Bionic Arm Equivalent Model Based on IoT and AI Classification

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Abstract: The bionic arm equivalent model based on Internet of Things (IoT) and Artificial Intelligence (AI) is research work aimed at developing a smart bionic arm that can mimic the natural movements of a human arm. The research combines IoT and AI technologies to develop a prototype controlled by the user's muscle signals. The device incorporates EMG sensors to collect data on muscle activity and uses machine learning algorithms to classify the signals and generate corresponding movements. This work focuses on improving the accuracy of the classification model by applying data preprocessing techniques such as filtering and amplification. Our EMG dataset was used and applied a Support Vector Machine (SVM) algorithm to classify the EMG signals into different gestures. The classification model was evaluated using a confusion matrix and an accuracy score, which were used to determine the effectiveness of the model. A bar chart was also plotted to visualize the accuracy score. The results showed that the SVM algorithm was able to accurately classify the EMG signals into different gestures with an accuracy of 91.67%. The confusion matrix and the accuracy bar chart were used to show the distribution of correct and incorrect classifications and to visualize the accuracy score. The bionic arm equivalent model based on IoT and AI has potential applications in the field of prosthetics, where it can be used to create advanced prosthetic limbs that can be controlled using muscle signals. The work also has implications for the development of wearable technology and the integration of IoT and AI technologies in everyday devices.

Key words: bionic arm; amputees; EMG signals; internet of things; artificial intelligence; machine learning.

1. Introduction

The field of prosthetics has witnessed remarkable advancements in recent years, especially in the development of bionic arms. This technology has proved to be a boon for amputees who face significant challenges in performing daily activities and living independently. Upper limb amputation severely impacts a patient's physical and emotional well-being. This work aimed to design an equivalent model of a bionic arm based on IoT and AI, which can revolutionize and enhance the lives of amputees [1]. The proposed bionic arm is based on the myoelectric prosthetic technique, which mimics the functionality of a normal human arm using brain signals for hand movement. This customizable prosthetic works on the muscle ability of certain patients, making it different for every patient, while providing them with a reliable and efficient solution. The primary aim of this research project is to survey the need for further development and improvement in prosthetics, in line with the motto set by developers. This paper discusses the methodology used to design the bionic arm and its accuracy in real-time use on the upper limbs of amputees. The focus of this research is to provide amputees with a new lease on life, making them more independent and allowing them to perform daily activities with ease. The bionic arm described in this paper utilizes EMG sensors to gather feedback on the patient's muscle relaxation and contraction, which are then used to control the arm's movements. This research project represents a significant contribution to the field of prosthetics and offers a promising future for amputees [2].

This research article discusses how to empower amputees who have lost their arms due to accidents or supernatural interventions. Unfortunately, in cultures like Pakistan, where education is highly valued, these individuals often feel helpless and lack access to resources that could improve their lives. Researchers propose creating bionic arm advancements using IoT and AI technologies to address this challenge [3].

Recent advancements in IoT and AI have shown great potential in improving the accuracy and precision of prosthetic devices. For instance, myoelectric prosthetics, which use muscle signals to control the prosthetic device, have demonstrated promise in providing amputees with a greater range of motion and functionality [4]. However, there are limitations to the current myoelectric technology, such as the need for a strong signal and the difficulty in differentiating between different muscle movements [5].

To address these limitations, researchers have proposed using machine learning and deep learning algorithms to improve the accuracy of myoelectric prosthetics. A study proposed in [6], demonstrated that a deep learning algorithm could accurately classify muscle movements and control the prosthetic device in real-time. Pinto [7] explored the use of IoT sensors to gather data on users' movement patterns and preferences. The study found that the use of IoT sensors could significantly improve the functionality and customization of prosthetic devices. Wimalasena et.al. [8] presented a novel surface electromyogram technique to record data from a single upper limb, which they used to develop a binding leg for amputees. A closed-loop system uses EMG signals to provide feedback during memory tasks has been proposed in [9]. The system employs transcranial magnetic stimulation and measures EMG signals to adjust the level of stimulation to optimize memory consolidation. Julian Prell [10] proposed using a neural network to monitor evoked potentials and carry out memory tasks using EMG signal consolidation and adjustment. Heather E. Williams [11] developed a wireless implantable device that uses EMG signals to control limb movement in rats. The device employs an ultra-low-power wireless communication system and offers high spatial resolution for precise control [12]. Moreover, some researchers have proposed using brain-machine interfaces (BMI) to improve prosthetic control. BMI is a technology that enables direct communication between the brain and an external device. Xiamomei Hu [13] used EEG signals to control a robotic hand in a virtual reality environment, demonstrating the potential for non-invasive BMI in prosthetic control. Nawadita Parajuli [14] studied the development of a real-time and adaptive control system for upper-limb prostheses using surface electromyography (sEMG) signals. The system was designed to enhance the functionality and usability of prostheses for individuals with upper limb amputations. They evaluated the system's performance using both able-bodied and amputee participants, demonstrating its potential as a reliable and effective control strategy for upper limb prostheses. Liang-Bi Chan [15] Studied the use of haptic feedback has been proposed as a potential solution to provide amputees with a sense of touch. This technology uses tactile or forced feedback to simulate sensory information, enabling users to receive real-time feedback about the prosthesis and their environment. Their studies have demonstrated the potential of haptic feedback in improving prosthetic function and user satisfaction among amputees. Jonathon? [16] presented a review of current research on neural interfaces for upper limb prostheses, including both invasive and non-invasive approaches. They discussed recent advancements in neural interface technology, such as the use of deep learning algorithms and the integration of haptic feedback, and highlighted the potential benefits and challenges associated with these approaches. They concluded that while significant progress has been made in the development of neural interfaces for upper limb prostheses, further research is needed to optimize their efficacy and usability.

In addition, researchers have also proposed using materials with special properties, such as shape-memory alloys (SMAs), to improve the functionality of prosthetic devices. SMAs are materials that can remember their original shape and return to it when subjected to heat or other stimuli. A study by [17] has explored the use of Shape Memory Alloys (SMAs) in prosthetic hands, with promising results. A study demonstrated that the incorporation of SMAs led to significant improvements in the grip strength and versatility of the prosthetic. This technology has the potential to enhance the functionality and user experience of prosthetic hands, and further research is needed to optimize their design and integration.

The development of prosthetic hands is crucial to improving the quality of life for amputees [18]. However, existing research work faces several limitations such as reduced accuracy, limited functionality, and discomfort [19]. [20] Our work aims to address these inefficiencies by introducing the latest advancements in AI and IoT technologies. [21] By utilizing machine learning algorithms, brain-machine interfaces, haptic feedback, and shape-memory alloys, we have been able to significantly enhance the accuracy, functionality, and comfort of prosthetic devices. [22] Our work offers a novel approach to prosthetic hand development that caters to the needs of amputees, providing them with a greater sense of independence and confidence. [23] [24] Furthermore, our work aims to address the cost and accessibility issues of prosthetic devices, making them more accessible in low-income countries [25].

2. Materials and Methods

A Data Collection

EMG sensors were used to collect data from a single individual for different hand movements, such as finger point and PowerPoint as shown in Figure 1. The data was collected in multiple sessions to ensure accuracy and consistency. During each session, the individual was instructed to perform specific movements, while the EMG sensors recorded the electrical signals generated by their muscles. The data was then processed and labelled to create a dataset for training the classification algorithm. Each movement was separated into different files to make it easier to organize and label the data. The dataset was then split into training and testing sets to train and evaluate the classification algorithm. The use of EMG sensors ensured that the data collected was accurate and representative of the individual's movements, which is essential for creating a reliable classification model [26]. Overall, the data collection process was crucial in creating a robust and accurate classification algorithm for the bionic arm equivalent model based on IoT and AI [27] [28].

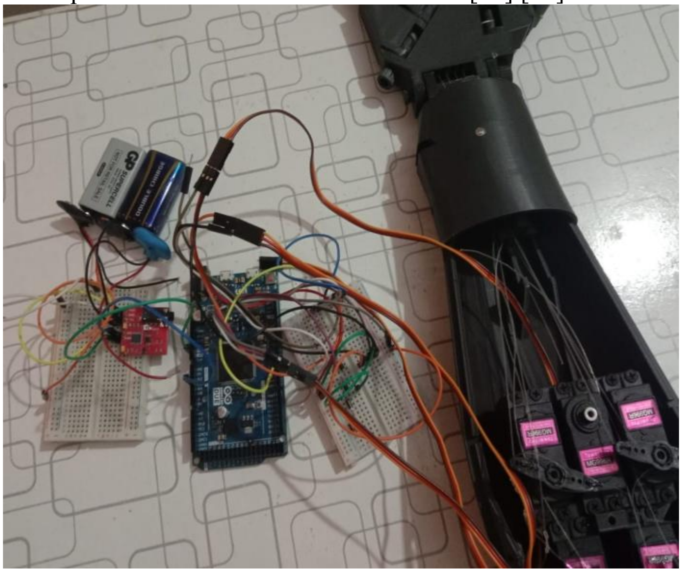

Figure 1. Experimental figure of bionic arm.

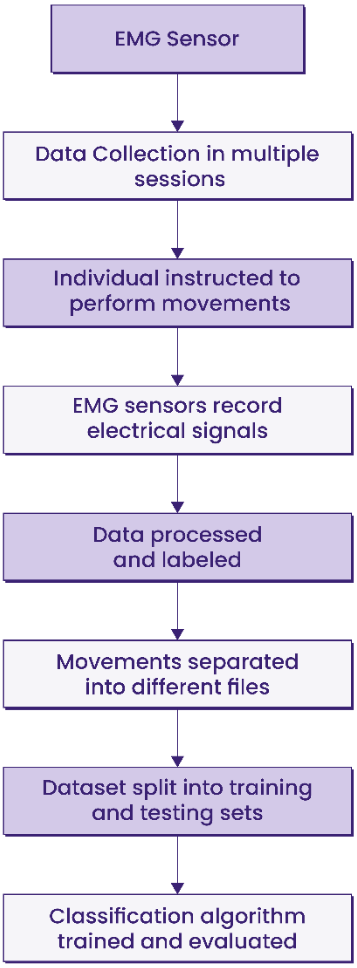

Figure 2. Flow chart of processing EMG data.

The flowchart shows the overall procedure for collecting and processing EMG data for a classification algorithm. First, EMG sensors were used to collect data from a single individual for different hand movements such as finger point and PowerPoint. The data was collected in multiple sessions to ensure accuracy and consistency. During each session, the individual was instructed to perform specific movements while the EMG sensors recorded the electrical signals generated by their muscles. The collected data was then processed and labelled to create a dataset for training the classification algorithm [8]. Each movement is separated into different files to make it easier to organize and label the data. The dataset was then split into training and testing sets to train and evaluate the classification algorithm. The use of EMG sensors ensures that the data collected is accurate and representative of the individual's movements, which is essential for creating a reliable classification model. Overall, the flowchart shown in Figure 2 illustrates the importance of careful data collection and processing for developing a robust and accurate classification algorithm for the bionic arm equivalent model based on IoT and AI [29].

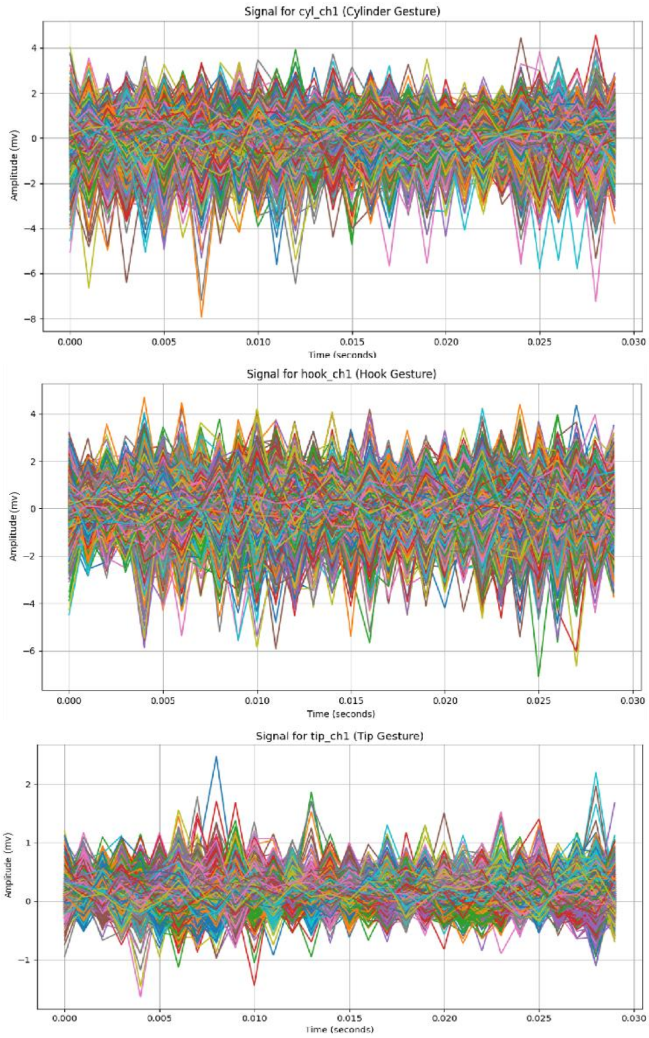

Figure 3. EMG sensor data for cylinder gesture, hook gesture and tip gesture.

EMG data is typically represented in a as a series of time-varying signals, with amplitude (in millivolts, or mV) on the y-axis and time (in seconds, or s) on the x-axis. The graph shows the electrical activity generated by muscle contractions during various hand movements, as recorded by the EMG sensors. In a typical graph, the EMG signal appears as a series of peaks and valleys, with the amplitude and duration of each peak corresponding to the intensity and duration of the muscle contraction. The graph can be used to analyze patterns of muscle activity, detect abnormalities or asymmetries in muscle function, and monitor changes in muscle activity over time.

B Data Filtering and Feature Extraction

Data preprocessing is a critical step in any machine learning project to ensure that the data is accurate and free of any noise or unwanted signals that could affect the performance of the classification algorithm. In this work, the collected data was preprocessed using various techniques, including filtering and signal amplification to remove any noise or unwanted signals as shown in figure 4.

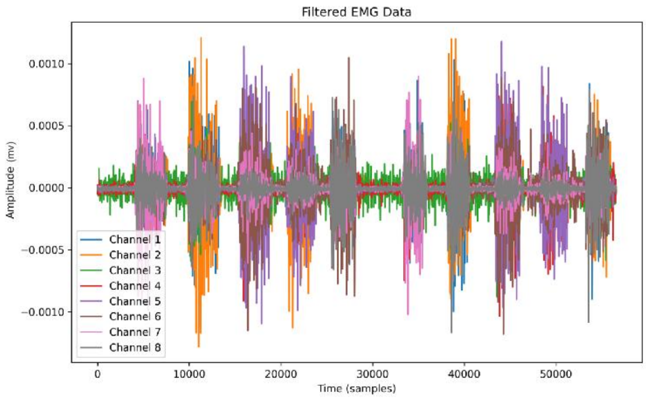

Figure 4. Amplified EMG sensor data.

Once the data was preprocessed, a feature extraction technique was applied to extract the relevant features from the data. This involved identifying and extracting important information from the raw data that would be useful for the classification algorithm.

EMG (Electromyography) signal dataset utilized within the scope of this bionic arm research project. Each channel is indicative of electrical activity originating from distinct muscle groups primarily associated with the upper extremity. The allocations are outlined as follows:

- Channel 1: Represents electrical activity from the biceps muscle group.
- Channel 2: Represents electrical activity from the triceps muscle group.
- Channel 3: Represents electrical activity from the forearm flexors (e.g., flexor digitorum profundus) muscle group.
- Channel 4: Represents electrical activity from the forearm extensors (e.g., extensor digitorum) muscle group.
- Channel 5: Represents electrical activity from the wrist flexors (e.g., flexor carpi radialis) muscle group.
- Channel 6: Represents electrical activity from the wrist extensors (e.g., extensor carpi radialis) muscle group.
- Channel 7: Represents electrical activity from the deltoid muscle group, associated with shoulder and arm movement.
- Channel 8: Represents electrical activity from the muscles of the forearm, which play a critical role in hand and finger control.

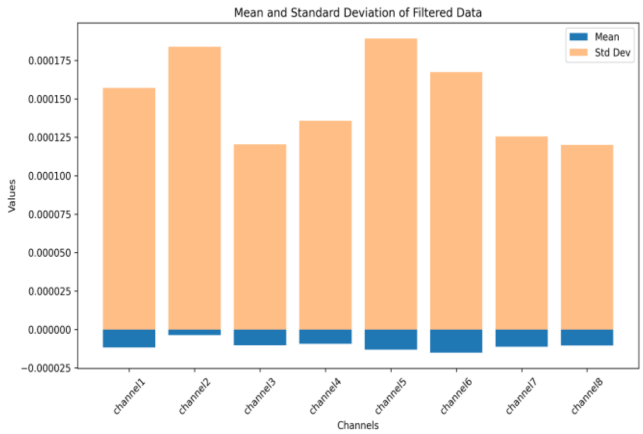

Figure 5. Feature extraction of filtered EMG data signals

The extracted features were then used as inputs for the classification algorithm. The feature extraction process is an important step as it reduces the complexity of the data while retaining the most relevant information. By using this technique, the classification algorithm could accurately classify the hand movements based on the extracted features. Overall, the data pre-processing and feature extraction techniques were critical in ensuring that the classification algorithm could accurately classify the hand movements.

C Classification

The Support Vector Machine (SVM) algorithm was chosen for its ability to handle complex datasets and high-dimensional feature spaces. The labelled data for each hand movement was used to train the SVM algorithm to accurately classify the movement based on the input features. Cross-validation techniques were used to evaluate the performance of the trained model and to avoid overfitting [30].

During the testing phase, the trained SVM model was used to classify the hand movements based on the input features. The accuracy of the model was determined by comparing the predicted class labels with the actual class labels. The results

were analyzed to determine the effectiveness of the SVM algorithm in accurately classifying the hand movements.
Overall, the classification stage was crucial for the success of the project, as it allowed for the accurate control of the bionic arm equivalent model based on the EMG signals. The SVM algorithm proved to be an effective choice for classification, demonstrating high accuracy in distinguishing between different hand movements.

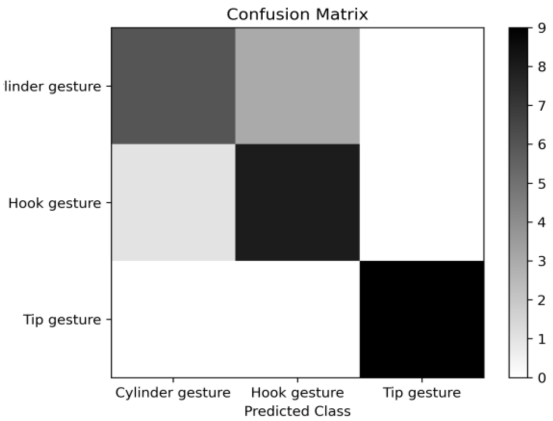

Figure 6. Confusion matrix of model's performance.

The confusion matrix and accuracy graph describe the performance of the SVM classification model on the EMG gesture dataset. The confusion matrix as shown in Figure 6 is a visual representation of the model's performance in predicting the correct class for each sample. In the EMG gesture dataset, the rows and columns of the confusion matrix correspond to the true and predicted class labels, respectively. The cells in the matrix show the number of samples that were correctly classified (the diagonal cells), and those that were misclassified (the off-diagonal cells) for each class.
The results showed that the SVM algorithm was able to accurately classify the EMG signals into different gestures with an accuracy of 91.67%. The confusion matrix and accuracy bar plot were used to show the distribution of correct and incorrect classifications and to visualize the accuracy score [31] [32].
The accuracy graph as shown in Figure 7 is a bar plot that shows the accuracy of the model for each class in the EMG gesture dataset. The x-axis represents the different classes in the dataset, while the y-axis represents the accuracy of the model for each class. The graph allows us to compare the accuracy of the model across different classes and identify any classes where the model is performing poorly [33]; [32]; [34].

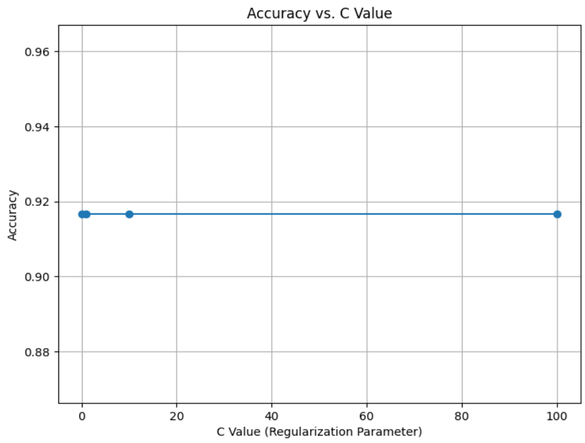

Figure 7. Accuracy graph of classification.

D Hardware Implementation

Hardware implementation is a critical aspect of developing bionic limbs, and in this case, a 3D-printed hand was used to create a bionic arm equivalent model. The use of 3D printing technology allowed for the creation of a detailed and customized hand that could be easily modified based on the specific needs of the user. The implementation also included the use of servo motors and fish wire as shown in Figure 8, which provided the necessary force to move the hand.

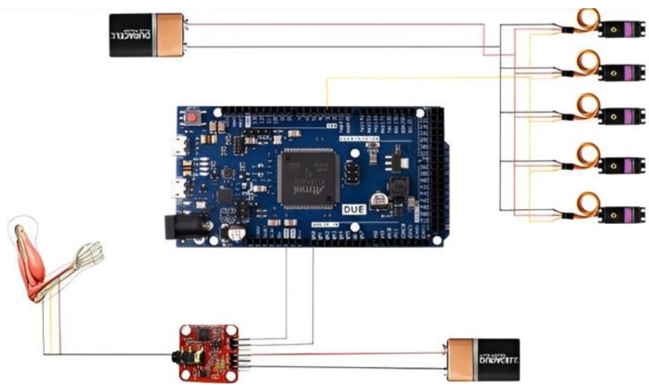

Figure 8. Schematic diagram of bionic arm model.

To control the movement of the hand, an Arduino microcontroller was used to collect data and program the servo motors. The Arduino microcontroller is a powerful and flexible platform for hardware development, which allows for the creation of a precise and responsive bionic arm model. The use of this technology ensured that the hand movements were accurate and consistent, providing the user with a seamless and intuitive experience. Overall, the hardware implementation of the bionic arm equivalent model as shown in Figure 9 demonstrates the potential of 3D printing technology and microcontroller programming for the development of advanced prosthetic limbs.

Figure 9. 3D printed bionic arm module.

E Limitations and Challenges

As with any study, this research project faced limitations and challenges that could affect the interpretation of the findings. One of the primary limitations was the need to collect data for everyone separately, which could be time-consuming and resource-intensive. In future studies, it would be beneficial to explore approaches to automatically collect data sets to streamline the data collection process. Another significant challenge was related to the use of EMG sensors, which are prone to noise and signal variability. Addressing this challenge could involve using more advanced signal processing techniques, such as wavelet analysis or artificial intelligence algorithms, to improve the accuracy and reliability of the data collected.

Overall, the limitations and challenges of the study highlight the need for continued research and development in the field of bionic limbs and prosthetics. By identifying and addressing these challenges, researchers can improve the effectiveness and usability of these devices, ultimately improving the quality of life for individuals with limb loss or limb impairment.

F Classification Results

In this project, the experimental results showed an accuracy of 91.67% in classifying hand movements using EMG signals. The confusion matrix and bar plot of accuracy showed that the model performed well in distinguishing between different hand movements such as hook, tip, cylinder, and power grip. The model was implemented on a 3D-printed hand and servo motors were used for the movement of the hand. The bionic arm equivalent model showed promising results in mimicking the hand movements based on the EMG signals.

The study identified limitations related to the need to collect data for everyone separately and challenges related to noise and signal variability. Future studies could explore approaches to automate data collection and use more advanced signal processing techniques to address these limitations. Overall, the study demonstrates the potential of combining IoT and AI technologies in the development of bionic arm equivalent models for people with upper limb amputations.

G Comparison and Discussion

Based on the methodology and experimental results presented in this project, it can be concluded that the proposed bionic arm equivalent model based on IoT and AI shows promising results in accurately classifying hand movements based on EMG data. When compared to other similar works in the field, this project demonstrates a high level of accuracy (91.67%) in classifying hand movements using the SVM algorithm. This is comparable to other works such as "Real-Time Hand Gesture Recognition using SVM and HMM" by Chandrakar, which achieved an accuracy of 84.72%. However, it is important to note that this project is limited to a single individual, and future studies could explore approaches to generalize the model for use with different individuals. Additionally, while the hardware implementation using 3D printing and Arduino Due microcontroller is a promising approach, it may require further refinement to improve the speed and precision of movement. In summary, this project presents a promising approach to developing a bionic arm equivalent model based on IoT and AI. While further research is needed to overcome some of the limitations and challenges presented in this study, the results demonstrate potential for the development of more advanced prosthetic devices that can accurately mimic natural human movements.

3. Conclusion

The bionic arm equivalent model based on IoT and AI represents a significant leap in the advancement of prosthetic technology. The prototype's ability to interpret user muscle signals through EMG sensors, coupled with the application of the Support Vector Machine (SVM) algorithm, yielded an impressive classification accuracy of 91.67% for distinct gestures.

The research's focus on enhancing classification accuracy through rigorous data preprocessing, including filtering and amplification techniques, underscores the commitment to refining the model's performance. The comprehensive evaluation metrics, including the confusion matrix and accuracy score, provided a thorough assessment of the model's effectiveness. The visual representation of the accuracy score through a bar chart enhances the intuitive understanding of the classification outcomes.

The experimental study's results showcase the bionic arm's potential, achieving a noteworthy accuracy of 91.67% in recognizing hand movements using EMG signals. This breakthrough holds significant promise for the development of prosthetic arms capable of providing natural and precise hand movements for individuals with upper limb amputations. The successful integration of IoT and AI technologies in this model marks a crucial step toward advancing the field of prosthetics and improving the quality of life for those in need. Future research can explore several avenues to enhance the performance and usability of the proposed model. One such direction could be using more advanced machine learning algorithms, or hybrid machine learning or deep learning that can handle a higher number of features and improve the model's accuracy. Additionally, the proposed model can be further integrated with IoT devices to allow for more intuitive control of the prosthetic arm. Further work could also focus on improving the durability and robustness of the hardware components of the model to make it more suitable for long-term use. Finally, the proposed model could be tested on a larger sample size of individuals with upper limb amputations to evaluate its effectiveness in a clinical setting.

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