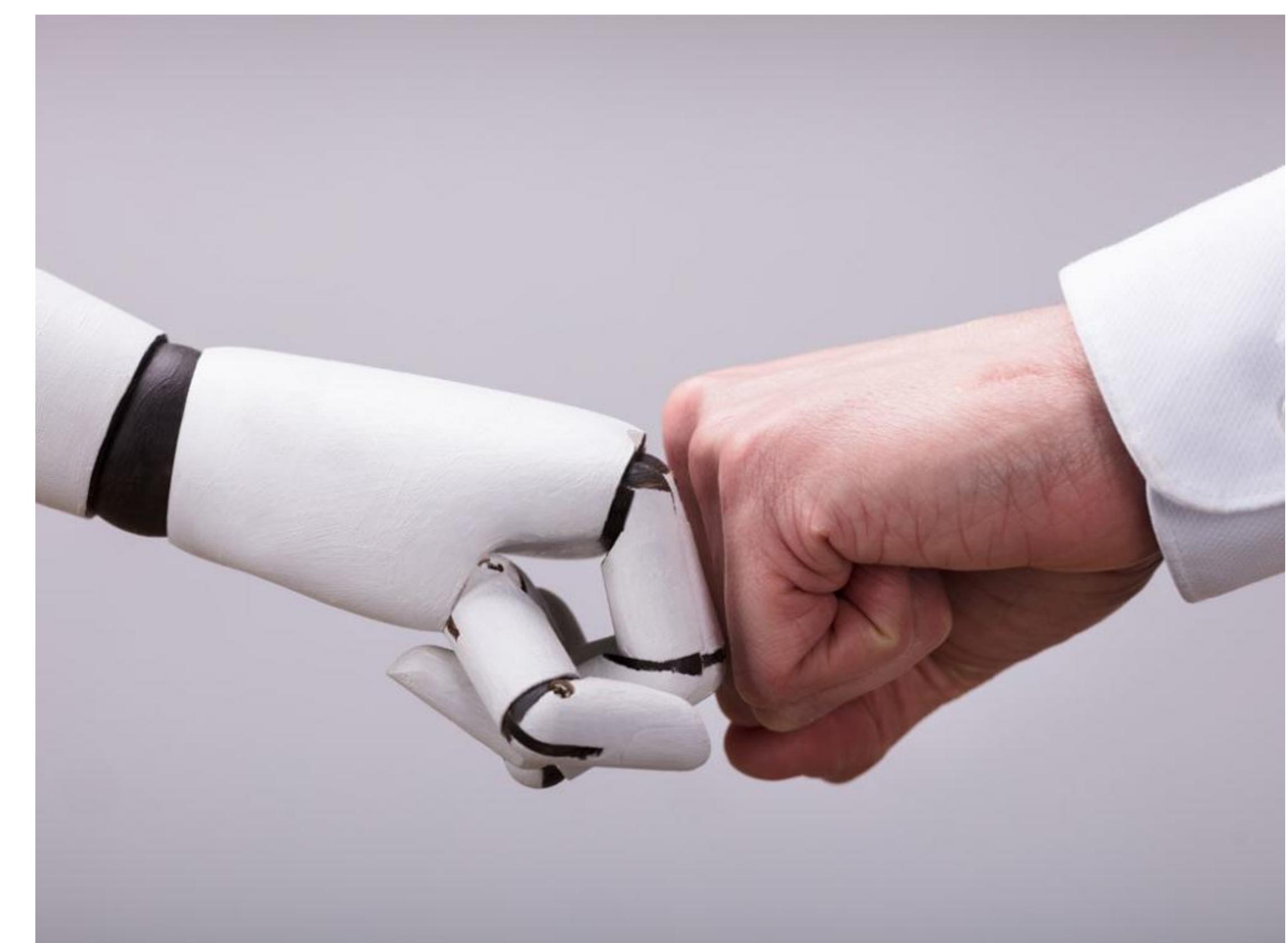


## Overview

Our project involved developing a collaborative robotic arm otherwise referred to as a cobot arm that imitates human arm movements. Such a robotic arm would find its application in various areas including industrial safety, surgical arm operations and prosthetics technology. Industrial safety involves offering safety in industrial operations where human involvement pose either a health or accident risk. With this robotic arm, personnel in industrial operations can conduct operations within a plant from a safe distance in high risk areas while minimizing health risks and accidents. A proper use case would be in nuclear power plants where operation in some areas could expose the human operator to harmful radiations and can hence be conducted using cobots. In surgical arms, the aim is to mimic a surgeon's careful incisions as its input and recreate them in a much more precise way. Prosthetic technology on the other hand involves creating prosthetic limbs for patients with locked in syndrome or limb loss. We picked up sEMG signals from the bicep muscle region of the human arm, filtered and conditioned the signals, extracted necessary features from the signals and subjected the features to a processing scheme that produced outputs that controlled the robotic arm. We successfully controlled the base joint of the robotic arm such that it imitated the movement of the elbow joint.



## Introduction

Cobots, mainly utilize computer vision to aid humans in conducting operations in industry. This comes with the advantage that the Cobots work independent of the human workers. However, they require a lot of programming to execute the given tasks. Cobots utilizing bio-signals for control on the other hand offer more synergy and less programming with the disadvantage that they are too dependent on human concentration. Bio-signal cobots are also more economical in the sense that they have less firmware requirements and hence less computational needs. Depending on the application, one would need different kinds of Cobots. Our objectives for this project included;

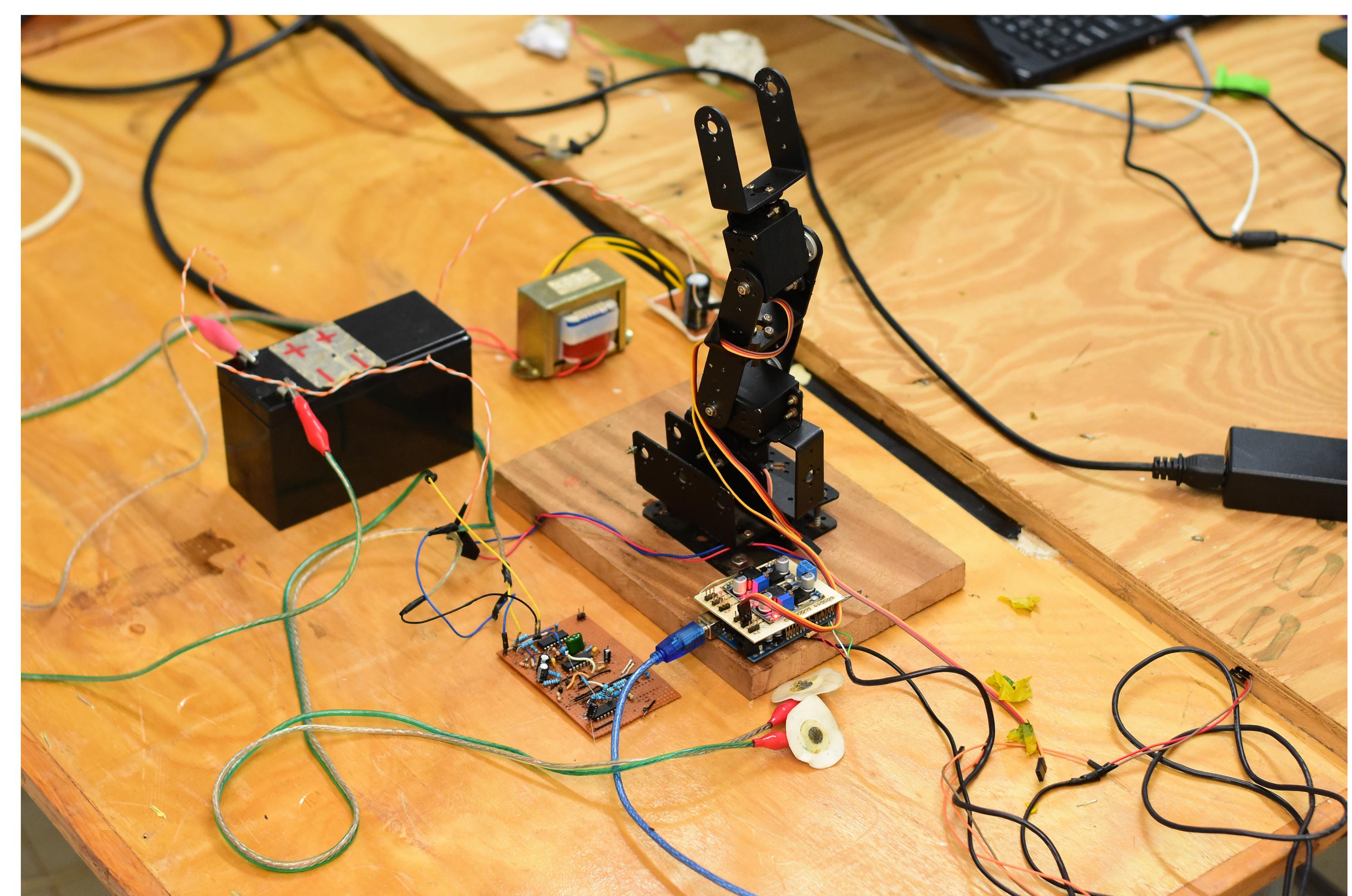
- ⇒ To design a data acquisition unit for collecting and conditioning sEMG signals.
  - ⇒ To further condition the sEMG signal in the digital domain and extract features.
  - ⇒ To teleport the human arm movements to the cobot arm by subjecting pre-processed feature extraction data to a designed/trained model.
- We sort to actualize this project using the available resources in the school while not compromising the performance of the system therefore, optimizing cost and performance.

## Methodology

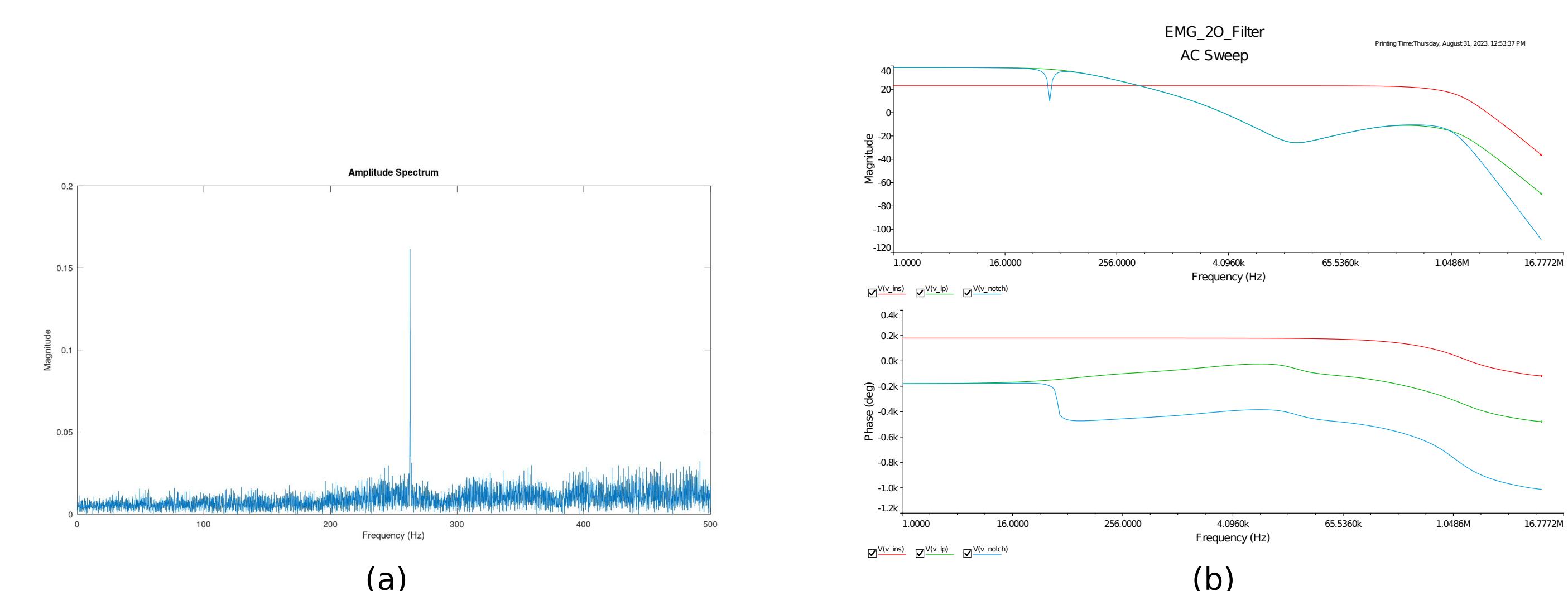
The project can be divided into four main parts; data acquisition, digital filtering, feature extraction and modelling. Signal collection is done using the data acquisition unit (DAQ). The data acquisition unit is used for collecting surface signals from the muscles using specialized electrodes and circuitry. The instrumentation amplifier is the heart of the DAQ. It picks up sEMG signals from the electrodes and amplifies them to a suitable level. The instrumentation amplifier together with all its circuitry that enable it to pick up signals is referred to as the preamplifier. The signal from the preamplifier has unwanted signal frequencies that need to be attenuated such that the bandwidth of the output signal falls within that of sEMG signals. Filtering happens in the analog and digital domain. Much of the filtering happens in the analog domain where a lowpass filter and a notch filter are implemented. The notch filter attenuates 50Hz noise that mainly comes from power lines. Digital filtering involves implementing a moving average filter which happens on the MCU as an embedded application. The moving average filter is a low pass filter that eliminates noise coming from power line interference and motion artefacts.

In the feature extraction stage, we implement the moving recursive RMS algorithm which is analogous to the Parseval's theorem in digital signal processing. We implement it recursively to save on memory. This feature aims to monitor the energy of the sEMG signal being collected in real time. That way, the extent of muscle contraction can be quantified. After collecting this feature, we subjected it to a model. Since the value of RMS corresponds to the extent of muscle contraction/movement on the human arm, the average RMS value was determined before the volunteer made any significant arm movements. This value, we refer to it as the threshold. When the user began moving his arm, the RMS values increased depending on muscles contraction level and the angle of movement. We sort to map particular values of RMS to particular joint angles on the robotic arm by tracing the difference between the RMS values and the threshold while mapping the difference to the servo motor control algorithm that in turn controls the motor joint. We picked a signal from the bicep brachii muscle of the right arm, extracted the RMS feature from the signal and used it to control the base joint motor of a robotic arm such that it imitated the movement of the elbow joint.

## Results



*Figure 1.* A picture of the setup for the system we designed. It shows the robotic arm, the DAQ, the processing unit and the power supplies(AC and DC).



*Figure 2.* (a) An FFT graph for the sEMG signal from the preamplifier. The graph shows that much of the signal was about 260Hz. (b) A Multisim simulation for the combined three stages of the DAQ.

## Conclusion

By conducting this research we showed that the use of bio-signals for robotic arm movement control is not only possible but highly effective. Bio-signal controlled cobots would be ideal for applications where human independence is traded off for cost effectiveness and human keenness. The project can further be improved by employing machine learning as opposed to thresholding to achieve more accuracy. Employing machine learning would involve subjecting the features to a machine learning model that produces spatial coordinates that match the position of the human arm in real time. The Center For Robotics and Biomedical Engineering is currently working on incorporating the same in this project. Hopefully, that can be realized in the near future.

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