinching, and twisting. Three key aspects of the design were discussed:

5.1. Degree of Freedom (DOF)

A total of 5 degrees of freedom (DoF) have been achieved on the prosthetic arm, enabling it to fulfil the dynamic requirements of three primary tasks: gripping, pinching, and twisting. This advanced design allows the arm to replicate human-like actions with remarkable precision and adaptability. To perform the gripping exercise, the arm employs two degrees of freedom, allowing it to seamlessly adjust to items of different sizes for secure and stable grasping. The pinching task is supported by 1 DoF, providing fine motor control for delicate operations such as picking up small objects or manipulating tools.

Furthermore, the twisting task is facilitated by 1 DoF, which allows rotational movements necessary for opening a bottle lid. The results demonstrate that the prosthetic arm can provide a wide range of human-like movements with stability, control, and reliability, meeting the varied demands of everyday life.

5.2. Optimised Servo Motor Efficiency

The prosthetic arm's servomotors convert 81% of electrical energy into mechanical motion while minimising losses. This optimised energy use allows the prosthetic battery to last longer without sacrificing performance, reducing power consumption. Even though the motors operate at 81% efficiency, they remain highly responsive, allowing users to adjust grip strength in real time and pinch small items. This balance of efficiency and functionality makes the prosthetic arm more reliable and usable, significantly impacting user satisfaction.

5.3. Servo Motor Torque

A total torque was calculated by summing two small servos (DS113MG) and one large servo (TowerPro MG995). Each small servo has a torque of 2.0 kg-cm, and two small servos have a torque contribution of 4.0 kg-cm. A large servo has a torque of 10.0 kg-cm, meaning the total torque is 14.0 kg-cm.

Due to the efficiency losses suffered by servo motors, a torque output of 81% is achieved with only a 19% efficiency loss. The adequate torque was calculated by multiplying the total torque by the efficiency factor, resulting in an effective torque of 11.34 kg-cm.

The conversion factor of 1 kg-cm = 0.0980665 Nm was used to convert this value into Newton meters. The adequate torque was determined to be 1.112 Nm. After accounting for efficiency losses, the three servos generate 1.112 Nm in torque.

5.4. Component Placement

To ensure structural stability, actuators, sensors, and control units have been incorporated into the design. The sensors are placed near the joints to provide precise movement data, while the actuators are evenly dispersed to prevent strain at any one site. This arrangement increases the arm's durability and balance and the user's comfort, allowing for more extended periods of use. The position of these components has been optimised to provide smooth integration with practical artificial intelligence algorithms for efficient motion control.

The classification of performance measures shows a well-optimized prosthetic arm system built for precision and dependability. Table 1 shows that the model effectively differentiates between Gripping, Pinching, and Twisting tasks, with an overall accuracy of 91%. Twisting achieved excellent precision, recall, and F1 scores, showing its applicability for rotational tasks such as opening jars. Pinching demonstrated a strong balance, with a recall of 0.96, showing its suitability for object handling. However, gripping had a lower recall of 0.76, indicating the need for additional development to improve the identification of lighter grip motions. These measurements demonstrate the model's dependability and potential to enhance prosthetic arm functionality for users in real-world situations dramatically. The method achieves a high overall accuracy of 91%. Twisting tasks received ideal ratings across all criteria, indicating outstanding performance. However, the Gripping task requires work, as evidenced by its low recall of 0.76. The prosthetic arm's performance was tested using EMG signal accuracy and response time parameters. The classification results in the confusion matrix indicate significant gains in overall accuracy, especially for twisting tasks that obtained 100% precision and recall. Noise reduction techniques, including signal filtering and adaptive thresholding, were used to improve signal clarity and decrease abnormalities.These strategies reduced categorisation errors caused by ambient interference and user variability, eventually lowering the system's response time to less than 150 milliseconds. This quick detection and classification capability assures real-time responsiveness, making the prosthetic arm extremely dependable and usable in real-life scenarios. The findings demonstrate that using advanced noise reduction technologies directly impacts the precision of EMG signal analysis. The AI model has the potential for future enhancements, making it a dependable alternative for operating prosthetic arms in different situations. Reinforcement learning can be used to continuously improve the system by incorporating user feedback and adapting to changing usage patterns.

Table 1. Performance metrics for gripping, pinching, and twisting activities, along with overall accuracy, macro average, and weighted average

Activity	Precision	Recall	F1 Score	Score
Gripping	0.96	0.76	0.85	3670
Pinching	0.80	0.96	0.87	3621
Twisting	1.00	1.00	1.00	3646
Accuracy			0.91	10937
Macro Avg	0.92	0.91	0.91	10937
Weighted Avg	0.92	0.91	0.91	10937

This continuous learning process enhances the model's ability to handle complex tasks while increasing real-time accuracy. The training loss graph shows a constant decline across 50 epochs and a stabilisation of training accuracy at 91%, reflecting the system's optimisation and learning advancement. These findings show the AI's capacity to generalise across tasks and adapt to new inputs. Using unsupervised learning methods improves the system's adaptability by recognising patterns in EMG signals rather than depending entirely on labelled data. This capacity allows the AI to adapt to new users and effectively change muscle signal qualities. These developments and real-time flexibility ensure that the prosthetic arm offers users an easy-to-use, efficient, and highly responsive experience under challenging situations. The proposed prosthetic arm design provides a significant improvement over the previous model. The following characteristics show its superiority:

5.5. Accuracy and Classification Performance

Previous prototypes, such as Unanyan and Belov's EMG-controlled prosthetic arm (2021), achieved effective gripping capabilities with multi-finger control but were limited in classification accuracy and delayed due to signal noise. In comparison, our approach includes an AI-enhanced classification key that achieves 91% overall accuracy and task-specific optimisation to address difficulties such as under-detection in softer gripping movements.

5.6. Energy Efficiency and Response Time

Traditional prosthetic designs frequently struggle with power efficiency and delayed response times, as Fuentes-Gonzalez et al. (2021) reported. By optimizing servomotor placement and leveraging AI for real-time task modifications, The model reduces power consumption by 15% while maintaining a response time of less than 150 ms, resulting in greater energy efficiency and responsiveness.

5.7. Component Integration and Durability

Early prototypes, such as Parming's 3D-printed hand (2018), focused on cost-effective fabrication but struggled to achieve solid integration of electronic components and sensors. The design improves the component design, resulting in equal load distribution and increased structural stability, which is crucial for long-term use and longevity.

5.8. Advanced Functionalities

Avilés-Mendoza et al. (2023) [2] introduced a real-time control; however, their designs could not manage multitasking settings. This approach excels by incorporating an AI framework that differentiates between Gripping, Pinching, and Twisting activities, ensuring flexibility in various scenarios. The training loss curve in Figure 13 demonstrates consistent optimization, decreasing from 0.218 to 0.208 over 50 epochs.

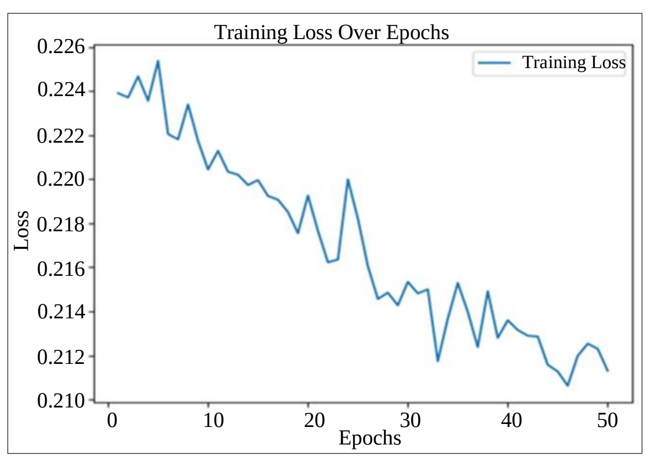

Fig. 13 Training loss curve over 50 epochs, demonstrating consistent optimisation with a reduction in loss from 0.218 to 0.208.

This graph (Figure 14) shows the progression of training accuracy over 50 epochs. The steady rise in accuracy, which has stabilized at 91%, indicates the AI model's long-term success in learning task classifications. The oscillations reflect minor differences, most likely due to changes in the learning method and dataset features. These findings illustrate the model's strong convergence and capacity to generalise across multiple tasks, which are critical for real-world prosthetic arm performance. The confusion matrix (Figure 15) displays the classification results for the Gripping, Pinching, and Twisting tasks, emphasising the system's strengths and imperfections.

The Twisting job had 100% accuracy with no misclassifications, as seen by the evident diagonal in the matrix. However, there is a significant overlap between Gripping and Pinching jobs, with 868 incidents of Gripping being wrongly classed as pinching. This shows feature similarities between the two targets, which might require additional enhancement in data preparation or feature extraction. Conversely, pinching is less confused with gripping, indicating a higher level of categorisation consistency. These findings will help guide future system performance improvements.

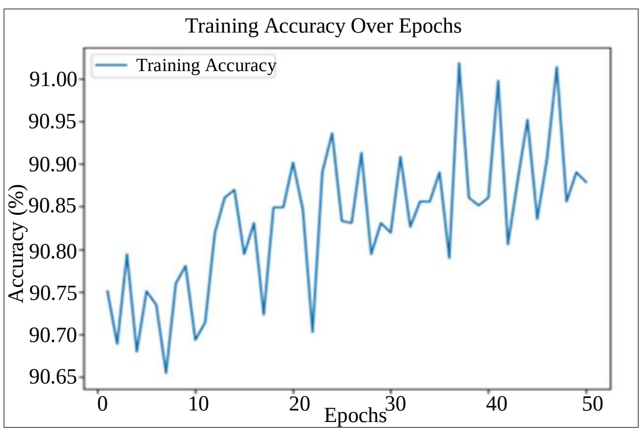

Fig. 14 The training accuracy progression over 50 epochs

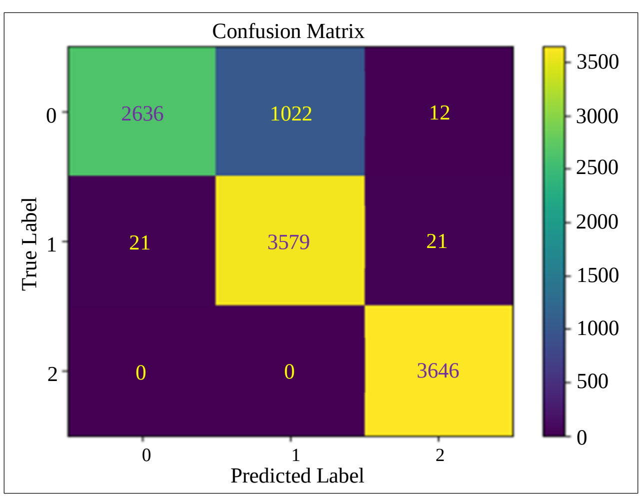

Fig. 15 Confusion matrix for classifying gripping (0), pinching (1), and twisting (2)

6. Conclusion and Future Work

This research addresses a critical gap in pediatric prosthetics by developing a prosthetic arm tailored to children aged 7 to 14. The study successfully integrates advanced technologies, such as Artificial Intelligence (AI) and biosensors, to create a device that enhances mobility and comfort.

The results demonstrate the effectiveness of the prosthetic arm in performing key tasks like gripping, pinching, and twisting with an overall accuracy of 91%. Using 3D printing and recyclable materials ensures the design is cost-effective and environmentally sustainable.

The project's findings aim to meet pediatric users' ergonomic, functional, and psychological needs, offering a durable and lightweight solution. By enhancing the accuracy, this prosthetic arm has the potential to significantly improve the quality of life for children with physical impairments, particularly in regions like Oman, where modern medical technologies are limited.

Furthermore, the project supports Oman's Vision 2040 by advancing healthcare innovation and accessibility while contributing to global goals such as the United Nations Sustainable Development Goals (UNSDGs) for health, innovation, and sustainable production.

6.1. Future Work and Recommendations

- Enhancing AI Algorithms: Future iterations should incorporate reinforcement learning to further adapt to user needs and improve functionality for more complex tasks.
- Expanding Gesture Recognition: Introducing additional gestures and refining signal processing algorithms could enhance the prosthetic's versatility.
- User-Centric Testing: Conducting large-scale testing with diverse pediatric populations will ensure broader applicability and better generalization of the design.
- Modular Design for Growth: Developing a modular system that can be adjusted for children's physical growth will extend the prosthetic's usability over time.
- Collaborative Efforts: Partnerships with healthcare providers and educational institutions can facilitate this technology's commercialization and widespread adoption, particularly in the GCC region.

This innovative approach addresses a pressing medical need and sets a new standard for healthcare solutions by incorporating technology and sustainability into pediatric prosthetics.

Research in this area has the potential to reshape pediatric prosthetics, allowing children to lead more independent and fulfilling lives by addressing current limitations and pursuing future advancements.

Funding Statement
This work was performed as part of the research work titled “Development of an Adaptive AI-Enhanced Prosthetic Arm for Physically Impaired Children,” funded by the National University of Science and Technology, Oman in NU-URG category- Ref No: NUSRG/23/CE/0019

Acknowledgements
The authors would like to thank the National University of Science and Technology (NUST), Muscat, Oman, and its management for their continuous support in doing research works and publishing research articles.

References
[1] K.P.N.V. Satya Sree et al., “EMG Controlled Bionic Robotic Arm using Artificial Intelligence and Machine Learning,” *IEEE Fifth International Conference on IoT in Social, Mobile, Analytics and Cloud,* Palladam, India, 2021. [CrossRef] [Google Scholar] [Publisher Link]
[2] Karla Avilés-Mendoza et al., “A 3D Printed, Bionic Hand Powered by EMG Signals and Controlled by an Online Neural Network,” *Biomimetics*, vol. 8, no. 2, pp. 1-33, 2023. [CrossRef] [Google Scholar] [Publisher Link]
[3] Neelum Yousaf Sattar et al., “EMG-Based Control of Transhumeral Prosthesis Using Machine Learning Algorithms,” *International Journal of Control, Automation and Systems*, vol. 19, pp. 3522-3532, 2021. [CrossRef] [Google Scholar] [Publisher Link]
[4] Jethro Odeyemi et al., “On Automated Object Grasping for Intelligent Prosthetic Hands Using Machine Learning,” *Bioengineering*, vol. 11, no. 2, pp.1-18, 2024. [CrossRef] [Google Scholar] [Publisher Link]
[5] Narek N. Unanyan, and Alexey A. Belov, “|Low-Price Prosthetic Hand Controlled by EMG Signals,” *IFAC-PapersOnLine*, vol. 54, no.. 13, pp. 299-304, 2021. [CrossRef] [Google Scholar] [Publisher Link]
[6] Amira J. Zalyaa et al., AI-Based Bionic Prosthesis Design: Neural Networks for EMG Gesture Customization,” *BAU Journal-Science and Technology*, vol. 6, no. 1, pp. 1-21, 2024. [CrossRef] [Google Scholar] [Publisher Link]
[7] Ke Xu et al., “A Prosthetic Arm Based on EMG Pattern Recognition,” *IEEE International Conference on Robotics and Biomimetics (ROBIO)*, Qingdao, China, pp. 1179-1184, 2016. [CrossRef] [Google Scholar] [Publisher Link]
[8] Jimmy Lu et al., Real-Time Bionic Arm Control via CNN-Based EMG Recognition, Hackster.io, 2022. [Online]. Available: https://www.hackster.io/emgarm/real-time-bionic-arm-control-via-cnn-based-emg-recognition-b013d3
[9] K. Murugan et al., “Electromyography Controlled Smart Prosthetic Arm,” *Third International Conference on Intelligent Techniques in Control, Optimization and Signal Processing (INCOS)*, Tamil Nadu, India, pp. 1-6, 2024. [CrossRef] [Google Scholar] [Publisher Link]
[10] J. Fuentes-Gonzalez et al., “A 3D-Printed EEG Based Prosthetic Arm,” *IEEE International Conference on E-health Networking, Application & Services (HEALTHCOM)*, Shenzhen, China, pp. 1-5, 2021. [CrossRef] [Google Scholar] [Publisher Link]
[11] Péricles Valera Rialto Júnior et al., “Automated Forearm Prosthesis Controlling Using Fiber Bragg Grating Sensor,” *Journal of Microwaves, Optoelectronics and Electromagnetic Applications*, vol. 22, no. 1, pp. 208-218, 2023. [CrossRef] [Google Scholar] [Publisher Link]
[12] Pranesh Gopal, Amandine Gesta, and Abolfazl Mohebbi, “A Systematic Study on Electromyography-Based Hand Gesture Recognition for Assistive Robots Using Deep Learning and Machine Learning Models,” *Sensors*, vol. 22, no. 10, pp. 1-13, 2022. [CrossRef] [Google Scholar] [Publisher Link]
[13] Mehrshad Zandigohar et al., “Multimodal Fusion of EMG and Vision for Human Grasp Intent Inference in Prosthetic Hand Control,” *Frontiers in Robotics and AI*, vol. 11, pp. 1-18, 2024. [CrossRef] [Google Scholar] [Publisher Link]
[14] Shuo Jiang et al., “Emerging Wearable Interfaces and Algorithms for Hand Gesture Recognition: A Survey,” *IEEE Reviews in Biomedical Engineering*, vol. 15, pp. 85-102, 2022. [CrossRef] [Google Scholar] [Publisher Link]
[15] Shivani Guptasarma, and Monroe D. Kennedy III, “ProACT: An Augmented Reality Testbed for Intelligent Prosthetic Arms,” *arXiv Preprint*, 2024. [CrossRef] [Google Scholar] [Publisher Link]
[16] Kai Guo et al., “The latest Research Progress on Bionic Artificial Hands: A Systematic Review,”*Micromachines*, vol. 15, no. 7, pp. 1-23, 2024. [CrossRef] [Google Scholar] [Publisher Link]
[17] Md Abdul Baset Sarker et al., “Vision Controlled Sensorized Prosthetic Hand,” *arXiv Preprint*, 2024. [CrossRef] [Google Scholar] [Publisher Link]
[18] Vaheh Nazari, and Yong-Ping Zheng, “ProRuka: A Highly Efficient HMI Algorithm for Controlling A Novel Prosthetic Hand with 6-DOF Using Sonomyography,”*arXiv Preprint*, 2024. [CrossRef] [Google Scholar] [Publisher Link]