Advancing Affordable Bionic Limbs: Critical Research Gaps in Deep Learning-Based Transradial Prosthetic Arm Development

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Abstract

Background: Upper-limb amputation significantly affects an individual's ability to perform daily activities, creating an increasing demand for intelligent, lightweight, and affordable prosthetic systems. Recent advances in electromyography (EMG), artificial intelligence, deep learning, computer vision, soft robotics, and additive manufacturing have substantially improved prosthetic arm technology. However, challenges related to reliable intention recognition, grasp force regulation, sensory feedback, affordability, and personalization continue to limit widespread clinical adoption.

Objective: This review critically analyzes recent developments in transradial prosthetic arm technology, identifies current research gaps, and proposes future directions for developing affordable and intelligent EMG-driven prosthetic systems.

Methods: A comprehensive review of recent literature was conducted covering prosthetic classifications, anthropometric requirements, commercial prosthetic devices, material selection, EMG-based control strategies, deep learning techniques, computer vision, force myography, sensory feedback, soft robotics, and rehabilitation technologies. Existing approaches were comparatively analyzed to identify technological limitations and emerging research opportunities.

Results: The review indicates that although EMG-based control and deep learning have significantly improved gesture recognition and prosthetic functionality, existing systems still suffer from limitations in adaptive control, sensory feedback, lightweight design, affordability, and real-time performance. Emerging technologies such as multimodal sensing, artificial intelligence, and additive manufacturing demonstrate considerable potential for improving prosthetic functionality; however, their integration into a unified prosthetic control framework remains limited.

Conclusion: The review identifies critical research gaps in intelligent prosthetic arm development and highlights the need for integrated frameworks combining multimodal sensing, deep learning, advanced control strategies, and low-cost manufacturing. The presented analysis provides a foundation for future research toward developing affordable, adaptive, and intelligent transradial prosthetic arms capable of enhancing rehabilitation outcomes and improving the quality of life of amputees

Keywords: Computer Vision, Convolutional Neural Network (CNN), Deep Learning, Electromyography (EMG), Force Myography (FMG), Gesture Recognition, Grasp Force Control, Intelligent Prosthetics, Myoelectric Prosthesis, Rehabilitation Engineering, Sensory Feedback, Transradial Prosthetic Arm

1. Introduction

The human upper limb is a highly complex and versatile biological structure that plays a crucial role in performing daily activities such as grasping, lifting, holding, manipulating objects, communication and interaction with the surrounding environment **[1,18,29]**. The coordinated operation of the shoulder, elbow, forearm, wrist and fingers enables humans to perform both gross and fine motor tasks with remarkable precision **[18,29]**. Anatomically, the human arm consists of three major bones, namely the humerus, radius and ulna, while the hand contains twenty-eight bones that collectively contribute to its dexterity and functionality. The combined movement of these structures provides a large number of degrees of freedom, allowing the upper limb to execute complex motions required for routine and occupational activities **[4,18,29]**.

The loss of an upper limb can have a significant impact on an individual's physical independence, emotional well-being and social participation **[1,18,27]**. Limb amputation may result from several causes including severe trauma caused by road traffic accidents, vascular diseases, diabetes-related complications, cancerous tumors, gangrene, frostbite, peripheral arterial disease and other medical conditions that lead to irreversible tissue damage **[1,18]**. Regardless of the cause, amputation often results in permanent functional impairment, making it difficult for affected individuals to perform everyday tasks independently **[1,18,27]**. Among the various levels of upper limb amputation, transradial amputation is one of the most common **[11,18,29]**. It involves the removal of the limb below the elbow while preserving elbow functionality **[11,18]**. Since the elbow joint remains intact, transradial amputees retain a considerable amount of arm movement and therefore can benefit significantly from appropriately designed prosthetic devices **[11,18,27]**. The restoration of hand, wrist, and forearm functions through prosthetic technology has consequently become an important area of research and development **[1,5,11,18,23,29]**.

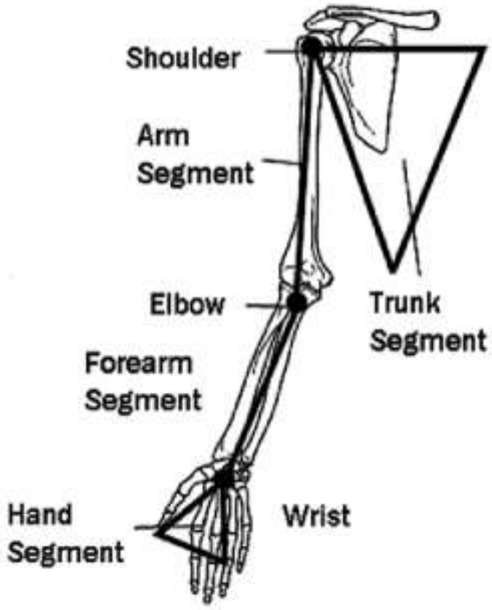

Figure-1: Biomechanical Segmentation of the Human Upper Limb PubMed

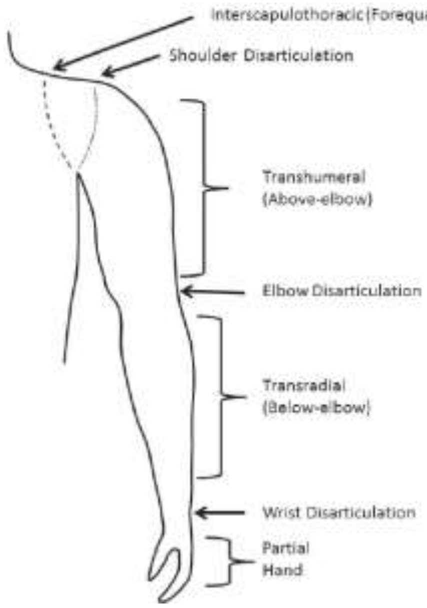

Figure-2: Anatomical Levels of Upper Limb Amputation Segura et al. (2024)

The growing number of amputees worldwide has created an increasing demand for functional and affordable prosthetic solutions **[1,15,18]**. It is estimated that India has nearly two to three million amputees, with approximately twenty-three thousand new cases reported annually **[15]**. Although lower limb amputations account for the majority of cases, upper limb amputees represent a substantial population requiring rehabilitation support **[1,18]**. A significant proportion of these individuals are transradial amputees, highlighting the need for prosthetic systems capable of restoring lost functionality and improving quality of life **[1,11,18,27]**.

Prosthetic arms are artificial devices designed to replace partially or completely missing upper limbs **[1,18]**. Over the years, prosthetic technology has evolved from simple cosmetic replacements to advanced electromechanical systems **[1,18,29]**. Presently, upper limb prostheses can be broadly classified into passive prostheses, body-powered prostheses, myoelectric prostheses, implanted myoelectric systems, and hybrid prostheses **[1,18,29]**. Passive prosthetic arms primarily serve cosmetic purposes and provide limited functional assistance **[1,18]**. They are relatively inexpensive and require minimal maintenance but lack active control mechanisms **[1,18]**. Body-powered prostheses utilize cables and harness systems to convert body movements into mechanical actions **[12,18]**. Although these devices are more affordable than advanced alternatives, they often restrict natural movement and may cause user discomfort during prolonged use **[12,18,27]**.

Myoelectric prostheses represent a significant advancement in upper limb rehabilitation **[5,18,26,29]**. These systems utilize electrical signals generated by residual muscles to control prosthetic movements **[2,5,26,29]**. By interpreting muscle activity, myoelectric prostheses can provide more intuitive control and improved functionality compared to conventional devices **[2,5,10,26,29]**. However, their widespread adoption is limited by factors such as high cost, frequent battery charging requirements, extensive user training, and challenges associated with precise grasp control **[1,5,18,29]**. Implanted myoelectric systems offer enhanced signal acquisition and control performance but involve invasive surgical procedures and substantially higher costs **[27]**. Hybrid prosthetic systems combine multiple control approaches to improve functionality; however, their complexity, weight, and manufacturing cost remain major concerns **[9,12,18,23]**.

Despite substantial technological progress, existing prosthetic arms are still unable to fully replicate the dexterity, adaptability, and sensory capabilities of the natural human hand **[5,18,23,28]**. Many commercially available devices face challenges in accurately controlling grip force, performing complex grasp patterns, and manipulating objects of varying shapes and sizes **[4,5,10,17,23]**. In addition, factors such as device weight, durability, user comfort, customization requirements, and affordability significantly influence user acceptance and long-term usage **[8,18,23,27]**. In developing countries, the high cost of advanced prosthetic systems often forces amputees to rely on passive prostheses that provide limited functional benefits **[1,15,18]**.

The human hand performs object manipulation through a sophisticated interaction between muscles, joints, sensory receptors, and neural control mechanisms **[5,13,29]**. Replicating these capabilities in an artificial system requires the integration of advanced sensing, signal processing, actuation, and control technologies **[5,17,23,28]**. Consequently, researchers have increasingly focused on developing intelligent prosthetic systems capable of interpreting user intent and generating natural movements **[2,10,17,25,26]**. Recent advances in biomedical signal acquisition, electromyography-based control, artificial intelligence, machine learning, deep learning, and sensor technologies have created new opportunities for improving prosthetic performance **[2,4,9,10,17,19,25,26,29]**. These technologies have shown considerable potential in enhancing gesture recognition, grasp control, object classification, and overall user interaction **[4,9,10,17,19,26]**.

Although significant progress has been achieved, several challenges remain unresolved **[1,5,18,23,29]**. Robust interpretation of muscle signals, reliable grasp force regulation, lightweight design, biocompatible material selection, affordability, and personalized customization continue to be important research concerns **[5,18,23,26,28,29]**. Addressing these issues is essential for developing next-generation prosthetic systems that can more closely emulate natural hand function and improve the daily lives of transradial amputees **[1,5,18,23,27]**. Therefore, a comprehensive review of existing prosthetic technologies, current developments, and emerging research directions is necessary to identify existing limitations and guide future advancements in the field of intelligent upper limb prosthetics **[1,2,18,29]**.

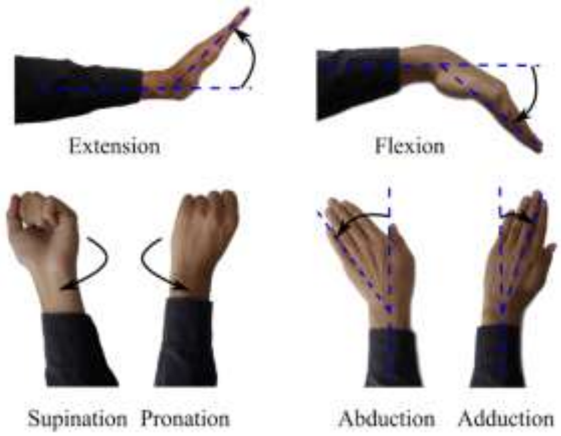

Figure-3. Major movements of the human upper limb illustrating flexion, extension, pronation, supination, abduction, and adduction, which collectively contribute to the 27 degrees of freedom of the arm and hand. Atzori et al. (2015)

1.1 Degree of Freedom (DOF) of the Human Upper Limb

The human upper limb is a highly articulated biomechanical system capable of performing a wide range of movements required for daily activities. The coordinated action of the shoulder, elbow, forearm, wrist, and fingers provides a total of 27 Degrees of Freedom (DOF), enabling precise positioning, grasping, and manipulation of objects.

The shoulder joint contributes 3 DOF, namely flexion/extension, abduction/adduction, and internal/external rotation, while the elbow joint provides 1 DOF through flexion and extension. Together, the arm contributes 4 DOF.

The forearm provides 1 DOF through pronation and supination, allowing rotational movement of the radius around the ulna. The wrist contributes 3 DOF, including flexion/extension, radial/ulnar deviation, and midcarpal flexion/extension.

The fingers contribute the majority of the upper limb's dexterity. Each finger contains a Metacarpophalangeal (MCP) joint with 2 DOF (flexion/extension and abduction/adduction), a Proximal Interphalangeal (PIP) joint with 1 DOF (flexion/extension), and a Distal Interphalangeal (DIP) joint with 1 DOF (flexion/extension). For the four fingers, these joints collectively provide 16 DOF. The thumb contributes an additional 3 DOF, comprising 2 DOF at the thumb MCP joint and 1 DOF at the Interphalangeal (IP) joint.

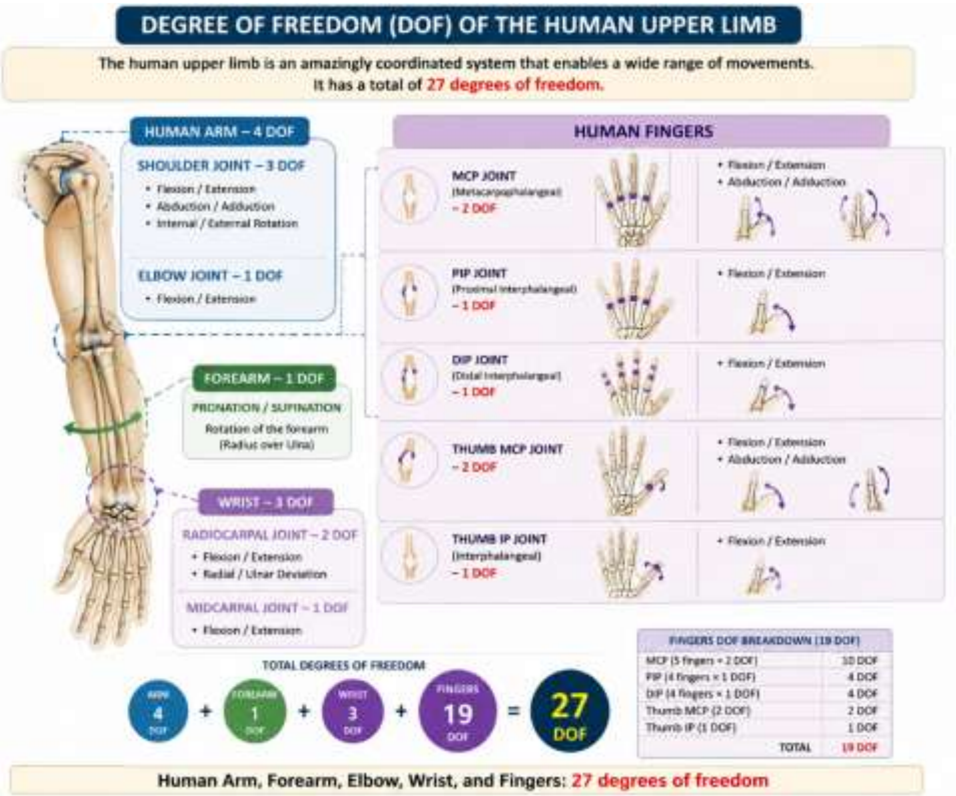

Figure-4: Kinematic Structure and Degrees of Freedom of the Human Arm, Wrist and Fingers

Figure-5: Transradial, Transhumeral and Shoulder Disarticulation Amputations

1.2 Upper Limb Amputation Statistics and Rehabilitation Challenges: Indian Scenario

A prosthetic limb is an artificial device designed to replace a missing body part and restore, to some extent, the functionality and appearance of the lost limb **[1,18]**.

Prosthetic technologies have evolved significantly over the years and play an important role in the rehabilitation of individuals affected by limb loss **[1,18,29]**. The increasing number of amputees worldwide has created a growing demand for functional, comfortable, and affordable prosthetic solutions **[1,15,18]**.

India has a considerable population of individuals living with limb amputations. Current estimates suggest that nearly 2–3 million people in the country are affected by upper or lower limb loss, with approximately 23,500 new amputation cases reported annually. The majority of these cases involve lower limb amputations, accounting for nearly 80–90% of the total amputee population. Consequently, the estimated number of lower limb amputees ranges between 1.6 and 2.7 million individuals. Upper limb amputations, although less common, represent a significant rehabilitation challenge and constitute approximately 10–20% of all amputation cases. The estimated population of upper limb amputees in India ranges from 200,000 to 600,000 individuals.

Among the various categories of upper limb amputations, transradial amputation, commonly referred to as below-elbow amputation, represents a substantial proportion of cases **[11,18,29]**. It is estimated that between 100,000 and 300,000 individuals in India live with transradial limb loss. In comparison, transhumeral amputations and shoulder disarticulations occur less frequently, with an estimated combined population of 50,000 to 150,000 individuals. Owing to the relatively large number of transradial amputees and the preservation of elbow functionality, considerable research efforts have been directed toward the development of advanced prosthetic arms capable of restoring hand and forearm functions while improving the quality of life of affected individuals **[1,11,18,23,27,29]**.

2. Prosthetic Arm Classification Based on Control Mechanisms

The advancement of prosthetic technology has led to the development of various upper limb prostheses designed to address the functional requirements of amputees at different levels of limb loss **[1,18,29]**. These prosthetic systems differ in terms of design complexity, control mechanisms, material composition, cost, and functional capabilities **[1,7,11,12,18,23,29]**. The selection of an appropriate prosthetic arm depends on several factors, including the level of amputation, user requirements, affordability, comfort, and intended daily activities

[1,8,18,27].

2.1 Passive Prosthetic Arm

Passive prosthetic arms are primarily intended to restore the appearance of a missing limb while offering limited functional assistance during daily activities **[1,18,29]**. These prostheses are generally manufactured using materials such as silicone, polyurethane, thermoplastic elastomers, polyethylene, aluminum, and titanium **[18,23]**. Due to the absence of active actuation systems, passive prostheses are comparatively lightweight and require minimal maintenance **[1,18]**. Their cost typically ranges from ₹10,000 to ₹1,00,000 depending on the material quality and cosmetic finish. However, the lack of electrical or mechanical control mechanisms restricts their ability to perform active grasping and object manipulation tasks **[1,18,29]**.

2.2 Body-Powered Prosthetic Arm

Body-powered prosthetic arms utilize cables, harnesses, and mechanical linkages to translate body movements into prosthetic motion **[12,18]**. Commonly used materials include thermoplastics, aluminum, stainless steel, thermoplastic elastomers, rubber, and silicone **[18,23]**. These devices are generally more affordable than advanced electronic prostheses, with costs ranging between ₹20,000 and ₹2,00,000. Although they provide functional grasping capabilities, users often experience discomfort due to harness systems **[12,18,27]**. Furthermore, studies have reported rejection rates ranging from 16% to 58% **[18,27]**. Limitations such as restricted movement, user fatigue, and difficulty in achieving precise grip control continue to affect their usability **[12,18,29]**.

2.3 Myoelectric Prosthetic Arm

Myoelectric prosthetic arms operate by detecting electrical activity generated by residual muscles and converting these signals into movement commands **[2,5,26,29]**. These systems are commonly fabricated using silicone, aluminum, stainless steel, thermoplastic elastomers, and polyurethane **[18,23]**. Compared with conventional prostheses, myoelectric devices offer improved functionality and more natural control **[2,5,10,26,29]**. However, their adoption is often limited by their high cost, which may range from ₹2,00,000 to ₹15,00,000. Additional challenges include frequent battery charging requirements, lengthy user training periods, and difficulties in achieving accurate grip force modulation during object handling **[5,10,18,26,29]**.

2.4 Implanted Myoelectric Prosthetic Arm (IMES)

Implanted Myoelectric Prosthetic Systems (IMES) represent an advanced category of prostheses in which implanted sensors acquire muscle signals directly from within the body **[27]**. These devices typically employ biocompatible materials such as titanium, silicone, polyimide, gold, and specialized biomedical coatings **[18,23,28]**. IMES technology has the potential to provide enhanced signal quality and intuitive control **[5,27]**. Nevertheless, the requirement for surgical implantation makes the procedure invasive and costly **[1,27]**. The overall expenditure can range from ₹50 lakhs to ₹1 crore, limiting accessibility for most amputees. Additionally, achieving reliable and precise grasp control remains a significant technical challenge **[5,27,29]**.

2.5 Hybrid Prosthetic Arm

Hybrid prosthetic arms combine features of multiple prosthetic technologies, integrating mechanical, body-powered, and myoelectric control approaches to improve overall functionality **[9,12,18].** These systems are generally constructed using materials such as silicone, aluminum, stainless steel, thermoplastic elastomers, and polyurethane **[18,23].** Hybrid designs aim to balance functionality and control performance; however, they are associated with increased system complexity **[9,12,18].** The cost of such prostheses typically ranges from ₹4,00,000 to ₹15,00,000. Other limitations include increased weight, complex integration of components, and challenges in achieving smooth and precise grasping operations under varying conditions **[5,9,18,23,29].**

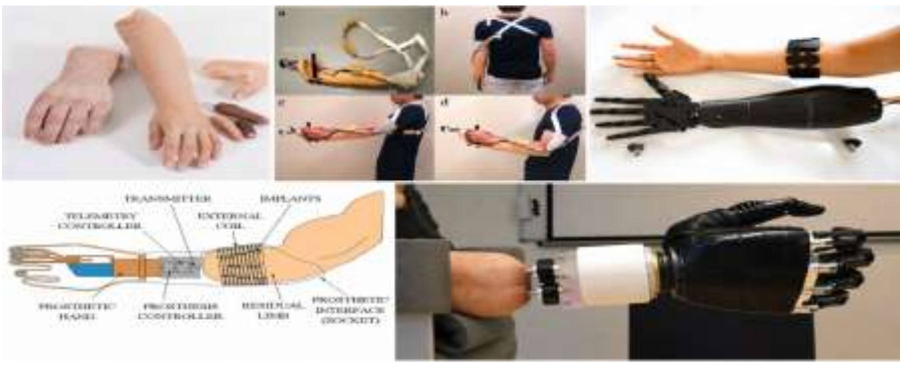

Figure-6: Passive, Body-Powered, Myoelectric, IMES, and Hybrid Prosthetic Arms

3. Anthropometric Analysis of the Human Upper Limb

The anatomical characteristics of the human upper limb provide essential information for the design and development of prosthetic arms **[18,22,29]**. Parameters such as limb weight, segment dimensions, grip force, and movement capabilities directly influence the mechanical structure, actuator selection, material choice, and control strategy of a prosthetic device **[18,22,23,24,29]**. Understanding these biomechanical characteristics helps in

designing prostheses that closely resemble the natural arm in terms of functionality, comfort, and usability **[18,23,27,29]**.
The weight of the human arm typically constitutes approximately 5–6% of an adult's total body weight. On average, the total arm weight ranges between 2.7 kg and 3.2 kg in males and between 2.2 kg and 2.7 kg in females. The upper arm contributes the largest portion of the weight, followed by the hand and forearm. These weight distributions are important considerations when determining the target weight of a prosthetic limb to ensure user comfort and reduce fatigue during prolonged use **[18,23]**.
Anthropometric measurements indicate that the average upper arm length ranges from 32 cm to 36 cm in males and from 28 cm to 32 cm in females. Similarly, the forearm and hand dimensions vary according to gender and body structure. These measurements serve as reference values for the customization and fabrication of prosthetic components. In addition, average wingspan measurements provide useful information for maintaining anatomical proportionality during prosthetic fitting **[18,22,23]**.
Grip force is another critical parameter in prosthetic arm design **[5,17,23,29]**. The human hand can generate substantial pinch and power grip forces, enabling effective object manipulation during daily activities **[5,17,29]**. Furthermore, the natural grasping speed of the human hand allows smooth and coordinated interaction with objects. Replicating these biomechanical characteristics remains a key objective in the development of advanced prosthetic arms **[4,5,17,23,29]**. Therefore, anatomical and anthropometric data serve as fundamental design guidelines for achieving improved functionality, comfort, and human-like performance in upper limb prosthetic systems **[18,22,23,29]**.

4. Review of Commercial Upper Limb Prosthetic Systems

The rapid advancement of prosthetic technology has resulted in the availability of numerous commercial myoelectric prosthetic hands with varying levels of functionality and performance. A market analysis of these devices provides valuable insights into their technical specifications, including weight, degrees of freedom, actuator configuration, grip force, and grasping speed. Understanding the capabilities and limitations of existing commercial prostheses helps identify current technological gaps and serves as a benchmark for the development of improved prosthetic solutions for upper limb amputees.

Figure-7: Commercial Prosthesis

Table-1: Benchmarking Commercial Prosthetic Hands Based on Mechanical and Functional Parameters

Commercial	Weight(grams)	DoF	Actuators	Grip Force(N) [Pinch, Power]	Grasp Speed
Sensorhand by Ottobock	480-500	1	1	[-,100]	30mm/s at tip
i-limb Ultra Revolution by Touch Bionics	504	6	5	[6.54, 136]	1.2 sec
Bebionic(RSL Steeper)	495-539	6	5	[12.47,77]	1.9 sec
Michelangelo by OttoBock	420	2	2	[-, 80]	-
Remedi	400	6	6	[-, 9.2]	-
MANUS Hand	1200	3	2	[-,60]	2.5 sec
Smart Hand	520	16	4	[-,18]	1.4 sec
Fluid Hand III	400	8	1	[-,45]	1 sec
Soft Hand Pro	520	2	2	[20,40]	1.5 sec

5. Literature Review: Recent Developments in Myoelectric and Intelligent Prosthetic Arms

The development of upper limb prosthetic systems has attracted significant attention from researchers across the fields of biomedical engineering, robotics, artificial intelligence, rehabilitation science, and material engineering. Continuous advancements in sensing technologies, machine learning algorithms, computer vision, additive manufacturing, and human-machine interfaces have contributed to the evolution of prosthetic devices from simple mechanical replacements to intelligent assistive systems capable of performing complex functional tasks.
A comprehensive review of recent literature is essential to understand the current state of prosthetic technology, identify existing challenges, and recognize emerging research trends. The studies reviewed in this work encompass various aspects of upper limb prosthetics, including prosthetic embodiment, electromyography (EMG)-based control, deep learning-assisted grasping, sensory feedback mechanisms, musculoskeletal modelling, prosthetic wrist design, computer vision integration, and user-centric prosthetic development.

Alexander Hopkins, Rodney Ho and Derrick Varner (2023)
Hopkins et al. presented a comprehensive discussion on the evolution of prosthetic technologies and their impact on the lives of amputees. The study highlighted the historical development of prosthetic devices from simple mechanical replacements to modern intelligent systems. The authors emphasized that prosthetic limbs serve not only as functional rehabilitation tools but also contribute significantly to psychological recovery, social integration, and user confidence. The work further discussed the growing demand for advanced prosthetic solutions and the importance of developing technologies that can improve both physical and emotional well-being.

Sahand C. Eftekari et al. (2023)
Eftekari and co-authors investigated the concept of prosthetic embodiment and its significance in successful prosthetic adoption. The study explored the mechanisms through which users perceive a prosthetic limb as an extension of their own body. The authors identified several physiological and cognitive factors that influence embodiment and highlighted the role of sensory integration in establishing a natural connection between the user and the prosthesis. The findings provide a valuable framework for understanding user acceptance and improving human-prosthesis interaction.

Bahareh Ahkami et al. (2023)
Ahkami et al. conducted a systematic review on electromyography-based prosthetic control systems. The study examined various EMG acquisition techniques, signal processing approaches, and control strategies used in prosthetic applications. The authors reported that although EMG remains one of the most widely adopted control methods, several challenges such as signal variability, electrode positioning, muscle fatigue, and environmental noise continue to affect system performance. The review emphasized the need for more reliable control algorithms and improved hardware solutions for daily prosthetic use.

Rachel L. Hybart and Daniel P. Ferris (2023)
Hybart and Ferris reviewed embodiment mechanisms in robotic exoskeleton systems and discussed the role of neural control in human-machine interaction. The study described how the nervous system generates motor commands and utilizes sensory feedback to regulate movement. The authors explained the significance of predictive models and feedback mechanisms in achieving coordinated motion. Their findings offer useful insights for the development of prosthetic control systems that mimic natural human motor behavior.

Rhys Newbury et al. (2023)
Newbury and colleagues reviewed recent deep learning approaches for robotic grasp synthesis. The study examined several learning-based techniques for object grasping, including reinforcement learning, direct regression, exemplar-based methods, and sampling-based strategies. The authors demonstrated the growing importance of artificial intelligence in enabling robots to identify suitable grasp configurations for objects with varying geometries. The review highlighted the potential of deep learning techniques for enhancing prosthetic hand grasping capabilities.

Filip Gasparic et al. (2023)
Gasparic and co-workers proposed a sensory feedback framework for improving grasp force regulation in myoelectric prostheses. The study investigated the effectiveness of combining force feedback and EMG feedback during object manipulation tasks. Experimental evaluations indicated that multimodal feedback improved user awareness of grip force and enhanced control accuracy. The research demonstrated the importance of closed-loop control systems in achieving safer and more reliable prosthetic operation.

M. Romanato et al. (2023)
Romanato et al. explored the application of electromyography-informed musculoskeletal models using three-dimensional motion analysis. The study focused on estimating neuromuscular parameters and musculotendon forces from limited EMG inputs. The authors demonstrated that motion analysis can improve the interpretation of muscle activation patterns and contribute to more accurate biomechanical modelling. The findings provide useful information for developing advanced prosthetic control strategies based on human movement characteristics.

Alok Prakash et al. (2023)
Prakash and co-authors investigated the application of force myography (FMG) as an alternative control interface for multifunctional upper-limb prosthetic hands. The study focused on capturing muscle deformation patterns from the residual limb and utilizing them as control signals for prosthetic operation. Experimental evaluations demonstrated the feasibility of FMG-based control for executing multiple hand functions with improved reliability. The research highlighted the potential of force myography as a non-invasive and computationally efficient approach for prosthetic hand control, particularly in situations where conventional electromyographic signals may be unstable or difficult to acquire.

Benchabane et al. (2023)
Benchabane and colleagues proposed an advanced control methodology for conventional myoelectric prosthetic systems. The study emphasized the development of novel signal processing and decision-making algorithms to improve the responsiveness and functionality of upper-limb prostheses. By enhancing the interpretation of muscle

activity patterns, the proposed approach aimed to achieve smoother and more intuitive prosthetic movements. The findings demonstrated the importance of intelligent control architectures in improving the overall performance and usability of myoelectric prosthetic devices.

Hazem Bayoumi et al. (2023)
Bayoumi and co-authors addressed the challenge of grasp force sensing and control in upper-limb soft robotic prostheses. The study proposed an improved sensing and feedback framework capable of enhancing object manipulation performance. The authors demonstrated that accurate monitoring and regulation of grasp force can significantly improve user confidence, reduce object slippage, and prevent excessive gripping forces. The research emphasized the role of intelligent force control mechanisms in achieving more natural and adaptive prosthetic hand functionality.

Guangjie Yu et al. (2023)
Yu and colleagues developed a real-time prosthetic hand control system based on electromyographic signal classification using a convolutional neural network enhanced with a channel-attention mechanism. The proposed deep learning framework was designed to improve the recognition of multiple hand gestures directly from EMG signals. Experimental results demonstrated enhanced classification accuracy and faster response times compared with traditional machine-learning approaches. The study highlighted the effectiveness of attention-based neural networks in improving the reliability and intuitiveness of myoelectric prosthetic control systems.

Revanth Damerla et al. (2022)
Damerla and colleagues designed and evaluated a two-degree-of-freedom prosthetic wrist mechanism intended to improve wrist functionality. The study focused on enhancing the range of motion while maintaining acceptable mechanical performance. Although the proposed design demonstrated improved mobility, limitations related to actuator torque density, power density, and transmission efficiency were identified. The authors suggested further improvements to meet the practical requirements of prosthetic users.

Justine Jihyun Kim et al. (2022)
Kim and co-authors investigated user preferences toward 3D-printed prosthetic hands using statistical analysis techniques. The study revealed that prosthetic users exhibit varying preferences based on their lifestyle, daily activities, and occupational requirements. The findings highlighted the importance of customization in prosthetic design and emphasized that user-centered approaches are essential for improving acceptance and long-term utilization of prosthetic devices.

Maria Claudia F. Castro et al. (2022)
Castro and colleagues developed a hybrid prosthetic hand that integrates surface electromyography with an embedded computer vision system. The proposed system employed a convolutional neural network to recognize object characteristics and assist in selecting appropriate grasp patterns. The study demonstrated that combining EMG-based control with computer vision can improve object recognition and enhance prosthetic hand functionality. The research highlighted the potential of intelligent hybrid systems for next-generation prosthetic applications.

Ang Ke, Jian Huang, Jing Wang and Jiping He (2022)
Ang Ke and co-authors investigated the challenges associated with maintaining reliable myoelectric prosthetic control under varying arm positions. The study proposed a multimodal human-machine interaction framework that combines electromyography (EMG) and force myography (FMG) signals to improve gesture recognition performance. To enhance classification accuracy, the authors integrated a recurrent neural network-based learning model with a knowledge-driven post-processing strategy. Experimental findings demonstrated that multimodal sensing significantly improved grasp classification robustness when compared with conventional EMG-only approaches. The research highlights the importance of sensor fusion techniques for achieving dependable prosthetic control in dynamic environments.

Elif Hocaoglu and Volkan Patoglu (2022)
Hocaoglu and Patoglu presented the design and experimental validation of a variable stiffness transradial prosthetic hand. The proposed prosthesis employed tendon-driven actuation and nonlinear spring mechanisms to achieve adjustable compliance during grasping operations. By utilizing Bowden cable transmission, the design enabled lightweight construction while allowing critical components such as motors and controllers to be positioned remotely. The study demonstrated that variable stiffness mechanisms can improve adaptability, user safety, and object manipulation capabilities in prosthetic hands.

Vikranth H. Nagaraja, Jhonatan da Ponte Lopes and Jeroen H. M. Bergmann (2022)
Nagaraja and colleagues introduced an innovative body-powered prosthetic control concept aimed at overcoming limitations associated with traditional cable-operated systems. Instead of relying solely on harness-based actuation, the proposed approach utilized controlled airflow generated through user breathing patterns to drive prosthetic finger movements. A miniature turbine-based mechanism was incorporated to translate airflow into mechanical motion. The study demonstrated the potential of alternative control paradigms for improving user comfort,

reducing movement restrictions, and enhancing the functionality of body-powered prosthetic systems.

Neelum Yousaf Sattar et al. (2022)
Sattar and co-authors explored the application of functional near-infrared spectroscopy (fNIRS) for upper limb motion intention recognition. The study focused on detecting user intentions associated with multiple arm movements by analyzing cerebral hemodynamic responses. Artificial neural network models were employed to classify movement patterns from processed fNIRS signals. The results demonstrated the feasibility of using brain-related physiological signals as an alternative interface for prosthetic control, providing a promising direction for individuals with limited muscular activity.

Robbie Brack and Emeka H. Amalu (2021)
Brack and Amalu conducted a comprehensive review of upper limb prosthetic technologies, emphasizing materials, design methodologies, and research challenges. The study examined the suitability of different materials used in prosthetic fabrication and discussed their influence on durability, comfort, weight, and functionality. The authors also identified key challenges related to user acceptance, affordability, customization, and technological limitations. Their findings highlighted the need for prosthetic systems that better align with the diverse requirements of amputees.

Ejay Nsugbe (2021)
Nsugbe investigated the use of near-infrared sensing for gesture recognition in transradial prosthetic control. The research proposed hemodynamic monitoring as an alternative to conventional electromyographic control systems. The study demonstrated that physiological signals obtained through near-infrared sensing can provide useful information regarding user intentions while reducing some of the challenges associated with muscle fatigue and signal degradation. The findings suggest that non-invasive optical sensing technologies may complement future prosthetic control architectures.

Rani Kolaghassi, Mohamad Kenan Alhares and Konstantinos Sirlantzis (2021)
Kolaghassi and co-authors reviewed intelligent algorithms applied in robotic gait analysis and movement prediction systems. Although the study primarily focused on lower-limb robotic applications, the presented machine learning and predictive modelling techniques offer valuable insights for prosthetic control systems. The review emphasized the role of artificial intelligence in improving movement prediction accuracy, adaptive control, and human-machine interaction. Such approaches may be extended to upper limb prostheses for enhancing motion recognition and control performance.

Hasan Salman et al. (2021)
Hasan Salman and colleagues developed a three-degree-of-freedom robotic arm model and analyzed its kinematic behavior using MATLAB-based tools. The study employed forward and inverse kinematic formulations to determine the position and orientation of the end-effector. A graphical user interface was developed to visualize arm movements and evaluate system performance. The research provides useful insights into robotic arm modelling techniques that can be adapted for prosthetic arm design and motion planning applications.

Alireza Mohammadi et al. (2020)
Mohammadi and co-authors proposed a practical soft robotic prosthetic hand fabricated using additive manufacturing techniques. The prosthetic design incorporated multi-articulating finger mechanisms within a compact and lightweight architecture. Experimental evaluations demonstrated that soft robotic structures offer improved flexibility, adaptability, and safety during object manipulation. The study highlighted the advantages of 3D printing for producing cost-effective and customizable prosthetic solutions suitable for daily use.

Amalya Mkhiitaryan and Zaven Khanamiryan (2020)
Mkhiitaryan and Khanamiryan investigated the modelling and control of a prosthetic bionic hand using MATLAB/Simulink tools. The research focused on the development of a control framework capable of regulating prosthetic finger movements through feedback mechanisms. A proportional-integral-derivative (PID) controller was designed and evaluated to improve system responsiveness and stability. The study demonstrated the usefulness of simulation environments in validating prosthetic control strategies before hardware implementation.

Yue Li et al. (2020)
Yue Li and co-authors developed a highly selective biomimetic tactile sensor intended for neuroprosthetic applications. The proposed sensor was designed to emulate certain tactile sensing capabilities of the human skin, enabling improved detection of contact conditions during object interaction. The study demonstrated the potential of flexible tactile sensors in enhancing grasp stability and user perception. However, challenges associated with accurately distinguishing between static and dynamic frictional forces were identified, indicating the need for further research in artificial tactile feedback systems.

Table-2: Technology Maturity and Research Opportunity Matrix for Next-Generation Transradial Prosthetic Arms

Technology	Research Availability	Commercial Availability	Cost Effectiveness

EMG Control	High	High	Low
Deep Learning	Moderate	Low	Moderate
Computer Vision	Moderate	Low	Moderate
FMG Control	Low	Very Low	High
Sensory Feedback	Moderate	Low	Low
Soft Robotics	Moderate	Very Low	Moderate
Indigenous Manufacturing	Very Low	Very Low	High
AI + FMG + Vision Fusion	Very Low	Nil	High Potential

The Technology Maturity and Research Opportunity Matrix provides a comparative assessment of existing technologies used in transradial prosthetic arm development based on research progress, commercial adoption, and cost effectiveness. The analysis highlights that while EMG-based control systems have achieved significant maturity, emerging technologies such as multimodal sensing, deep learning, computer vision, and AI-driven prosthetic control remain underexplored, presenting substantial opportunities for future research and innovation

5.1 Critical Research Gaps

The literature review and field investigations reveal that despite substantial advancements in upper-limb prosthetic technology, several challenges continue to limit the widespread adoption and functional effectiveness of transradial prosthetic arms. Existing systems often suffer from unreliable intention recognition due to the limitations of EMG signals, inadequate sensory feedback, poor grasp force regulation, and restricted human-like dexterity. Although emerging technologies such as force myography, computer vision, deep learning, tactile sensing, and brain-computer interfaces have shown promising results, their integration into a unified, robust, and real-time prosthetic control framework remains limited. Furthermore, advanced prosthetic arms are often expensive, heavy, and largely dependent on imported technologies, making them inaccessible to many amputees, particularly in developing countries. Additional concerns include insufficient customization, lack of standardized evaluation methods, limited commercialization of soft robotic and biomimetic designs, and a significant gap between laboratory prototypes and practical clinical deployment. These challenges highlight the need for an affordable, lightweight, intelligent, and user-centric transradial prosthetic arm capable of providing accurate control, adaptive grasping, enhanced sensory feedback, and improved functionality for daily living activities.

Figure-8: Critical Research Gaps and Emerging Requirements for Intelligent Transradial Prosthetic Arm Development.

5.2 Field Visit Observations and Key Findings

A field visit was conducted at an Artificial Limb Centre to gain practical insights into the design, manufacturing, and adoption of upper-limb prosthetic devices. The observations obtained from interactions with clinicians, technicians, and prosthetic users are summarized below.

1. **Weight Considerations:** Feedback from the centre indicated that the overall weight of a prosthetic arm should ideally be maintained within the range of **1–2 kg** to ensure user comfort, reduce fatigue, and facilitate prolonged daily usage.
2. **Customization Requirements:** The fabrication of a prosthetic arm requires accurate anthropometric measurements of the user's intact limb to achieve proper dimensional matching and functional alignment. It was observed that while many amputees initially visit the centre for consultation and assessment, a portion of them do not return for subsequent fitting and rehabilitation procedures.
3. **Affordability Challenges:** Advanced myoelectric prosthetic arms are associated with a significantly high cost, often reaching **₹15 lakhs or more**. Due to financial constraints, many amputees are unable to access these

advanced technologies and instead prefer lower-cost passive prosthetic alternatives, despite their limited functionality.

4. Limited Domestic Manufacturing: The availability of indigenous manufacturers of advanced upper-limb prostheses remains limited in India. A considerable proportion of sophisticated prosthetic devices are either imported directly from international manufacturers or supplied through foreign companies operating within the country. This dependence on imported technologies contributes to increased costs and reduced accessibility for many users.

These field observations highlight the critical need for the development of lightweight, affordable, customizable, and locally manufactured intelligent prosthetic arms to improve accessibility and adoption among transradial amputees.

5.3 Material Selection for Prosthetic Arm Fabrication

The selection of an appropriate material plays a crucial role in the design and development of upper-limb prosthetic devices. An ideal prosthetic material should possess a balanced combination of mechanical strength, lightweight characteristics, biocompatibility, durability, chemical resistance, and ease of manufacturing. Since prosthetic arms are subjected to repeated loading, environmental exposure, and prolonged contact with the human body, material properties significantly influence the performance, comfort, safety, and lifespan of the device.

Recent advancements in additive manufacturing and biomedical engineering have expanded the range of materials available for prosthetic applications. High-performance engineering polymers such as Polyether Ether Ketone (PEEK) and Polysulfone (PSU/PES) offer excellent mechanical properties, biocompatibility, and chemical resistance, making them suitable for advanced prosthetic systems. Conversely, materials such as PLA, ABS, and PETG are widely used in rapid prototyping and low-cost prosthetic fabrication due to their ease of processing and affordability. Therefore, a comparative evaluation of these materials is essential to identify the most suitable candidate for developing lightweight, durable, and user-friendly transradial prosthetic arms.

Table-3: Comparative Analysis of Prosthetic Fabrication Materials Based on Thermal, Mechanical, Physical and Biocompatibility Properties

Property	PEEK	Polysulfone (PSU/PES)	PLA	ABS(Acrylonitrile Butadiene Styrene)	PETG(Polyethylene Terephthalate Glycol)
Melting Point (°C)	343°C to 387°C	185°C to 190°C	150°C to 160°C	210°C to 240°C	220°C to 260°C
Tensile Strength (MPa)	90 to 100 MPa	60 to 80 MPa	45 to 65 MPa	40 to 50 MPa	50 to 60 MPa
Flexural Strength (MPa)	100-140 MPa	90-110 MPa	60-70 MPa	70-80 MPa	70-80 MPa
Elongation at Break (%)	50-100%	20-60%	6-8%	10-20%	20-30%
Density (g/cm³)	1.3-1.45 g/cm³	1.24-1.37 g/cm³	1.24 g/cm³	1.04-1.06 g/cm³	1.27 g/cm³
Biocompatibility	ISO 10993-1 certified	ISO 10993-1 certified	Generally considered biocompatible	Not inherently biocompatible	Generally considered biocompatible
Chemical Resistance	Resistant to most chemicals	Resistant to most chemicals	Limited resistance	Moderate resistance	Good resistance
Radiolucent	Yes	Yes	Not suitable	Not suitable	Not suitable

5.4 Literature Outcome

The reviewed literature demonstrates significant progress in prosthetic arm technology, highlighting advancements in control systems, sensory feedback, artificial intelligence, computer vision, and soft robotics. The studies indicate that achieving reliable and intuitive prosthetic control remains a major challenge due to the limitations of conventional EMG-based systems. Researchers emphasize the importance of robust control algorithms, improved hardware architectures, and user-centric design methodologies to enhance functionality, comfort, and usability. Furthermore, deep learning has emerged as a promising approach for prosthetic control by enabling automatic feature extraction from EMG signals, thereby reducing the dependence on traditional feature engineering techniques and improving gesture recognition performance. Overall, the literature underscores the need for intelligent, adaptive, and affordable prosthetic systems that can provide enhanced mobility and quality of life for upper-limb amputees.

6. Deep Learning-Based Prosthetic Arm Control Architecture

The realization of intelligent transradial prosthetic arms relies on the seamless conversion of biological muscle activity into precise and reliable prosthetic movements. Electromyography (EMG) signals provide valuable information regarding the user's movement intention; however, their nonlinear, non-stationary, and noise-sensitive characteristics make accurate interpretation a challenging task. Recent advances in deep learning have significantly improved the ability to decode complex EMG patterns, enabling the development of prosthetic control systems with enhanced responsiveness, adaptability, and accuracy. Among various deep learning techniques, Convolutional Neural Networks (CNNs) have demonstrated exceptional capability in automatically learning hierarchical representations of EMG signals, eliminating the need for extensive manual feature extraction while improving gesture classification performance.

The proposed deep learning-based prosthetic arm control architecture consists of a sequence of interconnected processing stages that transform raw physiological signals into real-time prosthetic control commands. Initially, multi-channel EMG signals are acquired from the residual forearm muscles using surface electrodes during the execution of various hand gestures and daily living activities. These signals undergo preprocessing operations including amplification, filtering, normalization, segmentation, and artifact removal to improve signal quality and reduce the influence of motion artifacts, power-line interference, and baseline drift. The processed EMG signals are subsequently organized into structured training samples suitable for deep learning-based feature extraction and classification.

Following preprocessing, a Convolutional Neural Network is developed to automatically extract spatial and temporal characteristics embedded within the EMG signals. Multiple convolutional layers progressively identify representative muscle activation patterns, while pooling operations reduce computational complexity and improve feature robustness. Fully connected layers subsequently establish the nonlinear relationship between extracted EMG features and predefined prosthetic movement classes. The network parameters are optimized during the training phase using labelled datasets, enabling the model to accurately distinguish between different hand gestures and intended prosthetic actions. Model validation and testing are then performed using independent datasets to evaluate classification accuracy, robustness, and generalization capability under varying operating conditions.

The classified movement intention generated by the CNN serves as the input to the prosthetic arm control module, where mathematical modelling and kinematic analysis are employed to convert gesture predictions into coordinated joint movements. Forward and inverse kinematic models determine the corresponding joint configurations required to achieve the desired end-effector position and orientation, while trajectory planning algorithms generate smooth and continuous motion profiles for the wrist, fingers, and other prosthetic joints. The computed trajectories are subsequently translated into actuator control commands that drive the prosthetic arm with high precision, enabling stable grasping, object manipulation, and coordinated movement during activities of daily living.

The integration of deep learning, mathematical modelling, and robotic control provides a comprehensive framework for intelligent prosthetic arm operation. By combining automatic EMG feature learning with kinematic modelling and trajectory generation, the proposed architecture enhances intention recognition, improves motion accuracy, supports adaptive grasp control, and enables real-time interaction between the user and the prosthetic device. Consequently, this integrated approach establishes a scalable and robust foundation for the development of next-generation intelligent transradial prosthetic arms capable of delivering improved functionality, user comfort, and rehabilitation outcomes.

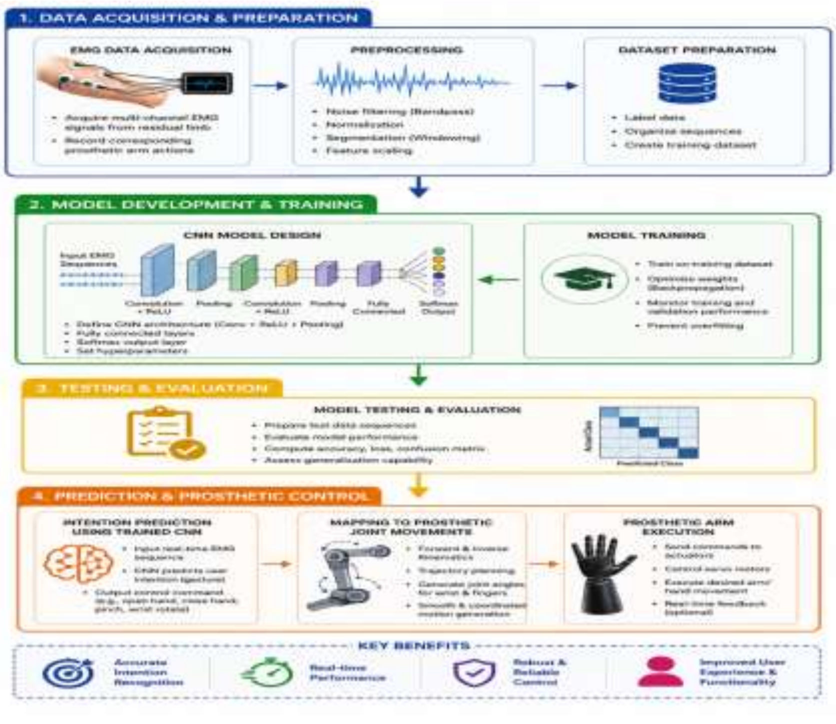

Figure-9: Proposed Deep Learning-Based Prosthetic Arm Control Architecture. The proposed framework acquires multi-channel electromyography (EMG) signals from the residual limb, performs signal preprocessing and dataset preparation, extracts discriminative features using a Convolutional Neural Network (CNN), classifies user movement intentions, and generates real-time prosthetic arm control commands. The architecture integrates EMG-based intention recognition with intelligent control to facilitate accurate, robust, and intuitive prosthetic arm movements for transradial amputees.

7. Conclusion

The present study comprehensively examined the current state of transradial prosthetic arm technology by reviewing prosthetic classifications, anthropometric requirements, commercial devices, material selection strategies, intelligent control methods, and recent research advancements. The findings indicate that although significant progress has been achieved in myoelectric control, sensor technologies, artificial intelligence, and soft robotics, existing prosthetic systems still face challenges related to affordability, weight, reliable intention recognition, grasp force control, sensory feedback, and user acceptance. Literature analysis and field observations further reveal that high costs, dependence on imported technologies, and limited customization continue to restrict the adoption of advanced prosthetic devices among amputees. To address these limitations, a CNN-based deep learning architecture has been proposed to establish an intelligent mapping between EMG signals and prosthetic arm movements, enabling more accurate, adaptive, and intuitive control. Furthermore, the evaluation of advanced materials highlights the importance of balancing mechanical strength, biocompatibility, durability, and lightweight construction in prosthetic design.

Overall, this work identifies critical research gaps and provides a foundation for the development of affordable, lightweight, locally manufacturable, and intelligent prosthetic arms capable of enhancing functional independence and improving the quality of life of transradial amputees.

Future Research Directions

Future advancements in transradial prosthetic arm technology should focus on developing affordable, lightweight, and intelligent systems capable of delivering improved functionality and user acceptance. The integration of multimodal sensing technologies, including EMG, FMG, computer vision, and tactile sensors, combined with advanced deep learning algorithms, offers significant potential for enhancing gesture recognition, grasp control, and adaptive decision-making. In addition, research on biomimetic sensory feedback, digital twin-based design frameworks, soft robotic structures, and low-cost additive manufacturing can contribute toward achieving more natural and human-like prosthetic performance. Furthermore, the development of indigenous prosthetic technologies and personalized user-centric designs is essential to improve accessibility and reduce dependence on expensive imported systems. These advancements are expected to play a vital role in realizing next-generation bionic limbs that provide greater independence, comfort, and quality of life for transradial amputees.

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