EMG SIGNAL ANALYSIS FOR DETECTING HUMAN KNEE ABNORMALITY

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INTRODUCTION

Nowadays many problems are being faced by people who are aging and sports persons in the lower limbs like the onset of muscle weakness, sudden numbness or loss of feeling, and difficulty in moving the limbs, walking, standing, or sitting upright. So, to detect the severity of this abnormality in muscles, we are trying to analyze this through processing the EMG signal. By continuously monitoring the processed signal of the patient at regular intervals, we can inform the patient through the IOT interface by sending messages through mobile, sound for blind people.

MATERIALS USED

SEMG Sensor: To record the electrical activity of the muscles

Arduino Board: To process sEMG data

Amplifiers: To increase the voltage of the SEMG signal

Electrodes: Capture bioelectric signals from muscle activity.

Jumper wires: To connect the SEMG sensor to the Arduino board.

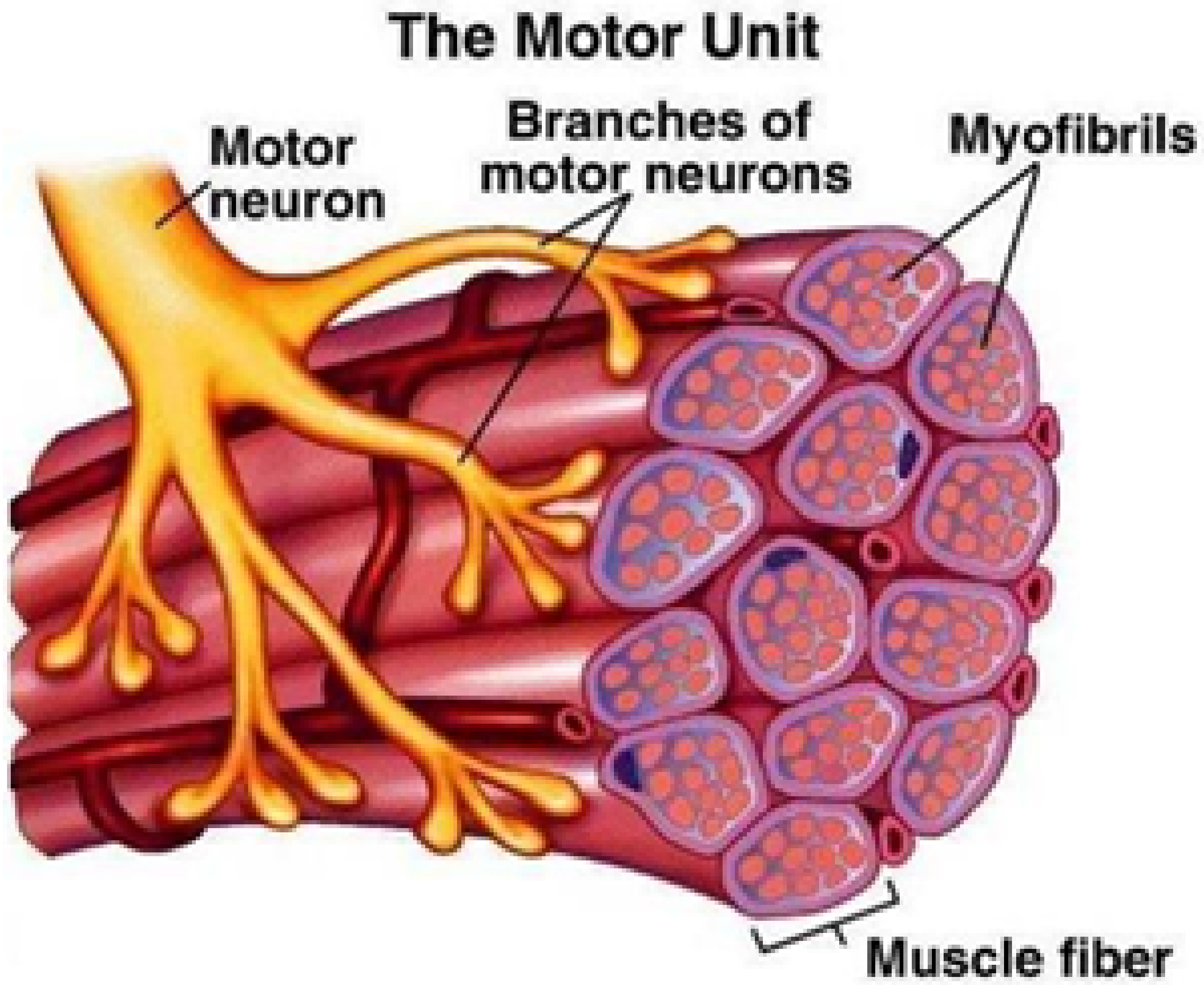
Power Supply: To provide a steady power supply to the SEMG amplifier and Arduino board.

PC: To control the Arduino board and store the SEMG data.

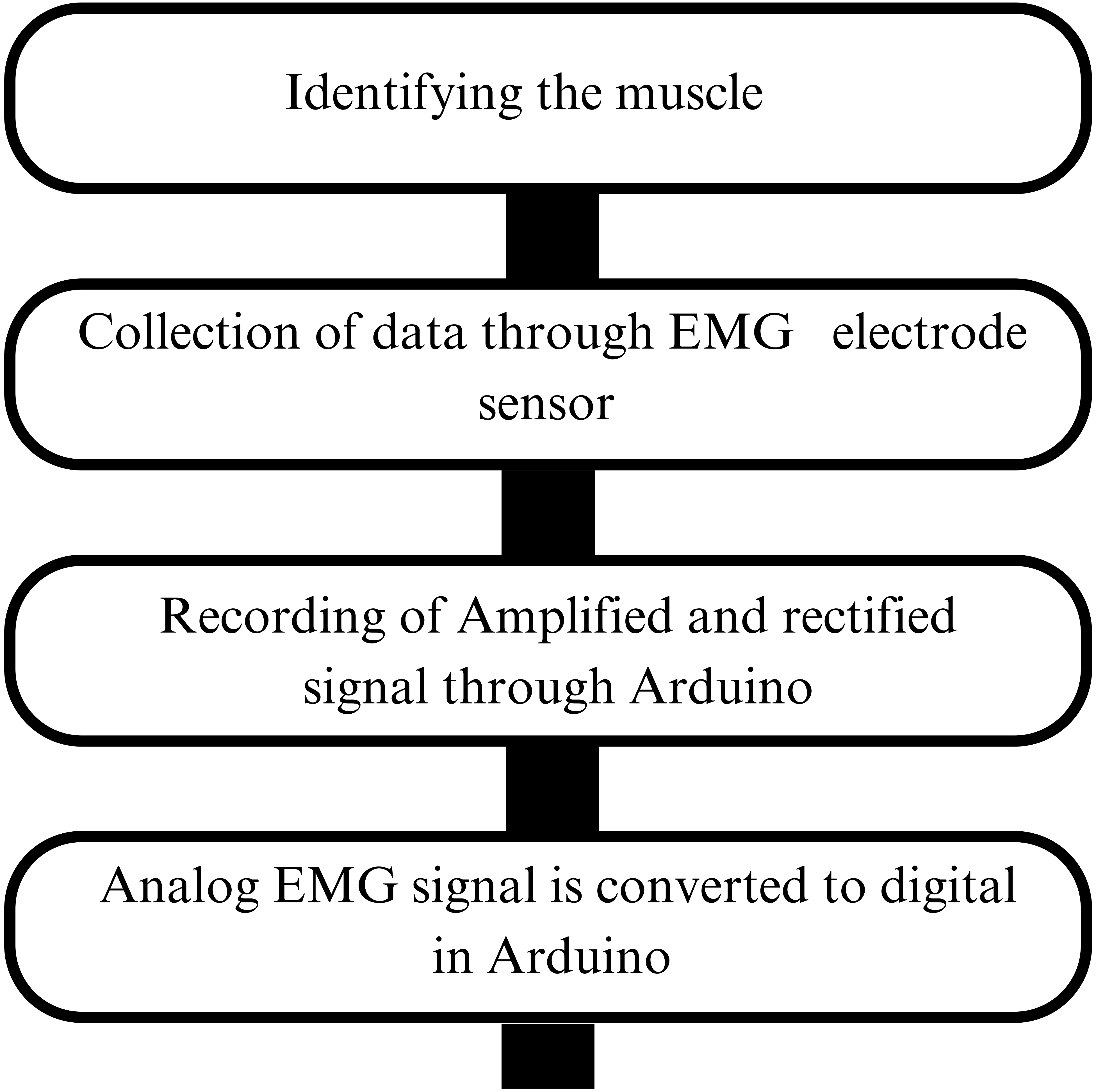
Software: To control the Arduino board, store the SEMG data, and perform the analysis.

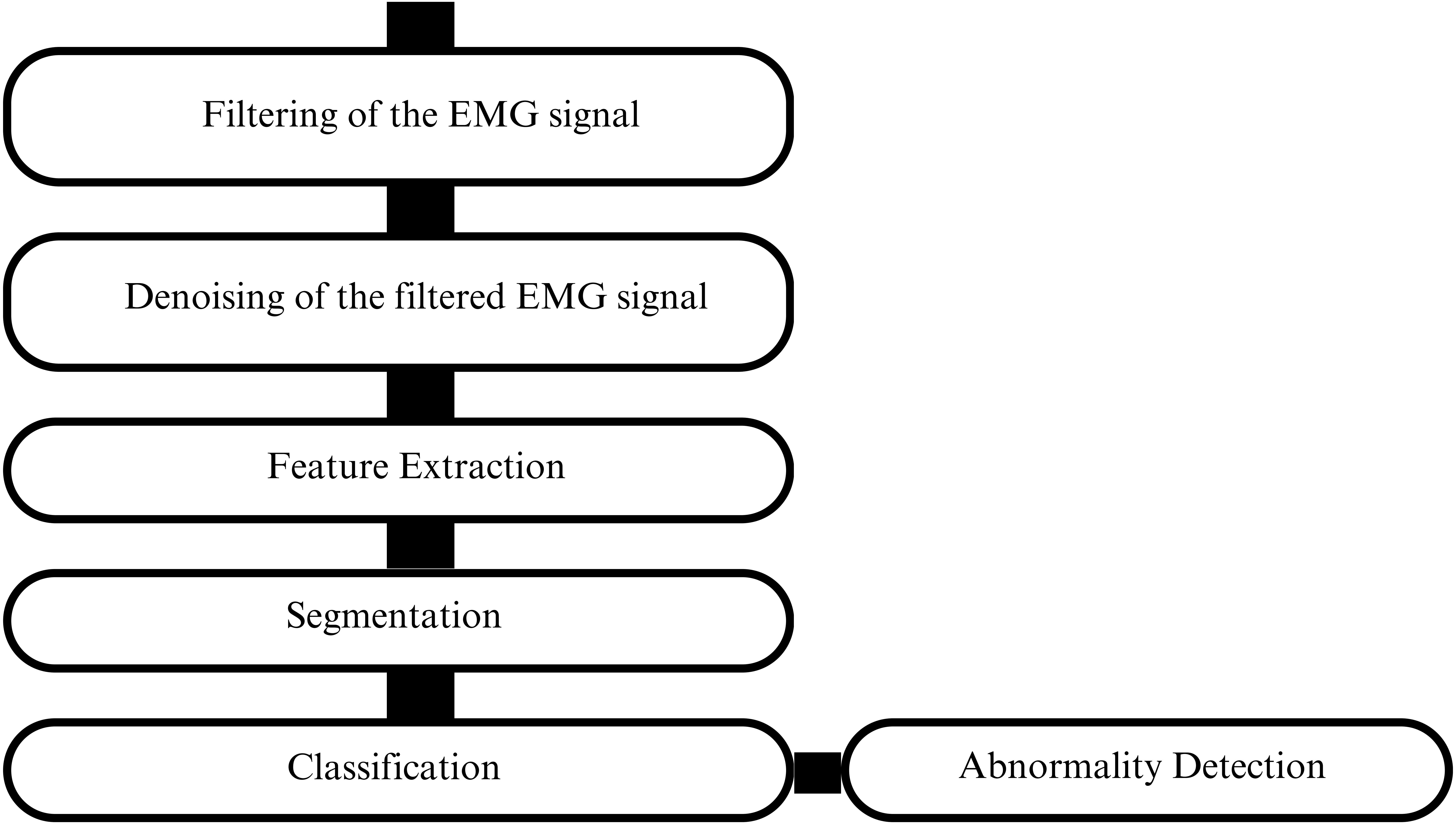
Motor Unit

- Muscle activation generates tiny electrical currents from ion exchanges, detected by electrodes.
- Muscles and the brain work together to move the body, with the CNS transmitting impulses to motor units, where motor neurons intersect with muscle fibers.
- Electromyography (EMG) uses surface and implanted electrodes to measure bioelectric activity in muscles, aiding in force production, movement, and prosthetic control.



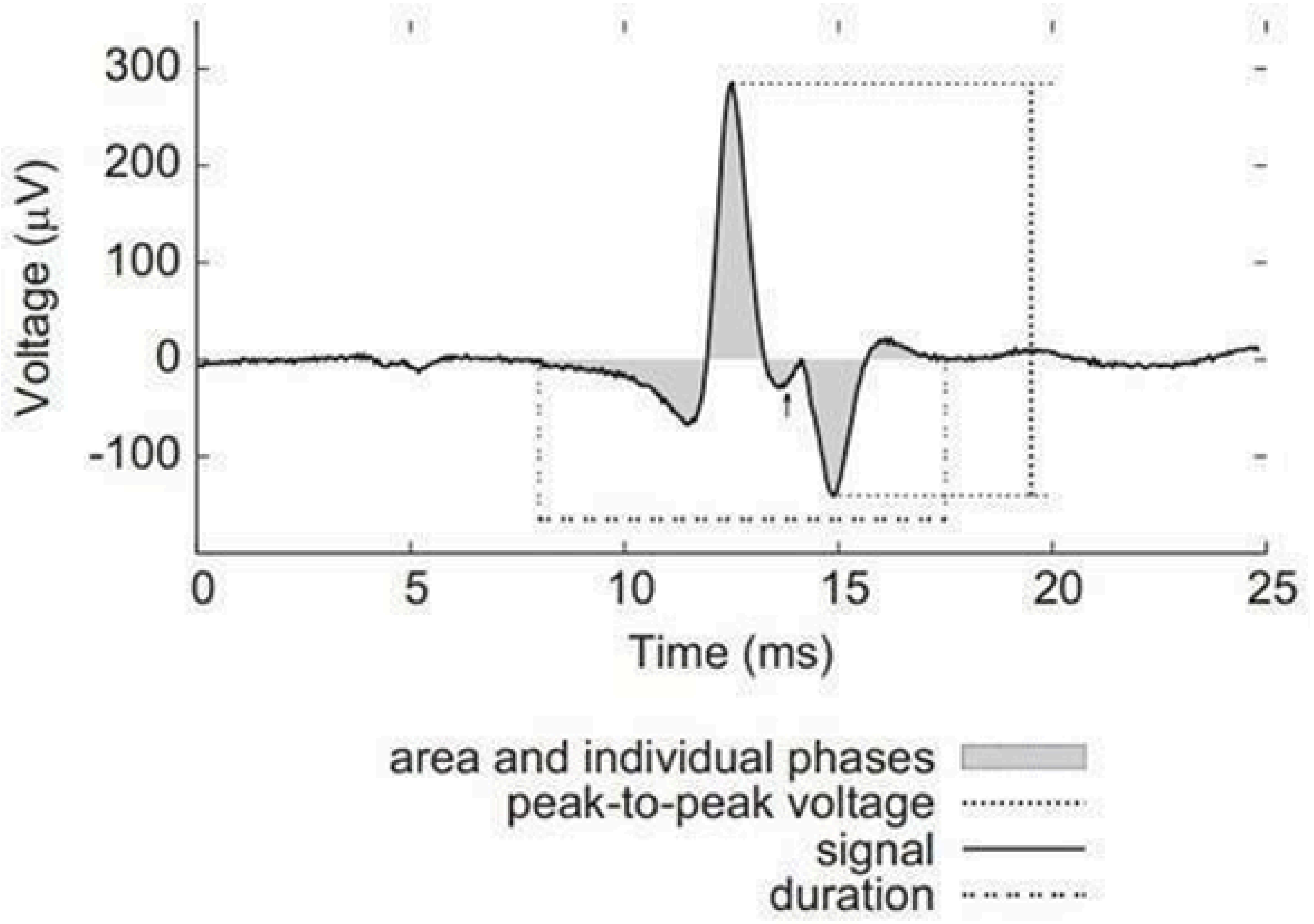
Work Flow


Identifying the muscle
Collection of data through EMG electrode sensor
Recording of Amplified and rectified signal through Arduino
Analog EMG signal is converted to digital in Arduino


Filtering of the EMG signal
Denoising of the filtered EMG signal
Feature Extraction
Segmentation
Classification
Abnormality Detection

IMPLEMENTATION

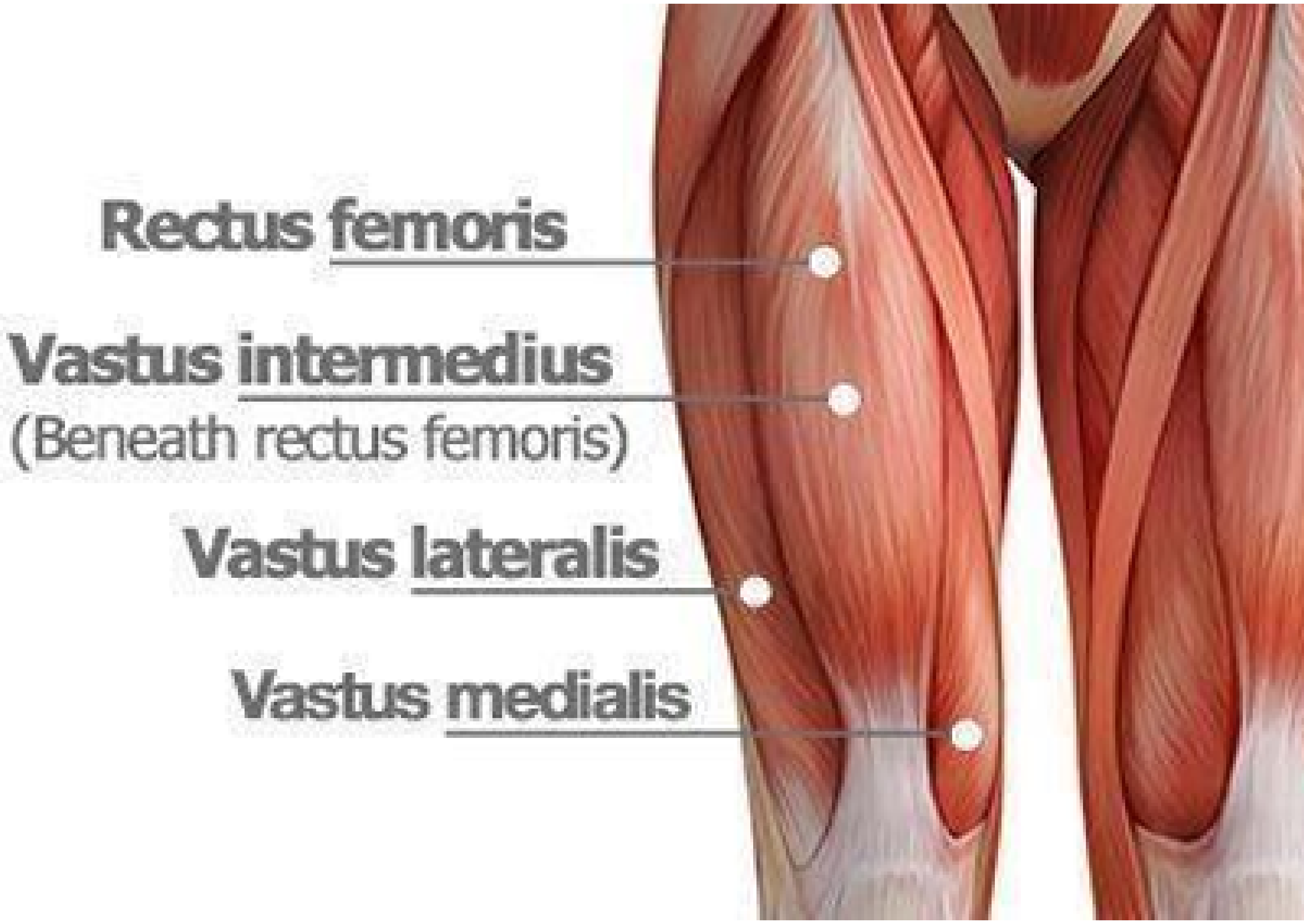
Machine learning, a subset of AI and computer science, employs data and algorithms to mimic human learning, aiding in classification and prediction through statistical methods, crucial for data-driven insights and informed business decisions.



- many features can be extracted from EMG- signals and several features are commonly used to classify EMG- signals in neuromuscular disease studies. These characteristics include duration, (peak-to-peak) amplitude, number of phases, turns, and area.

DATA SET

- The dataset includes 22 participants aged 18 and above, focusing on knee health.
- 11 participants showed knee abnormalities at rest, without prior medical records of knee issues.
- Participants performed tasks like leg bending, leg extension from sitting and walking.
- Data was collected using Biometrics Ltd DataLOG (MWX8) and a goniometer for muscle activity (VM, ST, BF, RF).
- Abnormalities included 6 with ACL injuries, 1 with sciatic nerve injury, and 4 with meniscus injuries.



Description of different classification models:

SUPPORT VECTOR MACHINES:

- SVM is a powerful classifier that maximizes the margin between classes to ensure robust separation.
- It utilizes kernel functions to handle complex, non-linear data transformations effectively.

KNN (K-Nearest Neighbors) :

- K-Nearest Neighbors (KNN) classifies data by comparing it to its nearest neighbors in the feature space.
- It's easy to understand and implement, making it a popular choice for classification tasks in machine learning.

Logistic regression:

- Logistic Regression models probabilities using a logistic function, making it suitable for binary classification.
- It learns coefficients to predict outcomes based on feature relationships, providing interpretable results but assuming linear relationships and independence of observations.

Naive Bayes:

- Naive Bayes utilizes the Bayes theorem and assumes feature independence to compute posterior probabilities for classification tasks efficiently.
- It is suitable for high-dimensional data and works well with both continuous and categorical features, commonly applied in tasks like text classification and spam detection for its simplicity and decent accuracy.

Pre-Processing

Segmentation:

- Segmentation in machine learning involves dividing a dataset into meaningful subsets based on certain criteria or patterns.
- It helps in understanding and analyzing different segments or groups within data, aiding targeted analysis and decision-making.

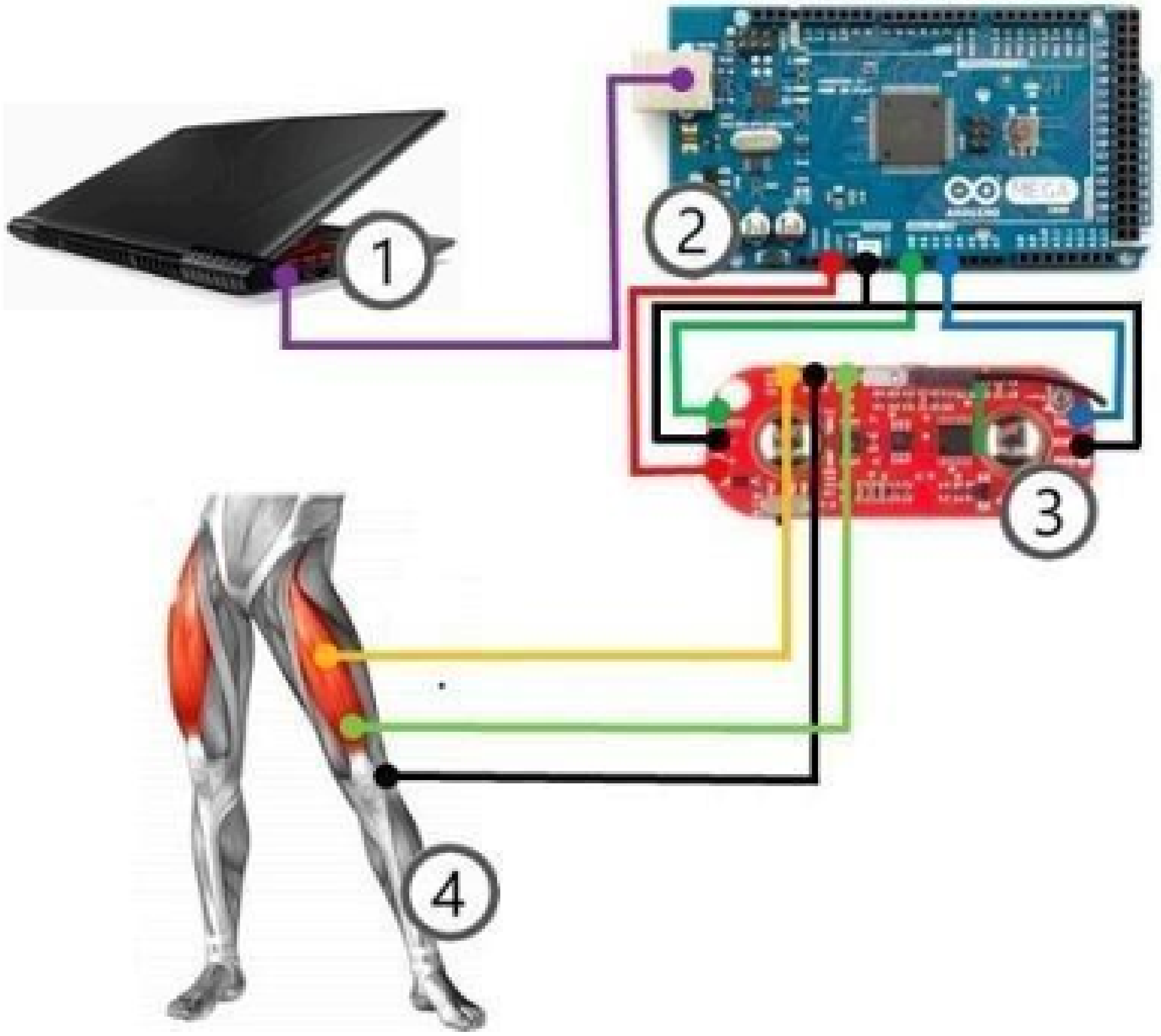
Feature Extraction:

- Feature extraction enhances data analysis by identifying key characteristics like mean, median, mean absolute value, and standard deviation.
- Effective feature extraction improves model accuracy and efficiency by focusing on informative data attributes, crucial for pattern identification and decision-making.
- These methods transform raw data into concise representations that capture essential details for further analysis or categorization.

Using Hardware

EMG SESNOR:

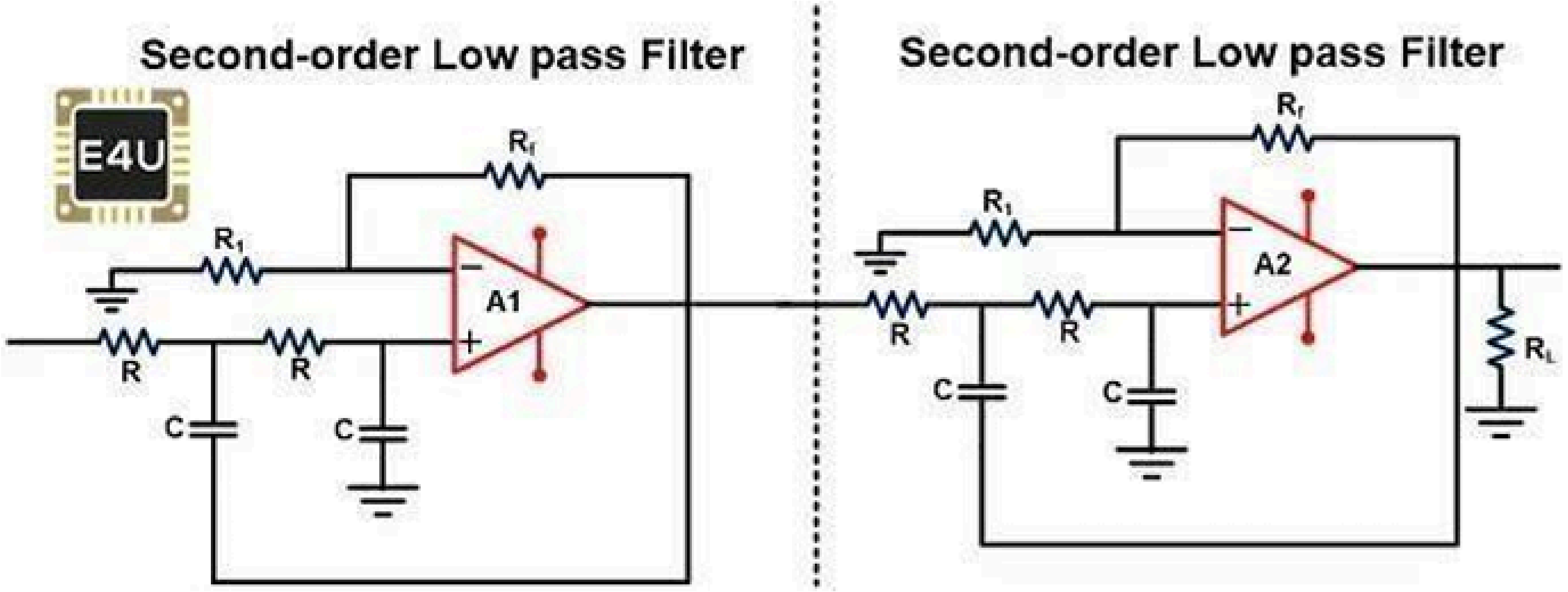
- EMG stands for Electromyography and measures electrical signals associated with muscle contractions.
- EMG is based on three steps: Resting Potential, Depolarization, and Repolarization, and is derived from the brain to muscle control.
- The combination of all the muscles' action potentials of a motor unit is called a motor unit action potential (MUAP).



- A muscle is selected in the lower limb for which abnormality is to be detected.
- Data is collected with the help of an SEMG sensor.
- Acquired EMG Signal is filtered with the help of 4th order Butterworth filter.

Filtering using Butterworth Filter

Butterworth filter provides a flat frequency response in the passband, allowing all frequencies within the passband to pass through without distortion or attenuation.



The general form of frequency response for nth-order Butterworth low-pass filter is,

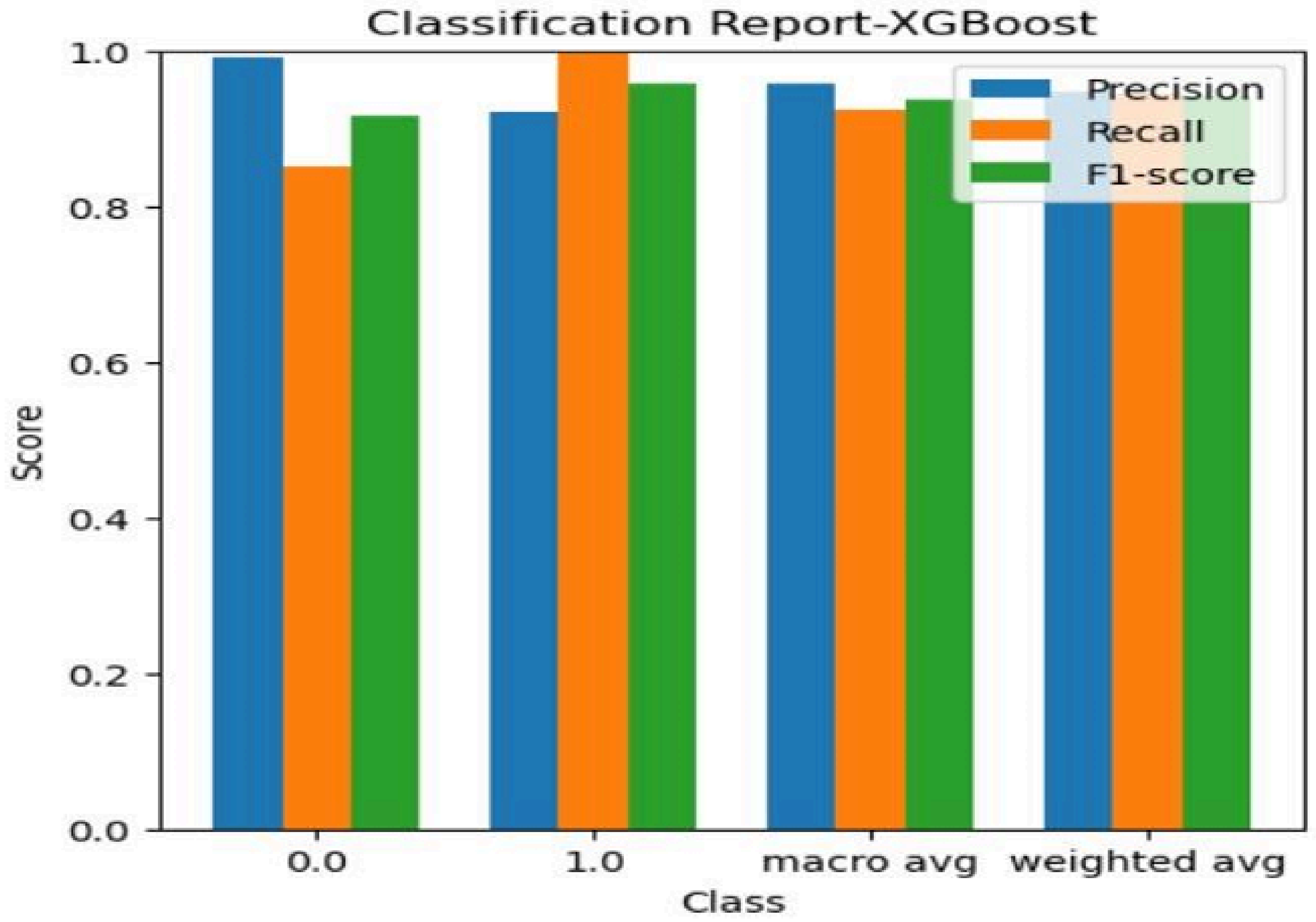
$$H(j\omega) = \frac{1}{\sqrt{1 + \varepsilon^2 \left(\frac{\omega}{\omega_C}\right)^{2n}}}$$

Where,
n = order of the filter,
ω = operating frequency (passband frequency) of circuit
ωC = Cut-off frequency
ε = maximum passband gain = Amax

Results

Classification Report:

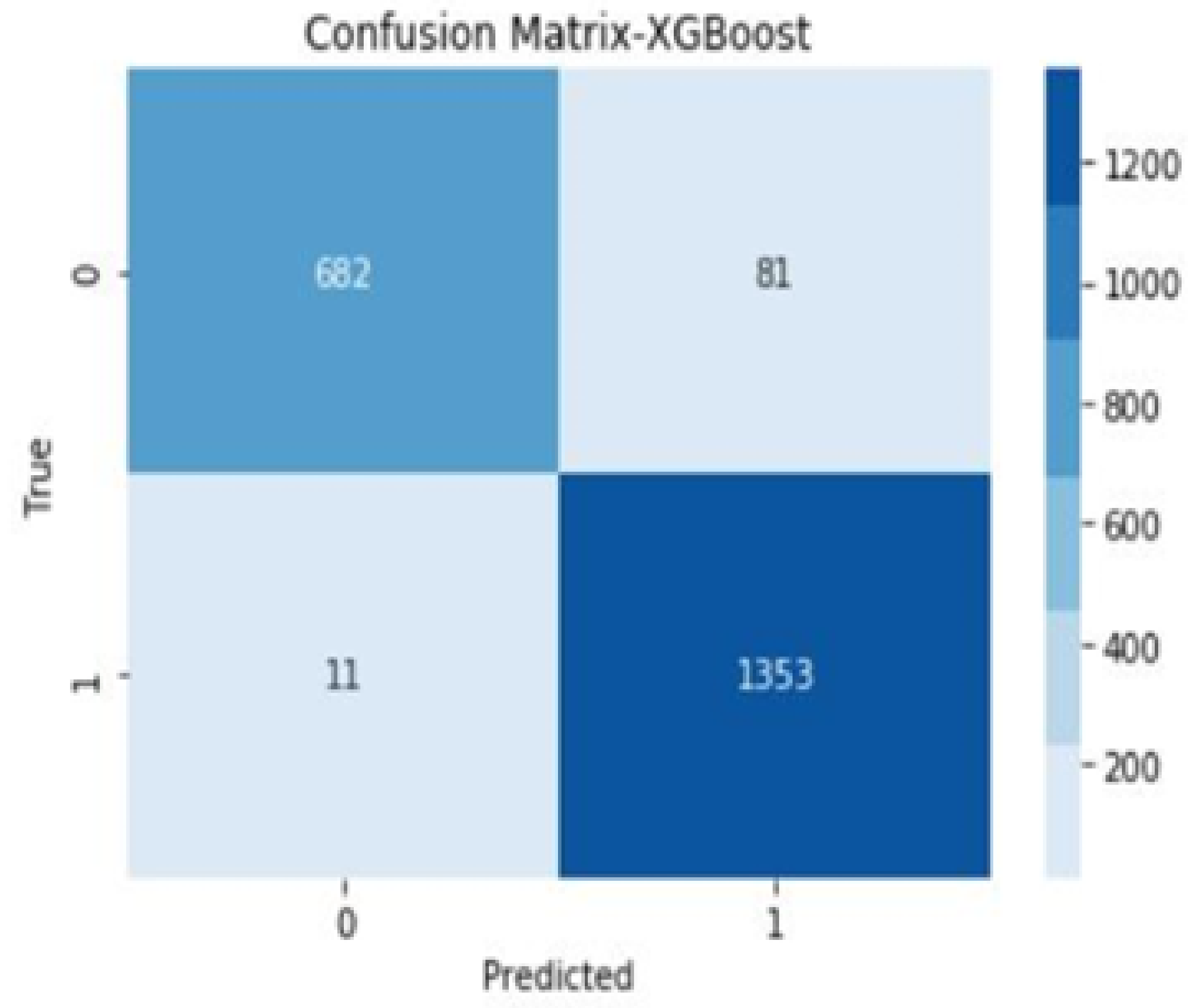
- The performance metrics for each class in a classification task are summarized in the classification report.
- **Precision:** The ratio of true positives to all expected positives is known as precision.
- **Recall:** It measures the proportion of true positives correctly identified among all actual positives.



- **F1-score:** It combines precision and recall into a single metric by taking their harmonic mean. The F1-score is particularly useful when dealing with unbalanced classes or when both precision and recall are important.

Confusion Matrix

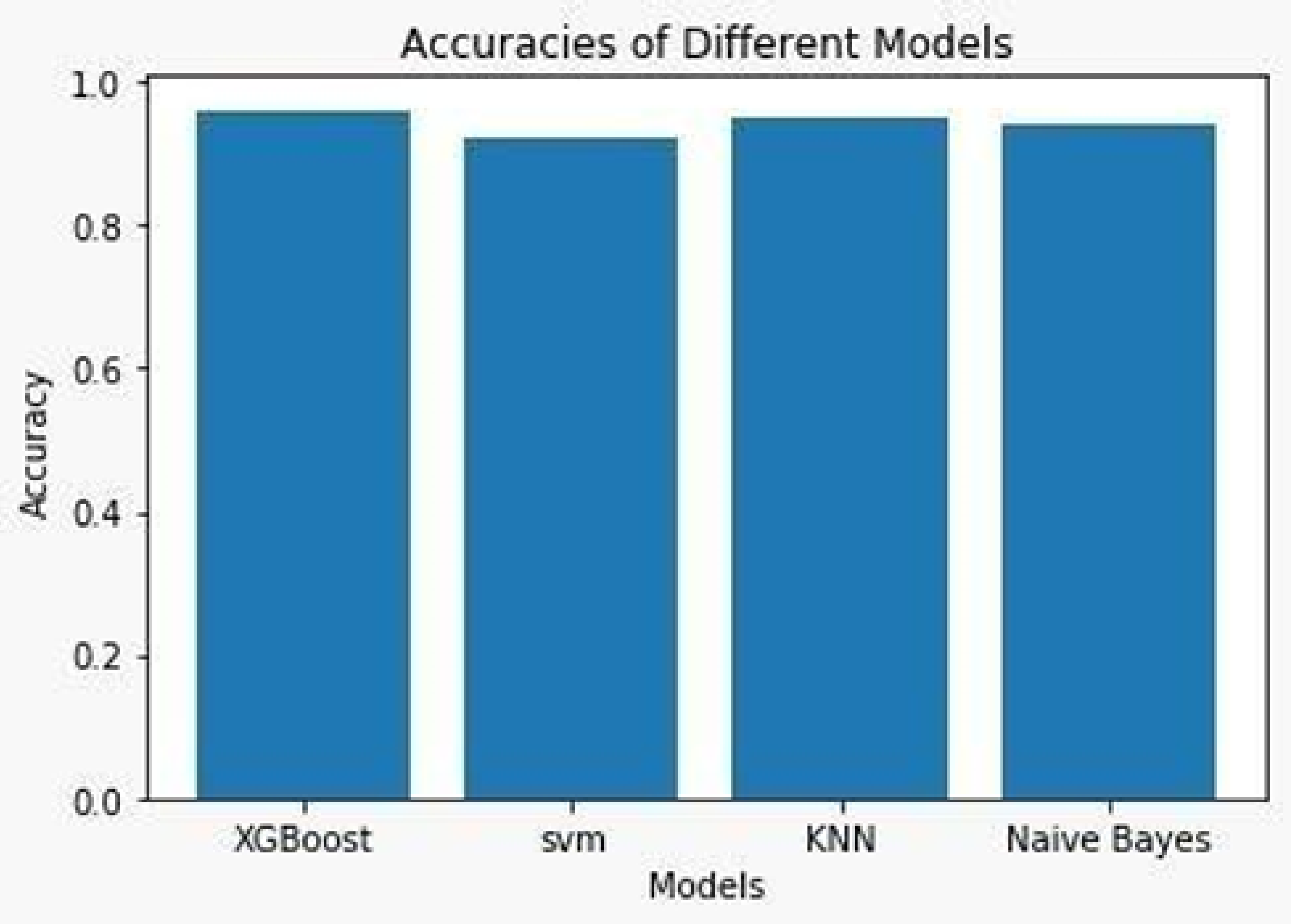
- **True Positive (TP):** Instances where the model correctly predicts positive (class 1) and the actual class label is also positive. Example: 1353 instances.
- **True Negative (TN):** Instances where the model correctly predicts negative (class 0) and the actual class label is also negative. Example: 682 instances.



- **False Positive (FP):** Instances where the model incorrectly predicts positive (class 1) but the actual class label is negative (class 0). Also known as Type I error or false alarm. Example: 81 instances.
- **False Negative (FN):** Instances where the model incorrectly predicts negative (class 0) but the actual class label is positive (class 1). Also known as Type II error or missed detection. Example: 11 instances.

- Class 0 (Negative Class): Represents the non-target or common class.
- Class 1 (Positive Class): Represents the target or rare class.

The confusion matrix provides a snapshot of model performance, showing accurate and inaccurate predictions for each class. In this scenario, the model demonstrates more true positives and true negatives than false positives and false negatives, indicating effective classification of both positive and negative samples and overall good performance.



Accuracies of different models

CONCLUSION

- **Issue Identification:** Older individuals and athletes often experience lower limb issues like muscle weakness and numbness, impacting mobility and quality of life.
- **Objective:** This study analyzes EMG signals to detect and diagnose lower limb muscle abnormalities early for effective treatment and rehabilitation.
- **Methodology:** EMG data is processed using an SEMG sensor attached to an Arduino UNO, and mean values of segmented data windows are calculated for classification.
- **Classification:** Mean values above 480 indicate normal EMG data, while values below 480 indicate abnormalities, helping differentiate between normal and pathological patterns.

FUTURE SCOPE

- **Real-Time Datasets:** Use real-time datasets to improve classification accuracy.
- **Mobile App:** Develop a mobile app for continuous and regular monitoring by patients and doctors.
- **Multimodal Sensor Fusion:** Combine EMG with accelerometers, gyroscopes, and force sensors for comprehensive lower limb movement analysis.
- **Real-Time Classification:** Implement real-time classification for immediate feedback during rehabilitation or prosthetic control.
- **Wearable Devices:** Create wearable devices for easy and user-friendly EMG monitoring and rehabilitation.
- **Advanced Techniques:** Apply deep learning and other machine learning techniques to enhance classification results.

REFERENCES:

- *Ankit Vijayvargiya, Chandra Prakash, Rajesh Kumar, Sanjeev Bansal, Joao Manuel R. S. Tavares Human Knee Abnormality Detection from Imbalanced sEMG Data*
- *Qin P, Shi X. Evaluation of feature extraction and classification for lower limb motion based on semg signal. Entropy. 2020*
- *Gandjar Kiswanto, Muhammad Fathin Juzar, Adjeng Ayu Setiani, Dody Rakhmat Ramadhan, Ferdiansyah Zhul-triza, Rachmad Muhammad Suryantoro Muscle Contraction Sensor Filtering and Calibration for Virtual Manufacturing Development*
- *Ashutosh Gupta, Tabassum Sayed, Ridhi Garg, Richa Shreyam Emg Signal Analysis of Healthy and Neuropathic Individuals*
- *Sapsanis C, Georgoulas G, Tzes A. Emg based classification of basic hand movements based on time-frequency features. In: 21st Mediterranean Conference on Control and Automation, IEEE; 2013.*

THANK YOU

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