IoT-Based Muscle Activity Monitoring and Posture Correction

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Final Year Project Report submitted in partial fulfillment of the requirements for the Degree of BCS (Hons.)

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Certificate of Approval

We, certify that we have read the report titled: **IoT-Based Muscle Activity Monitoring and Posture Correction**, by **Shehryar Akbar, Ubaid Ali Shah and Muhammad Minhas**, and in my opinion, this work meets the criteria for approving the report submitted in partial fulfillment of the requirements for BCS (Hons.) at Institute of Management Sciences, Peshawar.

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Declaration

We, **Shehryar Akbar, Ubaid Ali Shah and Muhammad Minhas**, hereby declare that the Final Year Project Report titled: **IoT-Based Muscle Activity Monitoring and Posture Correction** submitted to FYP Coordinator and R&DD by us is our own original work. We are aware of the fact that in case, our work is found to be plagiarized or not genuine, FYP Coordinator and R&DD has the full authority to cancel our Final Year Project and We will be liable to penal action.

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Dedication

We dedicate this Final Year Project to our parents and teachers, who have always supported and helped us in every aspect of life.

Acknowledgement

All the praise to Allah that induced the man with intelligence, knowledge, and wisdom. Peace and blessing of Allah be upon the Holy Prophet who exhort his followers to seek for knowledge from cradle to grave.

Foremost, We would like to express our sincere gratitude to our supervisor Mr. Omar Bin Samin for his continuous support, patience, motivation, enthusiasm, and immense knowledge. His guidance helped us throughout the project. Last, but not the least, We would like to thank our parents for supporting us morally and spiritually throughout our life.

Abstract

The thesis outlines the creation of a classification system that utilises surface Electromyography (sEMG) sensor data to distinguish between accurate and inaccurate posture during targeted workouts for the bicep and tricep muscles. A comprehensive dataset was meticulously generated by two volunteers who performed bicep curls, hammer curls, tricep kickbacks, and bench tricep extensions. The data was collected under two conditions: correct posture and incorrect posture. The exercises were conducted at three distinct angles: 180°, 90°, and 20°. The vast dataset consisted of several components, including the individual's body weight, the weight lifted, the specific muscle targeted, the kind of exercise performed, the posture adopted, and the averaged surface electromyography (sEMG) findings. The Naive Bayes approach's simplicity and efficiency in handling the conversion of categorical data into numerical form played a crucial role in guiding the decision-making process. The model achieved a 91% accuracy rate due to its extraordinary ability to accurately forecast posture and flawlessly identify incorrect ones. The model exhibited a somewhat diminished ability to accurately remember ideal posture, although achieving satisfactory results. This indicates the need for more enhancements. The evaluation criteria employed for a comprehensive performance assessment included precision, recall, F1-score, and the confusion matrix. The findings suggest that while the current model is successful, using sophisticated methodologies and more datasets might potentially improve its performance.

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Chapter 1

Introduction

1.1 Overview

The development and implementation of an Internet of Things (IoT) system monitoring muscle activity in real-time is the main objectives of this project. It is especially built to monitor the bicep and triceps muscle activity during workout. This project is carried out so that it provide users real-time feedback on their muscle activation and posture, so assisting in improving their exercise routines and minimizing the likelihood of harm. The system utilizes Surface Electromyography (sEMG) sensors and NodeMCU microcontroller, to gather and send data. This data is then displayed using a custom web application.

sEMG sensor is used to measures the electrical activity produced by skeletal muscles, therefore it is very vital in this system. This sensor is designed to especially track the activity levels of the tricep and bicep muscles, therefore providing essential data on muscular involvement across many activities. The core component of the system, the NodeMCU microcontroller allows data from the sEMG sensor to be collected and transferred. For analysis and instantaneous presentation, the NodeMCU sends this data to the web application via Wi-Fi connection.

Development of a web application serving as the user interface is an essential aspect of this project. Using animations and real-time feedback on muscle activity and exercise posture. The UI is designed to be simple and user-friendly so that users may quickly understand their muscle activation and change their approach as required. Using data from the sEMG sensor to evaluate the user's posture during exercises, the posture analysis feature of the web application is rather amazing. Users receive quick comments to help them to decide if their posture is right or not, therefore guiding their approach and preventing mishaps.

Given their importance in upper body activities, close examination is focused on tracking the bicep and tricep muscles. By giving these particular muscle groups top priority, the system provides the thorough evaluation required for users trying to maximise the effectiveness of their exercises by increasing muscle activation. An additional area of emphasis is the accurate identification of correct posture, since it is crucial for avoiding injuries and optimizing the advantages of physical activity. The posture recognition tool assists users in maintaining proper form, hence improving the effectiveness of their exercises. figure 1.1 represnets a broader view of the project working.

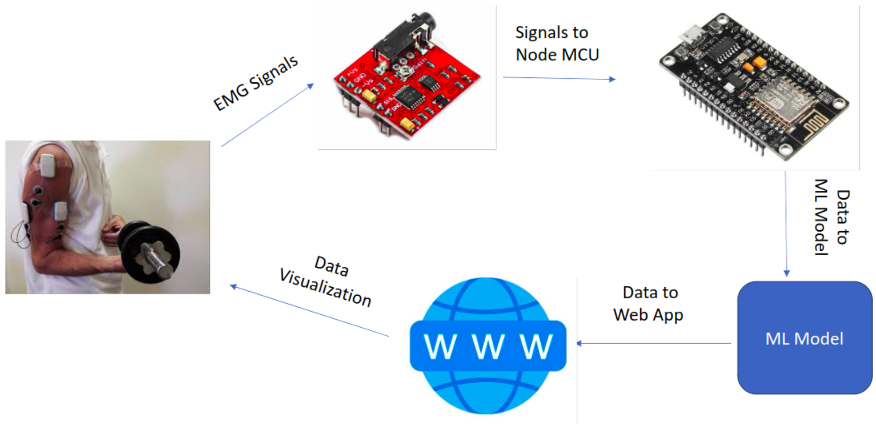

Figure 1.1: System Working Overview

1.2 Project Motivation

The motivation for the project stems from the needs of individuals who choose to engage in home-based exercise and those who are dedicated to their training regimens. Although exercising at home may offer convenience, it can be challenging to maintain ideal posture and maximize the efficiency of the workout without professional guidance. This can lead to ineffective exercise sessions and potentially severe injuries.

By offering real-time and data-driven insights into muscle activity and exercise posture, this muscle monitoring system, which employs IoT technology, effectively resolves these concerns. The objective of this endeavour is to promote the development of the triceps and biceps muscles. It provides users with immediate feedback on their technique, enabling them to optimise the safety and efficacy of their upper body exercises. Fitness devotees and professional trainers can optimise their training regimens and monitor muscle activation by employing this technology in gym environments, which is particularly advantageous. Our system is advantageous for both residential and gym use, as it is adaptable and assists customers in accomplishing their fitness objectives. The objective of this project is to improve the exercise experience by utilising cutting-edge fitness technology to promote well-being and health, thereby guaranteeing that all individuals have access to immediate and precise feedback.

1.3 Project Vision, Scope, and Glossary

1.3.1 Vision

The aim of this project is to revolutionise the workout experience by leveraging cutting-edge Internet of Things (IoT) technologies. Users can enhance their training routines by receiving immediate and precise info on muscle activity and posture. This technique is customised to maximise individuals' ability to reach their fitness goals, with a specific emphasis on the bicep and tricep muscles. This ensures improved effectiveness and safety. Our objective is to create a future where fitness enthusiasts, whether they are at home or at the gym, may use state-of-the-art equipment that provides useful data, resulting in improved workout results and less chance of injury.

1.3.2 Scope

This project involves developing and implementing a muscle monitoring system that uses Internet of Things (IoT) technologies. The primary goal is to observe and record the activity of the bicep and tricep muscles during workouts. The procedure involves integrating Surface Electromyography (sEMG)sensors to record electrical activity and muscle activation levels. The NodeMCU microcontroller will serve as the central hub, collecting data from the sEMG sensor and transmitting it wirelessly over Wi-Fi to a web application. This web application will provide a user-friendly interface for displaying real-time data visualization animations to determine whether the posture is correct or incorrect. This system is versatile, catering to individuals who like working out in the privacy of their own homes as well as fitness enthusiasts and trainers in gym settings who aim to maximise their training regimens. An extensive assessment will be conducted, involving a wide range of users participating in different activities, to validate the precision and dependability of the system. The input from the system will ultimately help consumers optimise workout efficiency, decrease the probability of injury, and enhance their overall fitness experience.

1.3.3 Glossary

- **EMG:** electromyography
- **IoT:** Internet of Things
- **HTML:** Hypertext Markup Language

- **CSS:** Cascading Style Sheets
- **JavaScript:** Programming language for web development
- **Firebase:** A web and mobile application platform
- **nodeMCU:** it is a Microcontroller board

1.4 Problem Statement

Especially in bicep and tricep movements, improper exercise postures can cause injuries and ineffective workouts. Conventional approaches of evaluating and correcting posture lack accuracy and real-time feedback, so it is challenging to guarantee good form. Some people wish to work out at home and require a guide to help them perform their workout in the right way. Our project intends to build a dependable system employing surface Electromyography (sEMG) sensors and machine learning to reliably classify workout postures in real-time in order to solve this. Real-time input from this technology will improve training results, help to prevent injuries, and raise general fitness and rehabilitation effectiveness.

1.5 Objectives

These objectives have a purpose which is to establish a thorough and user-friendly system for measuring muscle activation during exercise sessions. Our objective is to help users in enhancing their exercise technique, maximising the efficiency of their workouts, and reducing the probability of injury by offering immediate feedback and user-friendly visual representations. The system's versatility ensures its effective use in both residential and fitness facility environments, thereby allowing a wide range of individuals to benefit from contemporary training innovations.

- To develop a system for tracking muscular activity, particularly in the bicep and tricep muscles. This requires employing Surface Electromyography (sEMG) sensors to track the electrical activity of these muscles during training sessions. The sEMG sensors will collect data on muscle activation levels, which will be useful for measuring muscle engagement and monitoring.

- To provide the real-time transmission of data from the sensors to the user interface. The NodeMCU microcontroller will be utilised to gather data from the sEMG and transmit it wirelessly to a web application. The prompt transmission of data is essential for offering individual with quick feedback on their muscle activity and workout posture, allowing for rapid adjustments and optimizations.

- To develop a web application that present the collected data in a user-friendly and understandable manner. The web application will utilise animation to visually represent the user's posture during exercise sessions. The muscle activity data will be shown in real-time using user-friendly graphics, allowing users to easily understand the information and make needed modifications to their training regimens.

- To offer full feedback on the user's exercise position. The device will utilise data from the sEMG sensors to ascertain whether the user is maintaining proper posture throughout workouts. Users will receive immediate feedback if their posture is incorrect, allowing them to quickly adjust their technique and so lowering the likelihood of accidents and improving the effectiveness of their activities.

1.6 Tools

1.6.1 Software Tools

1. Hypertext Markup Language (HTML):

· **Role:** HTML is the main language used to organise online content; it also specifies the fundamental foundation around which the whole user experience is built. · **Importance:** It is a good choice for building a well-organized and user-friendly internet interface appealing to a broad spectrum of consumers because of its simplicity and versatility.

2. Cascading Style Sheets (CSS):

· **Role:** This is the computer language that provides the web interface vibrancy and visual coherence, therefore ensuring an aesthetically pleasing and homogeneous presentation across devices.

· **Importance:** Through design element modification, CSS transforms the incomplete HTML structure into an exciting and user-friendly interface, therefore enhancing the user experience overall.

3. JavaScript:

· **Role:** JavaScript is a versatile programming language that improves web pages with dynamic behaviour and interactivity therefore facilitating real-time modifications and user engagement.

· **Importance:** The system may provide an interactive and responsive user experience by means of its client-side scripting tools, therefore enabling features such dynamic content generation and real-time data changes.

4. Firebase: Firebase is a full cloud platform offering all required backend services like hosting, authentication, cloud operations, and real-time No SQL database hosting.

· **Importance:** It allows secure user identification, effective online application hosting, real-time data preservation and retrieval, thereby simplifying backend development.

1.6.2 Hardware Tools

1. Surface Electromyography (sEMG) Sensors:

· **Role:** The electrical signals produced by the arm's muscles—particularly the bicep and tricep muscles—are detected and measured using sEMG sensors during exercise.

· **Importance:** Gathering essential data on the intensity of muscular activity depends much on these sensors. Evaluating the degree of muscle engagement and determining the accuracy of user exercise performance depend on this information. Usually acting as the primary processing unit of the system, NodeMCU

2. NodeMCU Microcontroller:

· **Role:** The technology uses surface electromyography (sEMG) sensors to compile data that it then wirelessly forwards to the web application.

· **Importance:** Delivering quick feedback to consumers on their training posture and muscle activity depends on the NodeMCU enabling immediate data transfer and processing.

3. Power source:

· **Role:** The power supply is in charge of providing the sEMG sensor with the needed electrical voltage.

· **Importance:** Reliable and accurate data collecting depends on the sensors continuous and regular operation, which is ensured by a consistent electrical supply.

4. Wi-Fi Module (Integrated in NodeMCU):

· **Role:** The Wi-Fi module of the NodeMCU is used to provide wireless connectivity between the web application and the hardware components.

· **Importance:** Transmission of real-time data to the web application depends on wireless connectivity, therefore allowing users to quickly get feedback on their exercises free from the restrictions placed on wired connections.

5. electrode pads:

· **Role:** Attached to the skin, they sense electrical impulses produced by the muscles.

· **Importance:** These pads are essential for precisely recording the muscle activity signals required by the sEMG sensors for measurement. They provide optimal skin contact and dependable signal capture.

Together, these hardware and software components provide a unified technological framework that combines innovation and practicality to fulfill the goal of creating an Internet of Things (IoT)-based health monitoring system with an integrated feature that suggests diets. Every tool has been carefully chosen based on how it fits into the larger picture of a smooth, adaptable, and user-focused health management ecosystem. Combining these technologies not only strengthens the system's technological capabilities but also demonstrates the dedication to developing a comprehensive, easily accessible, and revolutionary tailored wellness solution.

Chapter 2

Background Study

In now a days the applications of technology in health and fitness have progressed tools like posture assessment systems substantially. Though traditional methods of assessing exercise form have value, they have significant restrictions. Emerging to tackle these problems are ideas include machine learning-powered exercise analytics, IoT-enabled fitness trackers, and sEMG-based posture classification systems. By way of more precise and tailored evaluations and suggestions, these developments aim to boost fitness outcomes. Reviewing these advances with an eye towards their characteristics and constraints within the current scene of fitness technology, this study

Liu et al [1], This work presents a wearable electromyography (EMG) device intended to continuously monitor muscle fatigue during exercise. The device calls for a Bluetooth Low Energy (BLE) module, an electromyography (EMG) sensor, and a microcontroller unit (MCU). The MCU examines the EMG signal's electrical activity of the muscles after which it determines the median frequency (MF). A quantitative assessment of muscular exhaustion, the MF, or Muscle tiredness, is provided. Higher MF levels relate to more degrees of tiredness. The MF data are then delivered straight to a smartphone app for instantaneous viewing via BLE. Monitoring the MF values of the quadriceps femoris muscle during cycling action let one evaluate the performance of the gadget. The results showed that the device precisely noted changes in MF and identified the beginning of muscle tiredness.

Garcia-Hernandez et al [2], This work describes the development of electromyography (EMG) technology an exergame system for isometric muscle training. Later analysis examined the effects of this system on strength, performance, and muscle hypertrophy. The new isometric muscle training method tracks and interacts with the daily exercise programme of the user using electromyography data. The effect of the method on motivation, general performance, and muscle hypertrophy is investigated in this work. The researchers examined the effectiveness of the muscles in addition to assessing people's participation and motivation while playing the exergame using a qualitative evaluation process. The results of the study show that

EMG-based exergaming systems significantly increase user motivation, hence improving performance and muscle tone. The benefits of using EMG equipment into isometric muscle training regimens are shown in this work. It also shows how these technologies may help the body and joints during exercise. By providing a more interactive and enjoyable experience, the use of technology—especially EMG-based systems—may revolutionise the muscle training process and help to reach fitness goals.

D. Toro et al [3], This research identified a solution for the problem of muscular damage brought on by overworking oneself. This involved the creation of an affordable electromyography (sEMG) tool able to precisely identify muscle weariness. Using reasonably priced sEMG sensors, Arduino boards, and PCs, a research with 28 subjects revealed physiological activity. Specific measures like root mean square (RMS), mean value (MAV), and mean frequency (MNF) serve to clarify the fatigue patterns that have been found in past studies. The lighting of the programme confirms the research concept and helps its utilisation at a lower cost. The results not only demonstrate the validity of the fatigue detection method but also highlight the efficiency and cost-effectiveness of the design, thereby allowing the monitoring of muscle exhaustion in numerous spheres.

Rajkumari et al [4], This article explores the relevance of electromyography (EMG) signals in healthcare, with a focus on their applications in neurological diagnostics, physical therapy, yoga therapy, retherapy, biofeedback, training, and sports medicine. Developed from electromyographs, electromyography sensors play a major role in diagnosis as well as in data collecting on muscle mass in many disciplines including medical research, ergonomics, rehabilitation, biomechanics, and sports. Rapid evaluation of muscle tone offered by EMG biofeedback helps one understand muscle tone and identify issues like muscular spasms. The limits of commercial electromyography (EMG) acquisitions are underlined in this paper in light of their outrageous cost, maintenance issues, and the problems resulting from the need of electrical connections all during the recovery process. Researchers investigated low-resolution alternatives and conducted extensive analyses of different EMG collecting systems, including elements including performance, delivery methods, signal conditioning, and mode of operation, in order to address these concerns. Four receiver systems for electromyography (sEMG) are investigated in this work along with their design, advantages, and shortcomings. It especially stresses the need of low power consumption, acceptable data quality, cost, and good design. It also provides recommendations for effective electromyography collecting and processing. monitoring systems and fatigue identification.

Sayyed et al[5], This paper discusses the cost-effectiveness of electromyography (EMG) data acquired using our remote patient monitoring system. This methodology addresses the need of amplifying weak EMG signals by using various devices and pre-processing methods to remove any remnants of the EMG signal. The computer receives digitized EMG signals for the purpose of visualization. The system is driven by the ARM Cortex M3 LPC1768 and enables GSM/GPRS and Internet connectivity in Wireless Sensor Networks (WSN) using the HTTP protocol. This configuration transmits electromyography (EMG) data wirelessly to a database server that stores medical information. The stored data may be retrieved by a web application or a browser. The ability to immediately observe EMG waveforms allows for the identification of muscle or nerve problems. The portability of EMG monitoring, when integrated with the Internet of Things (IoT), has the capacity to provide remote patient monitoring. Storing EMG data on the cloud enables clinicians to monitor patients in real time, hence minimizing the need for patients to be in the clinic at all times. Furthermore, this novel approach not only offers convenience to patients but also has the potential to identify a wide range of muscular and neurological disorders and ailments, hence presenting significant benefits to the field of medical technology.

H. Khan et al [6], This research focuses on the difficulties individuals have when engaging in physical activity in their residences, particularly in the context of the COVID-19 epidemic. Insufficient professional oversight may result in the dissemination of inaccurate information during the biceps curl exercise, potentially resulting in back discomfort and shoulder injury. This technique is especially designed to help people maintain their exercise programmes at home without the supervision of a certified instructor. The study endeavors to enhance the recuperation of the biceps and mitigate the risk of injuries by using Myoware electromyography sensors and triaxial accelerometers. Employ machine learning algorithms such as Naive Bayes, Logistic Regression, K-Nearest Neighbors, Decision Trees, and Random Forests to evaluate the acquired outcomes. The random forest model has the maximum accuracy, reaching 90.90%. Research indicates that correct movement control plays a crucial role in avoiding injury and muscle deformation. This highlights the significance of excellent mechanics in minimizing compensation and the risk of injury. The integrated built-in application architecture incorporates Bluetooth and Google Firebase to streamline real-time data exchange and collecting. The research continues by showcasing the potential of the suggested methodology for promptly identifying and preventing long-term consequences linked to improper physical activity, so contributing to the progress of health and overall well-being. The study also showcases potential future uses, such as expediting the creation of energy-efficient models and using electromyography and muscle devices, fostering advancements in the field of health and wellbeing.

Q. Gong et al [7], The researchers of this study have created an innovative muscle monitoring system that operates in real-time. The device consists of a flexible wireless setup, which includes a stretchy skin patch and a flexible circuit board worn as a band. The flexible patch attaches well to the skin, reducing interference and allowing accurate signal collection from the muscles. The device can quickly evaluate muscular strength and tiredness by examining several characteristics of muscle signals. One significant benefit is its wireless capacity to transfer data to a smartphone for quick display. This technology is a major breakthrough, offering a simplified and pleasant way to continuously monitor, especially useful for long-term usage. The researchers foresee its potential uses in providing continuous advice for secure and efficient training, recuperation, and fitness monitoring. The research is optimistic about the future adoption of the system, as it anticipates its potential function in preventative healthcare by possibly preventing chronic pain and muscular diseases associated with weariness. The results indicate favorable implications for using this technology into therapy practices and wider health monitoring settings.

S. Chun et al [8], This research emphasizes the need for home exercise equipment that might enhance muscular strength, particularly in light of the COVID-19 pandemic. The product had a wearable casing that housed nine electrically charged, pliable hydrogel electrodes. Neoprene-impregnated high-purity single-walled carbon nanotubes (SWCNTs) are used to produce dry electrodes, which exhibit lower levels of noise compared to hydrogels. The arm cuff captures electromyographic (EMG) signals while doing wrist curls, biceps curls, and dumbbell kickback workouts. Machine learning models shown exceptional accuracy in categorizing various sports, showcasing the potential of the sought-after equipment for efficient home training without the need of a personal trainer. The research revealed broader applications, demonstrating that the gadget may provide comprehensive insights into exercise, including physical analysis, transportation, exercise quantification, and optimal study hours. The technology provides contemporaneous monitoring and evaluation while also advancing digital health, allowing for injury prevention and muscle strength improvement. Future research aims to improve the methods of strengthening the body and especially focused on muscles, therefore expanding the variety of useful tools in other digital health fields.

G. Jia et al [9], The paper proposed a new deep learning model combining a convolutional auto-encoder and a convolutional neural network (CAE+CNN), therefore addressing the difficulties in electromyogram (EMG)-based hand gesture categorising. Particularly for activities like operating prosthetic hands, the model aims to improve the accuracy, capacity to apply to different circumstances, and durability in identifying EMG signals connected to hand movements. The study employed computer-aided engineering (CAE) to automatically identify characteristics and minimise the number of dimensions, thus lowering redundancy in the raw electromyography (EMG) data, so overcoming restrictions peculiar to the issue. Using data from many people to improve generalizability, the proposed method shows resilience against practical factors such electrode dislocation and muscle weariness. Comparing windowing, majority voting, and CAE+CNN to other classifiers results in the highest test accuracy (99.38%). Moreover, whilst it has minimal effect on deep learning models, feature extraction greatly enhances conventional classifiers. Together with windowing and majority voting procedures, the comprehensive evaluation of the research emphasises the feasibility of merging computer-aided engineering (CAE) with convolutional neural networks (CNN), allowing exact categorisation of hand motions based on electromyography (EMG) data. This has significant consequences for medical uses like prosthetic device control and movement intention detection. The paper presents a powerful and effective framework for EMG signal classification and solves the issues in present methods.

L. Bi et al [10], This article examines electromyography (EMG)-based movement theory for upper-body coordination in humans, with a focus on human-robot collaboration (HRC). As robots grow more widespread in our daily lives, the connection between people and technology becomes more important. The paper emphasizes the importance of precisely forecasting individuals' intentions to enhance cooperation, particularly in the context of working together. The applications of HRC include several fields, and it is crucial to comprehend individuals' intended motions in order to facilitate efficient cooperation. The article categorizes the prediction scheme into two groups: biological indicators and non-biological markers. It specifically examines electromyography markers and their correlation with upper body prediction. This paper focuses on the estimation of persistence from EMG signals, specifically addressing the variations in estimation compared to previous research that have examined the distribution pattern for control isolation. Qualitative reviews include several aspects such as models, methodologies, kinematic predictions, and performance assessments. They provide valuable insights into potential areas of future study. This curriculum offers a thorough examination of EMG-based HRC systems, with a specific emphasis on predicting upper limb movements. It also explores the present challenges and potential future directions in the theory of EMG-based prediction.

Z. Ahmad et al [11], Scientists used wireless surface electromyography (sEMG) and heart rate monitoring to track muscle exhaustion while observing arm motions in both static and dynamic activities. This research, which specifically examines isotonic and isometric exercises, has significant significance in the field of sports due to the crucial role that muscle exhaustion plays in influencing sports-related judgments. sEMG employs wet electrodes, namely Ag/AgCl electrodes, as an invasive but very efficient method for recording muscle activity. An integrated heart rate sensor is used to assess the correlation between muscle activity and cardiac response. The specialized type incorporates a 10-bit analog-to-digital converter microcontroller that transmits signals wirelessly to a computer for further analysis and processing. The reduction in signal amplitude during physical activity serves as a dependable metric of muscle tonicity. Curiously, the biceps brachii exhibited its maximum strength during forearm raises, highlighting the distinct functions of different muscles in varied activities. Furthermore, research has shown a correlation between heightened physical exertion, heightened muscular exhaustion, and heightened heart rate per minute. These discoveries not only enhance our comprehension of muscles, but also provide a pathway for further investigation, namely in the realm of forecasting and mitigating tiredness. This study has the capacity to enhance athletic performance and mitigate the risk of injuries, particularly those affecting the musculature.

S. Suprapto et al [12], This research examines the possibility of measuring biceps brachii muscle exhaustion in real-time during sporting activities utilizing the Myoware muscle sensor (AT-04-001), Arduino Uno, and Xbee for wireless communication. This EMG is a critical tool for precisely measuring muscle activity. The study describes a unique approach for assessing muscle weariness that employs the envelope and sliding window methods. When a 5-second window size is used, the results show that weariness is indicated by an increase in EMG amplitude. The findings highlight the capability of quantifying muscular depletion and provide important information regarding the biceps brachii muscle's endurance capacity during physical exercise. The researchers discovered that the right arm had more endurance than the left arm. On average, the right arm lasted 41.87 s, 53.53 s, and 76.87 s, whereas the left arm exhausted more quickly, lasting 23.53 s, 41.87 s, and 23.53 s. The project focuses on the development of a prototype for a sports monitoring system that uses the Internet of Things (IoT). This system uses the Myoware sensor, Arduino Uno, and Zigbee for efficient and wireless data transport. The research found an average relative inaccuracy of 2.64% when comparing tool data to voltage impulses produced by the biceps muscle. This study confirms the suggested monitoring system's dependability for detecting muscle tiredness and adds to advances in sports-related Internet of Things (IoT) applications.

W. Ting et al [13] Electromyography (EMG) signals are critical in recognising human movements without requiring complex calculations, particularly in the control of prosthetic arms and exoskeleton robots. Nonetheless, researchers have hurdles in constructing precise algorithms for categorising human motions using raw EMG data. This study looks at methods for acquiring and processing EMG signals, highlighting the need of proper amplification, filtering, and noise reduction. This paper focuses at a variety of feature extraction techniques utilized by researchers as well as classifiers like kNN, SVM, and ANN, which are frequently applied to identify human movements using EMG data. With an eye on their significance in examining neuromuscular function, the scope includes the current usage of EMG signals. The results underline how important EMG signal categorization is for prosthetic and robotic control in anticipating human motions. Often looking at the combination of many procedures, researchers aim to develop feature extraction methods and classifiers to get better accuracy. Still, the paper highlights the shortcomings of earlier studies, including small sample numbers, few cross-subject comparisons, and poor reporting of electromyography (EMG) results. Expanding databases, increasing sample sizes, and advocating data sharing openness underline the requirement of raising the dependability and usefulness of research findings in EMG signal classification.

B. Hwang et al [14], This research explains the effects of postural correction and visual feedback on muscle activation and head position in patients with forward head posture (FHP). The research included 40 individuals, 20 with forward head posture (FHP) and 20 with normal head posture. The individuals were divided at random to either the experimental or control groups. Whereas the control group received no intervention, the intervention group received visual feedback and posture correcting procedures. Head position variances were assessed and muscle activation was tracked using electromyography (EMG). Correcting posture and offering visual feedback significantly changed head position and muscle activation patterns during the overhead arm lift test in individuals with forward head posture (FHP). These findings show that correcting posture and offering visual feedback are efficient treatments for forward head posture (FHP) and could have therapeutic consequences in lowering musculoskeletal problems related with the condition.

N. Burhan et al [15], This research investigates the relationship between different degrees of arm mobility and load resistance bands. Using electromyography (EMG) to grasp the intricate electrical signals the Biceps Brachii muscle creates under various experimental settings, the study carefully examines this muscle. The study looks at how varied weight resistance bands and increasing arm movement intensity affect the Biceps Brachii. It seeks to reveal the complex reflexes displayed by this muscle thereby enabling complete awareness of their activity patterns and purpose. This major addition to the field offers understanding of exercise physiology, rehabilitation strategies, and sports science developments. It clarifies our knowledge of the functioning of the Biceps Brachii muscle under various arm motions and resistance degrees. Moreover, it affects a broad spectrum of uses including sports training courses, physical therapy treatments, and exercise schedules.

M. Al-Ayyad et al [16], The paper focus is at the use of surface electromyography (sEMG) in rehabilitation and health monitoring. This statement emphasizes the need of correct procedure in clinical research and the clinical use of sEMG in evaluating muscle diseases. The work addresses wearable SEMG detectors, methods for EMG data processing, and tele-rehabilitation applications. This underlines the relevance of surface electromyography (sEMG) in physical therapy as well as the pragmatic uses in treating neuromuscular diseases, post-stroke recovery, and sports rehabilitation. Using commercial data and scientific literature, the paper offers a thorough assessment of portable and wearable technologies. It emphasises their technological capabilities and simplicity of usage. The key contributions include discussions on signal processing, EMG acquisition system topologies, and a comparative evaluation of commercial wearable EMG detectors. The research emphasises the importance of surface electromyography (sEMG) in clinical assessments and rehabilitation. It defines the critical conditions for the development of improved wearable EMG sensors and suggests prospective research routes for practical applications, such as anticipating motor intentions and increasing human-robot cooperation.

A. Hannan et al [17], This article introduces a highly portable intelligent fitness suite that enables anyone to engage in home workouts without the need for a physical trainer. The technology specifically targets two workouts, namely the T-bar and bicep curl, and utilizes gyroscope and EMG sensors. An Android application that operates in real-time serves as a virtual gym trainer, providing assistance and alerts about incorrect or improper posture. The system employs machine learning, notably the K Nearest Neighbor (KNN) model, to anticipate and provide guidance to users during workout sessions. The intelligent fitness suite seeks to tackle issues related to poor posture and possible injuries that may arise during high-intensity exercises by providing real-time feedback and assistance. This study demonstrates that wearable sensors, such as accelerometers and gyroscopes, have the capability to monitor and direct physical activity. The suggested system demonstrated an accuracy rate of 89%, indicating its efficacy in delivering portable and digitally aided gym instruction. The report emphasizes the significance of technology in advancing fitness, averting injuries, and fostering consistent physical activity, particularly within the COVID-19 epidemic.

Table 2.1: Comparison Table

s#	Title	Mob/Web App	Visualization	Posture
1	[1]	yes	no	no
2	[2]	no	no	no
3	[3]	no	no	no
4	[4]	no	no	no
5	[5]	yes	no	no
6	[6]	yes	yes	no
7	[7]	no	no	yes
8	[8]	no	yes	no
9	[9]	no	no	no
10	[10]	no	no	no
11	[11]	no	no	no
12	[12]	no	no	no
13	[13]	no	no	no
14	[14]	no	no	yes
15	[15]	no	no	no
16	[16]	no	no	no
17	[17]	yes	yes	no

The comparison table above shows three features mob/web application, visualization, and posture. The background study contains some of the papers in which all the three features have been searched and the feature which is present in any paper there is yes infront of it and the one which is not presnet there is no infront of it. In this project all the three features are carried out. It guides the user with the correct and incorrect posture and lets them monitor their posture while working with animation via web application.

Chapter 3

System Requirements, Architecture, and Design

3.1 Flow Chart

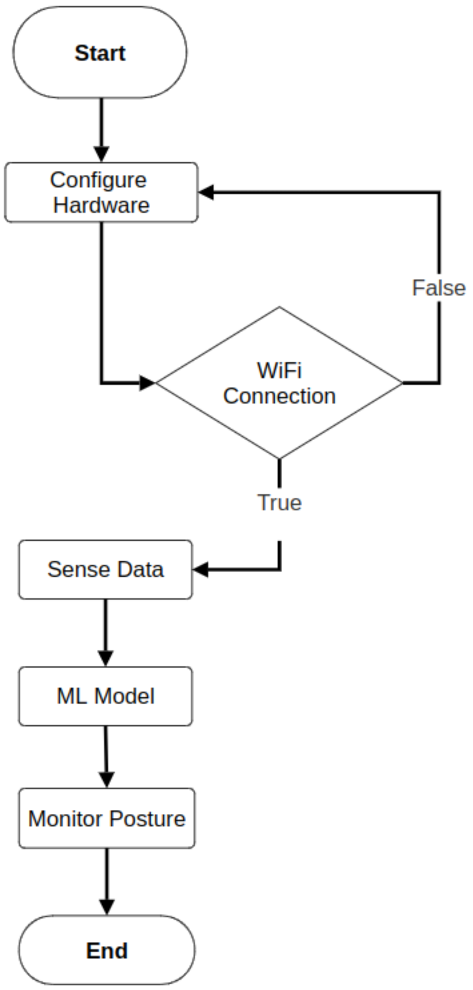

Figure 3.1: Flow Chart Hardware

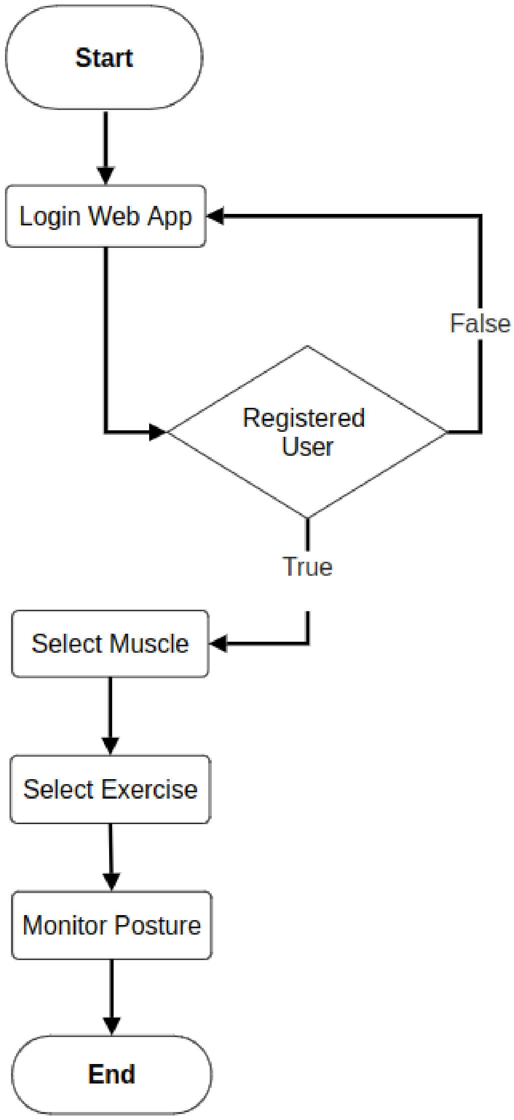

Figure 3.2: Flow Chart (Website)

3.2 Use Case Diagram

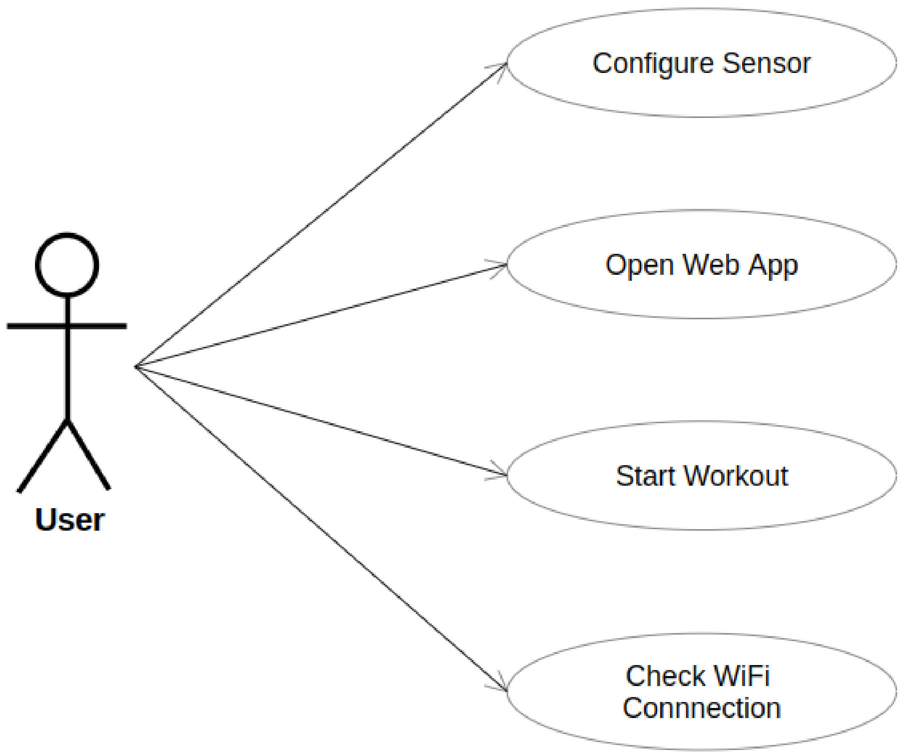

Figure 3.3: Use Case Diagram

3.3 Fully Dressed Case Diagram

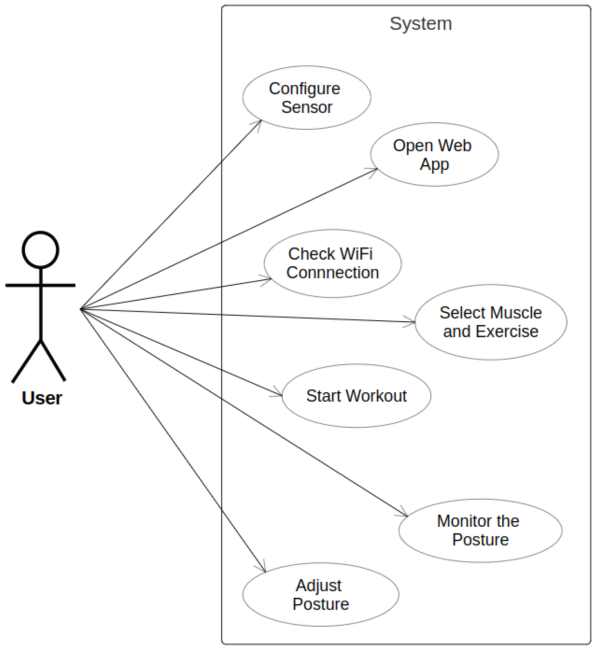

Figure 3.4: Fully Dressed Use Case

3.4 System Sequence Diagram

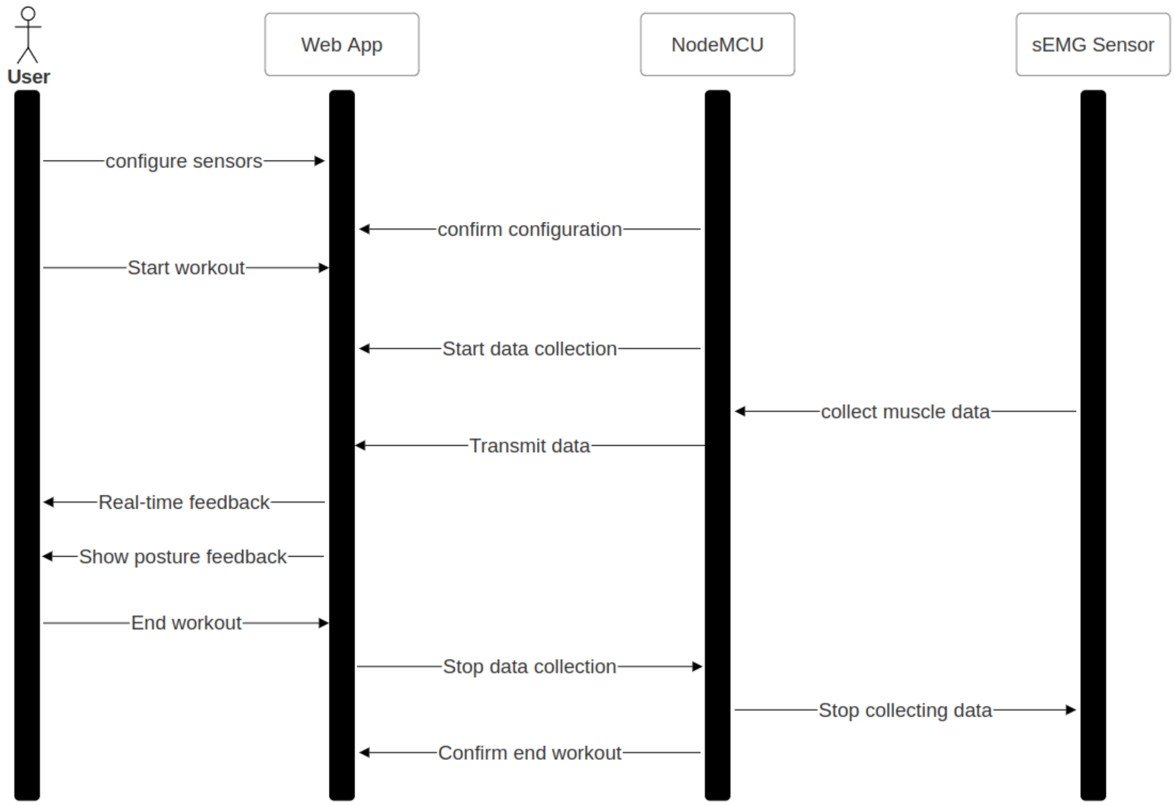

Figure 3.5: System Sequence Diagram

3.5 Software Requirements Specification (SRS) Document

Introduction

1. **Purpose**
   This document aims to give a detailed explanation of the sEMG-based posture classification system. It outlines the characteristics, prerequisites, and extent required for the system to be successfully built and applied.

2. **Audience**
   Software developers, system architects, project managers, and other stakeholders engaged in the design, development, and deployment of the sEMG-based posture categorization system are targeted users of this document.

3. **Use**
   The system is meant to be used in environments related to fitness and rehabilitation to track and categorise exercise positions as appropriate or inappropriate, therefore preventing injuries and guaranteeing good exercise.

4. **Scope**
   The product covers hardware as well as software aspects. The hardware consists in sEMG sensors and a data processing computer unit. The programme features preprocessing techniques, data collecting tools, a Naive Bayes classifier, and a user interface allowing real-time comments.

5. **Definitions and Acronyms**

   - **sEMG:** Surface Elctromyography
   - **Naive Bayes:** A probabilistic Classifier based on Bayes' theorem
   - **IoT:** Internet of Things
   - **ML:** Machine Learning
   - **SRS:** Software Requirements Specification

Overall Description

1. **User Needs**
   The technology provides real-time tracking of health data, automatic BMI assessment, and customized recommendations for gym patrons. Tools are needed by the administrator to manage members and configure the system.

2. **Assumptions and Dependencies**

   - Assumeption: sEMG sensors are calibrated and positioned correctly.

- Dependency: Data processing and analysis of the system depend on a steady computing tool.

System Features and Requirements

Functional Requirements

1. **Data Collection Model**
   - Bicep and tricep data shall be collected with sEMG sensor.
   - The system shall record data at three angles: 180°, 90°, and 20°.
2. **Preprocessing Data**
   - System shall normalize that collected data.
   - The categorical data shall be converted into numerical data.
3. **Model Training**
   - System shall use the Naive Bayes algorithm to train a classifier.
   - The system will assess the model applying confusion matrix, F1-score, precision, and recall.
4. **Classification Model**
   - Based on sEMG data, system shall classify postures as either correct or incorrect.
   - The system shall provide feedback based on the classification.

Nonfunctional Requirements

1. **Performance**
   - System response within 3 to 4 seconds.
   - Posture classification has to be done within 4 to 5 seconds.
2. **Security**
   - The system must ensure that collected data is securely stored and processed to protect user privacy.
3. **Usability**
   - The system should be easy to use, with clear instructions and visual feedback for users.

4. **Reliability**

    - The system should provide consistent classification results and feedback.

5. **Maintainability**

    - The system should be easy to maintain.

This Software Requirements Specifi-cation (SRS) contains a thorough overview of Muscle Monitoring System based on the Internet of Things for Gyms. It ensures effective application of the system by guiding development and evaluation.

3.6 Number of Development Iterations

Iteration 1: Initial Website Development and Project Setup

- Establish the project environment by configuring the required software, tools, and hardware components.
- Create a rudimentary web application framework.
- Create a database, such as Firebase, to record the data.
- The website will retrieve the data from the database in order to provide feedback.

Iteration 2: Data Collection and Sensor Integration

- Integrate sEMG sensors with NodeMCU and the website.
- Attach surface electromyography (sEMG) sensors to the NodeMCU and create a connection between the hardware and the web application.
- Create a feature for the NodeMCU to gather data on muscle activity and send it to the website.
- Verify the integration of muscle activity data with the database to guarantee precise recording.

Iteration 3: Feedback and Data Visualization

- Establish a mechanism for transmitting data in real-time from NodeMCU to the web application to guarantee uninterrupted and immediate flow of data from the sensors.

- Create animations that provide posture feedback, using visual cues to indicate the accuracy or inaccuracy of the user's workout posture, as determined by muscle activity data.
- Ensure that the process of synchronizing data is consistently and reliably maintained across all components.

Iteration 4: User Interface Enhancement

- Enhance the user interface on the website to provide immediate feedback, enhancing both the visual and functional elements to optimize the user experience.
- Create a feature that enables users to examine their muscle activity.
- Animation that will help the user to monitor the exercise whether it is correct or incorrect.

Iteration 5: Initial ML Integration and Feedback Enhancement

- Initiate the incorporation of machine learning algorithms to provide recommendations for correcting posture, by using fundamental ML models to examine data on muscle activation and deliver individualized feedback.
- Perform preliminary testing and fine-tuning of machine learning-generated input to enhance exercise posture.
- Enhance the existing functionality by incorporating user input and integrate new features or enhancements proposed during the testing phase.

Iteration 6: System Testing

- Perform thorough system testing to verify the flawless integration of all components, including end-to-end testing of the complete system.
- Enhance performance by detecting and fixing any performance-related problems to guarantee seamless operation.
- Conclude the construction and improvement of machine learning models for providing reliable feedback on posture correction recommendations.

Iteration 7: User Acceptance Testing

- Enlist users to participate in User Acceptance Testing (UAT), including actual users and stakeholders in testing the system and offering feedback.

- Collect user input and execute appropriate improvements to enhance the system.
- Resolve any remaining issues, including any lingering bugs or problems, prior to the final release.

Iteration 8: Deployment and Documentation

- Write comprehensive documentation for the final iteration of the system, including user guides and technical documentation.
- Create thorough documentation for both users and developers.
- Get ready for deployment by verifying the readiness of all components for production usage, and confirm that all pieces of the system are fully operational and prepared for public release.
- Implement the system in the production environment, making it available for usage by the general public or specific user group.

Chapter 4

Implementation

4.1 Adopted Methodology for each iteration

The IoT-based Muscle Monitoring System is developed over a series of eight carefully planned iterations, each with specific aims and results that together contribute to the project's advancement from ideation to implementation. This iterative technique not only enables gradual development and testing, but also permits ongoing improvement based on feedback and technical progress.

- The first iteration is the foundational phase when the project's digital infrastructure starts to form. Emphasizing the establishment of a strong project environment and the implementation of fundamental website functions provides a solid foundation for future improvements and the integration of hardware components.

- Second iteration is to establishes the essential connection between the physical contact with hardware via sEMG sensors and the digital domain. This step is crucial for connecting the user's physical inputs with the system's digital reaction, preparing for the real-time processing of muscle activity data.

- The third iteration improves the system's core functionalities by ensuring seamless data synchronisation with the web application and integrating real-time data transfer. Verifying the system's ability to deliver timely, useful input on exercise posture requires this iteration.

- The fourth iteration improves visualizing data and improving the user interface, resulting in more reliable real-tim feedback. This phase improves user engagement and prepares the system for displaying the muscle signals detected by the sEMG sensor, as animation on the web application.

- In the fifth iteration the focus is shifted towards the use of a machine learning model that will classify the posture as correct or incorrect based on the data from the sEMG. The model has to be provided with the specific features in order to predict the posture during workout. A dataset is also need to be produced to train the model so that it can give the desired feedback.

- The sixth iteration prioritizes efficiency and reliability through testing and improvement efforts. This phase ensures the system works properly in most of the conditions and provides a smooth user experience. It can be testing the web application user interface or it can be the hardware testing.

- User input is also taken into account in order to implement their suggestions in the project's seventh iteration. This iteration prepares the system for deployment and ensures it satisfies the needs of real-world users.

- Final iteration is all about providing a complete documentation about developments and implementation of the system. The document must contain all the information about the system. It has to be easy to read and understand everything that is included in the development and implementation of the system. This will help users to understand how this system can help users to enhance their exercise and posture during workout.

4.2 Iterations Requirements

The requirements for each iteration of the IoT-based Muscle Monitoring System are established to ensure a rigors and efficient development process. The initial stage of the procedure are to set up the project environment and create the primary web functionality. The integration of sEMG sensors with NodeMCU is then described, enabling the collection of real-time muscle activity data. Subsequent modifications have focused on enhancing the user experience, such as employing machine learning algorithms to adapt posture correction and providing real-time feedback through animation. Comprehensive system testing and user acceptance testing ensure the system's reliability and efficiency, while thorough documentation and deployment prepare the system for practical usage.

- Iteration 1: The first step is setting the groundwork for the Internet of Things (IoT)-powered Muscle Monitoring System. Building up the project environment include setting hardware components like the NodeMCU and sEMG sensors, as well as installing software tools like version control systems and integrated programming environments. Users' triceps and biceps are passed to a machine learning model. Muscle signals must be acquired before the web application can show the animation and feedback.

- Iteration 2: The second iteration requires connecting the system's physical and virtual components. This includes establishing a communication connection between the hardware and the web application, as well as connecting the sEMG sensors to the NodeMCU. Electromyography (EMG) data collection is setup on the NodeMCU and then sent to the web application. It is critical to ensure reliable data is passed to the machine learning model and conduct comprehensive testing to check that data flows smoothly from sensors to the database.

- Iteration 3: Real-time data transmission and visualisation become more important in the third iteration. The system has been enhanced to provide a minimally delayed, seamless, and quick flow of data from the NodeMCU to the web application. Animations are made to show users whether their training posture is accurate or erroneous based on muscle activation data, allowing for quick feedback to be provided. The establishment of consistent and reliable data synchronisation across all components is given top priority in this iteration to ensure that users receive accurate and timely feedback during their activities.

- Iteration 4: Improving the user interface to make the real-time feedback presentation more aesthetically beautiful and user-friendly is the goal of the fourth iteration. The focus is on making the database's storage and retrieval of data as efficient as possible so that users can track changes over time.

- Iteration 5: In the fifth iteration, advanced suggestions for improving posture are given by means of machine learning algorithms. Machine learning algorithms are made to evaluate muscle activation data and offer personalised recommendations. To increase the precision and applicability of these machine learning-generated concepts, testing and refinement are initially carried out. Based on user feedback, new features are added, which leads to ongoing enhancements in the functionality of the system and user involvement.

- Iteration 6: The major aims of the sixth iteration are to improve performance and undertake rigors system testing. End-to-end testing is carried out to confirm that all components have been seamlessly integrated and to identify and remedy any performance concerns. The machine learning algorithms were carefully trained and calibrated to deliver reliable posture classification as correct and incorrect. This step is important for verifying that the system works in most of the settings.

- Iteration 7: In the seventh iteration, users are asked to do user acceptance testing (UAT). Gathering input from actual users and stakeholders is necessary to verify the system is ready for deployment. In response to this feedback, changes are made to ensure that the system meets the expectations and practical needs of the intended users. Following the resolution of any unresolved issues, the system is ready for final deployment.

- Iteration 8: Creating comprehensive documentation and facilitating a seamless transition of the system from a development to a production environment are given top priority in the final iteration. Detailed user manuals and technical documentation are produced to offer accurate direction to developers as well as users. The configuration of the system is finished for real-world use, and every component has been confirmed to function flawlessly. At last, the system is put into use in a production setting, making it available for usage by the general public or a particular user group. This marks the end of the development process.

4.3 Web Application Design

- **Home page**

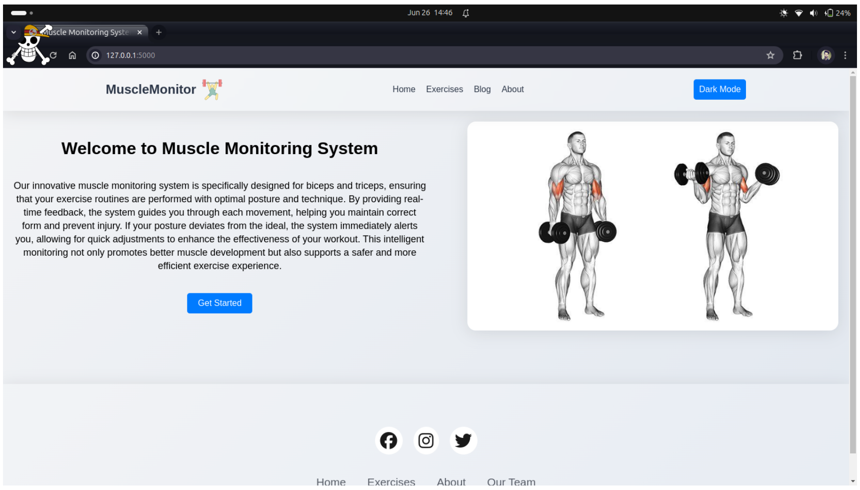

Figure 4.1: Home Page

- **Page for selecting bicep or triceps muscle**

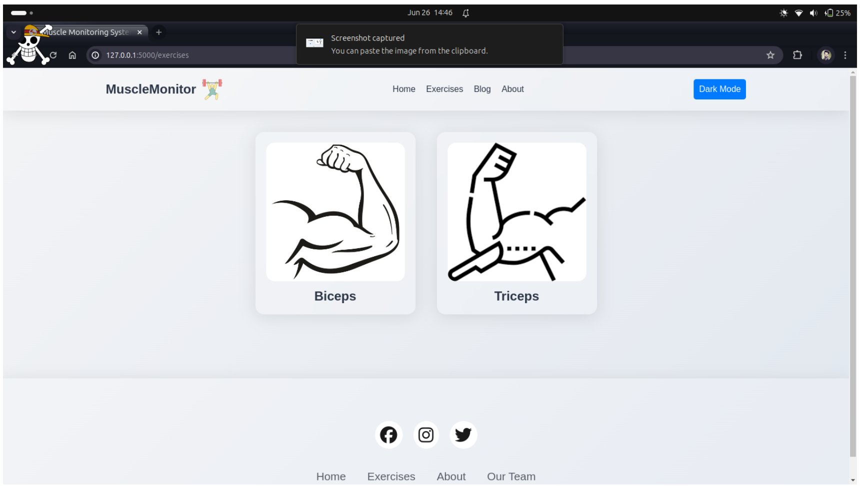

Figure 4.2: Muscle Selection Page

- **Page for selecting bicep exercise**

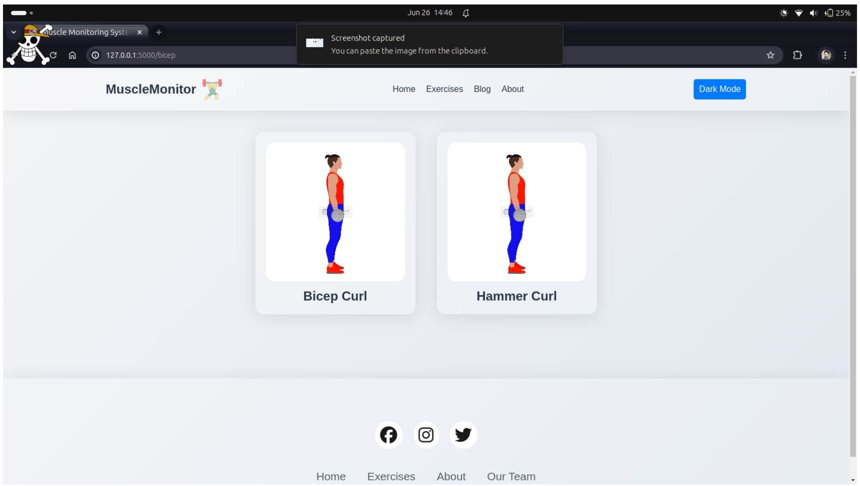

Figure 4.3: Bicep Exercise Selection Page

- **Page for selecting bicep or triceps muscle**

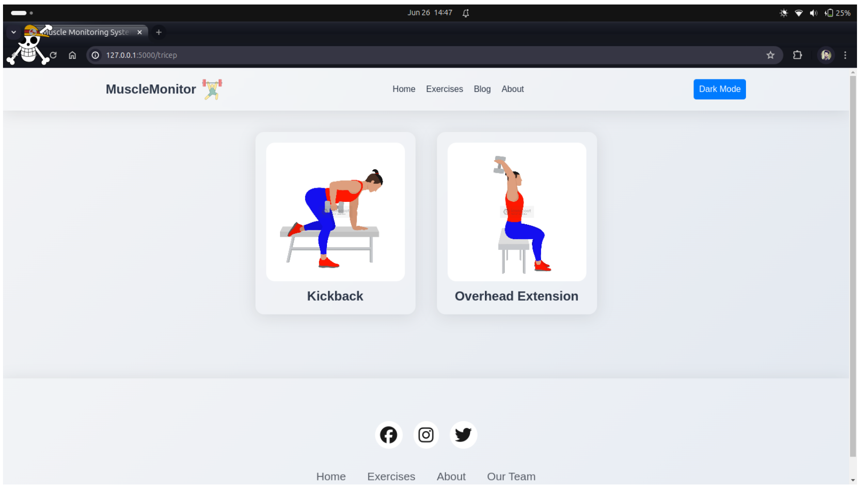

Figure 4.4: Tricep Exercise Selection Page

4.4 Dataset Details

Dataset comprises an extensive compilation of sEMG (surface electromyography) measurements acquired from the bicep and triceps muscles of two individuals. Every participant engaged in precise workouts tailored to isolate these muscles, and thorough data was collected to guarantee precision and dependability.

Data was gathered for the bicep muscle during participants' performance of bicep curls and hammer curls. Similarly, data was gathered for the triceps muscle by the performance of triceps kickbacks and bench triceps extensions. Data was obtained at three specific joint angles in each cases: 180 degrees, 90 degrees, and 20 degrees. This was conducted to record the muscle activation patterns at different stages of the activities. Significantly, the data collection included both accurate and inaccurate postures in order to get insights into the influence of position on muscle activation.

The individuals executed the workouts using two distinct weights: 6 kg and 8 kg. This facilitated the examination of the impact of different amounts of resistance on muscle activation. Ten surface electromyography (sEMG) measurements were taken at each of the specified angles throughout every workout and posture condition. Computed to represent the sEMG value at that particular angle, the mean of these 10 readings was By use of averaging, any anomalies or noise in the data is reduced, therefore producing a more exact representation of muscle activity.

To remove extraneous elements influencing the measures, data was collected under control. Every participant's body weight was recorded, and exercises under the direction of an expert guaranteed correct form and posture. For every data point in the dataset, participant ID, person's weight, weight lifted, target muscle, exercise type, posture correctness, sEMG readings at 180 degrees, sEMG readings at 90 degrees, sEMG readings at 20 degrees, and any further comments or observations noted during data collecting.

Examining the trends of muscle activation in various contexts becomes easier with the help of this collection. With data on both right and unsuitable postures as well as various angles and weights, the dataset lets one examine the factors influencing muscle activation thoroughly. In the analysis of muscle dynamics and electromyography, the rigors and methodical approach for data collecting guarantees the endurance of the dataset, so fitting for a wide spectrum of analytical and research objectives.

4.5 Data Preprocessing

The dataset has three categorical attributes: muscle, exercise, and posture. These need to be transformed into numerical format in order to train a model. This category data is being transformed into numerical representation using the provided code in Python, using a method available in the Pandas package. Rest of the dataset is already preprocessed.

```
data['posture'] = data['posture'].astype('category').cat.codes
data['muscle'] = data['muscle'].astype('category').cat.codes
data['exercise'] = data['exercise'].astype('category').cat.codes
```

4.6 Utilized Techniques

- During this part of the study, the primary objective was to choose a suitable machine learning model that could accurately predict the accuracy of posture using the obtained sEMG sensor data. Out of the other algorithms that were evaluated, the Naive Bayes' model was selected due to its simplicity, efficiency, and efficacy in dealing with categorical data.

- Before selecting the model, the dataset was preprocessed to guarantee that it is compatible with the selected method. Variables such as muscle type, exercise completed, and posture accuracy were transformed into numerical representation. In addition, numerical characteristics such as the amount of weight lifted, the weight of the participants, and the sEMG measurements were standardized to ensure uniformity in scale across the dataset.

- The Naive Bayes model was used as the main method for classifying posture. The decision was based on the algorithm's inherent simplicity and its successful handling of categorical data. Naive Bayes' algorithm, although assuming feature independence, often achieves good performance in real-world scenarios, particularly for problems involving text categorization.

- The Naive Bayes model was trained on the preprocessed dataset to acquire knowledge about the connections between the input characteristics (such as sEMG readings and workout kind) and the goal variable (posture accuracy). During the training process, the model used the probability-based method of Naive Bayes' to calculate the probability of a certain posture being accurate or wrong based on the observed characteristics.

- Following training, strong validation techniques were used to evaluate the model. Separate training and testing sets were created from the dataset to assess the generalising power of the model. Computation of evaluation metrics including accuracy, precision, recall, and F1-score helped to identify chances for development based on the predicted performance of the model.

- Naive Bayes's simplicity helps one to clearly grasp model predictions even though it lacks explicit feature significance measures like many other algorithms. Examining the predictions and decision bounds of the model helped one to gain understanding of the relative importance of several character-istics in controlling posture correctness.

- Different assessment criteria were used to test the accuracy of the Naive Bayes' model in forecasting correct posture using sEMG sensor data. These values provide a complete awareness of the accuracy, precision, recall, and general efficiency of the model.

4.7 Evaluation Metrics

In order to evaluate the accuracy of the Naive Bayes' model in predicting right posture using sEMG sensor data, various assessment criteria were employed. These measurements offered a thorough comprehension of the model's accuracy, precision, recall, and overall efficacy.

- **Accuracy:** This is a metric that compares, to the total number of instances, the percentage of precisely anticipated instances—including both correct and erroneous postures. Given a general picture of the performance of the model, the measure is crucial. Still, accuracy by itself could not be sufficient, especially in an imbalanced dataset.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Precision:** By use of this ratio of accurate positive predictions to all positive predictions produced by the model, one can evaluate the accuracy of positive predictions. High accuracy indicates that the model is making just minimal false positive errors.

$$\text{Precision} = \frac{TP}{TP + FP}$$

- **Recall:** This indicates the ratio of accurate positive predictions to the overall count of actual positive cases, therefore gauging the model's ability to appropriately identify all occur-rences that are really positive. Though it may possibly include some false positives, a high recall score indicates that the model is essentially spotting the bulk of the real positive occurrences.

$$\text{Recall} = \frac{TP}{TP + FN}$$

- **F1-Score:** Using the harmonic mean, another mathematical metric combining accuracy and recall into one metric. It balances both quite nicely. It is especially helpful in cases of unequal class distribution since it considers both erroneous positive and negative predictions.

$$\text{F1-Score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

- **Confusion Matrix:** The confusion matrix is a useful tool for evaluating a classification model. It provides a complete study of the forecasts of the model so enabling one to ascertain parameters including accuracy, precision, recall, and others. The confusion matrix displays the count of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) forecasts.
  - **True Positive (TP) :** It is the Positive class that is predicted correctly (correct posture).
  - **True Negative (TN) :** It is the negative class that is predicted correctly (incorrect posture).
  - **False Positive (FP) :** When the model incorrectly predicts the positive class.
  - **False Negative (FN) :** When the model incorretly predicts the negative calss.

Table 4.1: Confusion Matrix

	Predicted Positive	**Predicted Negative**
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

Chapter 5

Results and Discussions

1. **Achieved Results**

   (a) figure (5.1) shows the results of accuracy, precision, recall and F1-score.

Classification Report:

	precision	recall	f1-score	support
0	0.86	1.00	0.92	175
1	1.00	0.82	0.90	162
accuracy			0.91	337
macro avg	0.93	0.91	0.91	337
weighted avg	0.93	0.91	0.91	337

Figure 5.1: Accuracy, Precision, Recall and F1-score

   (b) figure (5.2) shows the confusion matrix results.

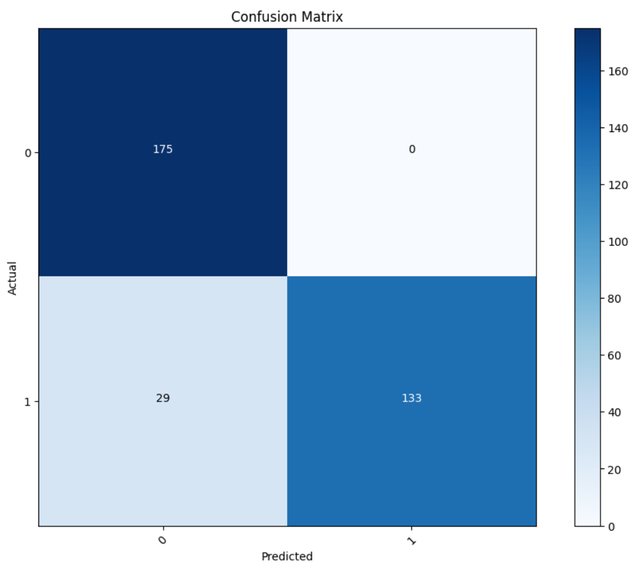

Figure 5.2: Confusion Matrix

2. **Results Analysis**

   (a) **Accuracy:** Figure 5.3 depicts the accuracy of a Naive Bayes classifier used on a dataset with two classes labelled '0' and '1'. The y-axis depicts accuracy, while the x-axis indicates the two classes. Each bar's height represents the fraction of properly categorised cases in each class. In this graphic, both classes have an accuracy close to 100%, indicating that the model performs extraordinarily well in both categories. However, such high accuracy may imply overfitting, particularly if the dataset is insufficiently wide or varied. Overfitting happens when a model learns the training data too well, including noise and outliers, which may result in poor generalisation to new data.

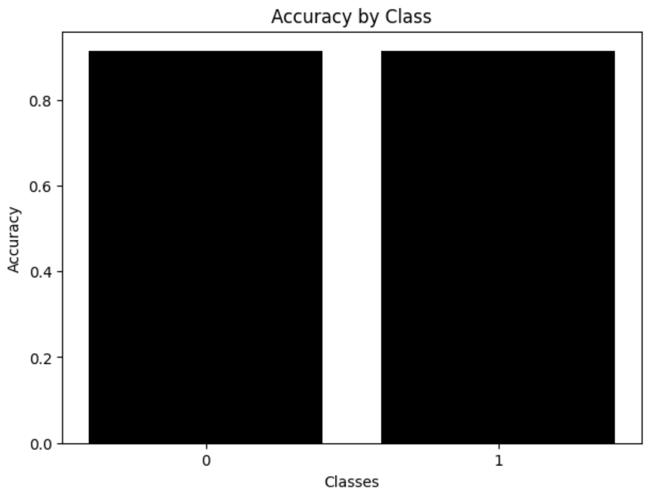

Figure 5.3: Accuracy Bar chart

(b) **Precision:** Figure 5.4 represents the precision of a Naive Bayes classifier for the two classes '0' and '1'. The y-axis denotes accuracy, while the x-axis represents the two classes. Precision is the ratio of real positive predictions to total positive predictions generated by the model. In this figure, the accuracy for class '0' is slightly less than 0.9, whereas the precision for class '1' is at or close to 1. This demonstrates that the model is more accurate in predicting occurrences of class '1' than class '0', resulting in fewer false positives. High accuracy for both classes indicates that the model is successfully differentiating between the two groups; nevertheless, the disparity may signal that further work is needed to equalize precision across both classes.

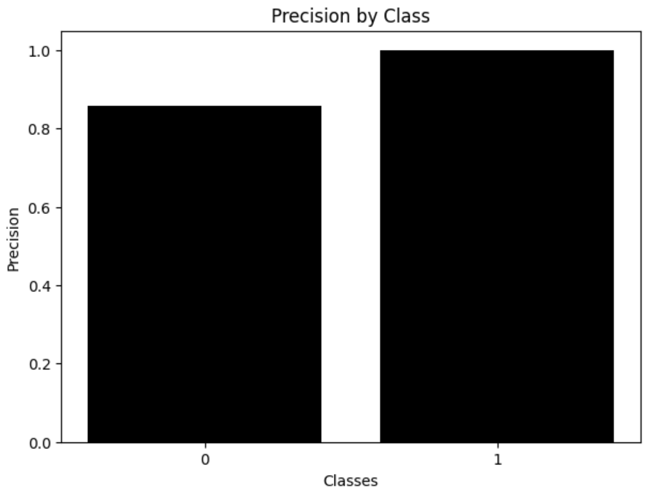

Figure 5.4: Precision Bar chart

(c) **Recall:** Figure 5.5 shows Recall, sometimes called as sensitivity, is a measure of the proportion of true positives correctly identified by the classifier. In this bar chart, the recall for class 0 is nearly 1.0, indicating that almost all instances of class 0 are properly identified. In contrast, the recall for class 1 is significantly lower, while still high, indicating that the classifier performs well but is slightly less successful at detecting all instances of class 1. Overall, the classifier performs well in recall for both classes, with a nearly perfect score for class 0 and a somewhat lower, but still excellent, score for class 1.

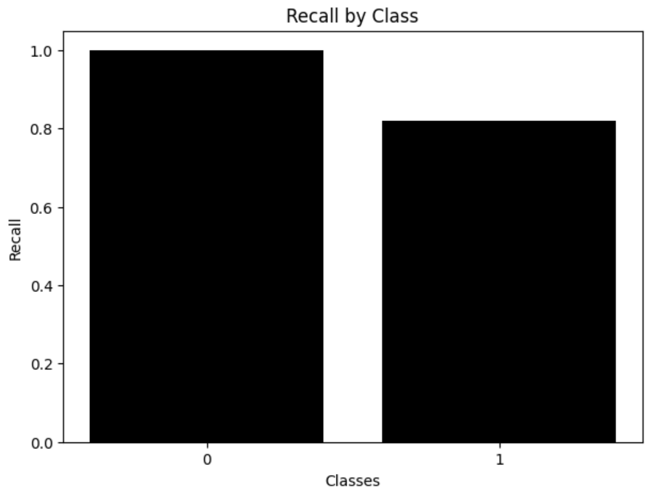

Figure 5.5: Recall Bar chart

(d) **F1-Score:** Figure 5.6 shows F1-scores of a Naive Bayes classifier. The F1-score is a measure of test accuracy that takes into account both precision and recall. This chart has two classes, labelled 0 and 1. Both classes have strong F1-scores, showing that the classifier predicts them correctly. The F1-scores for both classes are near to one, indicating that the Naive Bayes classifier is quite successful for this dataset, with a good balance of accuracy and recall for each class.

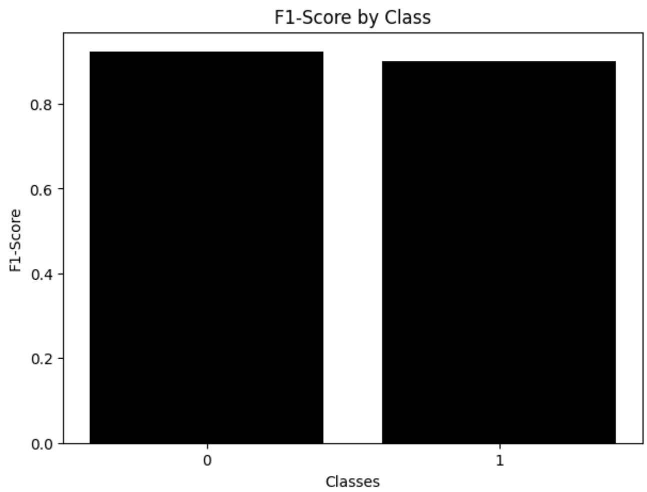

Figure 5.6: F1-score Bar chart

(e) **Support:** The support numbers (175 for poor posture and 162 for correct posture) represent the actual number of occurrences of each class in the dataset. These values aid in comprehending the distribution of the dataset.

(f) **Confusion Matrix:**

- **TP:** There are 133 instances where the model accurately predicts the correct posture.
- **TN:** There are 175 instances where the model accurately predicts that the posture is improper.
- **FP:** 0 occurrences where the model erroneously predicts the correct posture as incorrect.
- **FN:** There are 29 instances in which the model makes an inaccurate prediction by identifying a posture as improper when it is actually correct.

3. **Results Comparisons**

Table 5.1: Comparison of Classification Metrics

Metric	**Class 0 (Incorrect Posture)**	**Class 1 (Correct Posture)**	**Overall**
Precision	0.86	1.00	0.93 (Macro Average)
Recall	1.00	0.82	0.91 (Macro Average)
F1-Score	0.92	0.90	0.91 (Macro Average)
Support	175	162	337
True Positives (TP)	175	133	-
True Negatives (TN)	-	-	-
False Positives (FP)	0	-	-
False Negatives (FN)	-	29	-
Accuracy	-	-	0.91

4. **Expectations**
With the use of an extensive data set and the implementation of the Naive Bayes' model, the main goal was to create a strong classification system that could accurately differentiate between correct and improper postures using sEMG sensor data. The dataset included multiple attributes, including the person's weight, the weight lifted, the target muscle, the exercise performed, the posture, and the averaged sEMG values. The data was collected with great care from two participants who performed bicep curls, hammer curls, tricep kickbacks, and bench triceps extensions. The exercises were done with both correct and incorrect postures, and at three different angles (180°, 90°, and 20°). With an outstanding total accuracy rate of 91%, the performance measurements amply show the great degree of efficiency of the model in effectively achieving its goal. The great accuracy and recall scores of the model for erroneous postures show its capacity to precisely spot when a posture is bad. This lowers the possibility of false negatives in this category, which is particularly relevant in cases when maintaining appropriate exercise form or injury prevention depends on the identification of erroneous posture. Furthermore, the conservative approach of the model provides a high degree of accuracy in accurate posture prediction, so producing almost flawless precision. The findings are in line with the first presumptions, therefore providing a strong basis for useful application in settings of fitness and rehabilitation. Still, the somewhat poor capacity to precisely recognise proper posture points to a possible area for improvement. One can take into account oversampling the minority

class, changing prediction thresholds, or experimenting with ensemble methods to raise the performance of the model. All things considered, the Naive Bayes' model shows significant potential in motivating appropriate exercise technique and lowering the risk of accidents, therefore opening the path for more complex and flexible uses in the future.

Chapter 6

Conclusion

This work successfully developed a classification system employing sEMG sensor data to distinguish between accurate and inaccurate exercise postures. Two participants performed bicep curls, hammer curls, tricep kickbacks, bench tricep extensions at three different angles (180°, 90°, and 20°) with both proper and incorrect postures under observation. These observations produced data records. Methodically accumulating features including the person's weight, the weight lifted, target muscle, exercise, posture, and averaged sEMG values produced a comprehensive dataset. Selected for its simplicity and effectiveness in handling categorical data, the naive bayes model achieved an overall accuracy of 91%. The model consistently found instances of improper posture and showed great accuracy and memory in spotting incorrect postures. This capacity helps to prevent injuries and encourage best possible exercise form. The model's perfect accuracy in anticipating proper posture highlights even more its cautious and accurate approach.

The considerably decreased recall for proper postures suggests a possible area for future improvement even if the outcomes are excellent. Following studies will focus on addressing this problem using techniques such oversampling, adjusting prediction thresholds, and looking at advanced machine learning methods. Increasing participant count and include more variety of activities in the dataset helps to improve the generalizability and robustness of the model. Furthermore helping the model to improve will be its deployment in practical applications. All things considered, this experiment shows the great ability of using sEMG-based models to promote appropriate exercise technique and reduce injuries, so laying a strong platform for next studies and developments in fitness and rehabilitation settings. The success of this approach not only meets the first expectations but also opens the path for next research and improvement.

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