SMART SHOULDER: AN IMU-BASED WEARABLE FOR INJURY PREVENTION IN FITNESS

BS Electrical Engineering

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By

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Project Abstract

This project aims to develop a wearable device for real-time monitoring of shoulder joint health, enabling users to make informed decisions about their movement and posture. The proposed system will integrate inertial measurement unit (IMU) sensors with advanced edge or cloud computing technologies to analyze motion data using machine learning algorithms and data validation techniques. By keeping track of important joint angles, the device helps users maintain proper form during exercises, reducing the risk of injury. Beyond improving accessibility to musculoskeletal health insights, this system empowers individuals to proactively manage their well-being, potentially reducing the need for frequent medical consultations.

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Originality Certificate

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Chapter 1

Introduction

1.1 Motivation

The human shoulder is among the most complex joints in the body, enabling motion across three rotational degrees of freedom. While this flexibility is essential for daily activities and athletic performance, it also renders the joint particularly vulnerable to injury. Shoulder injuries are prevalent in both sports and rehabilitation contexts, especially during movements involving repetitive loading, poor technique, or high mechanical stress [2, 3]. Following an initial injury, the shoulder is also highly susceptible to reinjury, often as a result of improper movement patterns that remain undetected by the user.

A recurring challenge faced by athletes, fitness enthusiasts, and individuals undergoing rehabilitation is the absence of immediate and objective feedback regarding movement quality. In practice, users often rely on mirrors or intermittent supervision from coaches or clinicians. Outside of structured clinical or gym environments, such feedback mechanisms are limited, inconsistent, or entirely unavailable. Consequently, users frequently perform exercises with uncertainty, increasing anxiety and the risk of reinforcing unsafe movement patterns over time [4].

Recent advances in wearable sensing technologies have enabled detailed motion capture through inertial measurement units (IMUs). However, many existing systems focus primarily on recording or visualizing raw sensor signals or joint trajectories, delegating interpretation to clinicians or offline analysis tools [5]. For non-expert users, these representations are difficult to interpret and rarely translate into actionable guidance during movement. This disconnect between data acquisition and meaningful feedback significantly limits the practical utility of wearable motion-tracking systems in everyday settings.

The motivation behind this project is to bridge this gap by shifting the emphasis from raw motion capture toward interpretable, movement-level understanding. Rather than treating IMU data as an end product, this work processes sensor measurements through calibration, biomechanical modeling, and feature extraction to derive quantities directly related to exercise form and joint behavior. By doing so, the system aims to empower users to make informed decisions about their movements without the need for constant external supervision.

1.2 Problem Statement

Most existing shoulder monitoring systems are designed primarily for clinical assessment or offline analysis and therefore do not provide continuous, real-time feedback during movement. As a result, users performing exercises outside supervised environments receive little to no guidance on movement quality, increasing the likelihood of unsafe technique and reinjury [4, 5]. Even systems capable of detailed motion capture frequently rely on complex visualizations or extensive post-processing, limiting their practicality for everyday use.

The problem addressed in this project is the absence of an accessible, real-time framework that translates raw shoulder motion data into interpretable indicators of movement quality. Specifically, there is a need for a system capable of identifying potentially unsafe shoulder configurations during exercise and delivering immediate, intuitive feedback without requiring continuous clinical supervision. Addressing this challenge necessitates not only reliable motion sensing, but also robust calibration procedures, biomechanical modeling, and feature extraction methods capable of supporting timely feedback in non-clinical settings.

1.3 General Block Diagram

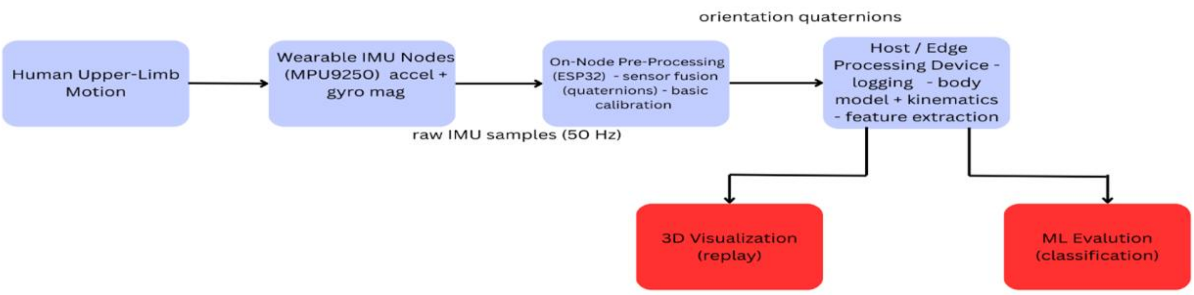


Fig. 1.1: General system level block diagram.

1.4 Social Benefits and Relevance

Developing a real-time joint monitoring technology can offer substantial social benefits, particularly within the domains of healthcare, injury prevention, and physical rehabilitation. This project contributes to democratizing access to high-quality biomechanical assessment technologies that have traditionally been limited to clinical environments or costly motion-capture systems. By enabling continuous and accessible monitoring of joint movement quality, the proposed system supports safer physical activity and informed decision-making across a broad user population.

The project aligns with the following United Nations Sustainable Development Goals (SDGs):

SDG 3: Good Health and Well-Being

- Prevents musculoskeletal injuries through real-time posture and movement correction.
- Supports remote rehabilitation by enabling users to perform exercises safely outside clinical settings.
- Promotes early identification of potentially dangerous movement patterns, reducing the risk of long-term joint damage.

SDG 9: Industry, Innovation, and Infrastructure

- Leverages embedded systems, wearable sensors, and wireless communication to build scalable digital-health solutions.
- Encourages innovation in low-cost, infrastructure-light health monitoring technologies suitable for widespread deployment.
- Demonstrates the integration of sensor fusion and real-time data processing as part of emerging smart healthcare infrastructure.

1.5 Goals

The goal of this project is to create a wearable device that tracks shoulder movement and joint angles to help users maintain proper form and prevent injuries. By using motion sensors and machine learning, the device will be able detect unsafe movements and alert users through vibrations, sounds, or visual cues. This project aims to make rehabilitation and exercise safer and more accessible.

1.6 Objectives

The objective of this project is to develop and validate a complete upper-limb motion analysis pipeline, spanning from wearable sensing to the extraction of interpretable movement-level features relevant to exercise form and joint health. The specific objectives of the project are as follows:

1. **Design and calibration of an IMU-based sensing system:** To design and calibrate a modular inertial measurement unit (IMU)-based sensing setup for upper-limb motion tracking. This includes establishing repeatable calibration procedures, estimating segment orientations using sensor fusion algorithms, and validating orientation estimates under controlled motion conditions.

2. **Evaluation of machine learning models for movement quality classification:** To evaluate multiple lightweight machine learning models for classifying movement quality using features extracted from the motion data. The models are compared in an offline setting to assess their suitability for distinguishing between safe and unsafe movement patterns under constrained feature sets.

3. **Development of biomechanical modeling and feature extraction framework:** To develop a biomechanical modeling and feature extraction framework for shoulder movement analysis. This involves computing joint angles, symmetry measures, and exercise-relevant features from calibrated segment orientations.

4. **Implementation of visualization and replay tools for qualitative validation:** To implement visualization and motion replay tools that enable qualitative inspection and validation of reconstructed motion and extracted features, supporting both system debugging and interpretability of results.

1.7 Outcomes

The desired outcomes of this project are that users feel safer and more confident when performing exercises, reducing their fear of reinjury. By receiving real-time feedback, individuals, especially athletes and those recovering from injuries—can develop better movement habits, potentially leading to fewer injuries and improved long-term joint health. Additionally, the system could contribute to more effective rehabilitation, helping users experience less pain and recover more efficiently.

1.8 Deliverables (Outputs)

The deliverables of this project comprise both hardware prototypes and software artifacts developed to support real-time upper-limb motion analysis and movement quality assessment. The primary deliverables are listed below:

- A modular IMU-based upper-limb sensing prototype consisting of multiple IMU nodes with calibrated orientation outputs, suitable for controlled motion tracking of the shoulder and arms.
- A sensor fusion and calibration pipeline, including supporting software scripts for estimating stable segment orientations and applying sensor-to-segment mounting corrections.
- A biomechanical reconstruction and feature extraction framework capable of computing shoulder and elbow joint angles, symmetry measures, and exercise-relevant motion features from calibrated IMU data.
- An offline three-dimensional visualization and motion replay tool for reconstructed upper-body movement, enabling qualitative validation of sensor behavior and verification of feature correctness using recorded datasets.
- A machine learning evaluation pipeline, including trained models and associated performance metrics, used to assess the feasibility of classifying movement quality based on extracted biomechanical features.
- A comprehensive technical report documenting the system architecture, implementation decisions, experimental validation, limitations, and potential future extensions of the proposed framework.

1.9 Timeline and Distribution of Work

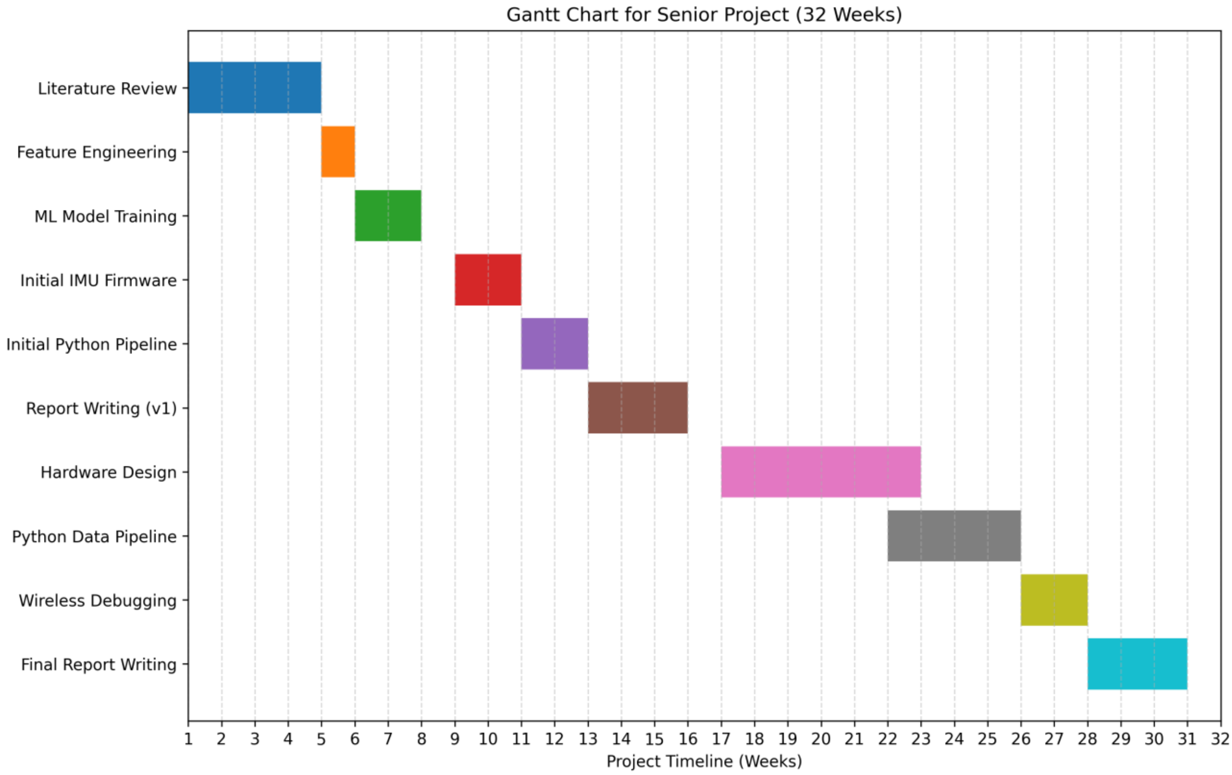


Fig. 1.2: Gantt Chart for Spring and Fall 2025.

Table I: Distribution of Work

Task	Responsible Person (only one)	Planned Duration
Literature Review & Problem Definition		Four weeks
Feature Design & Engineering		One weeks
Machine Learning Model Training & Evaluation		Two weeks
IMU Firmware Development (Arduino/ESP32)		Three weeks
Python Data Pipeline & Visualization		Four weeks
Hardware Design & Assembly		Six weeks
Hardware Debugging		Three weeks
System Validation & Demo Preparation		Two weeks
Report Writing & Final Documentation		Six weeks

Chapter 2

Background

2.1 Literature Review

A significant portion of shoulder injury prevention and rehabilitation depends on the ability to measure shoulder motion reliably and consistently. From a biomechanical perspective, the shoulder complex is typically modeled as having three rotational degrees of freedom, with range of motion (ROM) commonly assessed through a standardized set of movements. Chen et al. [4] demonstrate a rehabilitation-oriented workflow in which shoulder ROM is captured using a neutral calibration pose followed by primary shoulder motions such as abduction, flexion, extension, internal rotation, and external rotation. These pose definitions are particularly valuable because they provide a clear and repeatable structure for calibration and ROM assessment, a principle that directly informs the calibration strategy adopted in this project.

Once the target motions are defined, sensor wearability and placement consistency become critical constraints. The International Society of Biomechanics (ISB) recommendations emphasize standardization in the definition, estimation, and reporting of joint kinematics, noting that inconsistent sensor placement and calibration are among the primary reasons results fail to generalize across studies [2]. García-De-Villa et al. [3] similarly highlight that practical performance in inertial motion tracking is dominated by sensor placement, calibration procedures, and drift mitigation rather than the mere presence of an IMU. In upper-limb systems, garment-based or constrained mounting solutions are therefore attractive, as they naturally reduce relative sensor motion and improve repeatability compared to loosely attached or handheld devices.

Following placement, the central technical challenge becomes orientation estimation, namely the conversion of accelerometer, gyroscope, and optionally magnetometer signals into stable segment orientations. Quaternion-based representations are widely adopted in wearable motion tracking because they avoid singularities and allow clean composition when computing relative joint rotations [2, 3]. Among real-time wearable systems, two lightweight filtering approaches dominate the literature: gradient-descent orientation filters, such as the Madgwick filter, and nonlinear complementary filters on the special orthogonal group, such as the Mahony filter. Madgwick's method is particularly popular due to its low computational cost and effective drift correction using gravity and magnetic field references [13].

Table II: Literature Review Comparison

Study	Sensing Type	DoF	IMU Type / MCU	Data Analysis Methodology	Year	No. of Sensors
Sassi et al. [6]	Wearable IMU	3	Xsens DOT	Machine learning algorithms for classifying shoulder rehabilitation exercises; data extracted and analyzed using MATLAB	2024	3
MilaniZadeh [7]	Wearable sensor system	Not specified	YOST Labs IMU	Validation of a garment-based motion shirt for monitoring upper-limb motion; data validated using Dartfish and analyzed in MATLAB	2024	5
Chen et al. [4]	Wearable motion sensor device	Not specified	Not specified	Rehabilitation-oriented workflow for shoulder adhesive capsulitis using target pose-based ROM assessment	2020	5
van den Hoorn et al.	Smartphone camera (2D pose)	2	Smartphone-based vision framework	Comparison of 2D pose estimation against optical motion capture using linear mixed models and Bland–Altman analysis	2024	Single camera
Emmerzaal et al. [8]	Wearable IMUs	Not specified	Xsens DOT	Evaluation of upper-limb movement quality before and after surgery; MATLAB and Python-based statistical analysis	2024	1 (wrist worn)
Yao [9]	IoT-based wearable sensors	Not specified	Commercial wearable devices	RNN-based injury prediction and rehabilitation analysis implemented in Python and TensorFlow	2024	Not specified
Afsar et al. [6]	Body-worn sensors	6	MPU6050 with Arduino	Deep learning-based activity recognition for exergaming; Unity 3D and Python used for analysis	2023	Not specified
Baklouti et al. [10]	IMU-based system	10	MPU9250 with ESP8266	Risk assessment framework for work-related musculoskeletal disorders	2024	8
Galasso et al. [11]	Wearable sensors	Not specified	MyoMotion IMUs	Machine learning-based prediction of physical activity levels; MATLAB and Python with feature selection	2023	9
Faisal et al. [5]	Methods review	N/A	N/A	Comprehensive review of joint monitoring methods, feature extraction, and classification approaches	2019	N/A
García-De-Villa et al. [3]	Methods review	N/A	N/A	Comprehensive review of inertial sensors for human motion analysis	2023	N/A
Pathirana et al. [12]	Inertial sensor	Not specified	Not specified	Robust joint pose estimation using extended Kalman filtering	2018	1
Cereatti et al. [2]	Wearable inertial sensing	N/A	N/A	ISB recommendations for joint kinematics definition, estimation, and reporting	2024	N/A
Kaszyński et al.	Wearable IMU	Not specified	RSQ Motion sensors	Reliability and validity evaluation of shoulder ROM measurements using proprietary sensor data	2023	2

Mahony's filter formulates the same fusion objective as a nonlinear observer on SO(3), offering robustness and simplicity that make it well-suited for embedded implementations [14]. These approaches are frequently cited as practical alternatives to computationally heavier Bayesian filters when processing power and tuning complexity are constrained [3, 12].

Orientation estimation alone, however, is insufficient for meaningful biomechanical analysis. In upper-limb systems, the more challenging step is converting segment orientations into anatomically interpretable joint angles. A common strategy is to compute joint kinematics from the relative orientation between adjacent body segments, such as the forearm relative to the upper arm for the elbow, or the upper arm relative to the trunk for the shoulder. Picerno, Cereatti, and Cappozzo provide a foundational framework for estimating joint kinematics using wearable inertial and magnetic sensing modules through anatomical calibration procedures [15]. More recent systematic reviews focusing on upper-limb joint angle estimation confirm that modeling assumptions and calibration choices at this stage dominate overall accuracy and repeatability [16]. For this reason, the present project treats biomechanical modeling and calibration as first-class components rather than post-processing steps.

Beyond joint angles, several studies argue that movement quality is better captured through higher-level indicators such as symmetry, smoothness, stability, and variability. Emmerzaal et al. [8] analyze upper-limb movement quality in a clinical context and demonstrate that symmetry-related metrics can reveal compensatory strategies and functional limitations. Faisal et al. [5] provide a broader review of joint monitoring pipelines and emphasize that feature selection and post-processing strongly influence whether a system yields actionable insight or merely raw motion signals. These observations motivate the design of exercise-relevant features in this project, including joint angles, asymmetry measures, and stability-related indicators.

System-level constraints further shape the design of wearable motion analysis platforms. Baklouti et al. [10] present a representative architecture consisting of sensor acquisition, microcontroller-level processing, wireless transmission, and higher-level analysis. To reduce latency and bandwidth requirements, many systems push computation closer to the sensor through edge processing, transmitting compact features or classifications instead of high-rate raw data [11]. Despite these advances, much of the literature remains focused on clinician-facing tools or application-guided workflows rather than autonomous, real-time feedback systems suitable for unsupervised use [4, 5]. This gap motivates the present project's focus on interpretable, real-time form feedback.

Finally, because shoulder motion is inherently sequential, several studies employ temporal machine learning models to capture movement patterns from IMU time series. Yao [9] explores recurrent neural network-based pipelines for injury prediction using wearable sensor data, while the broader activity recognition literature demonstrates the effectiveness of deep learning models when large labeled datasets are available [6]. In practice, dataset availability remains a limiting factor for exercise-specific applications. Public datasets such as ERICA and WISDM are frequently referenced as starting points, even though they do not directly encode exercise form quality labels [7, 17]. Consequently, many applied systems adopt hybrid approaches that combine physically interpretable biomechanical features with lightweight classifiers capable of operating under limited training data, an approach adopted in this work.

Chapter 3

Methodology and Tools

3.1 System Level Design

The proposed system adopts a modular architecture that separates motion sensing, signal interpretation, and validation into clearly defined functional blocks. At its current stage, the system is optimized for controlled experimental validation rather than fully autonomous wearable operation. Consequently, the design prioritizes correctness, repeatability, and interpretability of the motion analysis pipeline, while maintaining the flexibility to support future extensions toward real-time feedback and wireless deployment.

The overall system is organized into three primary functional blocks, as illustrated in Fig. 3.1.

- **Sensing and Pre-processing Block**

  The sensing and pre-processing block is responsible for acquiring raw inertial data from multiple IMUs mounted on upper-body segments. Each IMU provides tri-axial accelerometer and gyroscope measurements, with optional magnetometer data where available. Sensor fusion is performed to estimate stable segment orientations, followed by calibration and mount correction procedures that align sensor coordinate frames with anatomical reference frames. This step ensures consistency and repeatability across recording sessions and subjects.

- **Computation and Feature Extraction Block**

  In the computation and feature extraction block, calibrated segment orientations are processed using a biomechanical body model to reconstruct upper-limb kinematics. Relative orientations between adjacent segments are used to compute joint angles for the shoulder and elbow, along with additional exercise-relevant features such as symmetry and asymmetry measures. At this stage of the project, feature computation and movement classification are performed offline, enabling detailed inspection and validation of intermediate outputs.

- **Visualization and Validation Block**

  The visualization and validation block provides tools for both qualitative and quantitative assessment of reconstructed motion and extracted features. This includes three-dimensional replay of the upper-body skeletal model and visualization of feature trajectories over time. These tools are used to verify correspondence between physical motion and reconstructed kinematics, serving as a critical validation step prior to the deployment of real-time feedback or embedded inference mechanisms.

While real-time feedback and on-device classification are not the focus of the current implementation, the modular system architecture supports their future integration without requiring fundamental changes to the sensing, calibration, or biomechanical modeling pipeline.

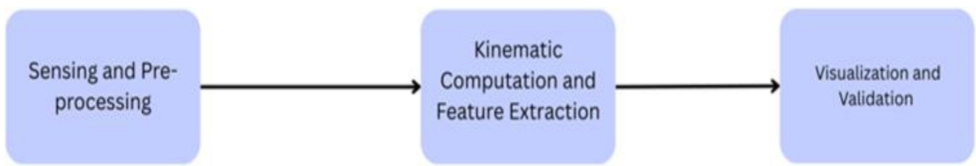


Fig. 3.1: System level design.

3.1.1 Block 1 – Sensing and Pre-processing Data

The sensing and pre-processing block is responsible for acquiring raw inertial data and converting it into stable orientation estimates suitable for kinematic analysis. This block is built around the MPU-9250 inertial measurement unit (IMU), which provides tri-axial accelerometer, gyroscope, and magnetometer measurements. The sensor can be mounted on upper-limb segments such as the chest, upper arm, or forearm, depending on the motion being analysed. Originally the IMU and microcontroller were to be housed in a compact 3D-printed enclosure designed to provide mechanical stability and repeatable placement across trials. Each IMU can be interfaced was meant to be interfaced with an ESP32-C3 Super Mini microcontroller, which handles sensor sampling and on-board signal processing. In the current implementation, due to hardware procurement related issues, data transmission is performed over a wired serial connection using a TCA multiplexer to handle a total of 5 IMU's attached to the subject being observed using double tape. Orientation estimation is performed locally on the microcontroller (or for each IMU's data stream individually) using a quaternion-based sensor fusion algorithm. This approach combines gyroscope integration with accelerometer-based correction to produce drift-limited orientation estimates at wearable-scale sampling rates. The output of this block consists of time-synchronized orientation quaternions expressed in a common reference frame, which form the input to subsequent kinematic processing stages. At this stage, no joint angles are computed on the microcontroller; the focus is on producing clean, calibrated segment orientations.

3.1.2 Block 2 – Kinematic Computation and Feature Extraction

The second block processes calibrated segment orientations to reconstruct upper-limb kinematics and compute interpretable motion features. This computation is performed off device using a host computer to allow detailed inspection, debugging, and validation of the processing pipeline. A simplified biomechanical body model is used to relate individual segment orientations to joint-level motion. Relative rotations between adjacent segments (e.g., forearm relative to upper arm, upper arm relative to trunk) are used to compute joint angles and other exercise-relevant quantities (this is developed further in section 3.1.4). From these kinematic representations, higher-level features such as symmetry measures, directional consistency, and angular deviations are extracted. In parallel, the extracted features are evaluated using lightweight machine learning models in an offline setting. Multiple model types are compared to assess their suitability for distinguishing between nominal and potentially unsafe movement patterns under constrained feature sets. Performing this step offline enables controlled experimentation with feature selection, model structure, and evaluation metrics without introducing real-time constraints during early validation.

3.1.3 Block 3 (Feedback and Closing the Loop)

The final block focuses on validating the correctness and interpretability of the reconstructed motion and extracted features. Rather than closing the loop with real-time user feedback, this stage provides visualization and replay tools that allow qualitative assessment of system behaviour under controlled motion scenarios. A three-dimensional replay environment is used to visualize reconstructed upper-body motion from recorded orientation data. This visualization enables direct comparison between physical motion and its reconstructed representation, making it possible to identify calibration errors, drift artifacts, or modelling inconsistencies. In addition, time-series plots of joint angles and derived features are used to verify that feature responses align with expected physical behaviour.

3.1.4 Biomechanical Body Model and Kinematic Computation

To convert raw IMU orientation estimates into interpretable joint-level motion, a simplified biomechanical body model is employed. The upper body is modeled as a kinematic chain of rigid segments—namely the trunk, upper arm, and forearm—each characterized by a fixed anatomical length and an associated orientation. This model provides a structured mapping from segment orientations to joint positions and joint angles.

3.1.4.1 Segment Representation and Reference Frames

The trunk (chest) segment defines the global reference frame for the system. All other segment orientations are expressed relative to this frame. Each limb segment is modeled as a rigid vector of fixed length L_i, defined in the local coordinate frame of the corresponding segment.

For example, the upper-arm segment is represented by the local vector

$$\mathbf{l}_{\text{upper}} = \begin{bmatrix} 0 \\ 0 \\ -L_{\text{upper}} \end{bmatrix}, \tag{3.1}$$

where L_{upper} corresponds to the anatomical length of the upper arm. The direction of this vector is chosen according to the sensor mounting convention, such that it points from the proximal joint (shoulder) toward the distal joint (elbow).

3.1.4.2 Segment Orientation Representation

Segment orientations are estimated using unit quaternions due to their numerical stability and absence of singularities. For a given segment, the orientation quaternion is defined as

$$\mathbf{q} = \begin{bmatrix} q_w & q_x & q_y & q_z \end{bmatrix}, \tag{3.2}$$

where q_w is the scalar component and q_x, q_y, and q_z are the vector components. All quaternions are normalized to unit magnitude prior to use to ensure valid rotational transformations.

3.1.4.3 Quaternion-to-Rotation Matrix Conversion

To apply segment orientations to physical vectors, each unit quaternion is converted into an equivalent 3×3 rotation matrix. Given a unit quaternion

$$\mathbf{q} = \begin{bmatrix} q_w & q_x & q_y & q_z \end{bmatrix}, \tag{3.3}$$

the corresponding rotation matrix $\mathbf{R(q)}$ is defined as

$$\mathbf{R(q)} = \begin{bmatrix} 1 - 2(q_y^2 + q_z^2) & 2(q_xq_y - q_zq_w) & 2(q_xq_z + q_yq_w) \\ 2(q_xq_y + q_zq_w) & 1 - 2(q_x^2 + q_z^2) & 2(q_yq_z - q_xq_w) \\ 2(q_xq_z - q_yq_w) & 2(q_yq_z + q_xq_w) & 1 - 2(q_x^2 + q_y^2) \end{bmatrix}. \tag{3.4}$$

3.1.4.4 Orientation of Segment Vectors

To express each segment vector in the global frame, the local segment vector is rotated using the estimated segment orientation. Given the orientation quaternion $\mathbf{q}_i$ of segment i, the corresponding rotation matrix $\mathbf{R}(\mathbf{q}_i)$ is applied as

$$\mathbf{l}_i^{\text{global}} = \mathbf{R}(\mathbf{q}_i)\,\mathbf{l}_i. \tag{3.5}$$

This operation produces a three-dimensional vector that represents the orientation and direction of the segment in physical space.

3.1.4.5 Forward Kinematic Reconstruction of Joint Positions

Joint positions are reconstructed by chaining the rotated segment vectors starting from a known reference point on the trunk. Let $\mathbf{p}_{\text{chest}}$ denote the reference position of the trunk. The shoulder joint position is computed as

$$\mathbf{p}_{\text{shoulder}} = \mathbf{p}_{\text{chest}} + \mathbf{l}_{\text{shoulder}}^{\text{global}}. \tag{3.6}$$

The elbow and wrist joint positions are then obtained sequentially as

$$\mathbf{p}_{\text{elbow}} = \mathbf{p}_{\text{shoulder}} + \mathbf{l}_{\text{upper}}^{\text{global}}, \tag{3.7}$$

$$\mathbf{p}_{\text{wrist}} = \mathbf{p}_{\text{elbow}} + \mathbf{l}_{\text{forearm}}^{\text{global}}. \tag{3.8}$$

This forward kinematic chain explicitly defines how each joint position is generated from the previous one. Because each segment vector is rotated independently using its estimated orientation, the resulting joint trajectories are smooth and anatomically plausible when orientation estimates are accurate.

3.1.4.6 Relative Joint Rotation and Angle Computation

While joint positions are primarily used for visualization and validation, joint angles are computed directly from relative segment orientations. Given the orientation quaternion of a parent segment $\mathbf{q}_p$ and a child segment $\mathbf{q}_c$, the relative joint rotation is computed as

$$\mathbf{q}_{\mathrm{rel}} = \mathbf{q}_p^{-1} \otimes \mathbf{q}_c, \tag{3.9}$$

where $\otimes$ denotes quaternion multiplication and $\mathbf{q}_p^{-1}$ is the quaternion inverse. This relative quaternion represents the rotation of the child segment expressed in the coordinate frame of the parent segment.

Joint angles are extracted from the relative quaternion by converting it to an equivalent axis–angle or Euler-angle representation, depending on the joint under consideration. For example, the rotation angle ϑ associated with a unit quaternion is given by

$$\vartheta = 2\cos^{-1}(q_w). \tag{3.10}$$

This formulation enables consistent computation of shoulder elevation, elbow flexion, and other joint-specific angles over time.

3.1.4.7 Role of the Body Model in Feature Validation

Although joint angles are derived from relative orientations, reconstructed joint positions play a critical role in validating the biomechanical model. Changes in physical motion should produce smooth, continuous trajectories in three-dimensional space. These trajectories are used to verify calibration quality, segment alignment, and the overall consistency of orientation estimates during visualization and replay.

By combining quaternion-based orientation estimation with an explicit vector-based body model, the system provides a clear and physically interpretable mapping from IMU measurements to joint motion. This ensures that computed outputs are not only numerically valid but also meaningful in terms of human movement.

3.2 Final Design

The final system integrates the sensing, computation, and validation blocks into a single end-to-end motion analysis pipeline. The original design intent was to realize a fully wearable, wireless system in which multiple IMU nodes transmit processed orientation data to a central device for real-time interpretation and feedback. This architecture remains central to the overall system concept and informs the modular structure of the implementation. Each sensing node consists of an IMU paired with a microcontroller and powered by a lithium-ion cell with onboard charging and regulation circuitry. Charging is supported through a USB-C interface, and the enclosure is designed to be modular, allowing sensors to be repositioned or additional joints to be instrumented without changes to the underlying processing pipeline. Due to hardware availability and procurement constraints, data transmission between sensor nodes and the host device is performed using a wired, multiplexed serial setup rather than a wireless link. This design choice does not alter the internal operation of the sensing or modeling blocks: sensor fusion, calibration, orientation estimation, and feature extraction remain unchanged once the data reaches the edge-processing stage. After acquisition, filtered orientation data is streamed to an edge device, where kinematic reconstruction and feature computation are performed. These features can then be passed to the machine learning evaluation pipeline for offline classification and analysis.

3.3 Tools/Instruments

3.3.1 Simulation Software Packages

- Python – offline IMU data filtering, model training, and visualization.
- Arduino IDE / PlatformIO – firmware development and serial debugging.

3.3.2 Hardware Instruments

- ESP32-C3 SuperMini + ESP-32 boards (processing + wireless)
- MPU-9250 IMU sensors (motion capture)
- TP4056 charging module and MT3608 boost converter (power management)

- TCA 9548A (multiplexer for up to 8 I2C connections)
- 3D-printed mount and fastening mechanism.

Chapter 4

Project Simulation

4.1 Simulation Setup

To evaluate the feasibility of movement-quality classification prior to deployment on inertial hardware, an offline simulation environment was established using a publicly available computer vision–based dataset. The dataset released by Ko et al. [18] contains three-dimensional joint coordinates extracted from video recordings of powerlifting exercises, including the bench press. For each video frame, Cartesian coordinates $(x,\ y,\ z)$ are provided for 33 body joints, along with annotations describing the movement phase (eccentric or concentric) and form quality (correct or incorrect).

Since each joint is represented by three spatial coordinates, the full pose description consists of 99 raw features per frame. However, as this project focuses exclusively on bench press analysis, lower-body joints were excluded from further processing. This reduction reflects the biomechanical relevance of the task and ensures that the simulated feature space closely matches the upper-body sensing configuration employed in the IMU-based system.

From the selected upper-body joints, joint angles were computed to obtain a representation that is both compact and physically interpretable. Given three joint positions **A**, **B**, and **C**, corresponding to two adjacent limb segments, the angle at joint **B** was calculated using the cosine rule:

$$\vartheta_{\mathrm{deg}} = \cos^{-1} \frac{(\mathbf{B} - \mathbf{A}) \cdot (\mathbf{C} - \mathbf{B})}{\|\mathbf{B} - \mathbf{A}\|\,\|\mathbf{C} - \mathbf{B}\|} \cdot \frac{180^\circ}{\pi}\ . \tag{4.1}$$

This formulation yields joint angles that are invariant to global position and scale, making them suitable for comparison across subjects and trials.

Using these joint angles as a base representation, additional higher-level features were constructed to capture exercise-relevant characteristics of bench press form. These include measures of elbow flare, bilateral asymmetry between left and right limbs, and relative shoulder motion. Feature construction was guided by biomechanical relevance rather than raw dimensionality reduction alone, ensuring that each feature corresponds to a meaningful aspect of physical movement.

To assess the discriminative power of the extracted features, correlation-based heat maps were generated to examine relationships between feature values and the provided form-quality labels, as shown in Fig. 4.1.

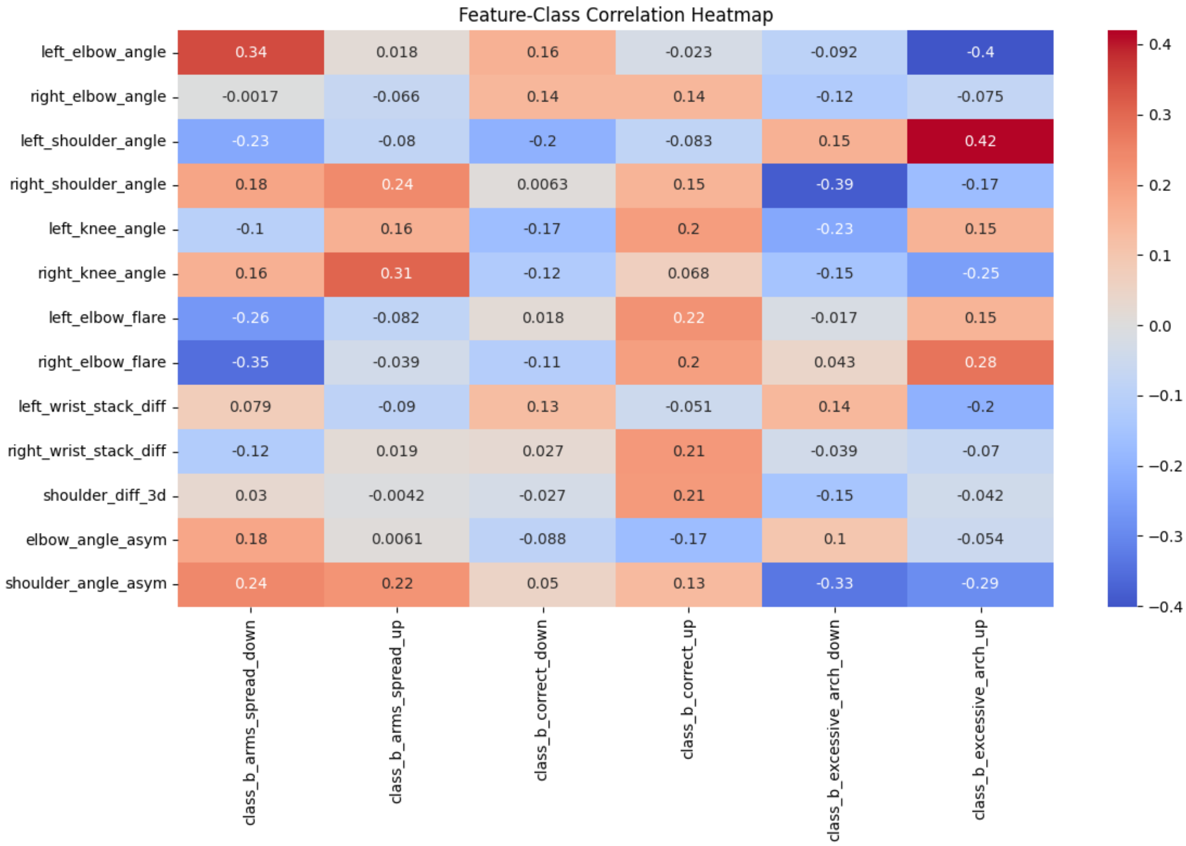


Fig. 4.1: Correlation heatmap comparing features and labels.

4.2 Simulation Results

Following feature reduction and construction, several supervised learning models were evaluated to assess their ability to classify movement quality in the simulated bench press dataset. The evaluated models included linear classifiers, ensemble-based methods, and neural network architectures. Performance was assessed using standard classification metrics, including accuracy, precision, recall, and F1-score, to ensure a balanced evaluation across class boundaries.

Initial experiments with linear models showed limited performance, particularly in cases where incorrect movement patterns differed subtly from correct form. This behavior is consistent with the nonlinear nature of human joint coordination during compound exercises, where relationships between joint angles, symmetry, and timing are not well captured by linear decision boundaries.

Ensemble-based models, including gradient-boosted methods and random forest variants, demonstrated improved performance due to their ability to model nonlinear feature interactions.

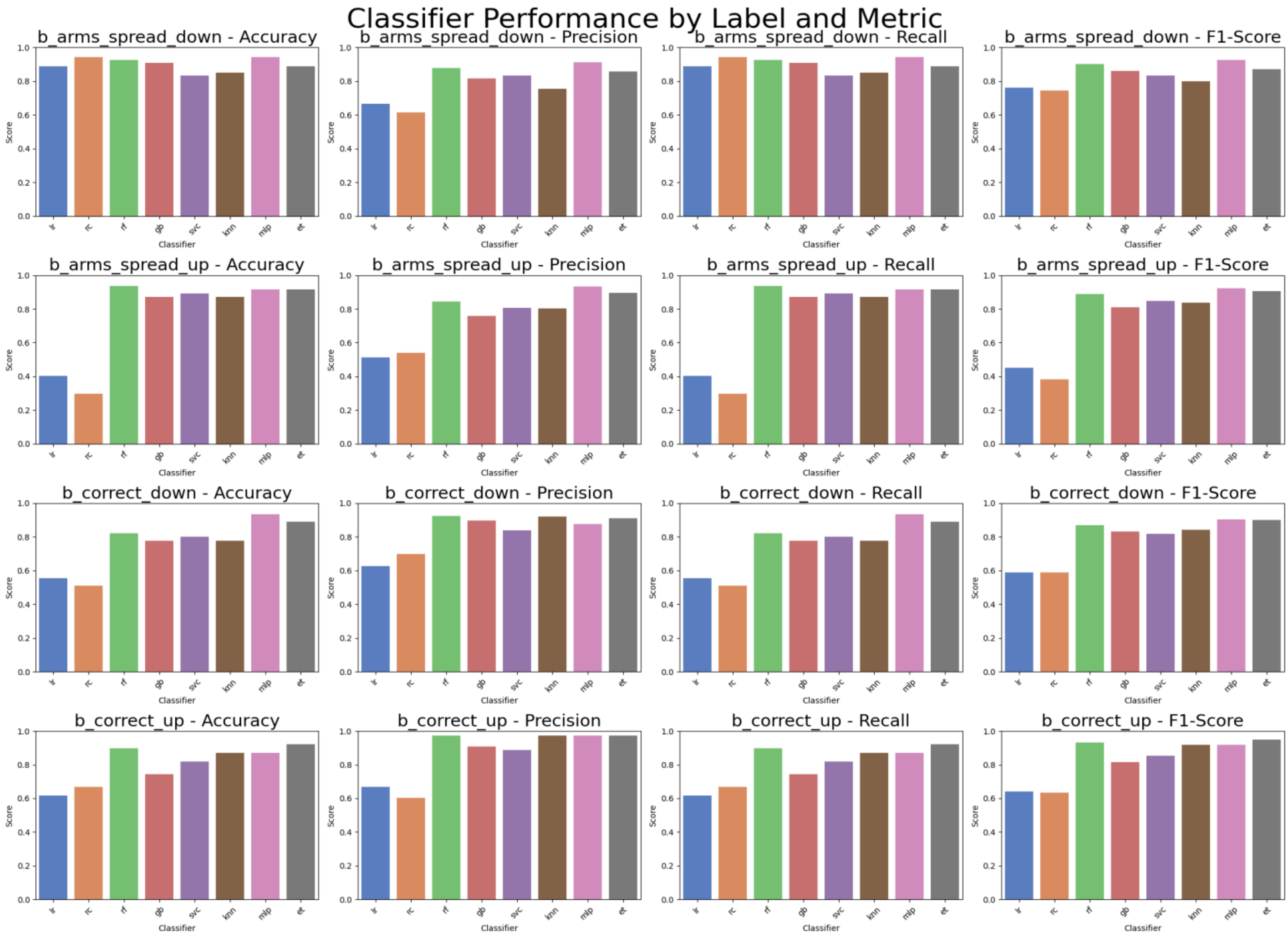


Fig. 4.2: Comparison plots of different models and their per label performance

Among these, the Extra Trees classifier consistently achieved strong results, benefiting from randomized feature selection and deep tree structures that reduced overfitting while preserving discriminative power.

Neural network–based models were also evaluated, with a focus on lightweight architectures suitable for constrained feature sets. A multi-layer perceptron (MLP) achieved competitive performance across all evaluation metrics, effectively capturing nonlinear relationships between joint angles, flare measures, and bilateral asymmetry features without requiring temporal sequence modeling at this stage.

Across all tested approaches, the Multi-Layer Perceptron and the Extra Trees classifier produced the most consistent and highest overall performance across the four primary evaluation metrics. These results motivated their selection for further analysis and informed subsequent design decisions regarding feature selection and model complexity in later stages of the project.

In the end, the multi-layer perceptron was selected for further testing, as it achieved the strongest overall performance across the four primary classification metrics.

Table III: A quick overview of average statistics for each model's performance

Model	F1- score	Accuracy	Precision	Recall
Logistic Regression	0.6153	0.6270	0.6176	0.6270
Ridge Classifier	0.5919	0.6162	0.6132	0.6162
Random Forest	0.8759	0.8757	0.8823	0.8757
Gradient boost reg	0.8321	0.8324	0.8406	0.8342
SVC	0.8377	0.8378	0.8395	0.8378
KNN	0.8450	0.8432	0.8532	0.8432
MLP	0.9298	0.9297	0.9306	0.9297
Extra Trees	0.9139	0.9135	0.9159	0.9135

4.3 Result Analysis and Outlook

The simulation results confirm that exercise-form classification can be performed effectively using a reduced set of biomechanically meaningful features derived from joint kinematics. Representing motion through joint angles and related asymmetry measures proved sufficient for distinguishing between correct and incorrect bench press execution. This observation supports the premise that high-level, interpretable features are more informative for form assessment than raw positional data alone.

Among the tested configurations, feature selection and quantization had the strongest influence on overall system performance. Reducing the original feature space from 99 variables to a compact set of 15 exercise-relevant features simplified the learning problem and improved inference efficiency without a measurable degradation in classification accuracy. This reduction is particularly important for future deployment on resource-constrained hardware platforms. Across all evaluated models, the multi-layer perceptron (MLP) achieved the most consistent overall performance across standard classification metrics.

Using joint angles and angular relationships as the primary motion representation also aligns closely with the physical interpretation of exercise form, making the results easier to analyze and validate. However, it is important to note that the simulation data were derived from computer vision–based pose estimates. As a result, the input signals are comparatively smooth and do not exhibit the sensor noise, bias drift, and transient disturbances commonly encountered in IMU-based measurements.

For this reason, the simulation results are treated as a validation of the feature design and model selection strategy rather than a final performance benchmark. The subsequent phase

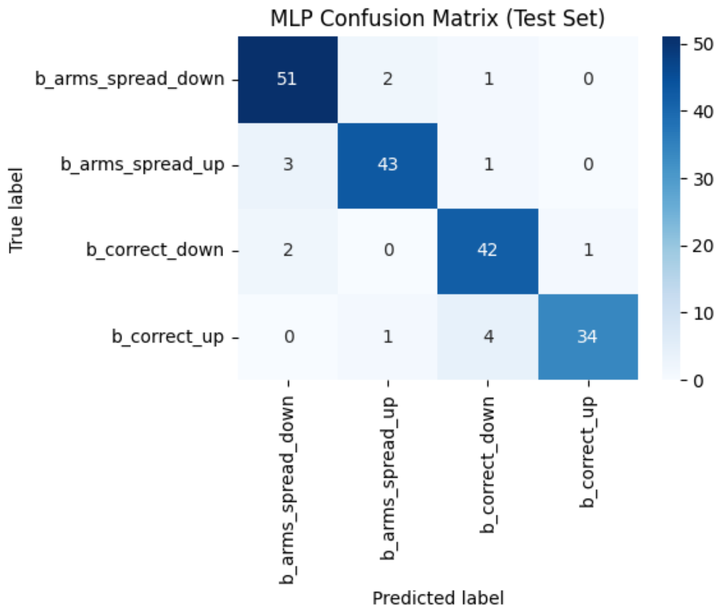


Fig. 4.4: Final confusion matrix for the MLP

of testing therefore focuses on validating the same processing pipeline using live IMU data collected from the prototype hardware.

Chapter 5

Project Implementation

5.1 Hardware Setup

The hardware platform was designed with an emphasis on low cost, modularity, and wearability, while maintaining reliable orientation sensing and rechargeable operation. Each prototype node integrates an inertial measurement unit (IMU), a microcontroller for on-board processing, and a lithium-ion power source, all housed within a compact, custom-designed three-dimensional printed enclosure.

Motion sensing is performed using the MPU-9250 family of IMUs, which provide tri-axial accelerometer and gyroscope measurements, with an optional tri-axial magnetometer in the MPU-9250 variant. These sensors were selected due to their wide availability, low cost, and extensive prior use in wearable motion-capture and human movement studies. The IMU is interfaced with the microcontroller via an I^2C bus, and sensor data are sampled at a rate of 50 Hz. Serial communication is configured at a baud rate of 115200 to ensure reliable data transfer during testing.

The central processing unit for each node is an ESP32-C3 Super Mini microcontroller. This device was selected for its compact form factor, low-power operating modes, and integrated wireless communication capabilities, including Wi-Fi and ESP-NOW support. In the current implementation, the ESP32 performs on-board sensor fusion to estimate orientation quaternions and streams the resulting data to a host system for further processing and validation. A minimal supporting circuit includes voltage regulation and USB-C connectivity for programming and charging.

To ensure comfort and repeatable sensor placement, the electronics and battery are enclosed within a custom three-dimensional printed housing. Early enclosure designs prioritized structural rigidity but resulted in excessive wall thickness and limited internal volume. A second design iteration introduced thinner walls, significantly reducing weight without compromising mechanical stability due to the low overall mass of the device. The final enclosure design incorporates the following features:

- Ventilation slots for passive heat dissipation

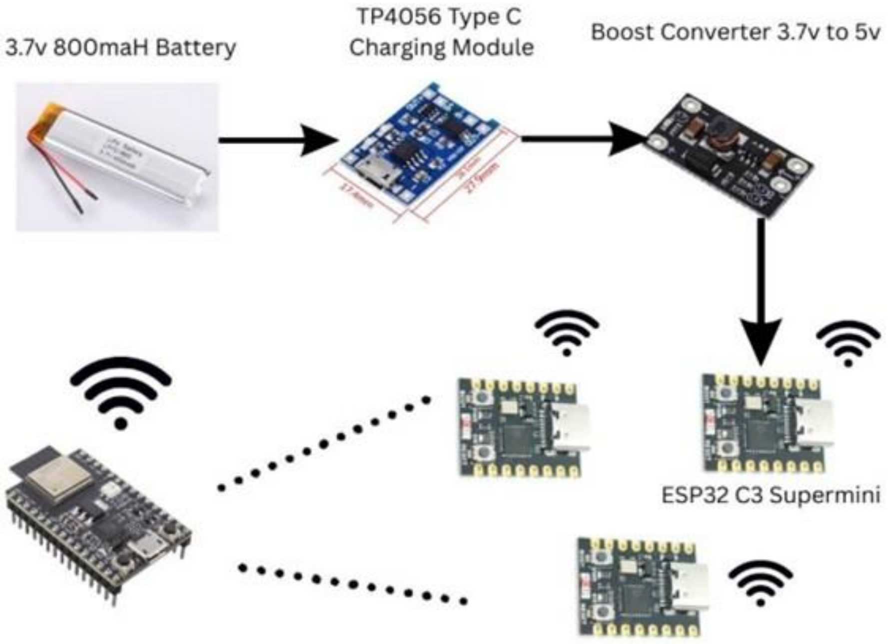


Fig. 5.1: High level block diagram of data flow

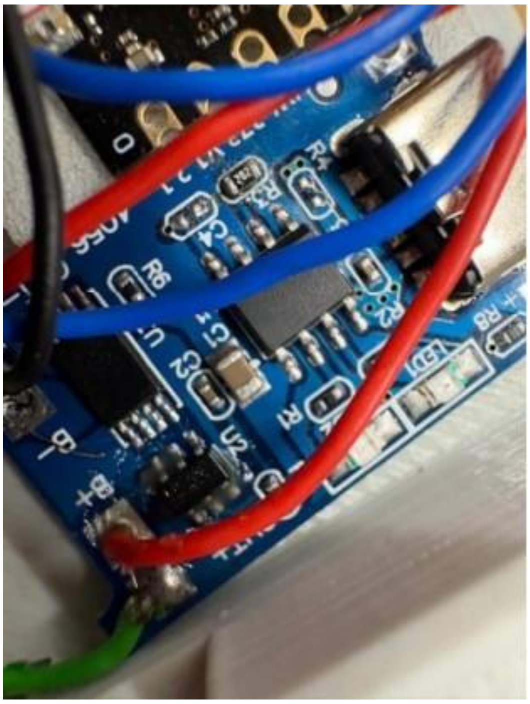
- A snap-fit lid enabling tool-free assembly
- Integrated strap channels for attachment using Velcro bands
- Internal supports for a 3.7 V lithium-ion battery and charging module

The enclosure design was developed by Shayaan Haider.

Each node is powered by a 3.7 V lithium-ion battery with a nominal capacity of 800 mAh. Battery charging and protection are handled using a TP4056-based charging module with integrated overcharge and overdischarge protection circuitry. The ESP32 and IMU are supplied from a regulated 3.3 V power rail.

To safely accommodate different battery capacities, the default charging current of the TP4056 module was reduced by replacing the onboard programming resistor. The original configuration allowed a charging current of approximately 1 A, which exceeded the recommended limits for smaller-capacity cells. By replacing the resistor with a 2 kΩ surface-mount component, the charging current was limited to approximately 580 mA, ensuring compatibility across all tested batteries. Under continuous operation at a 50 Hz sampling rate, the estimated runtime was approximately 1 hour for a 300 mAh cell and 3–4 hours for an 800 mAh cell.

Fig. 5.2: Inner circuitry and design of the wireless node



Rprog Current Setting

RPROG (k)	I_{BAT} (mA)
10	130
5	250
4	300
3	400
2	580
1.66	690
1.5	780
1.33	900
1.2	1000

Fig. 5.3: The changed SMD resistor and associated settings table from the TP4056 datasheet [1]

5.2 Experimental Procedure

The experimental procedure was designed to validate the end-to-end motion tracking pipeline under controlled conditions, with a focus on verifying sensing accuracy, calibration consistency, and kinematic reconstruction behavior.

5.2.1 Hardware Setup and Calibration

IMU nodes were mounted on rigid structures or garments to minimize unintended motion between each sensor and the anatomical segment it represented. Prior to data collection, all sensors were powered on and allowed to stabilize. A static calibration pose was then recorded to establish the reference orientation for each segment and to compute mount-to-segment alignment parameters.

All experiments were conducted using a wired, multiplexed serial connection between the sensor nodes and the host computer. This configuration was chosen to ensure reliable time synchronization, eliminate packet loss, and simplify debugging during early-stage validation. Although the original system design targeted wireless data transmission, the wired setup enabled robust verification of the sensing and modeling pipeline without requiring changes to downstream processing.

5.2.2 Data Acquisition and Processing Pipeline

During data collection, raw accelerometer and gyroscope data were sampled at 50 Hz and processed locally on the ESP32 microcontroller using a quaternion-based sensor fusion algorithm. The resulting orientation quaternions were transmitted to the host computer, where they were logged and processed offline.

On the host side, orientation data were passed through the biomechanical body model described in Chapter 3. Relative segment orientations were used to compute joint angles, and forward kinematics were applied to reconstruct joint positions for visualization. Feature extraction routines were then applied to compute exercise-relevant quantities such as joint angles, directional motion, and bilateral symmetry measures.

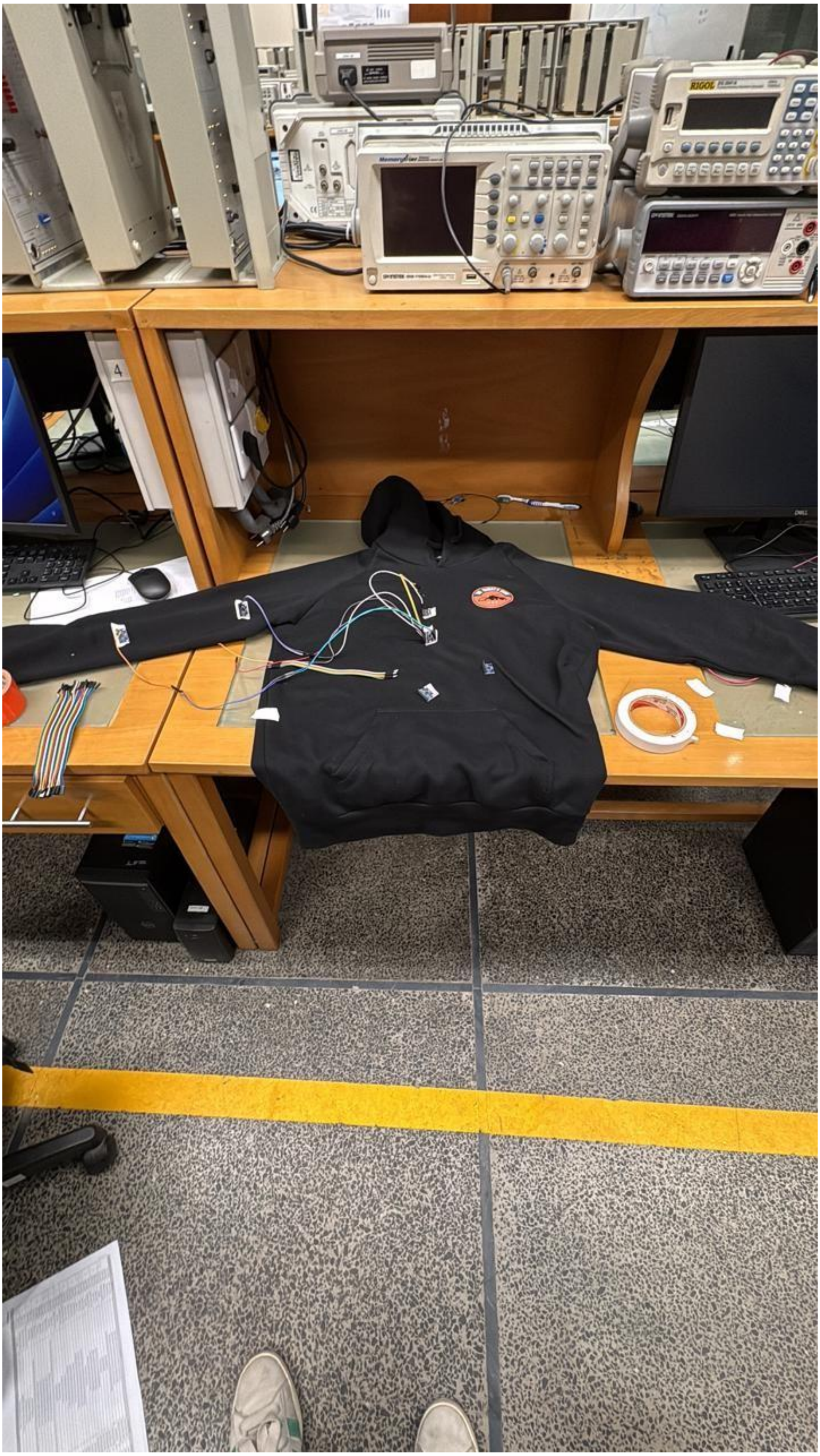


Fig. 5.4: Wired setup for just the right arm and chest (left arm was added shortly after)

5.2.3 Validation Procedure

Due to repeated hardware failures and limited system stability during dynamic human testing, full bench press trials could not be reliably recorded with synchronized IMU data. As a result, validation focused on controlled, repeatable motions using a garment-mounted prototype in which upper-limb segments were manually actuated.

A representative validation sequence involved lifting the arm of the wearable garment while simultaneously visualizing the reconstructed limb motion in the three-dimensional replay environment. This procedure enabled direct qualitative comparison between the physical motion of the prototype and the reconstructed motion displayed on-screen.

All recorded data were inspected for continuity, drift behavior, and consistency between physical motion and reconstructed kinematics.

5.3 Implementation Results

The implementation results focus on validating the correctness and stability of the sensing, processing, and visualization pipeline under controlled conditions. Due to hardware instability during extended dynamic testing, quantitative evaluation emphasizes timing behavior, signal consistency, and correspondence between physical motion and reconstructed kinematics rather than large-scale statistical performance metrics.

5.3.1 Orientation and Kinematic Reconstruction Performance

During controlled validation trials, IMU nodes produced continuous orientation quaternion streams at a nominal sampling rate of 50 Hz. Logged data showed no dropped samples during wired operation, and orientation estimates remained stable during static poses, indicating correct sensor fusion and calibration behavior.

Using the biomechanical body model described in Chapter 3, orientation data were successfully converted into joint positions and joint angles in real time on the host system. When the garment-mounted arm was lifted, the reconstructed arm in the three-dimensional visualization exhibited a corresponding elevation with consistent direction, magnitude, and timing. This behavior was observed repeatedly across multiple trials.

Latency from sensor acquisition to visualization update was dominated by serial transmission and host-side processing and remained below one frame interval at the selected sampling rate, resulting in visually smooth motion without noticeable lag. In the final trial runs, low battery voltage caused minor visualization lag; however, this behavior effectively enabled slow-motion replay of the movement, which proved useful for qualitative validation.

5.3.2 Visual Correspondence Validation

A representative validation sequence is documented in the accompanying demonstration video[1]. The video presents a side-by-side comparison of the physical motion of the garment-mounted arm and the reconstructed arm in the visualization environment. Key observations include:

- Correct directional mapping between physical motion and on-screen reconstruction
- Smooth joint trajectories without discontinuities
- Stable limb orientation during static holds
- Absence of sudden jumps or drift over short-duration trials

These observations demonstrate that orientation data propagate correctly through the kinematic chain and that the body model produces physically plausible motion reconstructions.

5.4 Result Analysis and Outlook

The implementation results demonstrate that the core objectives of the project—reliable orientation estimation, biomechanical modeling, and interpretable motion reconstruction—were successfully achieved. The system consistently translated raw IMU data into stable segment orientations, joint angles, and three-dimensional joint trajectories that aligned with observed physical motion.

From an objectives standpoint, the sensing and modeling components performed as intended. Calibration procedures yielded consistent reference alignment, and the biomechanical body model produced smooth and physically meaningful motion reconstructions. This validates the central design choice of prioritizing interpretable kinematic features over raw sensor signals.

However, the results also highlight practical limitations that prevented full end-to-end evaluation. Hardware instability, particularly associated with the ESP32-C3 Super Mini platform,

[1] https://youtube.com/shorts/BjmcQUmusw0?si=JCSay4fLwDadaEq7

disrupted prolonged testing and rendered multi-node wireless operation unreliable. After transitioning to a wired, multiplexed configuration to ensure data integrity, dynamic human subject testing became impractical due to discomfort, safety concerns, and inconsistent sensor placement during compound movements.

As a result, the machine learning components of the system were validated using simulation data rather than live IMU data. While this prevented quantitative evaluation of real-time form classification on hardware, it does not invalidate the modeling or feature extraction results. Instead, it underscores the importance of hardware reliability as a prerequisite for meaningful data-driven evaluation.

Looking forward, the most impactful improvement would be the adoption of a more stable microcontroller platform or a custom-designed printed circuit board to eliminate power and connectivity issues. Restoring a fully wireless architecture would enable safe and practical human testing during compound exercises such as the bench press. With reliable hardware and sufficient real-world data, the existing feature extraction and classification pipeline can be retrained and optimized for embedded deployment.

In summary, although real-time exercise classification using live IMU data could not be demonstrated in this phase, the project successfully established and validated the foundational components required for such a system. The results indicate that the sensing, modeling, and visualization pipeline is sound and can be extended toward full real-time wearable operation in future work.

Chapter 6

Cost Analysis

The proposed system was designed with cost efficiency as a primary constraint, alongside modularity and extensibility. The objective was to develop an upper-limb motion monitoring platform that is accessible, scalable, and suitable for both experimental validation and future wearable deployment.

6.1 Component-Level Cost Breakdown

Table III summarizes the approximate per-node hardware cost of the proposed system. The listed components include elements from both the originally designed wireless system and the final wired validation setup. The wired configuration is a direct derivative of the wireless design and requires only one additional component—the I^2C multiplexer—while removing the battery and boost converter. As a result, the cost difference between the two configurations is minimal.

Table IV: SPROJ per-node hardware cost breakdown

Description	**Approx. Cost (USD)**
MPU-9250 (9-DOF inertial sensor)	$5–7
ESP32-C3 Super Mini microcontroller	$4–6
3.7 V Li-ion battery (300–800 mAh)	$3–5
TP4056 charging module	$1
Boost converter module	$1–2
TCA9548A I^2C multiplexer (wired setup only)	$2
Miscellaneous components (PCB, connectors, wiring)	$2–3
Estimated total per node	**$18–26**

The use of the MPU-9250 sensor is a key contributor to the low overall system cost. Unlike newer inertial measurement units that integrate proprietary sensor fusion algorithms or higher-precision magnetometers at significantly increased cost, the MPU-9250 provides sufficient performance for upper-limb motion tracking at a fraction of the price. When combined with a low-cost ESP32 microcontroller and off-the-shelf power management components, the total per-node cost remains well below that of most comparable systems reported in the literature.

6.2 Comparison with Existing Academic and Commercial Systems

Table IV compares the proposed system with representative academic and commercial upper-limb motion monitoring solutions that explicitly disclose hardware cost or pricing.

Table V: Cost comparison with existing academic and commercial systems

System / Study	Sensor Type	Approx. Cost	Description
Chen et al. (2020) [4]	Commercial IMU modules	>$300	Clinician-oriented rehabilitation system
Xsens MVN (commercial) [19]	Proprietary IMU network	>$5,000	High-accuracy system, not suitable for daily wear
Perception Neuron (commercial) [20]	Proprietary IMU modules	$1,500–3,000	Full-body system, not exercise-specific
Baklouti et al. (2024) [10]	Custom IMU platform	>$500	Occupational risk assessment system
Proposed system	MPU-9250 + ESP32	**$18–26**	Modular, low-cost, exercise-focused

Academic systems frequently rely on commercial IMU modules or research-grade motion capture hardware, which significantly increases system cost and limits scalability [4, 10]. Commercial motion capture platforms such as Xsens and Perception Neuron offer high accuracy but are prohibitively expensive for personal rehabilitation, home-based exercise monitoring, or large-scale deployment [19, 20].

In contrast, the proposed system achieves comparable sensing functionality for upper-limb motion tracking at a substantially lower cost by leveraging low-cost inertial sensors, open-source processing, and lightweight biomechanical modeling. This cost reduction is particularly important for applications requiring multiple sensors or long-term deployment, such as home rehabilitation, gym-based monitoring, or longitudinal injury prevention studies.

Chapter 7

Conclusion and Future Recommendations

This project set out to design and evaluate a wearable system capable of monitoring shoulder motion, extracting meaningful joint-level features, and supporting exercise form assessment. Over the course of the work, a complete sensing-to-interpretation pipeline was developed, including inertial sensing, orientation estimation, biomechanical modelling, feature extraction, and offline machine learning evaluation. While not all objectives were fully realized in a real-time wearable configuration, the core technical foundations of the system were successfully implemented and validated.

From a methodological perspective, the primary objectives of the project were largely achieved. A modular IMU-based hardware platform was designed and implemented, capable of producing stable orientation estimates through on-board sensor fusion. A principled biomechanical body model was developed to convert these orientations into joint positions and joint angles using explicit vector- and quaternion-based formulations. The correctness and interpretability of this model were verified through controlled motion tests and three-dimensional visualization, demonstrating consistent correspondence between physical motion and reconstructed kinematics.

In parallel, a simulation-based evaluation using computer vision–derived joint data confirmed that exercise-form classification can be achieved using a compact set of biomechanically meaningful features. Feature reduction from high-dimensional pose data to joint angles, symmetry measures, and related indicators preserved classification performance while significantly reducing model complexity. This result supports the broader premise that interpretable, movement-level features are well suited for form assessment tasks.

Despite these successes, several objectives remain partially unmet due primarily to hardware-related limitations encountered during implementation. The ESP32-C3 Super Mini microcontroller exhibited persistent reliability issues, including repeated connection and disconnection during operation and unstable USB behavior that resulted in damage to multiple host USB ports. These issues disrupted prolonged testing and made stable multi-node operation difficult. As a result, the original plan to evaluate the full pipeline using wireless, body-mounted IMU nodes during dynamic bench press exercises could not be realized.

Furthermore, once the system transitioned from wireless nodes to a wired, multiplexed configuration to improve stability, testing on human subjects became impractical. The combination of adhesive mounting, cabling, and movement-sensitive joints introduced safety concerns, discomfort, and inconsistent sensor placement during dynamic motion. Under these conditions, collecting high-quality, repeatable human exercise data was not feasible. Importantly, these limitations affected only the data acquisition stage and did not invalidate the downstream processing, modelling, or simulation-based evaluation results.

As a result, the machine learning and hardware components of the system were validated independently rather than as a fully closed-loop wearable system.

Future Recommendations and Directions

Future work should focus first on improving hardware robustness before attempting further human trials. Replacing the ESP32-C3 Super Mini with a more stable development board or a custom-designed PCB would significantly reduce connection and power-management issues. A return to a fully wireless architecture is strongly recommended, as this is essential for safe and practical testing on human subjects during compound exercises.

Once hardware stability is ensured, the next priority should be the collection of synchronized IMU data during real bench press trials. This would enable retraining and validation of the machine learning models on sensor data that include realistic noise, bias drift, and motion artifacts. Additional refinement of calibration procedures, particularly sensor-to-segment alignment, would further improve robustness under dynamic conditions.

Finally, with reliable hardware and sufficient real-world data, the system could be extended toward real-time, on-device inference and user feedback. Lightweight model optimization and embedded deployment would allow the system to close the feedback loop through haptic, visual, or audio cues, completing the original vision of a wearable exercise-form monitoring device.

In summary, while practical constraints limited full real-time and human-subject evaluation, the project successfully established and validated the core technical framework required for IMU-based shoulder motion analysis. The results demonstrate that, with improved hardware stability, the proposed system has clear potential to evolve into a fully wearable, real-time exercise monitoring solution.

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