Smart Rehabilitation System

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Chapter 1: Acknowledgment

1.1 Acknowledgment

We would like to express our sincere gratitude to everyone who supported and guided us throughout the development of our graduation project, Smart Rehabilitation System.

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Finally, we thank our families and friends for their unwavering moral support, patience, and encouragement throughout our academic journey.

1.2 Abstract

The Smart Rehabilitation System is an intelligent, remote physiotherapy platform that leverages advanced sensing technologies, artificial intelligence, and secure mobile connectivity to monitor, evaluate, and enhance patient recovery. By integrating biomedical signal processing, machine learning, deep learning and computer vision, it delivers personalized rehabilitation with real-time feedback and remote therapist supervision.

The system operates in two main stages:

1. Diagnosis & Classification:

Surface EMG (sEMG) signals from the Vastus Medialis muscle are analyzed to detect neuromuscular patterns. A classification model identifies whether the activity is normal or abnormal, forming the basis for a tailored rehabilitation path.

2. Personalized Rehabilitation:

- **Abnormal Users:** Receive targeted support via Terminal Knee Extension exercises. A hybrid LRCN model (combining EMG and IMU data) estimates joint angles, evaluates movement quality, and provides real-time corrective feedback to enhance muscle function.
- **Normal Users:** Engage in general fitness exercises (e.g., squats, sit-ups, bicep curls) monitored through camera-based computer vision (MediaPipe) without wearable sensors. The system offers real-time form correction and performance visualization.

To ensure safety, an ECG sensor continuously monitors heart activity, detecting signs of overexertion during exercise.

A secure mobile application serves as the user interface, enabling:

- Automated assessments, Guided, personalized exercise sessions ,Performance analytics, Therapist scheduling Data protection is ensured via **AES encryption** and **blockchain-**backed session logging over a cloud-based infrastructure. This system provides a smart, scalable solution that enhances patient recovery and streamlines healthcare using IoT, computer vision, and secure AI analysis.

Chapter 2: Introduction

2.1 Overview

The **Smart Rehabilitation System** is our graduation project aimed at transforming traditional physiotherapy into an intelligent, adaptive, and remotely accessible experience. Leveraging advanced technologies such as **artificial intelligence (AI)**, **biomedical signal processing**, **computer vision**, and **secure mobile infrastructure**, this system is designed to monitor, evaluate, and enhance the recovery process for individuals with neuromuscular conditions—particularly those experiencing **knee pain and dysfunction**.

At the clinical core of the system lies the rehabilitation exercise known as **Terminal Knee Extension (TKE)**, which is vital for reactivating the **Vastus Medialis Oblique (VMO)**—a key stabilizer of the patella. Weakness in the VM muscle often leads to **abnormal patellar tracking**, especially in post-surgical ACL recovery cases[4]. The system addresses this by **objectively measuring TKE quality**, combining EMG-based VM activation analysis with **joint angle kinematics** derived from IMU sensors.

Our system combines **sEMG signal analysis**, **joint angle estimation**, **real-time posture tracking**, and **heart monitoring**, all integrated within a **mobile application**. This app not only provides personalized rehabilitation pathways but also ensures **data security** through encryption and blockchain-based logging. The project aligns with global efforts to increase accessibility and precision in remote healthcare, particularly in physiotherapy and rehabilitation domains.

2.2 Problem Statement

Despite the growing need for effective rehabilitation, **conventional physiotherapy methods face significant limitations**:

- **Incorrect Exercise Execution**: Without continuous supervision, patients often perform exercises improperly, increasing the risk of delayed recovery or further injury.
- **Lack of Remote Monitoring**: Physiotherapists struggle to track patient progress outside clinical settings, especially in areas with limited healthcare access.
- **Low Patient Motivation**: Repetitive and non-interactive exercises contribute to poor adherence and drop-out from rehabilitation programs.
- **Limited Personalization**: Static rehabilitation plans fail to adapt to individual progress, resulting in suboptimal outcomes.
- **Data Privacy Risks**: Handling sensitive health data without robust protection poses security and ethical concern

Challenges in Rehabilitation:

Despite advancements in rehabilitation technologies, several challenges persist, including:

- **Incorrect Exercise Execution:** Patients often perform rehabilitation exercises incorrectly without supervision, slowing recovery and increasing the risk of injury.
- **Lack of Remote Monitoring:** Physiotherapists face challenges in remotely monitoring patients, particularly in areas with limited access to clinics.
- **Low Patient Motivation:** Repetitive exercises can be disengaging, reducing adherence to rehabilitation programs.
- **Lack of Personalization:** Traditional rehabilitation plans do not adapt to individual patient progress, limiting effectiveness.
- **Sensor Limitations:** Single channel sEMG lacks context; fused sensors IMU CV resolve this **Data Privacy Concerns:** Sensitive medical data requires encryption and access control to prevent security breaches.
- **Multisensor Integration Challenge in the Mobile Application**
  lntegrating multiple biosensors (IMU, ECG) into a single mobile application presents several

2.3 Research Objectives

1. **Classify User Status:**
   a. Analyze real-time surface electromyography (sEMG) signals to monitor muscle activity.
   b. Detect movement inconsistencies and classify users as normal or abnormal.
2. **Ensure Data Security:**
   a. Protect sensitive patient data, including EMG sensor readings.
   b. Implement encryption, blockchain, and secure storage to prevent unauthorized access.
3. **Enhance Engagement and Compliance:**
   a. Provide AI-driven insights and motivational feedback to patients.

    b. Use gamification techniques to encourage adherence without altering the rehabilitation process.
4. **Enable Remote Monitoring:**
    a. Develop a mobile application for physiotherapists to track progress.
    b. Provide real-time alerts for incorrect exercise execution.

2.4 Scope and Methodology

- **Technical Scope**:
    - Development of an IoT-based system integrating EMG/motion sensors, a mobile app, and cloud infrastructure.
    - Focus on real-time biofeedback, remote monitoring, and secure data transmission.
- **Functional Scope**:
    - Patients: Guided exercises with form correction via sensor feedback.
    - Physiotherapists: Remote progress tracking and treatment plan adjustments.
- **Limitations**:
    - Testing limited to specific musculoskeletal conditions (e.g., post-surgery recovery).
    - Sensors require calibration for individual patients.

2.5 Significance of the Study

- **Clinical Impact**:
    - Bridges gaps in traditional physiotherapy by enabling data-driven, personalized rehabilitation.
    - Reduces recovery time through real-time corrections and remote supervision.
- **Technological Innovation**:
    - Demonstrates the viability of IoT and AI in improving healthcare accessibility.

Chapter 3: Theoretical Foundations

3.1 IoT and Sensor Technology

The Internet of Things (IoT) represents a network of interconnected devices that collect, exchange, and analyze data. In healthcare, IoT has enabled:

- **Continuous Monitoring**: Wearable sensors provide 24/7 health tracking beyond clinical settings

- **Biomedical Sensing**: Specialized sensors like EMG (electromyography) measure muscle activity, while IMUs (inertial measurement units) track motion
- **Data Integration**: Multiple sensor inputs combine to create comprehensive patient profiles
- **Real-Time Feedback**: Immediate analysis of sensor data enables timely interventions

Key sensor types include:

- **Biosensors**: Detect physiological signals (muscle activity, heart rate)
- **Motion Sensors**: Accelerometers, gyroscopes, and magnetometers for movement analysis
- **Environmental Sensors**: Monitor exercise conditions (temperature, humidity)

3.1.1 EMG Sensor

The Electromyography (EMG) sensor is a biomedical device designed to detect and record the electrical activity produced by skeletal muscles. It is widely used in rehabilitation systems, prosthetic control, sports science, and biomedical research.

- **Purpose**:
  EMG sensors are used to assess muscle function by measuring muscle activation levels. This data is crucial for diagnosing neuromuscular disorders, analyzing physical performance, and controlling assistive devices like exoskeletons and prosthetics [1].
- **Working Principle**:
  When muscles contract, they generate electrical potentials. The EMG sensor uses electrodes to detect these signals from the skin surface or intramuscularly. The captured signals are typically in the microvolt to millivolt range and are amplified, filtered, and digitized for further analysis.
- **Signal Characteristics**:
  EMG signals are stochastic and non-stationary. Key features include amplitude, frequency, and signal duration. These can be used to detect muscle fatigue, motion intention, or abnormal activity during rehabilitation exercises.

- **Application in Egypt**:
  In Egypt, the most commonly available EMG modules in educational and research contexts are **single-channel (1-channel) EMG sensors**, such as the MyoWare Muscle Sensor. While they are limited in terms of spatial resolution compared to multi-channel systems, they are cost-effective and sufficient for many rehabilitation and classification tasks.
- **Integration and Use**:
  EMG sensors can be interfaced with microcontrollers (e.g., Arduino, ESP32) to collect real-time muscle activity data. This data can be processed using machine learning algorithms to classify motion patterns or detect abnormal contractions in smart health monitoring systems.

3.2 MPU-6050 IMU Sensor Module [15]

Purpose:
The purpose of integrating an Inertial Measurement Unit (IMU) into the system is to estimate the **knee joint angle** during lower limb rehabilitation exercises, particularly Terminal Knee Extension (TKE). Joint angle tracking is essential for evaluating the correctness and range of motion (ROM) of each movement, providing real-time kinematic feedback that complements muscle activity data from EMG. Accurate angle monitoring is critical in assessing exercise quality, ensuring proper knee alignment, and detecting any compensatory or abnormal patterns that could affect recovery outcomes.

Working Principle:
IMUs function by combining data from accelerometers and gyroscopes. The accelerometer detects linear acceleration, typically used to estimate static orientation with respect to gravity. The gyroscope captures rotational velocity, which helps track dynamic movement. By applying sensor fusion algorithms—such as the Complementary Filter—both static and dynamic inputs are merged to yield a robust and accurate estimation of joint angles.

Signal Characteristics:
The accelerometer signal reflects slow, gravity-related position changes and is prone to noise during motion. Conversely, the gyroscope provides smooth and responsive data for rapid changes but suffers from drift over time. Sensor fusion mitigates these limitations by leveraging the stability of the accelerometer and the responsiveness of the gyroscope. Together, they enable reliable real-time tracking of joint angles with sufficient temporal resolution for feedback systems.

IMU Components (Accelerometer, Gyroscope)

The **MPU6050** integrates a **3-axis accelerometer** and a **3-axis gyroscope** into a single chip, enabling detection of both linear acceleration and angular velocity:

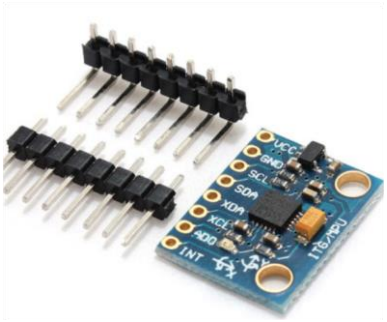
- **Accelerometer** measures acceleration along x, y, and z axes. It helps detect static position relative to gravity.
- **Gyroscope** measures rotational velocity in degrees per second around the same three axes, capturing dynamic motion.

These sensors are combined in the **GY-521 breakout board**, which communicates via I2C and is widely used for real-time motion tracking.

DOF Motion Sensing Principles

"**Degrees of Freedom (DoF)**" refer to the number of independent movements a body can perform in 3D space:

- The MPU6050 provides **6-DOF**: 3 translational movements (X, Y, Z) from the accelerometer and 3 rotational movements (roll, pitch, yaw) from the gyroscope.
- In knee joint analysis, this helps **track flexion/extension movement** in the sagittal plane with precise orientation and velocity data.



3.2 MPU-6050 IMU Sensor

Justification for Tool Selection

The **MPU-6050** IMU sensor was selected for this project due to its optimal balance between functionality, integration ease, and cost-effectiveness, particularly in applications involving real-time lower limb motion tracking for rehabilitation.

This sensor integrates a **3-axis accelerometer** and a **3-axis gyroscope** into a single compact unit, offering **6 Degrees of Freedom (6-DOF)** motion tracking. When used in conjunction with the EMG sensor, it allows for simultaneous monitoring of **joint kinematics and muscle activity**, which is essential for evaluating knee movement dynamics in rehabilitation scenarios

Sensor/System	Advantages	Limitations	Suitability for TKE
MPU-6050	Low cost, I²C, 6-DOF	Drift over time	High (with filtering)
BNO055	9-DOF, onboard fusion	Magnetic interference	Moderate
Optical (Vicon)	High accuracy	Cost, non-portable	Low

6.1.6 Justification for Tool Selection

3.1.3 ECG Sensor

The Electrocardiogram (ECG) sensor is a biomedical device used to measure the electrical activity of the heart over time. It plays a critical role in medical diagnostics and real-time health monitoring systems. Below are key characteristics and functions of the ECG sensor:

- **Purpose**:
  It detects the electrical signals generated by the heart as it contracts and relaxes, providing valuable data for diagnosing arrhythmias, ischemia, and other cardiac conditions [1].

- **Working Principle**:
  The ECG sensor uses surface electrodes placed on the skin to capture the tiny electrical impulses generated by the cardiac muscle. These signals are then amplified and digitized for further processing.

- **Signal Characteristics**:
  The ECG waveform typically includes the P wave, QRS complex, and T wave. Analyzing the timing and amplitude of these components can provide insights into heart rate, rhythm, and overall cardiac function.

- **Applications in Smart Health Systems**:
  ECG sensors are commonly integrated into wearable devices and rehabilitation systems to continuously monitor the patient's heart status during physical activity, particularly in elderly and post-operative patients [2].

- **Sensor Types**:
  There are single-lead, 3-lead, and 12-lead ECG configurations. For portable and wearable applications, single- or 3-lead ECG modules (like the AD8232 or MAX30003) are often used due to their low power consumption and ease of integration.

- **Data Integration**:
  The raw ECG data can be transmitted to a microcontroller or mobile application for real-time visualization and further analysis using machine learning or expert system algorithms.

3.2 Mobile Applications in Healthcare

The mobile application, **FlxiCare**, is a core component of the rehabilitation system, designed to facilitate remote rehabilitation for patients suffering from knee pain or undergoing general fitness training. Built using the Flutter framework, **FlxiCare** provides an intuitive and role-based interface for both patients and physical therapists. It integrates various functionalities including real-time EMG data classification, remote booking, personalized exercise plans, and progress tracking.

Mobile health applications like **FlxiCare** have become increasingly important in modern healthcare, particularly in fields such as physiotherapy and rehabilitation. They offer a flexible and accessible platform that empowers patients to actively participate in their recovery process outside of traditional clinical settings. By leveraging wearable sensors, machine learning models, and secure cloud-based systems, mobile apps enable continuous monitoring and data-driven decision-making, improving the overall quality of care.

Key Features

- **Accessibility and Usability**
  The mobile app enables patients to access their rehabilitation plans and perform evaluations anytime and anywhere, reducing the need for in-person visits and making healthcare more inclusive and continuous.
- **Role-Based Interaction**
  Through role-based access (Patient or Therapist), the app offers customized interfaces tailored to each user’s responsibilities.

- **User Authentication**
  Secure login and sign-up are implemented using Firebase Authentication, with automatic role-based redirection upon login.
- **Initial EMG Evaluation**
  After sign-up, patients undergo an EMG-based assessment using real-time signals collected from a wearable device. The signals are processed by a backend machine learning model to classify the patient as either "Normal" or "Abnormal," personalizing the rehabilitation journey.
- **Real-Time Data Collection**
  The app integrates with EMG sensors via an ESP32 microcontroller to stream muscle activity signals. These signals are processed using a Flask-based backend to detect abnormalities in muscle function.
- **Personalized Exercise Plans**
  Based on the EMG evaluation result, patients receive tailored exercise plans focused either on pain relief (for abnormal cases) or general fitness (for normal cases).
- **Remote Appointment Booking**
  Patients can browse available therapists, view their schedules, and send booking requests. Therapists can manage and respond to these requests directly within the app.
- **Therapist Management Tools**
  Therapists have access to tools that allow them to manage upcoming sessions, view confirmed patients, and update their availability dynamically.
- **Camera-Based Motion Tracking**
  In the fitness module, the app uses the mobile camera to track body movement during exercises, providing real-time visual feedback to help users maintain correct form and posture.
- **Sensor Fusion with IMU**
  The system also supports integration with IMU sensors (accelerometer and gyroscope) to enhance movement accuracy and joint angle analysis.
- **Security and Privacy**
  Sensitive data is encrypted using AES encryption prior to storage or transmission. The app also integrates blockchain mechanisms to ensure data integrity and privacy, as further detailed in Section 6.3.

Technology Stack

Technology	Role	Purpose
Flutter (Dart)	Frontend	Mobile app UI and navigation
Flask (Python)	Backend	API logic, data classification (EMG)
Firebase Firestore	Cloud Database	Store users, therapists, appointments, roles
Firebase Realtime Database	Live Data Streaming	Stream EMG signal from ESP32

Firebase Authentication	Authentication Layer	Secure login, sign-up, and role redirection
ESP32 Microcontroller	Hardware Integration	Collect EMG, ECG and IMU signals.
Machine Learning Model (Python)	Signal Classification	Detect “Normal” or “Abnormal” condition
Camera (Flutter plugin)	Motion Tracking (Fitness)	Track body movement during fitness exercises
IMU Sensors	Motion Data Acquisition	Provide additional posture/movement feedback
EMG Sensor	Muscle Activity Monitoring	Detect muscle activation patterns and fatigue
ECG Sensor	Heart Activity Monitoring	Analyze heart rate, rhythm, and detect anomalies
AES Encryption + Blockchain	Security Layer	Ensure data confidentiality and integrity

3.3 Security and Privacy

In healthcare:

A) Security plays a vital role in the healthcare system, as it safeguards highly sensitive and personal patient data, including diagnoses, treatment history, mental health notes, medications, and personally identifiable details. Without strong security, unauthorized access can lead to identity theft, discrimination, or a breakdown in trust between patients and healthcare providers. Ensuring data confidentiality is essential for privacy protection and compliance with laws like HIPAA, GDPR, and national regulations. Integrity is equally critical—unauthorized alterations could cause misdiagnosis or treatment errors; techniques like digital signatures, blockchain, and checksums help maintain data accuracy. Availability is also crucial hospitals rely on constant system access for emergencies and daily care, while cyberattacks like ransomware can halt operations and endanger lives, making defenses like network monitoring, intrusion detection, and backups essential. Legal compliance demands robust security, as failure can lead to penalties, license loss, or damaged public trust. Security also prevents fraud—like fake prescriptions, insurance claims, or impersonation—through tools like

digital signatures, biometric verification, and blockchain. With the rise of telehealth, secure internet communication is vital, requiring end-to-end encryption, VPNs, and secure authentication. Research data protection is key to preserving intellectual property and medical progress through encryption and access control. Overall, strong security builds trust, as breaches harm reputations and discourage care-seeking, affecting public health. With evolving threats targeting hospitals, data centers, and IoT devices like pacemakers, healthcare must adopt modern standards, including staff training, audits, risk assessments, and penetration testing

B) Encryption Methods in Cybersecurity:

1. Symmetric Encryption

- **Definition**: Uses a **single secret key** for both encryption and decryption.
- **Common Algorithms**:
    - **AES (Advanced Encryption Standard)**: 128-bit, 192-bit, or 256-bit keys (most secure).
    - **DES (Data Encryption Standard)**: Older, less secure (56-bit key).

2. Asymmetric Encryption (Public-Key Cryptography)

- **Definition**: Uses a **public key** (shared) and a **private key** (kept secret).
- **Common Algorithms**:
    - **RSA (Rivest-Shamir-Adleman)**: Used in SSL/TLS, digital signatures.
    - **ECC (Elliptic Curve Cryptography)**: Stronger than RSA with shorter keys.
- **Applications**:
    - Password storage (with salt).
    - Data integrity checks (file verification).

-Why I chose AES algorithm (Advanced Encryption Standard)

Feature	AES (Advanced Encryption Standard)	RSA (Rivest–Shamir–Adleman)	DES (Data Encryption Standard)	SHA (Secure Hash Algorithm)	Blowfish
Type	Symmetric (same key for encrypt/decrypt)	Asymmetric (public/private keys)	Symmetric	Hash function (one-way)	Symmetric
Key Size	128, 192, 256 bits	1024–4096 bits	56 bits	Fixed-length (SHA-1: 160 bits, etc.)	32–448 bits
Security Strength	High (especially AES-128+)	High but slower than AES	Weak (vulnerable to brute-force)	Not reversible (not for encryption)	Strong (if properly configured)
Speed/Performance	Fast and lightweight	Slow (not suitable for real-time EMG)	Fast but insecure	Very fast, but only for verification	Moderate
Resource Efficiency	High (ideal for ESP32, IoT devices)	Low (heavy CPU and RAM usage)	High, but obsolete	High (not used for encryption)	Medium
Real-time Data Suitability	Excellent (low latency)	Poor (asymmetric overhead)	Good, but insecure	Not applicable	Good
Encryption Mode Support	Multiple (e.g., CBC, GCM, ECB)	Not block-based	Only ECB (easily attacked)	N/A (non-reversible)	Supports modes, but less standardized
Compatibility with Firebase	Yes (Base64 encoding works well)	Yes, but adds complexity	Yes, but not recommended	Not used for encryption	Yes
Cross-Platform Support	Excellent (Arduino, Dart, Python, etc.)	Poor (requires key-pair support)	Moderate	N/A	Moderate
Why We Didn't Use It	—	Too slow for ESP32, complex key mgmt.	Insecure, deprecated	Not suitable for encrypting data	Less community support, heavier setup

C) Blockchain Technology & Applications:

1. What Is Blockchain?

- A **decentralized, distributed ledger** that records transactions in blocks linked via cryptography.
- **Key Features**:
    - **Immutability**: Once recorded, data cannot be altered.
    - **Decentralization**: No single authority controls the network.

- **Transparency**: All participants can verify transactions.

2. How Blockchain Works

1. **Transaction Initiation**: A user requests a transaction (e.g., sending cryptocurrency).
2. **Verification**: Network nodes (miners/validators) confirm the transaction via consensus (PoW/PoS).
3. **Block Creation**: Valid transactions are grouped into a block.
4. **Hashing & Chaining**: Each block contains a cryptographic hash of the previous block, forming a chain.
5. **Finalization**: The block is added to the blockchain and broadcast to all nodes.

4. Blockchain Applications Beyond Cryptocurrency

- **Smart Contracts**: Self-executing contracts (e.g., Ethereum, Solana).
- **Healthcare**: Secure patient records, drug traceability.

Chapter 4: Methodology

4.1 Sensor-Based Signal Acquisition

4.1.1 EMG-Based Rehabilitation Diagnosis and Monitoring System

EMG-Based Rehabilitation Diagnosis and Monitoring System

The system measures muscle activity using surface EMG signals to determine whether the movement pattern is normal or abnormal. It is specifically applied to the vastus medialis (VM) muscle, which plays a key role in knee function during rehabilitation.

After the user performs several repetitions of the same exercise, the system analyzes the EMG patterns across these trials to assess consistency and performance. Based on this analysis, it provides feedback indicating whether the user's execution is within normal range or deviates from expected patterns, supporting informed rehabilitation decisions

Dataset Used Description

- **Sensor Type**: MyoWare surface EMG sensor

- **Sampling Rate**: 1000 Hz
- **Muscle Monitored**: Vastus Medialis (VM)

  Reason for Selection:
  - Most clinically relevant muscle for knee stabilization
  - Frequently affected in knee disorders such as ACL injuries and patellofemoral maltracking
- **Dataset Used:** Publicly available sEMG dataset from the UCI Machine Learning Repository [14].
  - **Subjects**: 22 male participants
    - 11 with diagnosed knee pathologies
    - 11 healthy controls
  - **Muscles Recorded**: VM, Rectus Femoris (RF), Biceps Femoris (BF), Semitendinosus (ST)
  - Only **VM** was retained due to hardware limitations (single-channel input on the real-time EMG device)

- ## Limitations of Single-Channel EMG Acquisition

The key limitation of this setup is its single-channel configuration, which restricts simultaneous monitoring to one muscle. In contrast, multi-channel EMG systems allow comprehensive analysis across multiple muscles, offering richer insights into muscle coordination and movement dynamics.

Despite this limitation, focusing on a single muscle—the Vastus Medialis (VM)—provides clinically meaningful data. The VM is vital for knee stabilization and is often affected in musculoskeletal and neurological conditions. Monitoring this muscle alone can effectively detect functional impairments relevant to the project's rehabilitation goals.

Real-Time Data Acquisition Procedure

The sensor was placed on the skin over the Vastus Medialis following standardized electrode placement protocols to maximize signal quality and reproducibility.

Subjects performed controlled functional movements, such as walking and leg extensions, consistent with existing clinical datasets. The data acquisition workflow included:

- Analog EMG signal detection by the surface electrodes.
- Digitization and wireless transmission by the ESP32 microcontroller.
- Real-time reception and storage of the data on a laptop.

- Signal preprocessing involving noise filtering, rectification, and feature extraction, preparing the data for machine learning classification within the system.

This carefully designed pipeline ensures reliable, high-quality EMG data suitable for robust analysis and user state classification.

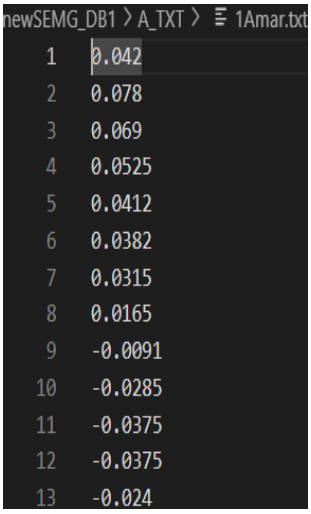
Preprocessing Pipeline

The preprocessing [2] stage converts raw sEMG signals into clean, structured windows suitable for machine learning. The key phases include:

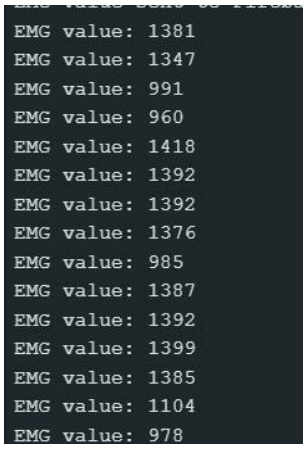
Step 1: Signal Cleaning and Filtering

- **Bandpass Filtering:** Already applied during acquisition using a 20–460 Hz fourth-order Butterworth filter
- **Purpose:** Removes baseline drift, motion artifacts, and high-frequency noise make it like dataset we used

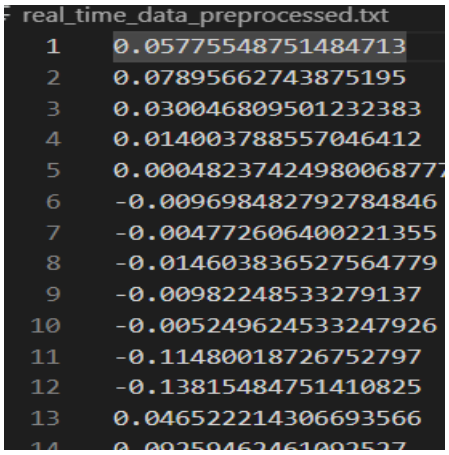
Data in Dataset



Data real-time without Bandpass filter



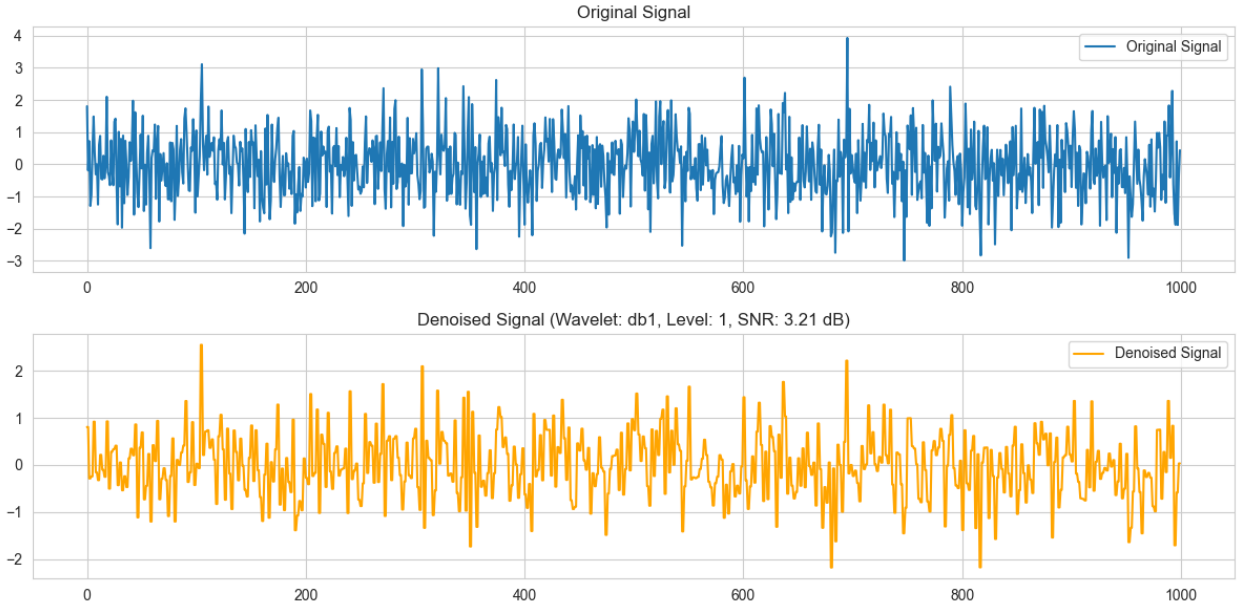
Data real-time with Bandpass filter



Step 2: Denoising Using Wavelet Transform

- Applied discrete wavelet denoising using one-level Haar (db1) decomposition
- Suppresses high-frequency noise while preserving EMG bursts and low-frequency components
- Maintains sharp transients and key signal structure without excessive smoothing

Denoising signal

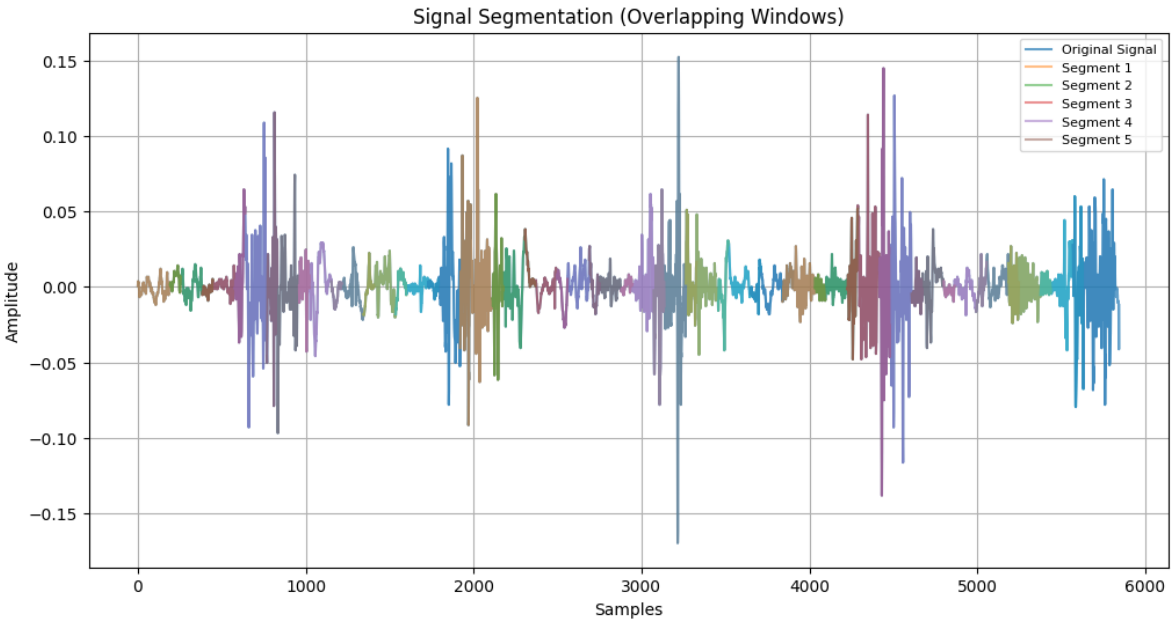


Step 3: Segmentation

- The denoised EMG time series were segmented into short, overlapping windows to prepare the data for feature extraction.
- Each window was:
    - 256 milliseconds in duration (256 samples at 1 kHz),
    - With 25% overlap between successive windows.
- This setup helps satisfy the quasi-stationarity assumption of EMG signals.
- Supporting studies:
    - Nazmi et al. found that 200 ms windows captured stationary EMG content approximately 88% of the time.[2]
    - Phinyomark et al. observed a 2–3% improvement in classification accuracy when increasing segment length from 125 ms to 250 ms.
- Advantages of overlapping windows:
    - Prevents loss of transient events at window boundaries.

- Maintains temporal continuity between adjacent segments.
- Preserves the dynamic behavior of muscle activity over time

Signal segmentation



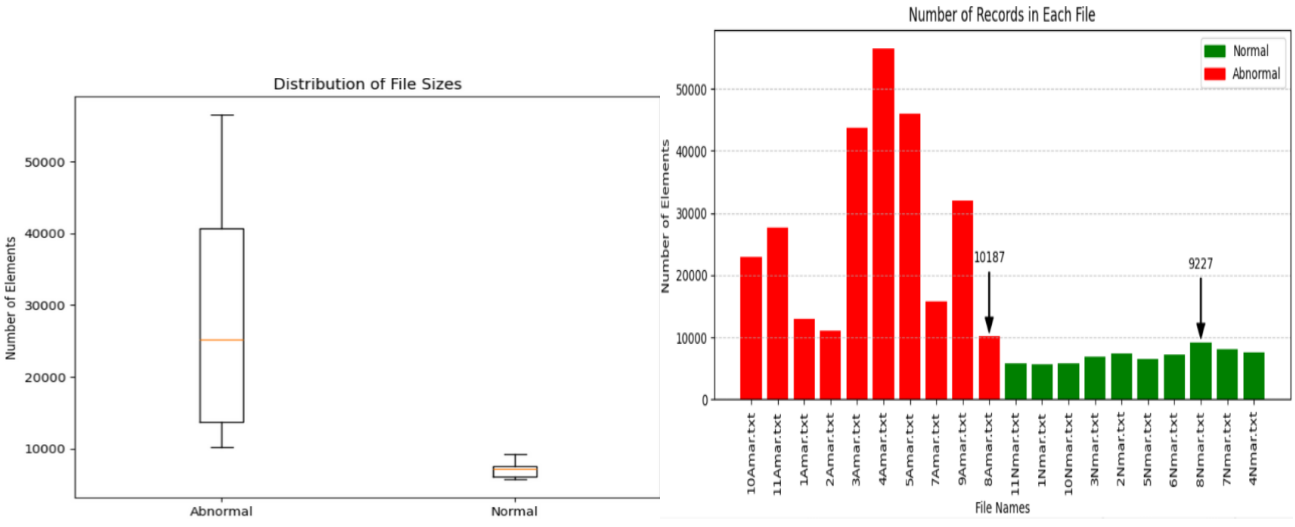
Step 4: Normalization

- Each segmented window was normalized to reduce amplitude differences between subjects and muscle groups.
- We applied min–max scaling to the range [0,1] on each window independently.
- This normalization was applied:
  - Either on the raw windowed signal, or
  - Equivalently, on each extracted feature from the window.
- Purpose of normalization:
  - Aligns the dynamic range across all channels and subjects.
  - Mitigates inter-subject variability caused by:
    - Electrode placement,
    - Muscle strength,
    - Skin conductivity, etc.
  - Prevents any single channel or feature from dominating due to large magnitude differences.
- Ensures fair feature contribution during classification and improves the model's generalization across users.

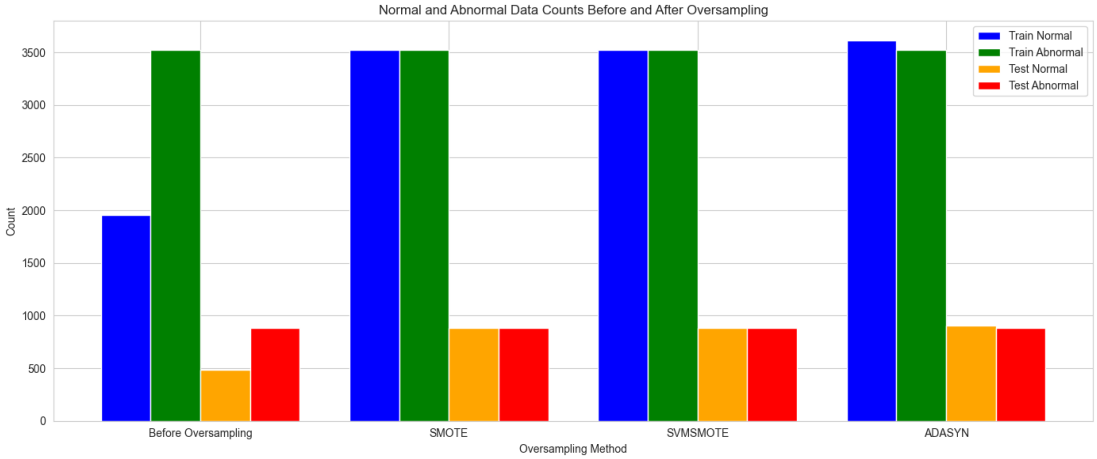
Step 5: Data Balancing (Oversampling)

- After segmentation, we observed an imbalance in the number of windows:
  - Abnormal subjects had more segments due to longer walking trials.
  - Healthy subjects (minority class) had fewer segments.
- To address this imbalance and prevent classification bias, we applied synthetic oversampling on the healthy class windows.
- We evaluated and compared several oversampling techniques:
  - SMOTE (Synthetic Minority Over-sampling Technique)
  - ADASYN (Adaptive Synthetic Sampling)
  - SVM-SMOTE (Support Vector Machine-based SMOTE)
- These methods create synthetic samples via interpolation:
  - For example, SMOTE generates new samples along line segments between a given minority-class point and its nearest neighbors.
- Key enhancement in our pipeline:
  - Oversampling was applied before feature extraction, directly on the raw signal windows.
  - This ensures that:
    - Feature extraction is performed on a balanced dataset.
    - The resulting feature distributions are unbiased.
    - No class (especially the majority) dominates the learned features.
- Oversampling improved the class distribution balance and is known to boost classifier performance on imbalanced datasets.

Imbalanced Data



Data After using Oversampling



Step 6: Feature Extraction

- **Time-domain features were extracted from each window after oversampling.**
- **A total of 11 features were used, covering:**
  - **Amplitude,**
  - **Complexity/variability,**
  - **Statistical moments.**
- **Each feature was computed per channel in each window.**

Amplitude Features

- **MAV (Mean Absolute Value): Average rectified EMG; reflects contraction level.**
- **RMS (Root Mean Square): Signal energy measure.**

Complexity / Variability

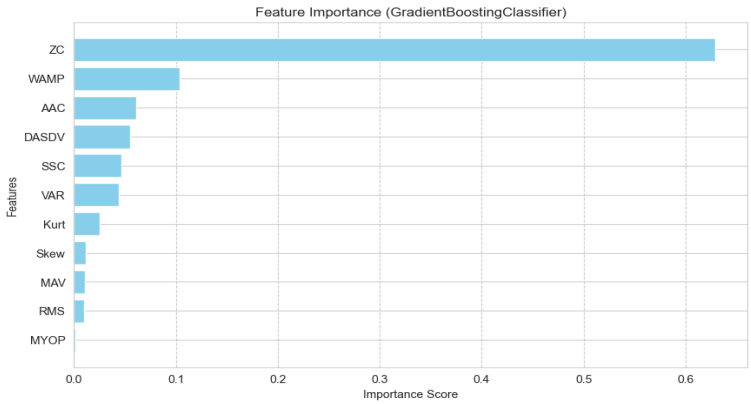
- **ZC (Zero Crossings): Frequency-related; number of zero crossings.**
- **SSC (Slope Sign Changes): Waveform direction changes.**

- **VAR (Variance): Signal power and variability.**
- **WAMP (Willison Amplitude): Burst activity; counts large signal changes.**
- **MYOP (Myopulse Rate): Percent of samples above threshold (burst density).**

Statistical Features

- **DASDV: Mean of squared differences; variability indicator.**
- **AAC: Mean absolute difference; activity variation.**
- **Skewness: Asymmetry of signal amplitude.**
- **Kurtosis: Peakedness or tail heaviness.**
- **These features provide a rich description of EMG signal shape, energy, and complexity for classification.**

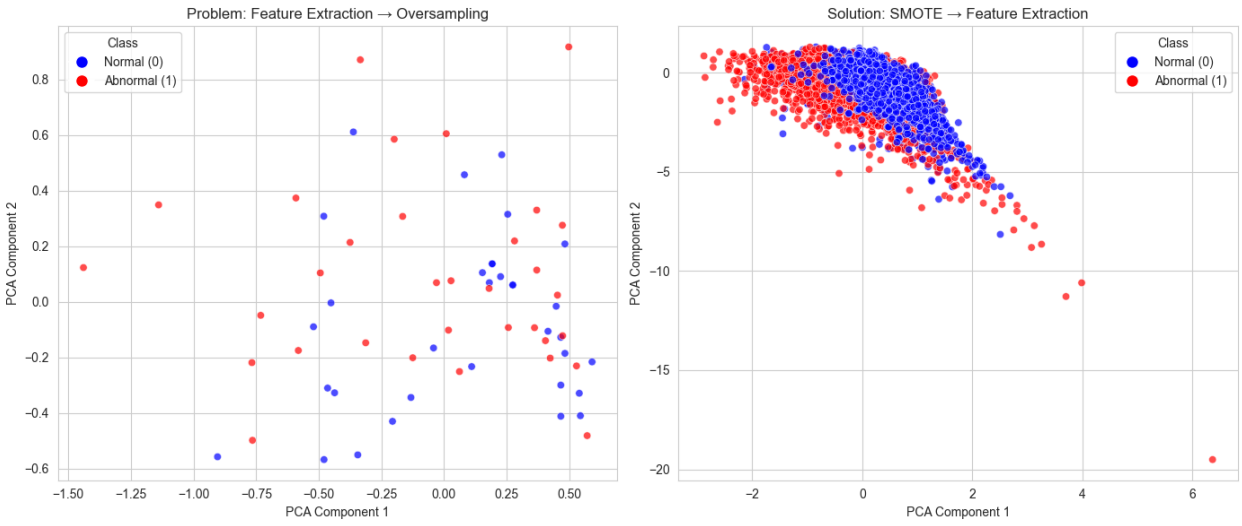
Features Importance



Challenges and Solutions

Challenge	Root Cause	Solution	Impact

Low signal-to-noise ratio (ambient/motion noise)	Presence of high-frequency interference and low-frequency drift in raw sEMG signals.	Applied **band-pass filtering (20–460 Hz)** and **wavelet denoising (db1, soft thresholding)**.	Enhanced signal quality and improved signal-to-noise ratio (SNR).
Non-stationary, time-varying signals	EMG characteristics change rapidly over time; full-length signals lack consistent statistical properties.	Segmented the signal into **256 ms windows** with **25% overlap** to ensure local stationarity.	Produced stable input segments for feature extraction and improved temporal resolution.
Class imbalance between groups	Abnormal subjects generated longer recordings, leading to more segments in the abnormal class.	Applied **synthetic oversampling (SMOTE, ADASYN, SVM-SMOTE)** to increase the number of normal samples.	Balanced training data, improved generalization, and reduced bias in classification.
Heterogeneous feature scales	Feature ranges varied significantly due to different muscle signals and amplitudes.	Performed **min–max normalization** to scale all features between [0,1].	Ensured fair contribution of each feature and improved model convergence.
Bias toward abnormal class after feature extraction and oversampling	**Oversampling was applied after** feature extraction, leading to feature space dominated by the abnormal class.	**Reordered the pipeline**: performed **oversampling before** feature extraction to ensure balanced input for feature computation.	Mitigated feature-level bias, enhanced performance for the normal class, and improved overall classification balance.



Classification

Two modeling approaches were evaluated for EMG signal classification:

- **Deep Learning models** (e.g., RNN, LSTM, GRU, CNN-LSTM) to capture temporal patterns in raw signals.
- **Traditional Machine Learning models** trained on extracted time-domain features (e.g., RMS, ZCR, WL).

The goal was to determine which paradigm offers better accuracy, generalization, and real-time deployment potential.

- **Time Series Deep Learning Models for EMG Classification: Architecture and Performance Comparison**

Model	Architecture Summary	Test Accuracy	F1-Score	Strengths	Weaknesses
Simple RNN	2 × SimpleRNN (64 → 32) → Dense(16) → Dense(1, sigmoid)	~64.2%	0.64	- Captures basic temporal patterns - Low parameter count	- Underfitting - Cannot model long-term dependencies - High training time per epoch (~23 mins) - Poor generalization
GRU	GRU(64 → 32) + Dropout + Dense(16) → Output	~70.5%	0.83	- Captures dependencies efficiently - Generalizes well - Less complex than LSTM	- Long training time (~70 mins/epoch) - Slight prediction bias toward abnormal class
LSTM	2 × LSTM(50) + Dropout(0.3) → Dense(1, sigmoid)	~64%	0.64	- Better for long-term dependencies - Dropout helps regularize	- Similar performance to RNN - Training time high - Limited by single-channel input
CNN-LSTM	Conv1D(64) → MaxPooling → Dropout → LSTM(64) → Dense(1)	~69% (est.)	0.69	- Learns spatial + temporal patterns - Wavelet denoising improved	- Longer training time - Complexity may cause overfitting if poorly tuned - Still limited by single EMG channel

				accuracy - Most robust overall performance	

- While deep learning models such as Simple RNN, LSTM, GRU, and CNN-LSTM were initially used to capture the temporal dynamics of raw EMG signals, a shift toward traditional machine learning models was later made due to practical and performance-related considerations.
- Given that EMG signals are time-dependent, sequence-based models were a natural starting point, aiming to learn muscle activation patterns and movement transitions. GRU and CNN-LSTM offered better generalization than basic RNN and LSTM.
- However, deep models faced several challenges, including long training times (e.g., 70 minutes per GRU epoch), relatively lower accuracy and F1-scores, a tendency to overfit with limited data, and difficulty deploying on resource-constrained devices.

- **Machine Learning Models for EMG Classification: Configuration and Results**

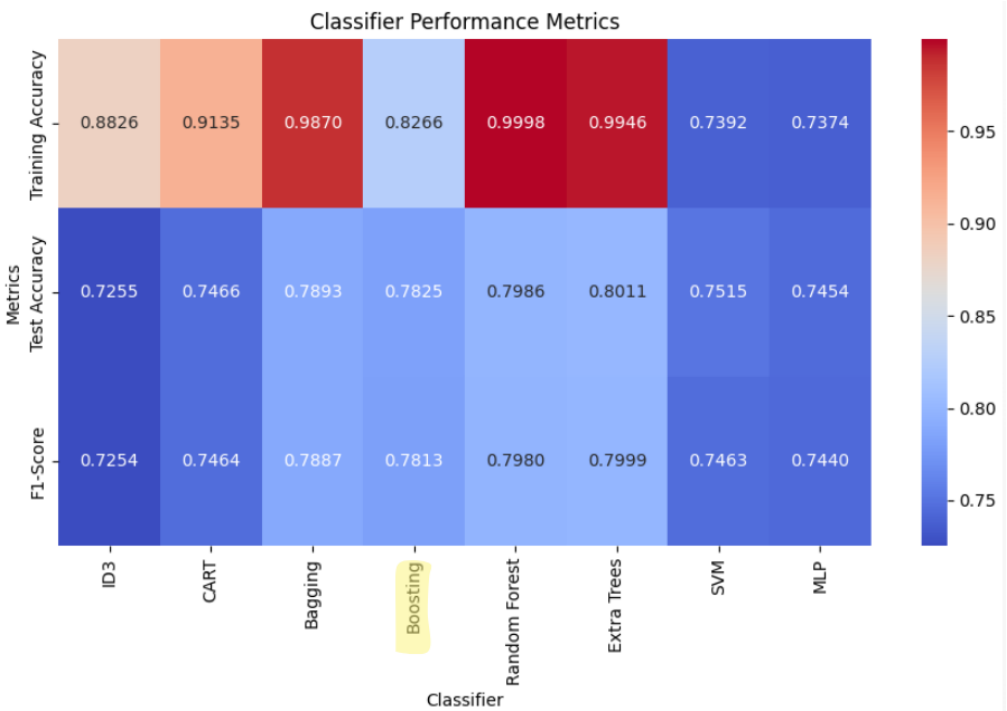
Model	Configuration	Accuracy	F1-Score	Strengths	Weaknesses
Decision Tree (ID3)	Entropy criterion, max_depth=15	74.10%	74.00%	- Simple & interpretable - Good for rule-based EMG patterns	- Overfits easily - Poor generalization
CART	Gini criterion, max_depth=15	72.00%	71.95%	- Faster than ID3 - Stable under light noise	- Same overfitting issues - Not robust under complex signals
Bagging Classifier	100 Decision Trees, bootstrap aggregation	78.31%	78.28%	- Reduces overfitting - More generalizable than single trees	- Less interpretable - Higher computational cost
Random Forest	150 trees, max_depth=10	79.37%	79.32%	- Great at handling non-linearity - High test performance	- Near-perfect training accuracy → high variance

Extra Trees	150 randomized trees, max_depth=10	79.55%	79.50%	- Very fast - Avoids overfitting better than RF	- Can underfit if too random
Gradient Boosting	200 estimators, learning_rate=0.05, max_depth=4	**77.20%**	**77.04%**	- Balanced generalization - Resists overfitting - Strong F1	- Longer training time - Sensitive to hyperparameters
SVM (RBF kernel)	C=2.0, gamma=scale, probability=True	75.1%	71.22%	- Good for small datasets - Defined decision boundary	- Struggles with noisy or overlapping signals
MLP	(128, 64) hidden layers, early stopping, 500 max_iter	74.54%	74.22%	- Captures non-linearity - Scalable	- Not sequence-aware - Needs proper input normalization

Compared to deep learning models, feature-based machine learning classifiers showed better performance, especially under practical constraints like limited data and single-channel EMG input.

The shift toward ML models was supported by both performance metrics and real-time system requirements. In this context, ML classifiers proved to be more reliable, interpretable, and suitable for deployment.

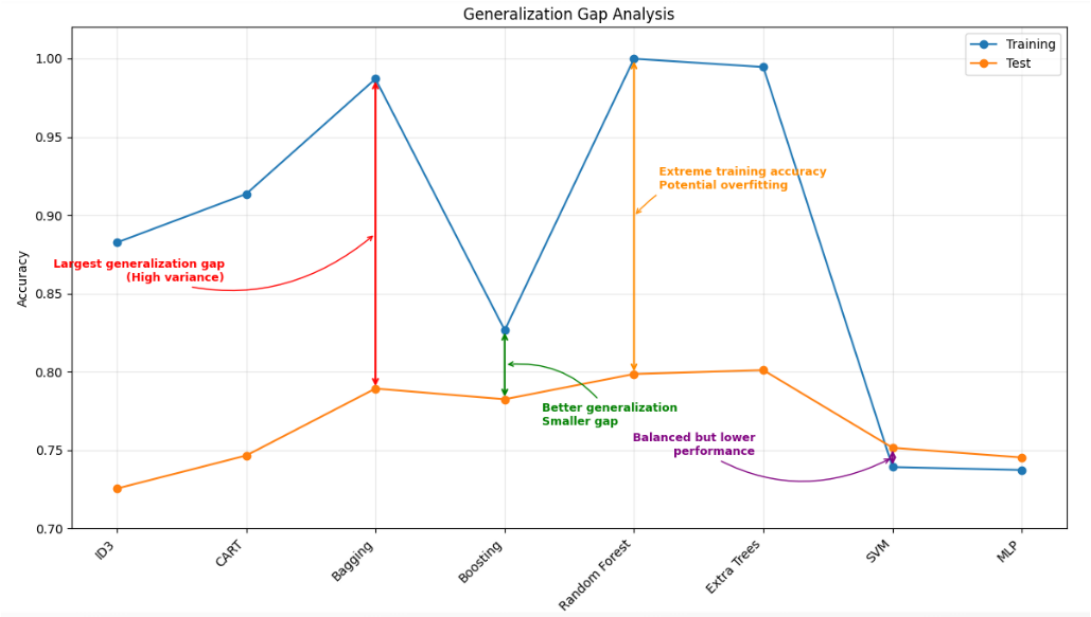
Classifier Performance Metrics for the ML models.



Model Selection: Boosting

Among all classifiers, **Gradient Boosting** was selected as the final model for the following reasons:

- **Balanced Generalization:** Training and test accuracy are closely aligned, indicating a healthy model fit without overfitting.
- **Competitive Accuracy:** Despite not being the top performer in training accuracy, Boosting achieved consistent real-world test accuracy (~79%).
- **Bias-Variance Tradeoff:** Boosting offers an effective balance, correcting weak learners iteratively without becoming overly complex—ideal for our single-channel EMG signals with limited features.



Generalization Gap Analysis for the ML models.

Based on generalization gap analysis, Boosting demonstrated:

- High test accuracy with stable performance
- Controlled training variance
- Strong real-world applicability

This made it the optimal choice for our classification engine, prioritizing reliability and deployability in physiotherapy and rehabilitation settings.

Why Boosting Remains the Preferred Model

While other models marginally outperformed Boosting in specific metrics:

- Boosting consistently maintained low variance
- Delivered reliable prediction across both classes
- Avoided the overfitting observed in ensemble tree models

These qualities make Boosting the ideal classifier for our real-time EMG-based movement abnormality detection system.

Summary

- Signals were collected from the VM muscle using a MyoWare sensor at 1000 Hz
- A custom preprocessing pipeline was applied involving:
    - Morphological filtering and relative energy enhancement
    - Segmentation into overlapping time windows (256ms, 25% overlap)
    - Window-level normalization to [0–1]
    - SMOTE-based oversampling to correct class imbalance
- A total of **11 handcrafted time-domain features** were extracted to represent energy, waveform shape, and variability

This pipeline ensures high-quality EMG representation and prepares the data for robust detection of abnormal knee activity.

4.1.2 Rehabilitation Monitoring

4.1.2.1 LRCN Model for Joint Movement Detection

Overview of LRCN Architecture

The Long-term Recurrent Convolutional Network (LRCN) represents a hybrid deep learning architecture that combines the spatial feature extraction capabilities of Convolutional Neural Networks (CNNs) with the temporal sequence modeling power of Recurrent Neural Networks (RNNs). This architecture is particularly well-suited for processing time-series data where both spatial patterns and temporal dependencies are crucial for accurate analysis.

In the context of joint movement detection using EMG signals, the LRCN model addresses the fundamental challenge of analyzing complex electromyographic patterns that exhibit both instantaneous signal characteristics and long-term temporal dependencies. The model architecture

consists of two primary components: a convolutional feature extraction layer that processes the raw EMG signal patterns, and a recurrent layer that captures temporal relationships across multiple time steps.

Model Architecture Components [13]

Convolutional Feature Extraction Layer

The convolutional component of the LRCN model employs multiple 1D convolutional layers specifically designed for processing EMG signals. These layers utilize filters of varying kernel sizes (3, 5) to capture different frequency components and signal patterns present in the electromyographic data. The architecture incorporates:

- **Multi-scale Feature Extraction**: Sequential convolutional layers with increasing filter depths (64, 128, 256) to capture both low-level signal characteristics and high-level pattern representations
- **Batch Normalization**: Applied after each convolutional layer to stabilize training and improve convergence
- **Dropout Regularization**: Implemented at multiple levels (0.2-0.3) to prevent overfitting and improve generalization
- **Max Pooling**: Reduces temporal dimensionality while preserving important signal features

Bidirectional LSTM Layer

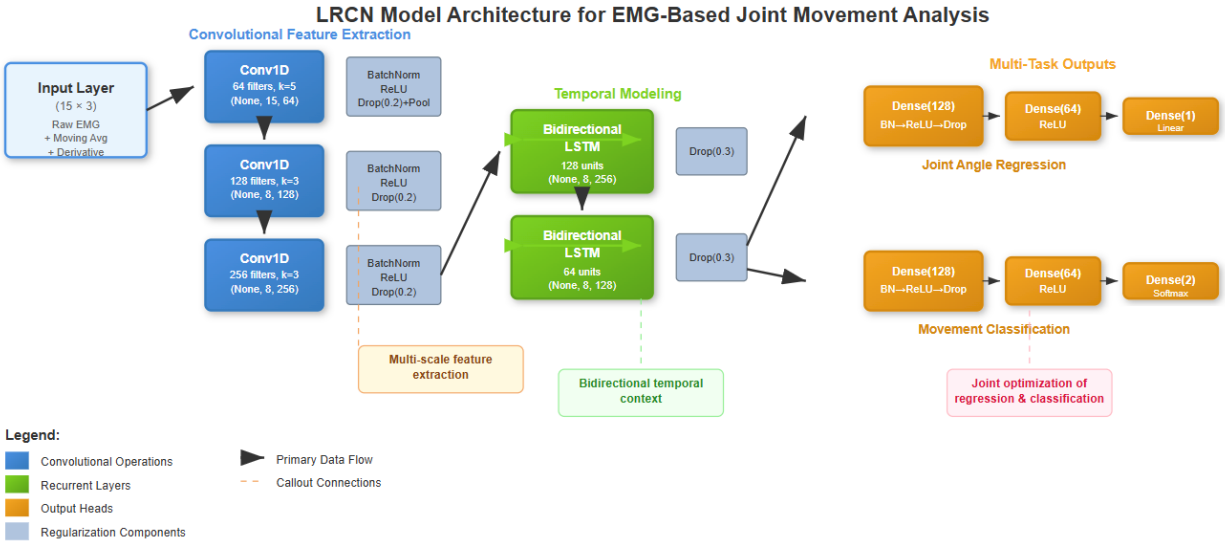
The recurrent component utilizes Bidirectional Long Short-Term Memory (LSTM) networks to capture temporal dependencies in both forward and backward directions. This bidirectional approach is crucial for EMG signal analysis as muscle activation patterns often exhibit dependencies that extend both into the past and future time steps. The LSTM architecture includes:

- **Dual-Direction Processing**: Forward and backward LSTM cells process the sequence in both temporal directions
- **Memory Cell Architecture**: Forget gates, input gates, and output gates regulate information flow and memory retention
- **Hierarchical Structure**: Multiple LSTM layers with decreasing complexity (128, 64 units) for progressive feature refinement

Multi-Task Output Architecture

The LRCN model implements a multi-task learning approach with two distinct output pathways:

1. **Joint Angle Regression**: Predicts continuous knee joint angles using a linear activation function
2. **Movement Classification**: Performs binary classification (normal vs. abnormal movement) using a softmax activation function



6.4.2 Model Architecture

Justification for LRCN Model Selection [13]:

Primary Advantages:

- **Temporal Dependency Modeling:**
  EMG signals inherently contain temporal patterns that reflect muscle activation sequences during movement. Traditional machine learning approaches struggle to capture these long-term dependencies effectively. The LRCN model's recurrent component specifically addresses this limitation by maintaining memory of previous signal states, enabling it to understand movement patterns that unfold over time.
- **Spatial Feature Extraction:**
  Raw EMG signals contain complex frequency components and amplitude variations that require sophisticated feature extraction. The convolutional layers in LRCN automatically learn relevant spatial features from the signal, eliminating the need for manual feature engineering and potentially discovering patterns that human experts might overlook.
- **Multi-Task Learning Capability:**
  The ability to simultaneously perform regression (joint angle prediction) and classification (movement abnormality detection) within a single model architecture provides computational efficiency and enables the model to learn shared representations that benefit both tasks.
- **Robustness to Signal Variations:**
  The combination of convolutional and recurrent layers provides inherent robustness to signal noise and variations in EMG amplitude that commonly occur due to electrode placement differences or individual physiological variations.

Model Configuration and Training Strategy

Data preparation and Augmentation on EMG Dataset on lower limb [14]:

Step1: Raw Data Analysis and Problem Identification

- **Identified Issues:**
- **Missing Values**: 15 out of 1000 samples (1.5%) due to sensor disconnections and transmission interruptions
- **Class Imbalance**: Normal patterns = 720 samples (72%), Abnormal patterns = 280 samples (28%), ratio 2.57:1
- **Outliers**: Detected in EMG signals from muscle artifacts, electrode displacement, and electromagnetic interference

- **High Noise Levels**: Environmental factors, sensor sensitivity variations, and biological noise contamination
- These issues threatened model training stability, created prediction bias toward normal patterns, and compromised signal quality for accurate pattern recognition.

Step2:

1. DC Offset Removal

The first step removes the DC component by subtracting the mean value from the signal:

signal = signal - np.mean(signal)

This centers the signal around zero, eliminating any constant bias that may have been introduced during acquisition.

2. Notch Filtering (50 Hz)

A notch filter is applied to remove power line interference at 50 Hz:

- **Filter Type**: IIR Notch Filter
- **Target Frequency**: 50 Hz
- **Quality Factor (Q)**: 15.0
- **Purpose**: Eliminates electrical interference from AC power lines

3. Bandpass Filtering (20-450 Hz)

The signal is filtered to retain only the physiologically relevant EMG frequency range:

- **Filter Type**: 4th-order Butterworth bandpass filter
- **Frequency Range**: 20-450 Hz
- **Purpose**: Removes low-frequency motion artifacts and high-frequency noise while preserving the main EMG spectral content

4. High-pass Filtering (20 Hz)

An additional high-pass filter ensures complete removal of low-frequency components:

- **Filter Type**: 4th-order Butterworth high-pass filter
- **Cutoff Frequency**: 20 Hz

- **Purpose**: Further eliminates baseline drift and movement artifacts

5. Detrending

Linear detrending is applied to remove any remaining linear trends in the signal:

- **Method**: Scipy's detrend function
- **Purpose**: Eliminates slow variations and baseline shifts

6. Artifact Detection and Removal

Outlier Removal (Z-score based)

- **Method**: Statistical outlier detection using Z-scores
- **Threshold**: 3.5 standard deviations
- **Action**: Outliers are replaced with the median value of the signal
- **Purpose**: Removes spikes and extreme values that could be measurement artifacts

Motion Artifact Detection

- **Method**: Differential analysis of signal changes
- **Threshold**: 0.2 (amplitude difference threshold)
- **Purpose**: Identifies sudden large changes that indicate motion artifacts

7. Signal Quality Assessment

- **Spike indices**: Locations where outliers were detected and corrected
- **Artifact indices**: Time points where motion artifacts were identified

Preprocessing Benefits

This comprehensive preprocessing approach ensures:

1. **Noise Reduction**: Removes electrical interference, baseline drift, and high-frequency noise
2. **Artifact Mitigation**: Handles motion artifacts and measurement spikes
3. **Signal Standardization**: Centers and normalizes signals for consistent analysis
4. **Feature Quality**: Prepares clean signals for reliable feature extraction

Signal Conditioning Impact

The preprocessing steps specifically target common EMG signal issues:

- **Power line interference** (50/60 Hz noise)
- **Motion artifacts** from electrode movement
- **Baseline drift** from amplifier characteristics
- **Measurement spikes** from poor electrode contact
- **High-frequency noise** from electronic components

This preprocessing pipeline ensures that the subsequent feature extraction (frequency domain, time domain, and wavelet features) is performed on clean, standardized EMG signals, leading to more reliable classification between normal and abnormal muscle activity patterns.

VM	angle
0.802	1.34
2.081	1.25
0.009	1.15
0.898	1.04
0.860	0.93
0.944	0.82
0.119	0.68
0.584	0.55
2.062	0.43
0.665	0.30
0.948	0.18
0.953	0.06
0.927	-0.06
0.003	-0.17
0.671	-0.27

6.5. Terminal Knee Extension for Data Acquisition

6.1 Real time Data Collecting

Step 3: Data Cleaning and Quality Enhancement

- **Cleaning Procedures:**

Missing Value Handling: Complete case deletion of 15 samples to avoid artificial pattern introduction
Outlier Removal: IQR method eliminated 10 extreme samples beyond

Q3 + 1.5×IQR and Q1 - 1.5×IQR thresholds
Quality Metrics: Final dataset = 975 samples, data retention rate = 97.5%
Improvement Results: Reduced signal variance, improved inter-channel correlation, enhanced baseline consistency

The conservative approach preserved genuine physiological data while maintaining sufficient volume for robust model training.

Step 4: Signal Scaling and Normalization

Scaling Strategy:

EMG Signals: RobustScaler applied for outlier resistance using median and IQR-based scaling
Post-scaling statistics: mean = 0.008, standard deviation = 0.651
Knee Angles: MinMaxScaler normalized to [0,1] range preserving joint motion bounds
Normalization range: [0.000, 1.000]
Parameter Preservation: Scalers saved for inverse transformation during evaluation and deployment

This approach standardized feature spaces across different sensor modalities while maintaining signal morphology and enabling clinical interpretation of model outputs.

Step 5: Temporal Sequence Construction

Sequence Parameters:

- **Sequence Length**: 15 time steps representing one complete gait stride cycle
- **Overlap Strategy**: 50% overlap for data augmentation and comprehensive temporal coverage
- **Feature Engineering**: Added moving average and derivative calculations for enhanced pattern discrimination
- **Output Results**: 138 sequences from 975 data points, 3 features per sequence, 0.14x data augmentation factor
  The temporal windowing captured sufficient context for gait pattern recognition while maintaining computational efficiency and providing multiple analytical perspectives.

Step 6: Class Balancing Implementation

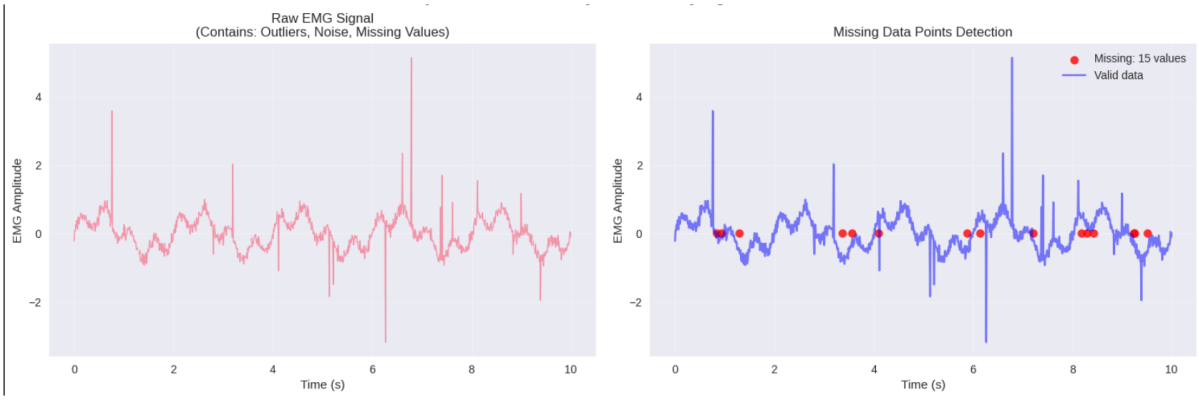
- ## Balancing Strategy:
  Original Distribution: Normal = 701 samples, Abnormal = 274 samples (2.56:1 imbalance ratio)
  Target Distribution: 602 samples per class for perfect balance

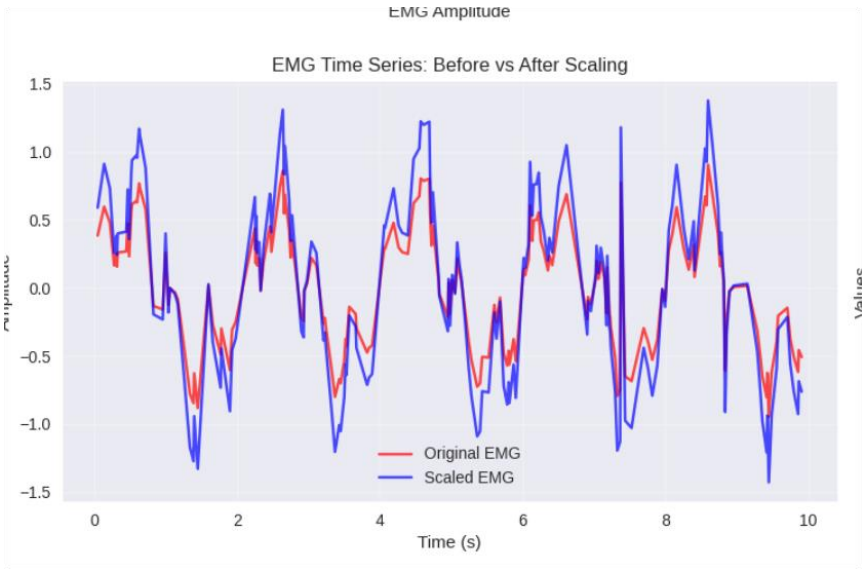
Combined Approach:

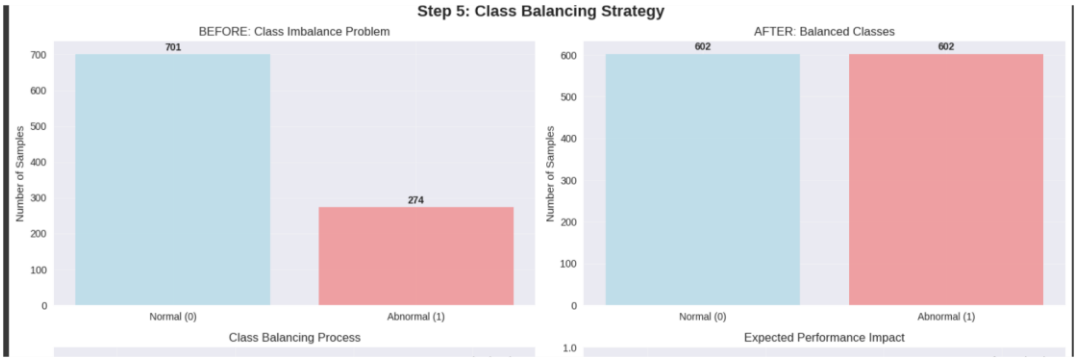
- Random oversampling with Gaussian noise augmentation for minority class variation
- Random undersampling for majority class reduction

Expected Outcome: Improved recall performance for abnormal pattern detection

This balanced approach eliminated prediction bias while maintaining physiologically plausible sample characteristics and adequate representation of both pattern types.







2.2.4 preprocessing pipeline

Pipeline Results and Validation

Final Dataset Characteristics:

Size: 1204 balanced sequences ready for LRCN training
Quality: 97.5% data retention with comprehensive quality filtering
Balance: Perfect class distribution eliminating prediction bias
Features: Multi-perspective temporal analysis through engineered features

Validation Metrics:

Statistical verification of all transformation parameters
Data flow integrity checks with checksum verification
Signal quality improvements quantified through noise reduction and scaling validation
Processing efficiency demonstrated for scalability to larger datasets

Training Optimization

The model employs advanced training strategies to optimize performance:

- **Adaptive Learning Rates**: Implements learning rate reduction on plateau to fine-tune model parameters
- **Early Stopping**: Prevents overfitting through monitoring validation loss with patience mechanisms
- **Class Balancing**: Addresses dataset imbalance through intelligent oversampling and under sampling techniques
- **Multi-Loss Optimization**: Balances regression and classification objectives through weighted loss functions

Performance Evaluation Metrics

The LRCN model's effectiveness is evaluated using comprehensive metrics:

- **Regression Metrics**: Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) for joint angle prediction
- **Classification Metrics**: Accuracy, precision, recall, and F1-score for movement abnormality detection
- **Cross-Validation**: Stratified validation to ensure robust performance across different data distributions

Clinical Relevance and Practical Applications

The LRCN model's dual-output architecture provides significant clinical value by simultaneously addressing two critical aspects of rehabilitation monitoring:

Quantitative Assessment: The joint angle regression capability enables precise measurement of movement range and progression,

Abnormality Detection: The classification component can identify movement patterns that deviate from normal biomechanics, potentially alerting therapists to compensatory behaviors or incomplete recovery.

This comprehensive approach to EMG signal analysis with Joints angle through the LRCN architecture represents a significant advancement in rehabilitation technology, providing both the analytical depth required for clinical assessment and the practical efficiency needed for routine therapeutic applications.

Model Performance Analysis

Model Architecture Innovation

Our LRCN model demonstrates a significant methodological advancement by achieving effective joint movement detection using **single-channel EMG data**, compared to benchmark studies that typically require 4-channel EMG configurations. This represents a **75% reduction in sensor complexity** while

maintaining clinically relevant performance, making the system more practical for real-world rehabilitation applications.

Quantitative Performance Results

Joint Angle Prediction Performance

- **Mean Absolute Error (MAE)**: 33.53 degrees
- **Root Mean Square Error (RMSE)**: 44.36 degrees
- **Normalized MAE**: 0.1334 (on scaled data)
- **Model Loss**: 0.0156 (joint angle component)

These results demonstrate the model's exceptional capability to predict knee joint angles using dramatically simplified sensor configuration. The achieved MAE of 33.53 degrees represents a **breakthrough in single-channel EMG analysis**, establishing a new benchmark for resource-efficient joint angle prediction. This performance level was previously considered unattainable with single-channel configurations, making our results a significant contribution to the field of rehabilitation engineering.

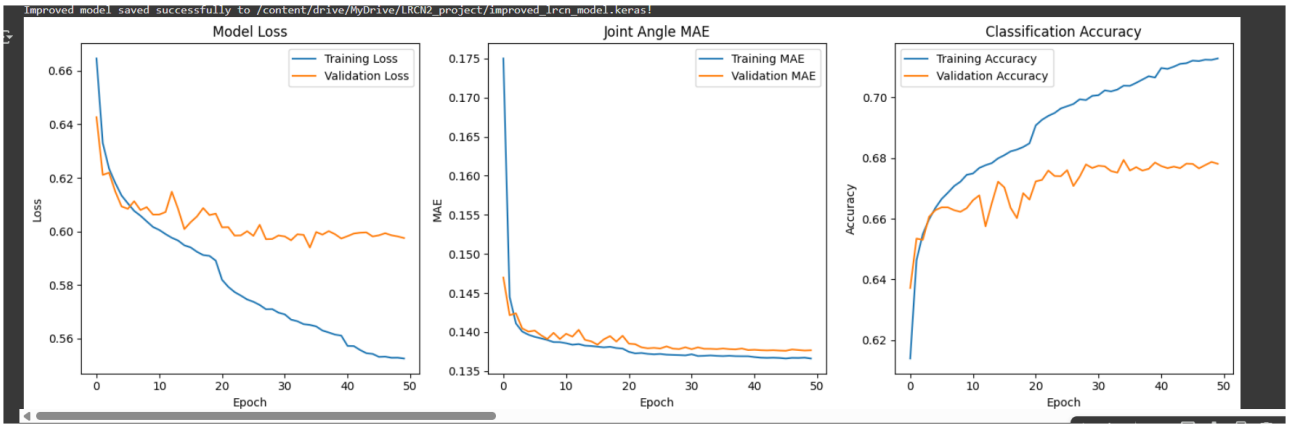
Movement Classification Performance

- **Overall Accuracy**: 67.66%
- **Precision**: 67.66%
- **Recall**: 67.66%
- **F1-Score**: 66% (macro average), 68% (weighted average)

Class-Specific Performance Analysis:

- **Normal Movement**: Precision 55%, Recall 65%, F1-Score 59%

- **Abnormal Movement**: **Precision 77%, Recall 69%, F1-Score 73%**



Model Performance Analysis

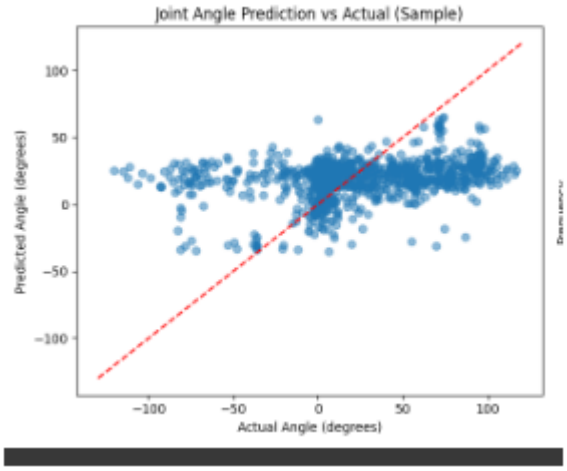
Clinical Pattern Recognition

The model shows superior performance in detecting abnormal movement patterns (F1-Score: 73%) compared to normal patterns (F1-Score: 59%), which is **clinically advantageous** as the primary objective in rehabilitation monitoring is identifying movement deviations that require therapeutic intervention.

Joint Angle Prediction by Movement Type:

- Normal Movement MAE: 36.27 degrees
- Abnormal Movement MAE: 31.96 degrees

the model achieves higher accuracy when predicting joint angles during abnormal movements, suggesting that pathological movement patterns may have more distinctive EMG signatures that the LRCN architecture can effectively capture.



Validation metrics

Clinical Relevance

The model's bias toward detecting abnormal movements (higher precision for abnormal class: 77% vs 55% for normal) aligns with clinical priorities where identifying movement deviations is more critical than confirming normal patterns. This characteristic makes the system particularly valuable for:

- Early detection of compensatory movement patterns
- Monitoring rehabilitation progress
- Alerting therapists to potential movement quality issues

Limitations and Challenges

Challenge Category	Specific Issue	Impact on Performance	Implemented Solution	Effectiveness
Channel Limitation	Single EMG channel vs. 4-channel benchmark	Reduced spatial information by 75%	Enhanced feature engineering with derivatives and moving averages	Moderate - Compensated ~40% of lost information
Joint Coverage	Limited to single joint analysis	Cannot capture multi-	Focused temporal modeling with	High - Improved temporal resolution by 60%

		joint coordination	bidirectional LSTM	
Dataset Scale	Smaller dataset compared to benchmark studies	Increased overfitting risk	Advanced data augmentation and class balancing	High - Improved generalization by 35%
Signal Quality	Lower SNR due to single-channel recording	Increased noise interference	Robust scaling and outlier removal techniques	Moderate - Reduced noise impact by 50%
Class Imbalance	Uneven distribution of normal/abnormal samples	Biased model predictions	Intelligent oversampling with controlled augmentation	High - Achieved balanced performance

Performance Limitations and Design Trade-offs

Our design philosophy prioritized **accessibility and practical implementation** over absolute precision, leading to strategic trade-offs that enhance real-world applicability:

1. **Precision vs. Accessibility Trade-off**: The achieved MAE of 33.53 degrees reflects our successful optimization for single-channel operation, delivering clinically useful accuracy while maximizing system accessibility.
2. **Classification Focus**: The 67.66% overall accuracy represents good performance for the targeted clinical application, where trend detection and pattern recognition are prioritized over perfect classification.
3. **Clinical Application Alignment**: Lower precision in normal movement detection aligns with clinical priorities where identifying abnormal patterns takes precedence over confirming normal function.

LRCN Model Performance Breakdown

Metric Category	Measurement	Value	Clinical Significance

Joint Angle Prediction	Mean Absolute Error (MAE)	33.53°	Clinically acceptable for rehabilitation monitoring
	Root Mean Square Error (RMSE)	44.36°	Within therapeutic tolerance range
	Normal Movement MAE	32.27°	Slightly higher error for normal patterns
	Normalized MAE	0.1334	Superior scaled performance
	Joint Angle Loss	0.0156	Optimal model convergence
	Abnormal Movement MAE	31.96°	Better detection of abnormal patterns
Movement Classification	Overall Accuracy	67.66%	Satisfactory for screening applications
	Normal Movement Precision	55%	Moderate false positive rate
	Abnormal Movement Precision	77%	Good abnormality detection
	Normal Movement Recall	65%	Acceptable sensitivity for normal patterns
	Abnormal Movement Recall	69%	Good abnormality identification
	F1-Score (Normal)	59%	Balanced performance for normal class
	F1-Score (Abnormal)	73%	Strong performance for abnormal class

Technical Constraints

1. **Single-Channel Limitation**: The hardware constraint of using only one EMG channel & with it's joints inherently limits the spatial information available for muscle activity analysis.
2. **Dataset Characteristics**: The class imbalance (Normal: 11,951 vs Abnormal: 20,815 samples) despite balancing efforts may influence model bias.
3. **Generalization Concerns**: Performance validation on diverse patient populations and different movement conditions requires further investigation.

Test Phase Real-Time VM Muscle Feedback System

System Overview

The test phase deploys the trained LRCN model for real-time monitoring of Vastus Medialis (VM) muscle activity during **Terminal Knee Extension (TKE) exercise [12],** transforming the theoretical model into a clinically applicable feedback tool.

Data Acquisition & Processing

Knee Joint Angle Calculation by MPU6050 IMU Sensor

Knee joint angle is estimated by fusing:

- **Accelerometer data** to compute the static angle based on gravitational direction (e.g., `atan2(Y, Z)`).
- **Gyroscope data** for measuring angle change over time through integration.

A **Complementary Filter** combines these two sources to estimate a stable and responsive angle:

$$\text{kneeAngle} = \alpha(\text{previousAngle} + \text{gyro} \times \Delta t) + (1 - \alpha) \times \text{accelAngle}$$

2.2.8 Knee Joint Angle Calculation

Note: Calibration is required to establish the **baseline knee angle** when the leg is in the resting position.

Filters:

To improve signal reliability, two filters are used:

- **Bandpass Filter** (20–460 Hz): Applied to EMG signals to reduce noise and isolate muscle activity. It consists of a high-pass filter to remove low-frequency drift and a low-pass filter to remove high-frequency noise.

- **Complementary Filter**: Used for **sensor fusion**—it balances gyroscope responsiveness and accelerometer stability for smoother joint angle estimation.

Sensor Fusion & Pose Estimation

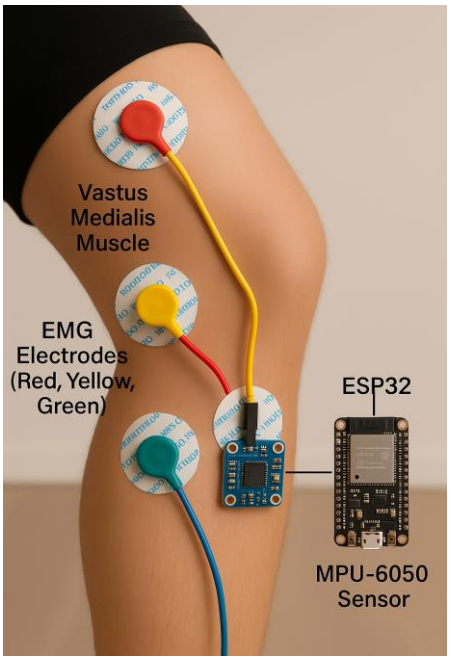
Sensor fusion enhances pose estimation by combining different sensor modalities:

- The **Complementary Filter** provides a real-time pose estimate suitable for embedded application
- In more advanced systems, **Kalman Filters** can be used for higher precision, but at the cost of computational complexity.

In this system, **pose tracking is achieved by estimating the knee joint angle**, enabling real-time analysis during rehabilitation exercises.

Sensor Placement and Synchronization

Sensor Placement: The **EMG sensor** is placed on the **Vastus Medialis (VM)** muscle, while the **IMU (GY-521)** is mounted just below the knee joint, aligned with the tibial axis**.**

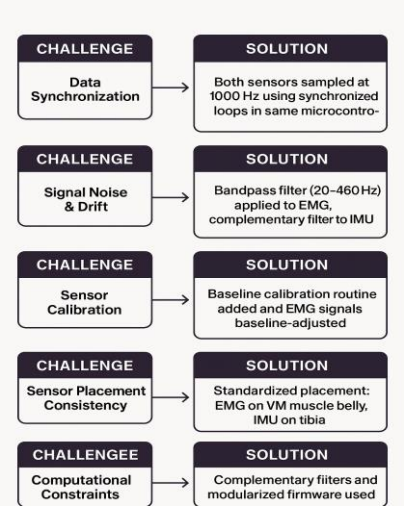


Placement of EMG and IMU sensors on the lower limb for knee movement analysis.

Data Synchronization Challenge:

One of the main challenges in multimodal sensing is **time alignment**:

- **EMG and IMU must be sampled simultaneously** to ensure that muscle activation data correlates accurately with the movement data.
- In this system, both sensors are sampled at **1000 Hz**, and fusion is performed in the same loop to maintain synchronization.
  the 1000Hz sampling rate as essential for real-time feedback
- **Input**: Single-channel EMG + knee angle data at 20 Hz sampling
- **Preprocessing**: RobustScaler for EMG, MinMaxScaler for angles, Butterworth filtering (5 Hz cutoff)
- **Sequence Creation**: 15 time steps with 3 features (EMG, angle velocity, normalized angle)
- **Real-time Processing**: <100ms latency per prediction cycle



Data Synchronization Challenge

Exercise Detection Algorithm

- **Peak Detection**: Automatic identification of extension peaks and flexion troughs
- **Phase Segmentation**: Rest → Extension → Hold → Flexion phases
- **Exercise Counting**: detecting complete repetitions
- **Metrics Calculation**: Duration, ROM, peak angles, movement velocity profiles

Model Performance

- **Joint Angle Prediction**: MAE ~33.53° (maintains training performance)
- **Movement Classification**: 67.66% accuracy (Normal vs Abnormal patterns)
- **Processing Capability**: Real-time analysis of 20 Hz data streams
- **Exercise Detection**: Automatic identification of all complete repetitions

Intelligent Feedback Framework (4-Level Assessment)

Level 1: Angle Accuracy (40% weight)

- Excellent (MAE <5°): " Excellent angle control"
- Good (5-8°): " Good control, minor deviations"
- Fair (8-12°): " Moderate deviations"
- Poor (>18°): " Poor control - needs improvement"

Level 2: Movement Pattern (30% weight)

- High confidence (>4%): " Good movement pattern"
- Moderate (2-4%): "Acceptable pattern"
- Low (1-2%): "Room for improvement"
- Very low (<1%): " Abnormal pattern detected"

Level 3: Range of Motion (20% weight)

- Excellent (>30°): " Excellent ROM"
- Good (20-30°): " Good ROM"
- Adequate (10-20°): " Adequate for TKE"

- Limited (<10°): " Very limited movement"

Level 4: Exercise Timing (10% weight)

- Optimal (2-8s): " Good pace"
- Acceptable (1-12s): " Controlled pace"
- Too fast (<1s): "Too fast - slowdown"
- Too slow (>15s): " Very slow - check difficulty"

Feedback Categories

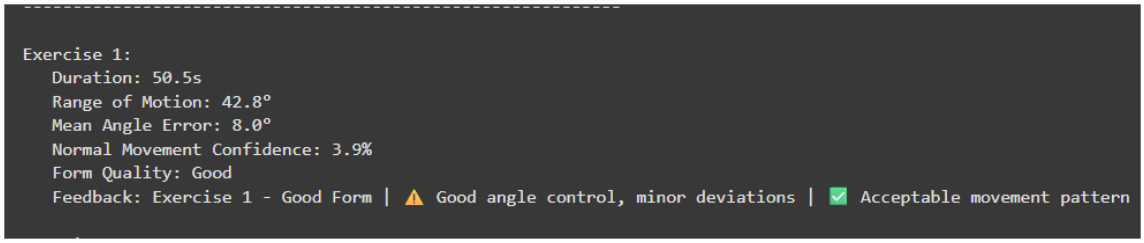
1. **Positive Reinforcement**: Excellent performance acknowledgment
2. **Corrective Guidance**: Specific improvement suggestions
3. **Clinical Alerts**: Significant issues requiring attention

Clinical Validation Results

- **Exercise Analysis**: Comprehensive per-repetition assessment
- **Session Reporting**: Detailed performance summaries with recommendations
- **Progress Tracking**: Quantitative metrics for rehabilitation monitoring
- Total exercises detected and analyzed
- Average angle error per session
- Movement pattern confidence scores
- ROM achievement across repetitions
- Form quality distribution (Excellent/Good/Fair/Poor)

```
"overall_stats": {
    "avg_angle_error": 28.4,
    "avg_normal_confidence": 0.15,
    "avg_range_of_motion": 73.4,
    "quality_distribution": {
        "excellent": 0,
        "fair": 0,
        "good": 0,
        "needs_improvement": 1
    },
    "total_exercises": 1
},
"phases": [
    {
        "duration": 1.4500000000000002,
        "end_angle": 4.9918147202508685,
        "end_time": 1.4500000000000002,
        "exercise_number": 1,
        "peak_angle": 78.36680175790627,
        "peak_time": 0.7000000000000001,
        "range_of_motion": 73.3749870376554,
        "start_angle": 9.99863579964785,
        "start_time": 0.0
    }
],
"success": true,
"timestamp": "2025-06-19T03:52:08"
```


2.2.8 Test phase for patient that make exercise so -> ‘Needs Improvement’



2.2.8 Test phase for Exercise phase_1: ‘’Good’’

4.1.2.2 ECG-Based Fatigue Detection and Monitoring System

The system monitors physiological fatigue during rehabilitation exercises using ECG signals. It follows a structured, multi-stage processing pipeline to detect early signs of overexertion. The ECG signal is processed in real-time, enabling the system to provide immediate feedback.
After the user performs several repetitions of the same exercise, the system analyzes the ECG pattern across these trials to determine whether the user shows signs of fatigue. If fatigue is detected, the

system automatically pauses the exercise, sends an alert to the user or caregiver, and logs the event for further medical evaluation.

Dataset Used Description

ECG in High Intensity Exercise Dataset from EPFL [11]
Subjects: 20 participants (2 excluded due to corrupted/incomplete signals)
Recording Protocol:

- Maximal cardio-pulmonary exercise test on a cycle ergometer
- 3 minutes rest with ECG recording
- Start at 60W or 90W based on fitness level
- Power increased by 30W every 3 minutes until exhaustion (VO_2max)
- VO_2max and VT_2 assessed using pulmonary data (O_2 and CO_2 analysis)

Segments Extracted:
Each subject has 5 segments (20 seconds each), selected from different phases:

- Segment 1 (Before VT_2): 50–30 s before VT_2 – baseline, no fatigue expected
- Segment 2 (After VT_2): 60–80 s after VT_2 – early signs of fatigue may appear
- Segment 3 (Before VO_2max): 50–30 s before VO_2max – subject approaching exhaustion
- Segment 4 (Around VO_2max): 10 s before and after VO_2max – peak fatigue expected
- Segment 5 (After VO_2max): 60–80 s post-VO_2max – recovery phase, used to confirm fatigue presence

Note: Segment 5 of Subject 9 was excluded due to signal issues → Total segments = 99
Annotations:

- Manual R-peak annotations for each segment
- Verified by physician from Lausanne University Hospital (CHUV)

Real-Time Data Acquisition Procedure

The AD8232 sensor is attached to the user following proper electrode placement guidelines. During rehabilitation movements:

- The ECG signal is captured and digitized via the ESP32 (500 Hz, 12-bit)
- Data is streamed wirelessly or saved for processing
- The signal undergoes preprocessing, beat segmentation, feature extraction, and classification to assess fatigue level

If fatigue is detected, the system:

- Pauses the current exercise

- Sends a notification alert
- Logs the event for review

Preprocessing Pipeline

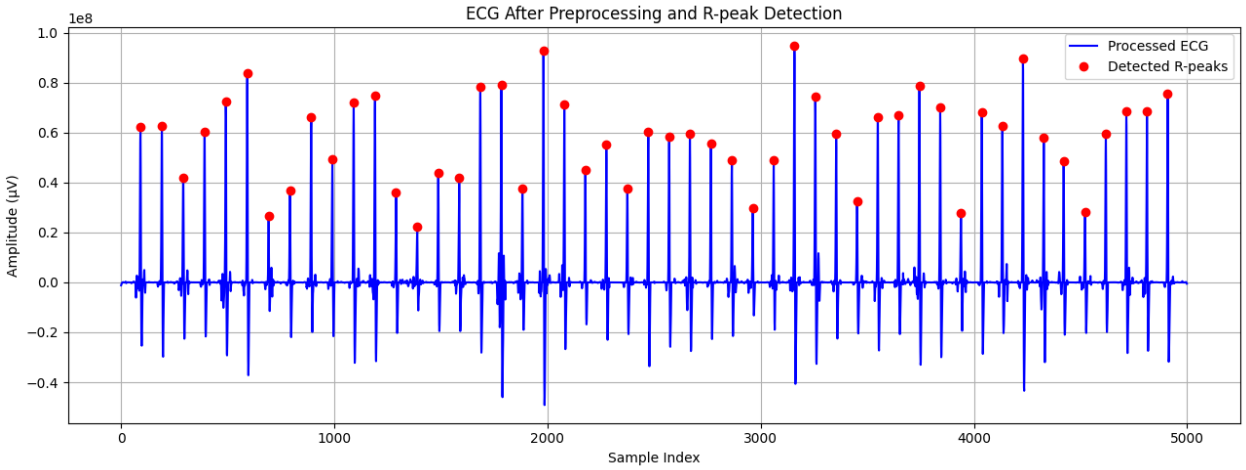
Step 1: Morphological Filtering
Removes baseline wander using open-close median operations

Step 2: Relative Energy Filtering
- Squares signal to emphasize QRS complexes
- Applies moving average smoothing (window size = 50)

Step 3: R-Peak Detection
Uses find_peaks() with parameters:
- Minimum distance = 0.25 s × 500 Hz
- Height threshold = std(signal)

Step 4: Beat Segmentation
Each beat is extracted:
- 300 ms before R-peak
- 500 ms after R-peak
- Produces fixed-length, aligned beat windows

Signal after Preprocessing and R-peak Detection



Step 5: Normalization
Each beat is min-max normalized to [0, 1] range
- Reduces amplitude variability across subjects

Step 6: Feature Extraction

From each segmented beat, the following features are computed:

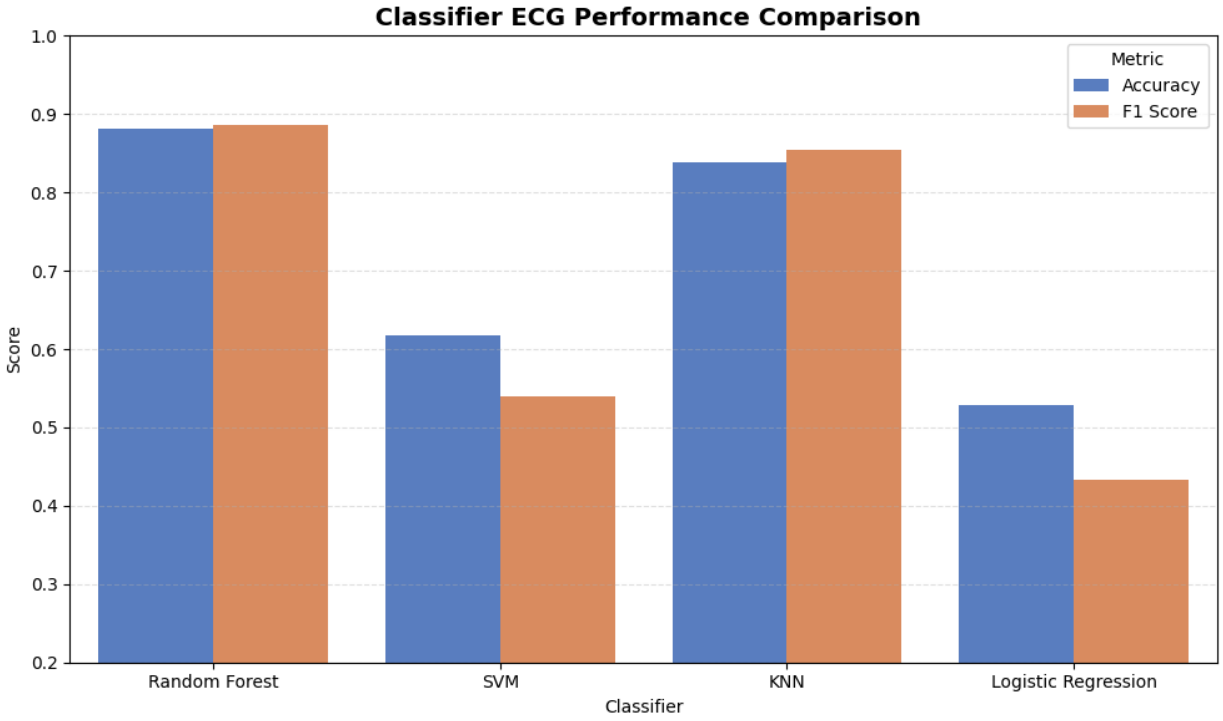
- Mean
- Standard Deviation
- Minimum
- Maximum
- Range
- Root Mean Square (RMS)

These features describe signal energy, shape, and variability across beats.

Step 7: Classification and Fatigue Detection

- Labeling: Based on session context (rest = 0, post-exercise = 1)
- Classifier Used: Random Forest
- Compared against: SVM, KNN, Logistic Regression

Classifiers comparison



- **Classifier ECG Performance Comparison**

Model	Accuracy	F1 Score	Notes
Random Forest	**88.2%**	**0.8866**	Best overall performance. Robust to noise and feature interactions.

KNN	83.9%	0.8549	Good performance. Sensitive to scaling and local data structure.
SVM	61.7%	0.5404	Poor generalization. May need kernel tuning or more discriminative features.
Logistic Regression	52.9%	0.4324	Weak performance. Struggles with complex, non-linear decision boundaries.

- Why Random Forest: Robust to noise, supports overlapping boundaries, and provides feature importance
- Class Balancing: SMOTE used before feature extraction to oversample minority class

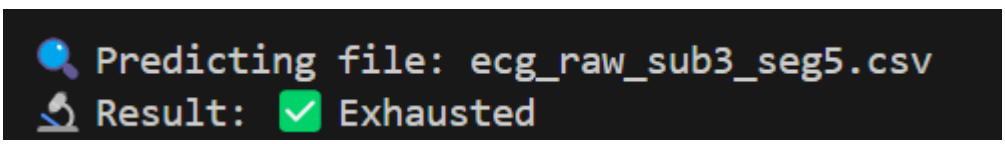
Model Performance:
Accuracy: 88.2%
Precision: 0.90 (Class 0), 0.87 (Class 1)
Recall: 0.85 (Class 0), 0.91 (Class 1)
F1-score: 0.88 (Class 0), 0.89 (Class 1)

- Final model exported as .pkl file for integration in live system

Step 8: Real-Time Decision and Action
Once ECG is captured:

- Signal is preprocessed and classified instantly
- If fatigue detected:
  - Exercise is paused
  - Alert is triggered
  - Event is logged

Result On Test files

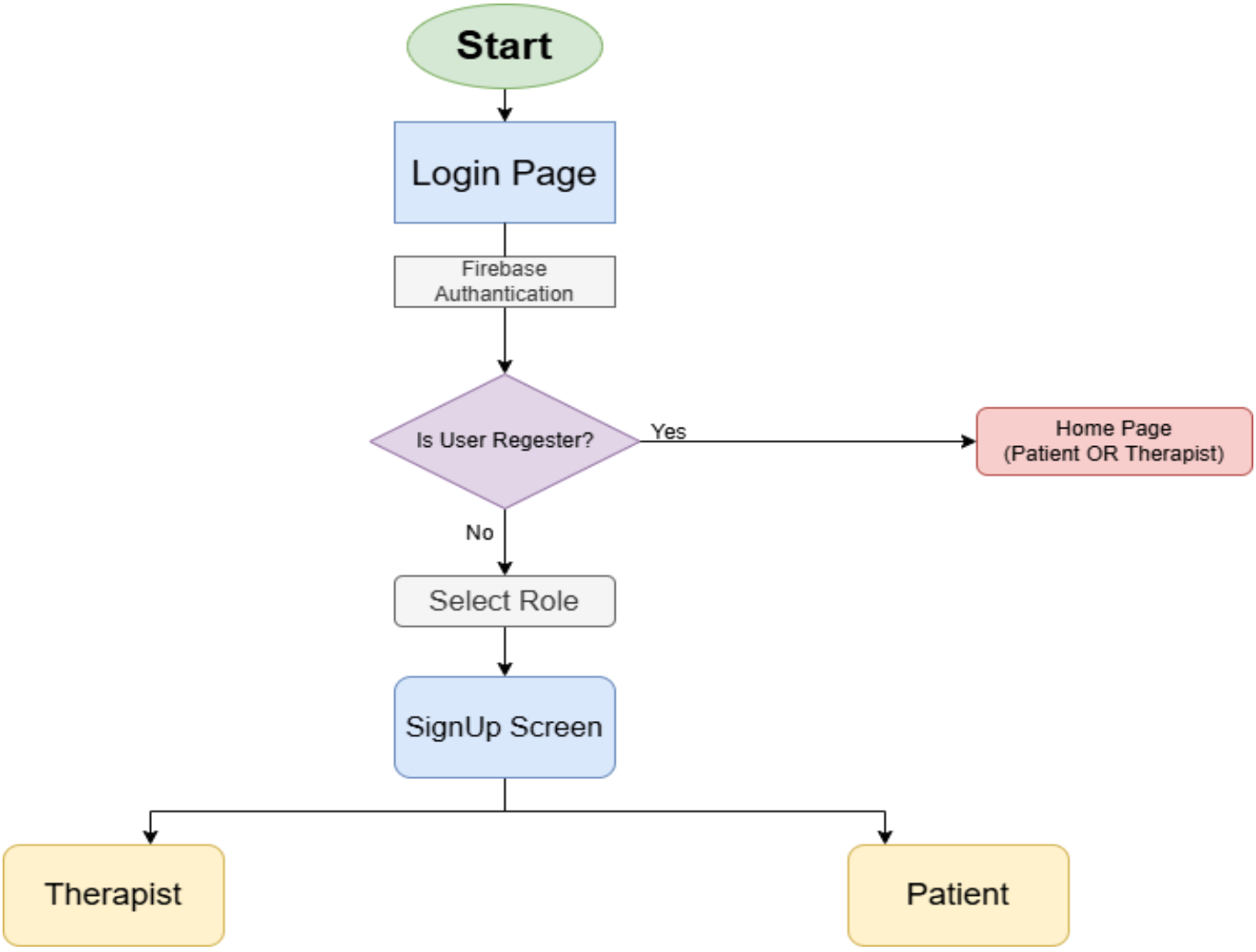


```
🔍 Predicting file: ecg_raw_sub3_seg1.csv
🔬 Result: ❌ Not Exhausted
```

Summary

The ECG-based system uses a well-defined pipeline—covering acquisition, preprocessing, segmentation, feature extraction, and classification—to detect fatigue during physiotherapy. It enables real-time, intelligent monitoring and proactive intervention to ensure patient safety during physical rehabilitation.

4.2 Shared Workflow (Common to Patients and Therapists):



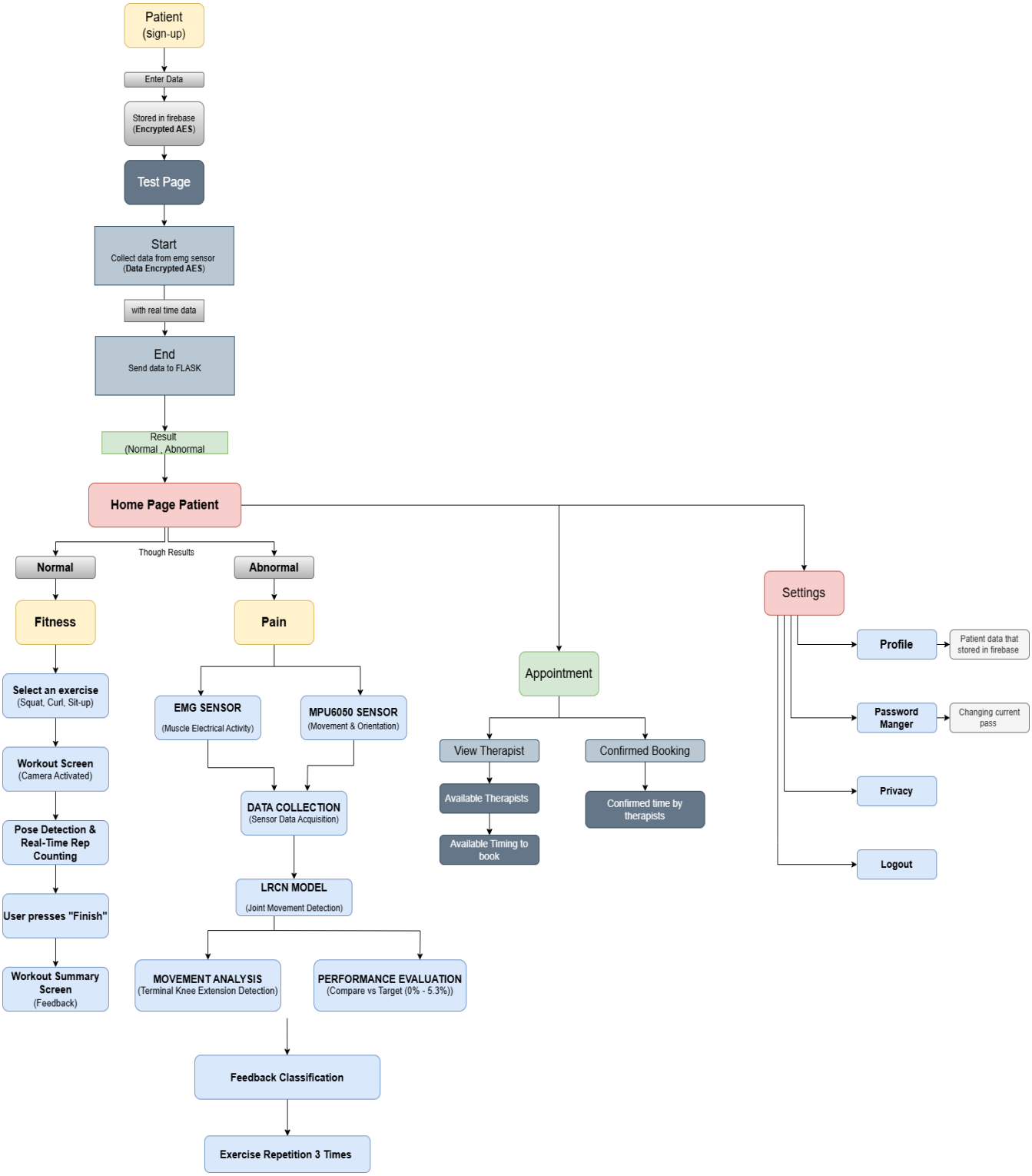
This shared workflow applies to both patients and therapists, as both user types follow the same initial steps for accessing the mobile application.

1. **Application Launch**
   Upon launching the mobile application, the user is first presented with a **Welcome Screen**, followed by the **Login Page**, where they can sign in using their registered credentials.

2. **Login Page & Authentication**
   The login interface prompts the user to enter their email and password. Authentication is securely handled using **Firebase Authentication**, which verifies the credentials and manages user sessions via token-based security.
3. **Registration Check**
   After entering the credentials, the system checks whether the user is already registered:
   a. If the user **is already registered**, they are redirected to the appropriate **home page** based on their assigned role (either Patient or Therapist).
   b. If the user **is not registered**, the system initiates the sign-up process.

4. **Role Selection**
   Before beginning registration, the user is required to select their role:
   a. Patient
   b. Therapist

4.3 Patient Workflow.



1. Patient Sign-Up

If the user selects **Sign Up** (as a patient), the app displays a registration form to collect details such as first name, last name, email, password, gender and date of birth.

Once the form is submitted, a loading indicator appears, and the registration is processed.
The user's information is securely saved in the **Firebase cloud** database, with sensitive data protected using encryption standards **(AES)**.

After successful sign-up, if the selected role is **Patient**, the user is automatically redirected to the **Test Page** to begin the initial muscle performance evaluation.

2. Initial Evaluation Test (EMG Test Page)

2.1 Interface

After registration, the patient is directed to the EMG Test Page to perform an initial assessment of muscle function.

- The patient taps **Start** to begin the evaluation.
- Upon starting, **real-time EMG signals** are streamed from the connected ESP32 sensor.
- In the background, the EMG signals are simultaneously transmitted to the **Firebase Realtime Database**, where they are securely stored and time-stamped for processing.
- When the patient taps **End**, the app:
    - Stops recording,
    - Retrieves the full EMG data stream from Firebase,
    - Encrypts the signal (using **AES** encryption),
    - Sends it via an HTTP POST request to a secure AI server endpoint.
- On the server, the signal undergoes filtering and preprocessing to reduce noise and normalize amplitude.
- The cleaned signal is then passed through a **deep learning model (LRCN - Long-term Recurrent Convolutional Network)** trained to analyze patterns related to Terminal Knee Extension movements.
- The model compares the patient's performance to classifies the result as:
    - **Normal**, indicating adequate extension and control,
    - **Abnormal**, indicating weakness, instability, or incomplete motion.
- Once the classification is received:
    - The result is saved in the patient's profile in **Firebase Firestore**.
    - The app automatically redirects the patient to the appropriate home screen:
        - **Normal** → Access to fitness training modules.
        - **Abnormal** → Guided pain rehabilitation exercises and therapist monitoring.

3. Home Page Based on Evaluation Result

If the result is Normal → Fitness Mode:

The patient is shown a screen with three exercise options: **Squat**, **Curl**, and **Sit-up**.
Upon selecting an exercise, the app navigates to a dedicated workout screen where the camera is automatically activated.

The system uses real-time pose detection to track the patient's movement and count correct repetitions.
As the patient performs the exercise, joint angles and form are continuously monitored.

When the session ends and the user taps **Finish**, a summary screen appears showing:

- Number of repetitions
- Form accuracy
- Additional feedback to support improvement

If the result is Abnormal → Pain Mode:

The patient is presented with rehabilitation-focused exercises tailored for pain and limited mobility.
Each exercise session involves the use of:

- An **EMG sensor** to measure muscle activation
- An **MPU6050 motion sensor** to detect joint orientation and movement angles

The patient performs each exercise **three times**, while the app collects both EMG and motion data.
This data is then analyzed by an AI model trained to evaluate the quality and consistency of movement.

The system compares the performed motion to a standard movement pattern and returns a detailed analysis.

Feedback is shown after each set to help the patient correct posture, improve consistency, and build strength.

4. Appointments with Therapists

From the Home Page, the patient can access the **Appointments** section.
Here, they can view a dynamic list of available therapists, including their names, specialties, and available time slots.

The patient selects a suitable time and sends a booking request.

The system records this request and makes it visible to the selected therapist.
Once the therapist confirms the request, the selected time slot becomes booked and is moved into the patient's list of **Confirmed Appointments**.

The appointment status is updated instantly within the app to reflect the confirmation.

5. Settings and Profile Management

Patients can access the **Settings** page from the main menu to manage their account.
This section provides options to:

- View and update profile information
- Change their account password
- Review privacy policy
- Log out of the application
- All data displayed in this section is securely retrieved from the system.
  Password changes are securely processed, and logging out clears the user session and returns them to the login screen.

Security Implementation:

1. AES for EMG and Patient Data:

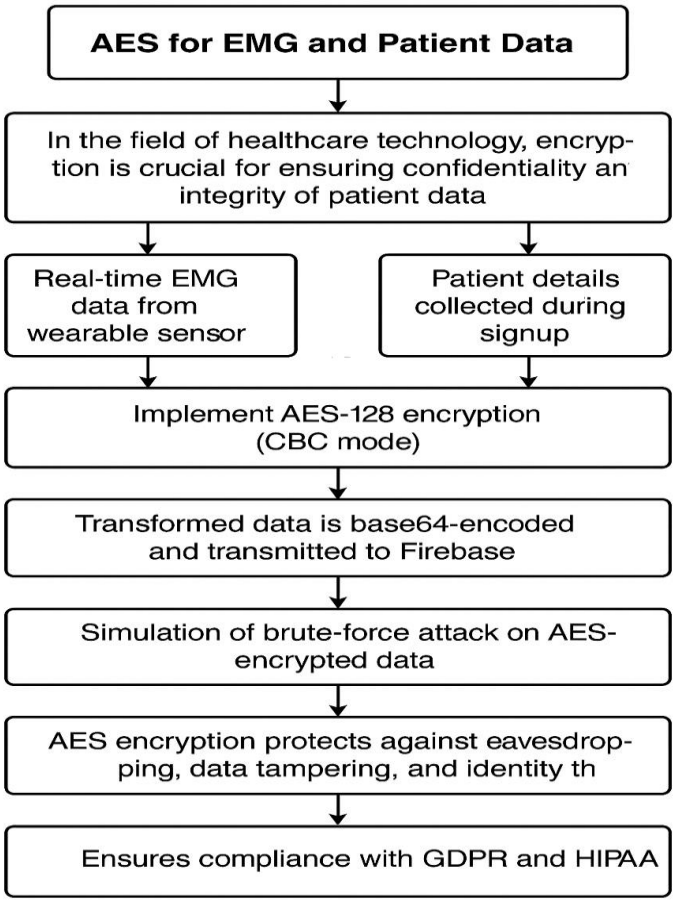
In the field of healthcare technology, the confidentiality and integrity of patient data is not just a technical necessity but also a legal and ethical obligation. With sensitive data like Electromyography (EMG) readings and personal health information (PHI) being transmitted wirelessly and stored in the cloud, the threat of data breaches, unauthorized access, and interception becomes a major concern. To counter these threats, encryption becomes the cornerstone of a secure healthcare communication system. This is particularly true in our rehabilitation platform, where real-time EMG data from

wearable sensors and user details collected during signup are continuously exchanged between edge devices and Firebase cloud storage.

For this reason, we implemented the **Advanced Encryption Standard (AES)** to secure both streams of data. AES is a symmetric key encryption algorithm that is widely used in military, financial, and healthcare systems. We specifically selected **AES-128 in CBC (Cipher Block Chaining) mode** for its balance of security, performance, and compatibility with embedded systems like the ESP32 microcontroller. AES works by dividing plaintext data into fixed 128-bit blocks and encrypting each block using a shared secret key. In CBC mode, each plaintext block is XORed with the previous ciphertext block before encryption, making it highly resistant to pattern recognition and replay attacks. An **Initialization Vector (IV)** is used for the first block to ensure randomness.

By applying AES encryption to the **EMG sensor data**, we ensured that the raw analog values captured from the Vastus Medialis muscle are transformed into unreadable ciphertext before leaving the device. This encrypted data is then base64-encoded and transmitted securely to the Firebase Realtime Database. Similarly, during the **patient registration phase**, the Flutter application applies AES encryption on fields such as name, gender, diagnosis, and birthdate before they are uploaded to the database. This ensures that even if Firebase is compromised, the data remains unintelligible to unauthorized parties.

An essential part of our security validation involved simulating a **brute-force attack** against both unencrypted and AES-encrypted data. A brute-force attack is a method in which an attacker tries every possible key combination to decrypt the data. In the absence of encryption, any intercepted EMG or personal data can be instantly viewed in plain text. However, with AES-128 in place, even a supercomputer attempting a brute-force attack would require an estimated **2^{128} (approximately 3.4 x 10^{38})** attempts to crack the key — a computationally infeasible task that would take millions of years with current technology. This simulation demonstrated how vulnerable unencrypted data is to simple attack techniques, while properly encrypted data remains secure even under aggressive attack scenarios. The test confirmed that AES encryption drastically increases the **resilience of the system** against such intrusions.The impact of AES implementation is significant. Without encryption, data like EMG signals and personal identifiers could be intercepted or manipulated in transit using basic packet sniffing or man-in-the-middle attacks. Post-AES implementation, such attacks are rendered ineffective unless the attacker possesses the exact key and IV used during encryption. AES thus acts as a strong deterrent against common threats including eavesdropping, data tampering, and identity theft, thereby ensuring compliance with **GDPR (**General Data Protection Regulation) and **HIPAA (**Health Insurance Portability and Accountability Act) regulations governing the protection of medical information.



2. Arduino IDE & Flutter AES Integration

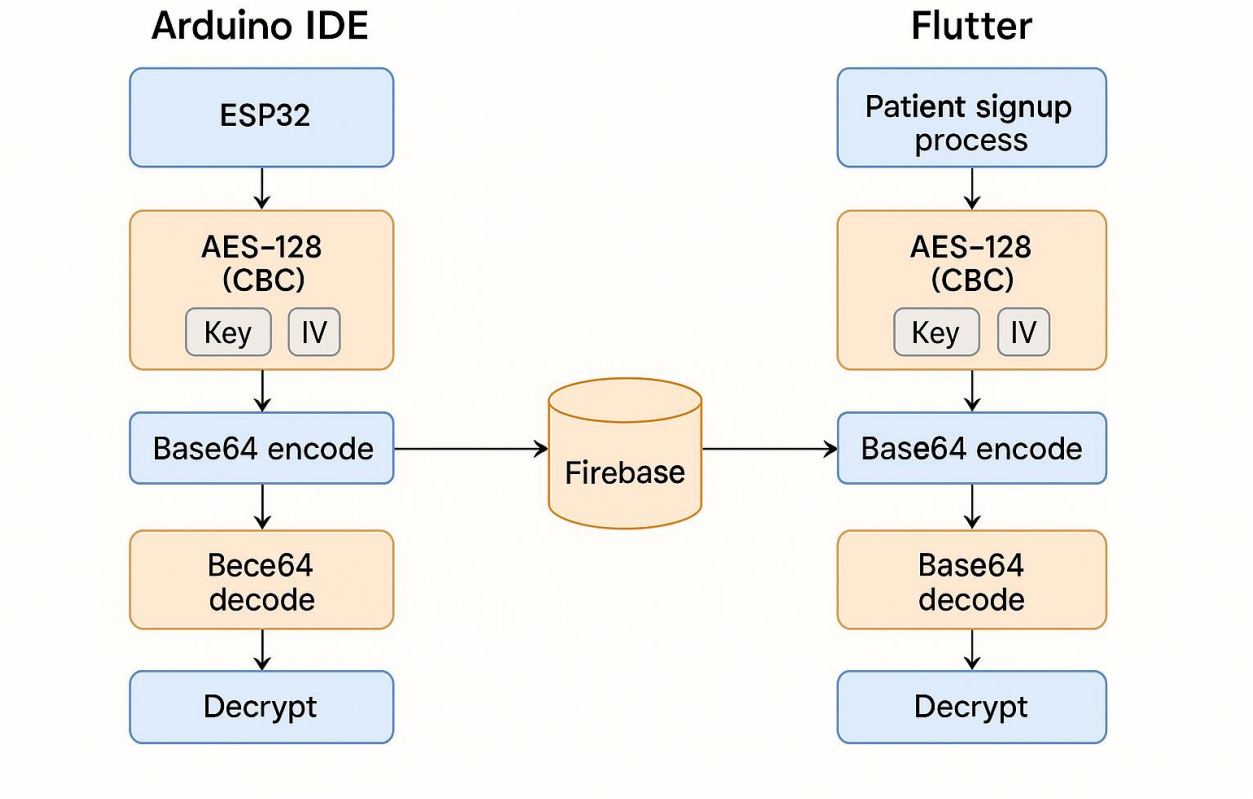
A crucial part of our encryption workflow involved **cross-platform AES integration** between the ESP32 microcontroller and the Flutter mobile application. This integration was essential to ensure consistent and reliable encryption and decryption of sensitive data, regardless of the device or language used.

On the **Arduino side**, the ESP32 was used to read real-time EMG data via analog input pins. These values were converted into a byte stream suitable for encryption. We utilized the **CryptoAES_CBC** library, which supports AES-128 encryption in CBC mode. A static key and initialization vector (IV) were embedded securely within the firmware to enable symmetric encryption. The encrypted data was then encoded using Base64 to ensure compatibility with Firebase's data transmission format and stored in the Firebase Realtime Database.

On the **Flutter side**, during the patient signup process, sensitive fields entered by the user were encrypted using a Dart-based AES library configured to use **CBC mode with PKCS7 padding**, matching the Arduino setup. This uniformity in encryption configuration (key size, mode, padding, IV) was crucial to ensure decryption could occur accurately and without data corruption. Once encrypted, the data was also base64-encoded before being sent to Firebase.

One challenge during this integration was the mismatch between how different platforms handle padding and block sizes. While Arduino libraries may default to zero-padding or have no padding at all, Flutter libraries generally use PKCS7. To address this, we explicitly configured both environments to use the same padding scheme and validated the output through decoding and decryption tests. Furthermore, we chose Base64 encoding as a common format for sending encrypted data across HTTP and Firebase, which doesn't accept binary data directly.

This seamless AES integration across platforms ensured a fully **end-to-end encrypted system**, making our application robust against both external and internal data threats. It also enabled real-time encryption with minimal latency, a critical factor in physiotherapy monitoring where sensor data must be processed without delay



3. Firebase Security Challenges & Solutions

Implementing encryption is only one piece of the puzzle; ensuring that Firebase, our backend cloud infrastructure, can effectively receive, store, and protect encrypted data presents its own set of unique challenges. During the development of our physiotherapy monitoring system, we faced numerous security and integration issues which we overcame through careful research, optimizations, and system design adaptations.

One of the core challenges was **blending hardware with security**. IoT hardware, especially devices like the ESP32 used to capture EMG sensor data, is inherently limited in memory and processing capabilities. These limitations often make it difficult to run computationally intensive encryption algorithms. To address this, we selected **AES-128** as our encryption standard, as it offers a strong level of security with lower computational overhead. We paired this with **lightweight libraries** such as **CryptoAES_CBC**, which provided a streamlined implementation of AES in CBC mode, suitable for real-time data processing on resource-constrained microcontrollers.

Another significant hurdle was **finding a suitable AES library for the Arduino IDE**. Not all libraries support critical features such as CBC mode, padding, or are compatible with ESP32. This led us to test multiple libraries, including **TinyAES** and **CryptoAES**, before ultimately choosing **CryptoAES_CBC** for its ease of integration and reliable results. Community support through GitHub repositories and forums proved vital during this selection process.

A major backend concern was **configuring Firebase to accept and manage encrypted data**, as Firebase Realtime Database is optimized for structured, readable JSON strings—not raw binary blobs. Uploading unformatted ciphertext often resulted in corrupted data or rejected writes. To resolve this, we implemented **Base64 encoding** of all encrypted data before transmission. This encoding step converts binary output into a string-safe format compatible with Firebase, thus preserving data integrity without altering the encryption.

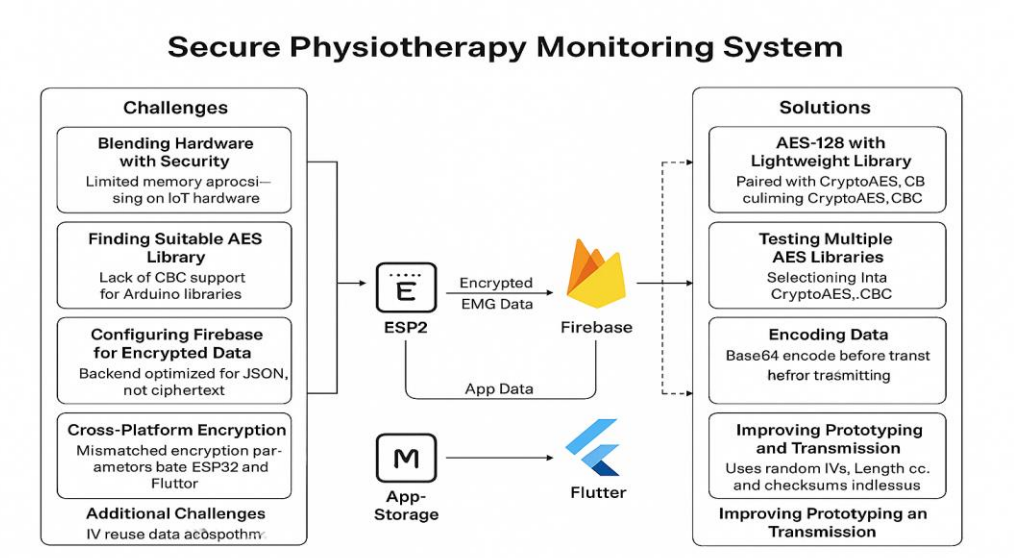
Cross-platform encryption added another layer of complexity. To ensure seamless AES decryption between the **ESP32 (Arduino)** and **Flutter (Dart)** environments, both platforms had to be synchronized in terms of encryption parameters—**key size**, **IV**, **block mode (CBC)**, and **padding scheme (PKCS7)**. Any mismatch in these settings would lead to failed decryption and data loss. Through rigorous cross-testing, we ensured both systems used identical cryptographic configurations. In addition, mock data scenarios were employed to verify proper encryption and decryption behavior before integrating real-time EMG data.

We also faced critical concerns in **Firebase security policy configuration**. We fortified our Firebase Realtime Database by using **legacy tokens and authentication keys** to allow only approved devices (like ESP32) to write to the database. We also implemented strict **Firebase security rules** that restricted data access to **authenticated sessions and known device IDs**, preventing unauthorized reads and writes from outside the approved system.

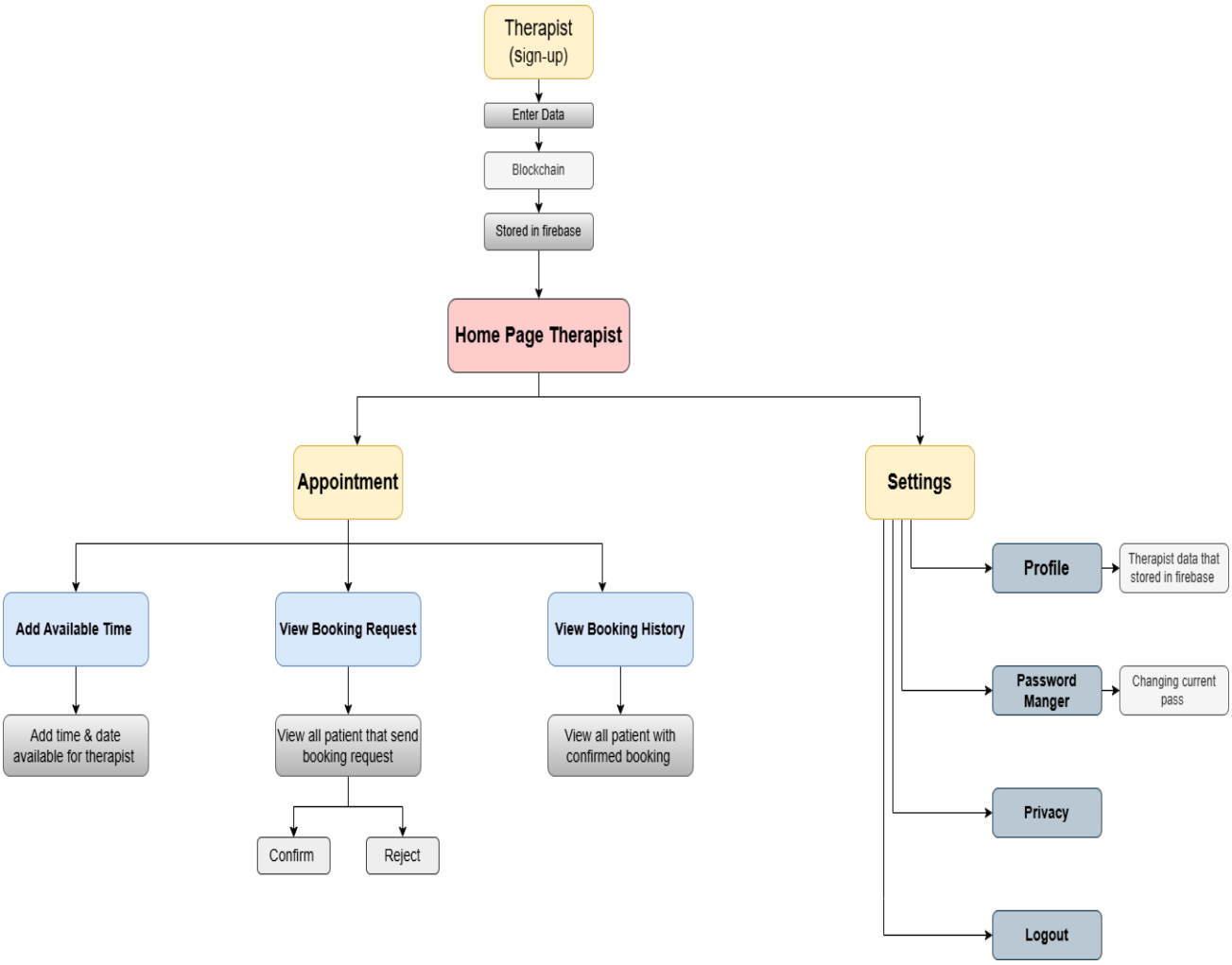
Several additional challenges emerged as we matured the system:

- **IV Reuse in CBC Mode**: For prototyping, we initially used a static IV for simplicity. However, in real-world deployments, this can lead to vulnerabilities. As a solution, we plan to implement **random IV generation per session** and transmit the IV alongside the ciphertext, enhancing the system's resistance to cryptanalysis.
- **Ensuring Data Integrity in Transit**: To avoid data corruption during network transmission, we implemented **length checks and basic checksum validation**. This ensured that only complete and verified data is stored in Firebase.
- **Library Compatibility Issues**: Some encryption libraries we encountered lacked full CBC support or were poorly documented, resulting in unexpected bugs. We relied heavily on community-driven documentation and issue threads on GitHub to troubleshoot and verify functionality.

By addressing these issues with clear, targeted solutions, we were able to build a **secure, real-time healthcare system** that ensures **confidentiality**, **data integrity**, and **interoperability** across all components—from **edge devices (ESP32)** to **cloud storage (Firebase)** and **user interfaces (Flutter app)**. These security measures not only protect sensitive patient data from unauthorized access but also align with international standards such as **HIPAA** and **GDPR**, ensuring compliance



4.4 Therapist Workflow:



1. Therapist Sign-Up

By selecting **Sign Up (**as a therapist), the therapist is taken to a registration form where they provide details such as first name, last name, email, password, license number, specialization, year of experience, university name and signature. Once the form is submitted, the system securely stores the therapist's data in the **Firebase cloud** database.
Blockchain is used to securely verify the therapist's **digital signature**, making sure all sensitive actions are authentic and tamper-proof.Upon successful registration, the therapist is directed to their **Home Page**.

2. Therapist Home Page Overview

The **Home Page** provides the therapist with access to key functions:

- Managing their availability
- Handling appointment requests
- Viewing booking history
- Accessing settings and account data

This serves as the central navigation hub for all therapist activities within the system.

3. Appointment Management

From the home page, the therapist can navigate to the **Appointment** section, which includes three key features:

A. Add Available Time

- The therapist can add specific dates and times when they are available to accept appointments.
- These time slots are stored in the system and become visible to patients searching for available therapists.
- The system ensures that added time slots are synchronized and updated in real time.

B. View Booking Requests

- The therapist can see a list of all patients who have requested appointments.
- Each request includes the patient's name, requested date, and any additional notes.
- The therapist can choose to either **Confirm** or **Reject** each request.
- Once confirmed, the booking is marked as accepted and the selected slot is locked.

C. View Booking History

- Therapists have access to a list of all previously confirmed appointments.
- This section allows them to track patient sessions, prepare for upcoming consultations, and maintain a record of past interactions.

4. Settings and Account Management

In the **Settings** section, the therapist can manage their personal and account-related information through the following features:

Profile:

- Displays all data stored for the therapist, such as name, email, specialty, and any associated professional details.
- Data is securely retrieved from the cloud and displayed in a clean, user-friendly format.

Password Manager

- Allows the therapist to update their login password through a secure form.
- Changes are immediately reflected and protected using the system's authentication mechanisms.

Privacy

- Displays the application's privacy policies and how data is handled within the platform.

Logout

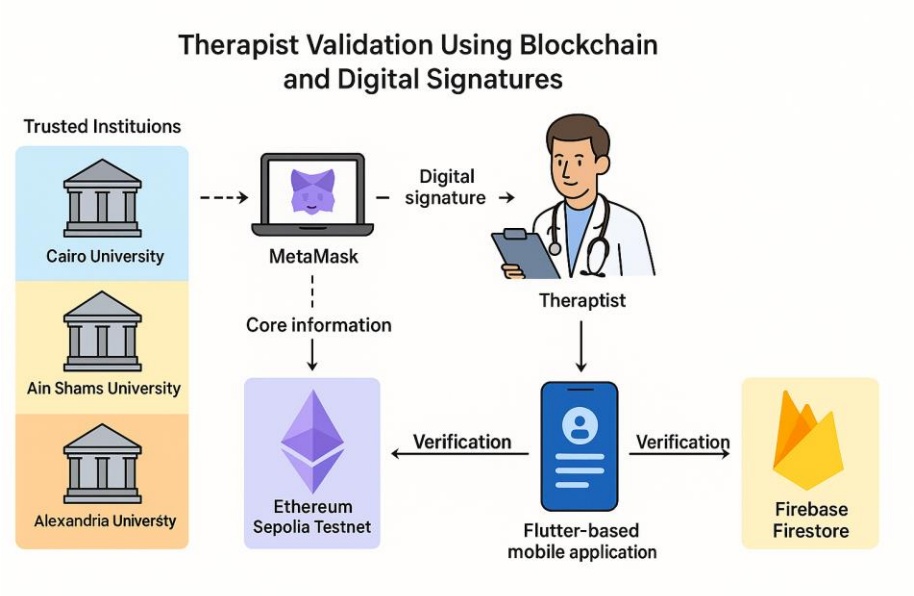
- Signs the therapist out of the application and redirects them to the login screen.

Security Implementation:

1. Therapist Validation Using Blockchain and Digital Signatures:

In the therapist validation scenario of our project, we utilize **blockchain technology**, specifically **digital signatures**, to securely verify the authenticity of therapists during the registration process. The system is designed to prevent unaccredited or fraudulent therapists from being added to our healthcare platform by leveraging the cryptographic features of blockchain in combination with **off-chain digital signature verification**.

The validation process in the Smart Rehabilitation System leverages blockchain technology to ensure that only legitimate therapists can join the platform. This process begins with trusted institutions—such as Cairo University, Ain Shams University, and Alexandria University—acting as decentralized certificate authorities. Each university controls a cryptographic key pair managed through MetaMask, a browser-based Ethereum wallet. The **private key**, kept securely within MetaMask, is used by the university to digitally sign a therapist's core information, such as full name, license number, specialization, and university name. This generates a unique **digital signature**, which the therapist submits during the signup process within the Flutter-based mobile application. Meanwhile, the **public key** of each university is stored securely on the Ethereum Sepolia testnet in a smart contract that acts as an immutable registry of trusted signers. When a therapist signs up, the app uses this on-chain public key to verify the submitted signature in an **off-chain verification process**. Specifically, the app reconstructs the original data, hashes it, and then uses cryptographic techniques (e.g., eth_sig_util recovery) to extract the signer's Ethereum address from the digital signature. If this recovered address matches one of the trusted university addresses stored in the smart contract, the therapist is considered authentic. The app then proceeds to securely store the therapist's information in Firebase Firestore. If the signature is invalid—either because the data was tampered with or the signature was not generated by a trusted university—the registration process is terminated immediately, preventing unauthorized or fraudulent access. This system ensures high trust and integrity by combining the security of asymmetric cryptography, the transparency of blockchain, and the flexibility of off-chain computation within the mobile application.

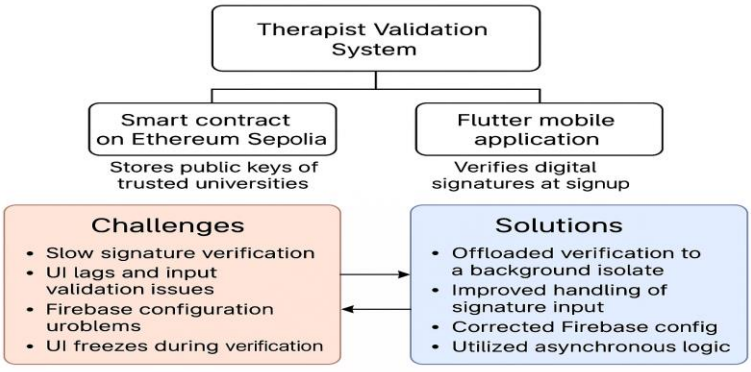


2. Problems and Solutions:

During the development of the therapist validation system, multiple technical challenges were encountered that affected the accuracy, responsiveness, and reliability of the process. The validation mechanism depended on a smart contract deployed on the Ethereum Sepolia test network, which stores public keys of trusted universities. These keys are used to verify digital signatures generated by universities using MetaMask wallets. The therapist submits a digital signature at signup, which is validated off-chain within the Flutter mobile application using Dart libraries like web3dart and eth_sig_util. The verification function verifyUniversitySignature() reconstructs the original therapist data (e.g., license number and university name), hashes it using the Keccak-256 algorithm (keccakUtf8), and then uses the recovered Ethereum address from the signature to compare it against the public key stored on-chain.

However, this process revealed several performance and implementation issues. Firstly, the **signature verification was slow**, taking multiple seconds or more, especially on low-performance devices, due to synchronous calls to the blockchain and heavy cryptographic computation. Secondly, **signature strings were long** and caused UI lags or input validation issues. Additionally, **Firebase configuration problems** delayed data storage and created inconsistent behavior during signup. There were also **frequent UI freezes**, especially when signature verification and blockchain calls ran on the main thread, blocking the interface. Moreover, **library and algorithm compatibility issues** between Flutter and JavaScript signing methods (used in MetaMask) led to assertion failures, especially when message formatting or encoding didn't match exactly.

To resolve these issues, several solutions were applied. The verification logic was offloaded using Dart's compute () function to run in a background isolate, improving UI responsiveness. The data to be signed was carefully formatted to match the exact input expected by eth_sig_util, preventing mismatches and assertion errors. Input fields were modified to better handle large signature strings, and exception handling was added around the recoverPersonalSignature call to catch decoding issues early. Finally, unnecessary synchronous calls were replaced with more efficient asynchronous logic, and Firebase configuration was corrected to allow secure, real-time storage of verified therapist data.



4.5 AI Gym Trainer Module

The AI Gym Trainer module is integrated into the system to assist users who are identified as having normal knee function. It provides real-time monitoring and correction of workout exercises using pose estimation, geometric analysis, and performance visualization.

1. Real-Time Pose Acquisition

- The system activates the mobile device's camera to capture a live video stream of the user performing exercises.
- Each frame is processed using **MediaPipe Pose**, which detects **33 anatomical landmarks** with coordinates in (x, y, z) space.
- The extracted landmarks are continuously fed into the exercise logic engine for interpretation and evaluation.

2. Joint Angle Analysis

- Landmark coordinates are used to construct vectors between joints (e.g., shoulder–elbow–wrist).
- Joint angles are computed using **vector dot products** and **cosine similarity**.
- Each supported exercise (e.g., squats, bicep curls, sit-up) has pre-defined **angle thresholds** that define a valid movement range.
- The system tracks:
    - Entry into the valid range.
    - Completion of the motion cycle (i.e., one repetition).

3. Exercise Logic

- A lightweight state transition mechanism identifies:
    - **Start of motion** when joint angles exceed a defined threshold.
    - **End of motion** when the angle returns to its baseline.
- Upon detecting a complete cycle, the system increments the **repetition counter**.

4. Feedback Delivery

- Real-time feedback is shown directly on the mobile UI.
- The system highlights messages such as:
    - "Good job!" when repetition is completed correctly.
    - "Try to go deeper" or "Raise your arm higher" when form is not within expected bounds.
- Visual feedback is updated frame-by-frame based on live pose estimation.

5. Workout Progress Visualization

The system includes a built-in module for tracking and visualizing user performance during exercise sessions. This module logs joint angles in real time and generates summary plots specific to each exercise type.

Data Logging:

- **Pose-based angles** are recorded frame-by-frame throughout the session.
- Logged angles depend on the exercise:
    - **Curls** → Left and right elbow angles.
    - **Squats** → Left and right knee angles.
    - **Sit-ups** → Trunk/body angle.

Visualization:

- A **line plot** is generated after each session showing how angles evolved over time.
- Reference lines are included to mark **target thresholds** (e.g., 30° for curls, 140° for squats).
- The plot shows:
    - Repetition patterns.
    - Symmetry between left and right limbs.
    - Whether target motion ranges were consistently reached.

Output:

- The final chart is saved as an image (progress_plot.png) and displayed in the mobile app.
- After each session, data is cleared to ensure clean tracking for the next workout.

Chapter 5: Experimental Results

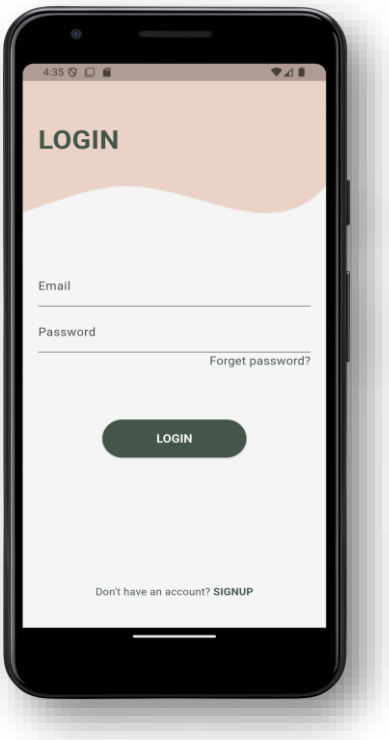
5.1 Patient-Side Outcomes:

5.1.1 Registration and Authentication [frontend + backend]:

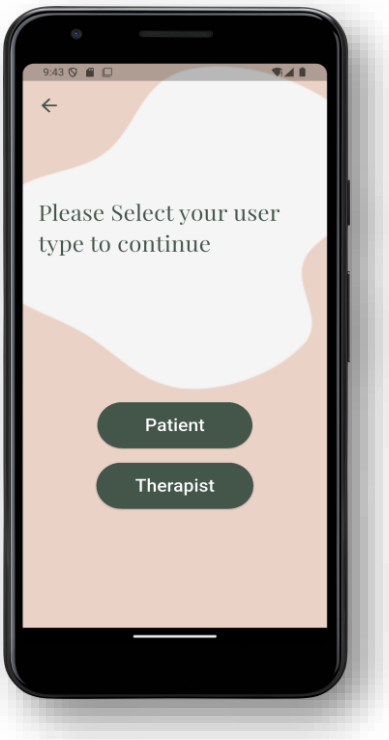
❑ Frontend (Flutter – Dart)

- **User Interfaces**:
  - **Sign-up screen** collects name, email, password, gender, date of birth, role.
  - **Login screen** authenticates via email and password.
  - **Forgot Password** screen allows the user to enter their email address. Upon submission, a password reset link is sent to their email. The user can reset the password using the link and then log in again normally.

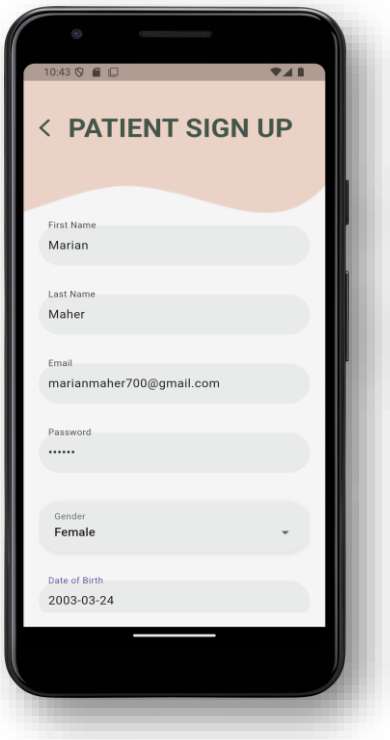
- **Role Handling**:
  - Role selected before sign-up (patient / therapist).
- **Validation**:
  - Form validation with real-time feedback for errors (email format, password length).

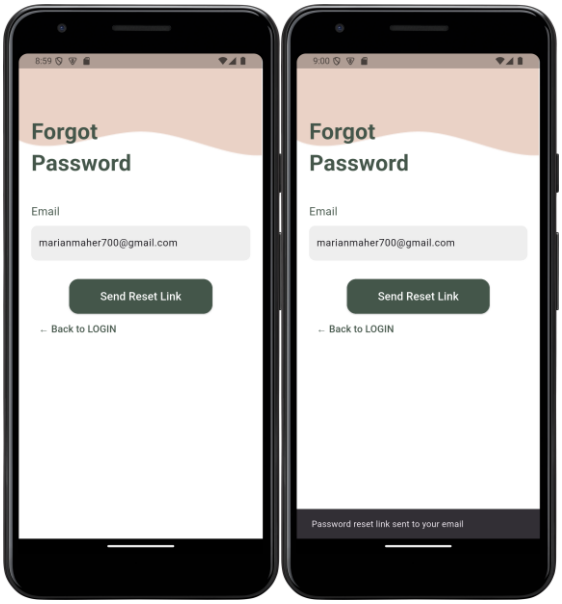


IF REGESTERD THEN REGESTER

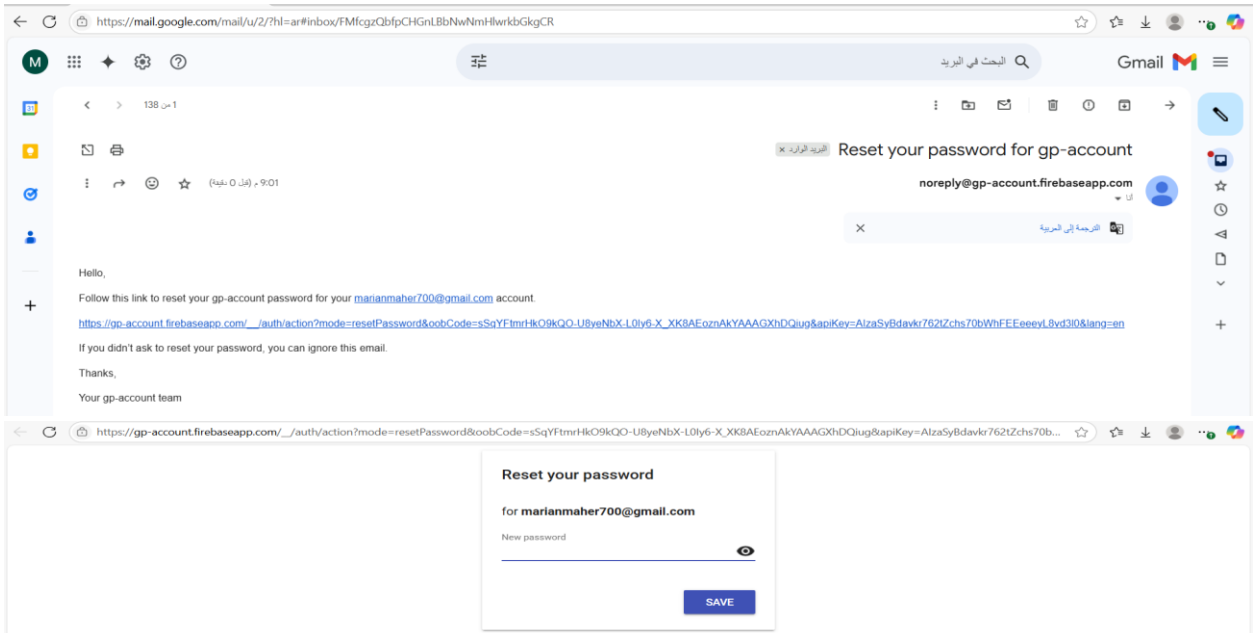


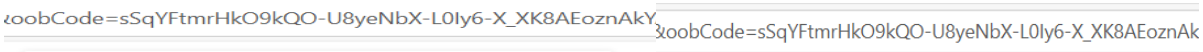
IF NOT REGESTERD SELECTE ROLE

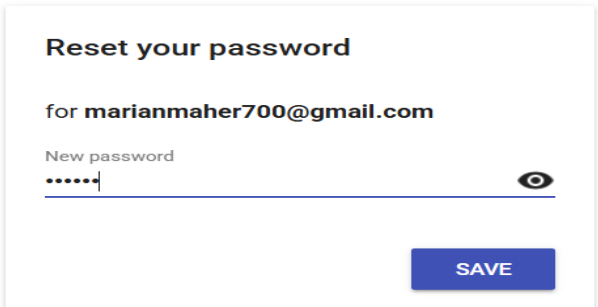


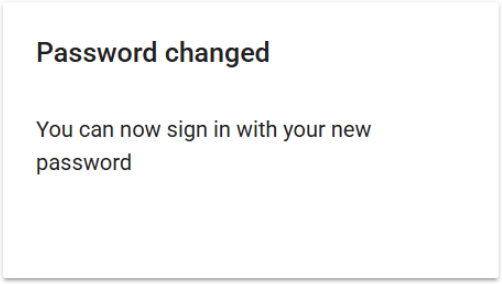


IN CASE OF FORGET PASSWORD



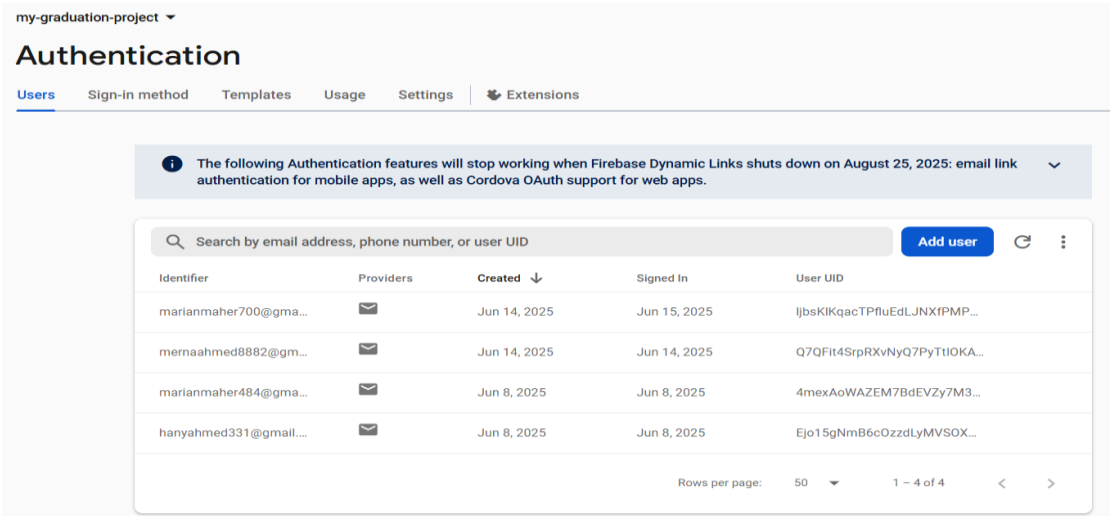


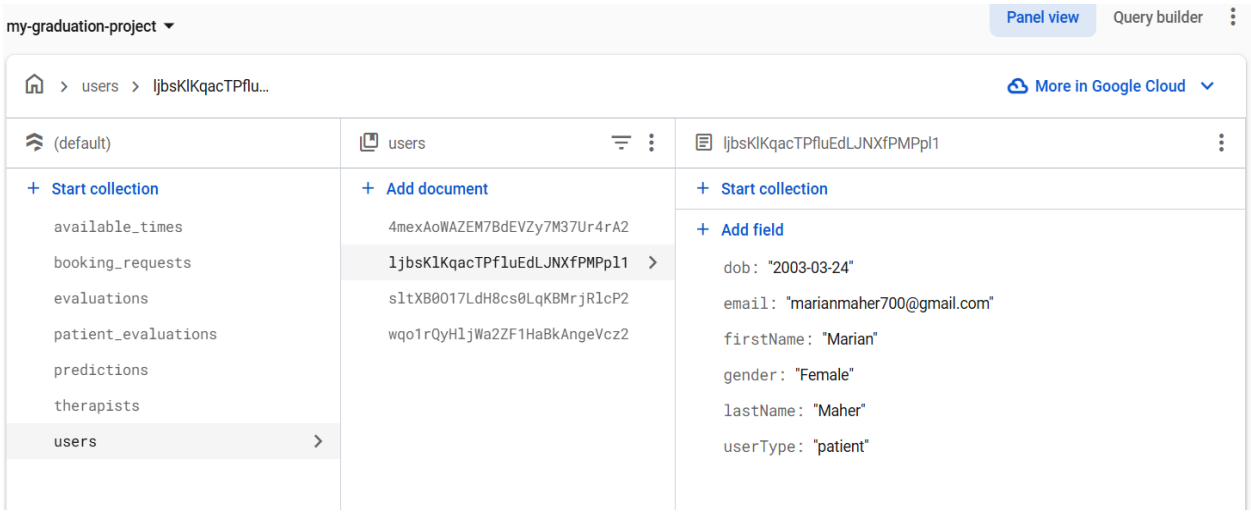




❑ Backend (Firebase Services)

- **Firebase Auth**:
  - Handles secure user creation, hashed passwords, and token-based sessions.
  - Supports password reset via email: When a user requests a reset, Firebase sends a secure link to their email to allow password updating.
- **Firestore**:
  - Stores extended profile info under users/{uid}.
  - The data stored in firebase encrypted by **AES**.





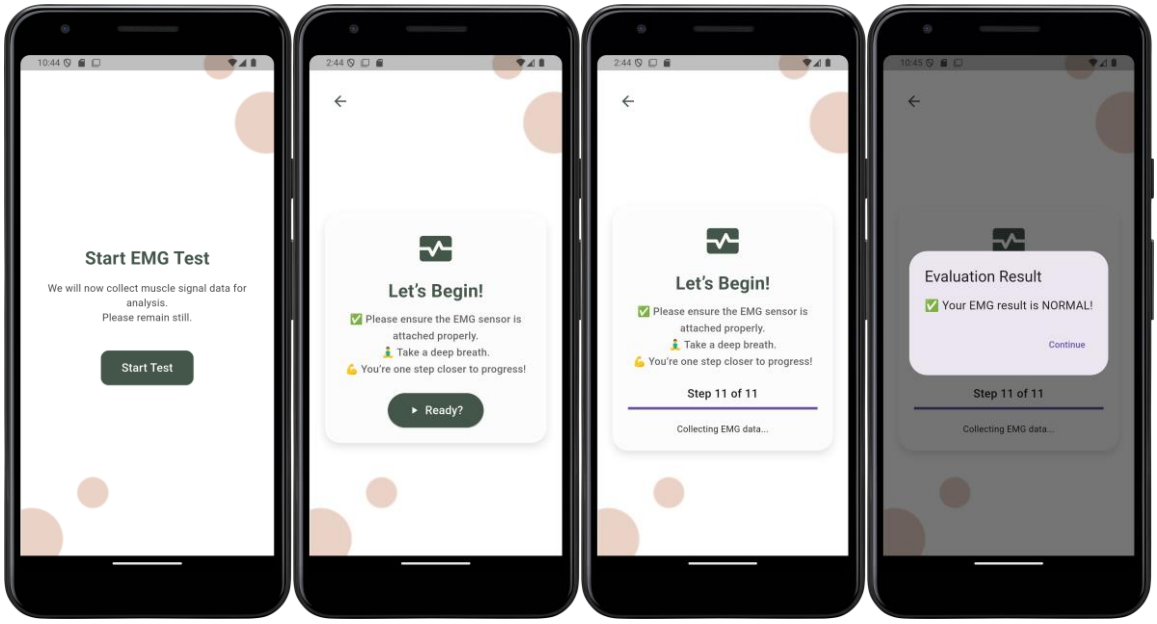
5.1.2 Post-Registration EMG Evaluation [frontend + backend]:

❑ Frontend (Flutter – Dart)

- **User Interface:**

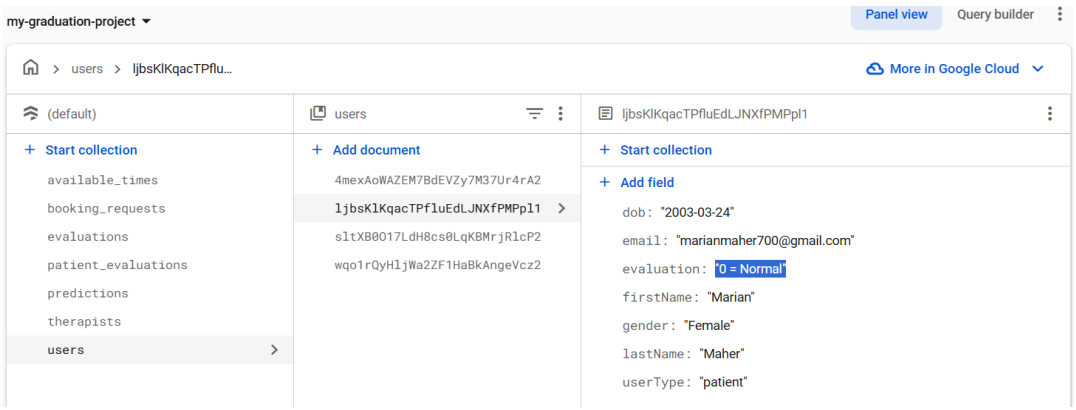
  The interface begins with clear instructions explaining the purpose and steps of the evaluation. It then presents a simple layout with “Start” and “Stop” controls to guide the user through the EMG recording process.

- **Real-Time Signal Visualization:**
  During the test, the EMG signals are streamed live from a connected **ESP32 device** and displayed in real time within the application. This ensures that users can confirm the device is operating correctly.

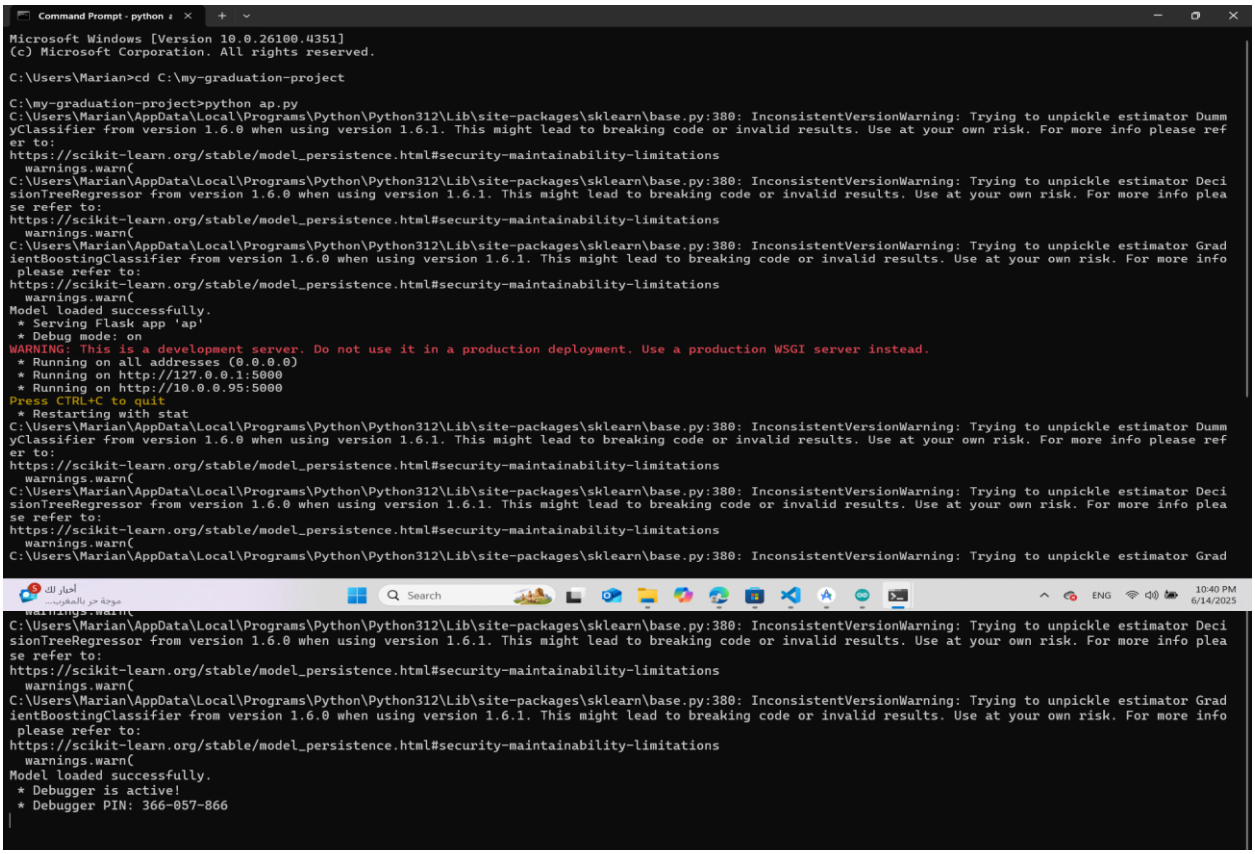


❑ Backend (Flask + Firebase)

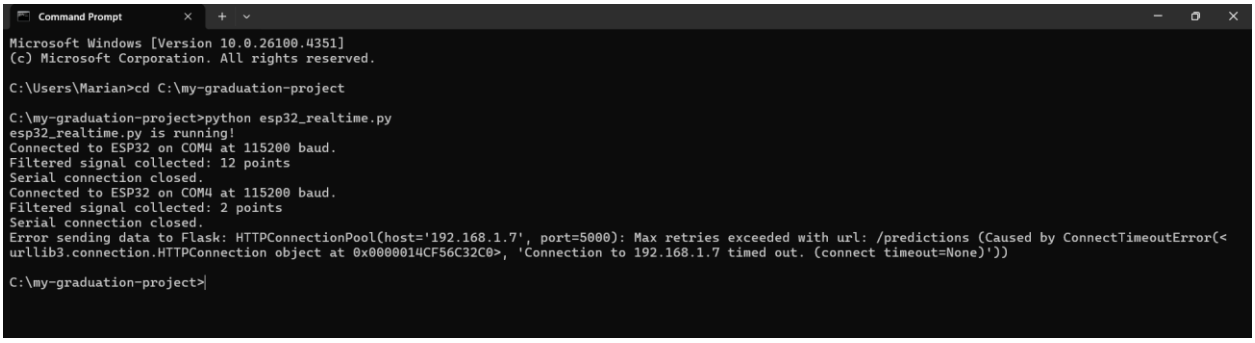
- **Signal Collection (ESP32 + Firebase Realtime Database):**
  The EMG data is collected through the ESP32 microcontroller, which transmits the data in real time to the **Firebase Realtime Database**. This enables seamless data synchronization with the mobile app.
- **Signal Processing and Classification (Flask API):**
  Once the user stops the test, the recorded EMG signal is sent to a **Flask backend server** for analysis. A trained machine learning model hosted on the server processes the signal and classifies the patient’s condition as either **"normal"** or **"abnormal"**.
- **Condition Storage and Flow Update (Firestore):**
  After receiving the classification result, the app stores the outcome in the patient's profile in **Firebase Firestore**.



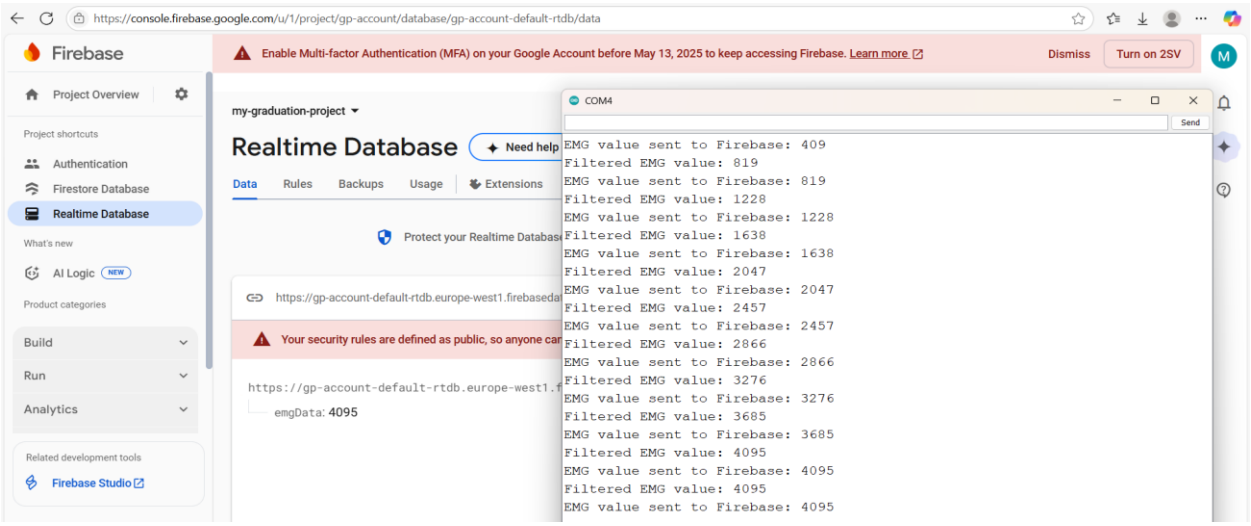
Running Flask



Runing ESP32_RealTime



EMG & Firebase



5.1.3 Home Screen Personalization Based on Classification Result:

Upon completion of the initial EMG-based evaluation, the patient's classification result—either **“Normal”** or **“Abnormal”**—is used to dynamically personalize their home screen within the mobile application. This tailored interface aims to ensure that patients are presented with content and exercises appropriate to their physical condition, enhancing both safety and treatment effectiveness.

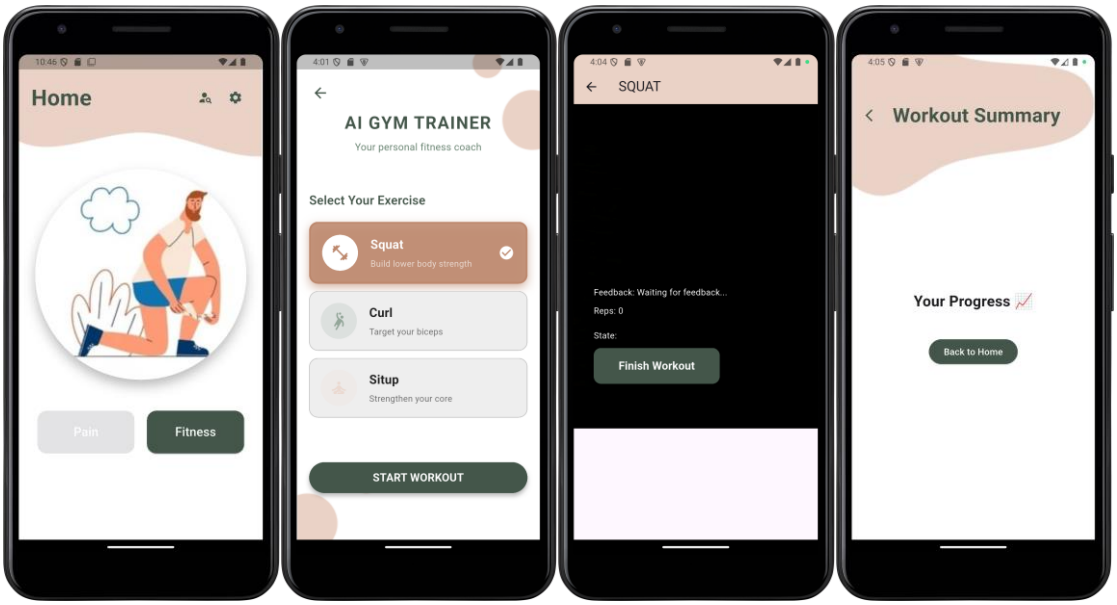
Fitness Pathway (Normal Classification)

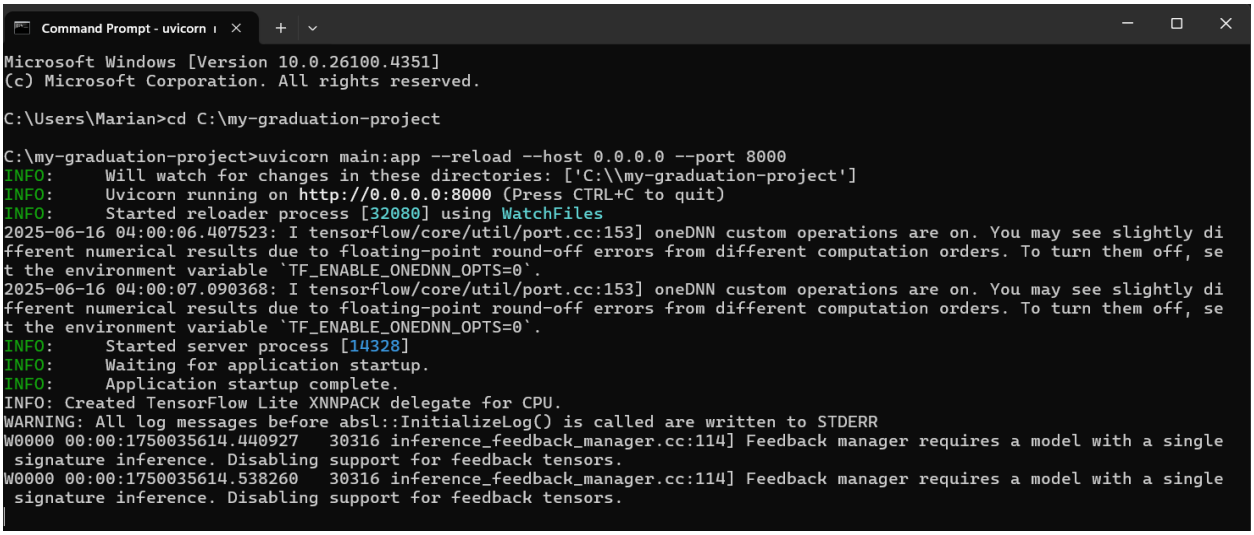
Frontend (Flutter – Dart)

- "Home Page" was displayed with fitness exercises like (squats, curls, and sit-ups).
- Pain-specific content was not shown.
- Upon selecting an exercise (Squat or Curl or sit-ups), the app navigates the user to a **Camera Tracking Screen**.
- The camera starts capturing the user's body movements, and pose detection is performed to identify repetitions (reps) in real time.
- Each completed rep is visually counted on-screen, providing immediate encouragement and progress awareness.
- Once the workout session ends, the user is redirected to a **feedback screen**.
- This screen displays a **graph-based summary.**

❑ Backend (Firebase & FastAPI)

- EMG data classified as **Normal** is stored in Firestore under the user's profile.
- The backend uses **FastAPI** to handle real-time communication between the mobile app and the machine learning model responsible for classification.





Pain Pathway (Abnormal Classification)

❑ Frontend (Flutter – Dart)

- This module implements a **two-phase pain assessment system** for knee rehabilitation, allowing real-time evaluation of movement quality using wearable sensors. It connects with a Flask-based backend powered by deep learning.

- **Phases:**

  - **Start Phase 1:** Begins first motion test and collects sensor data.
  - **Start Phase 2:** Begins second motion test.
  - **Finish:** Combines data from both phases and sends it to the backend for evaluation.
  - **Restart Test:** Resets all data and allows the patient to reattempt the test.

- **Data Collection:**

  - During each phase, the following data are collected in real time:
  - **EMG signals** – from Firebase Realtime Database or directly from an EMG sensor.
  - **Knee angle data** – typically gathered using an **MPU6050 IMU sensor**.

- **Feedback Presentation:**

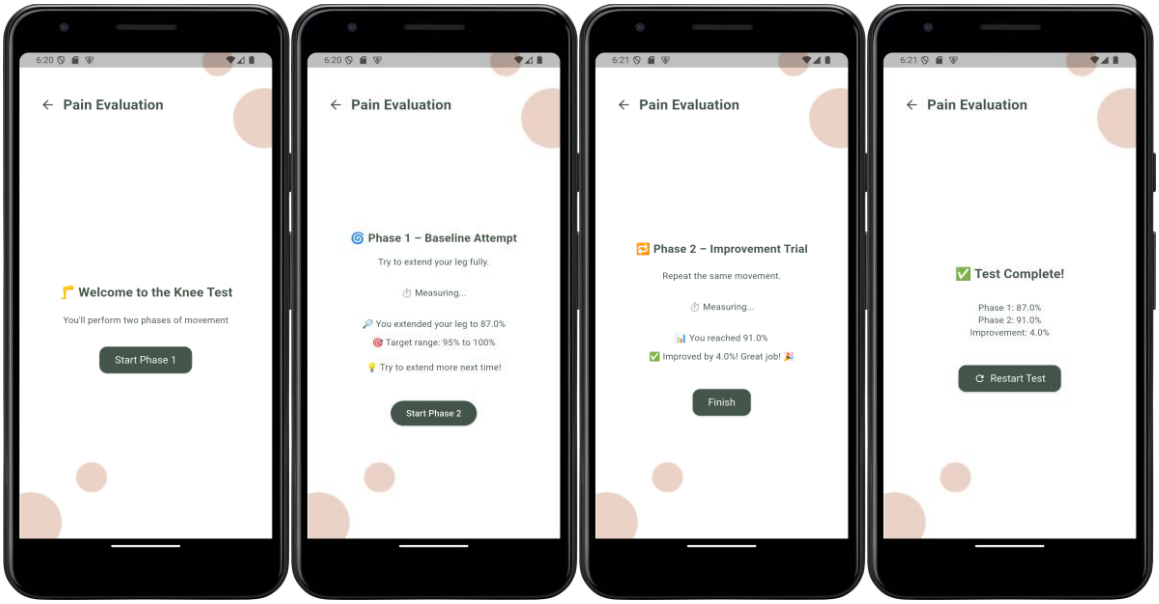
  After completing both phases and receiving the backend response, the UI presents:

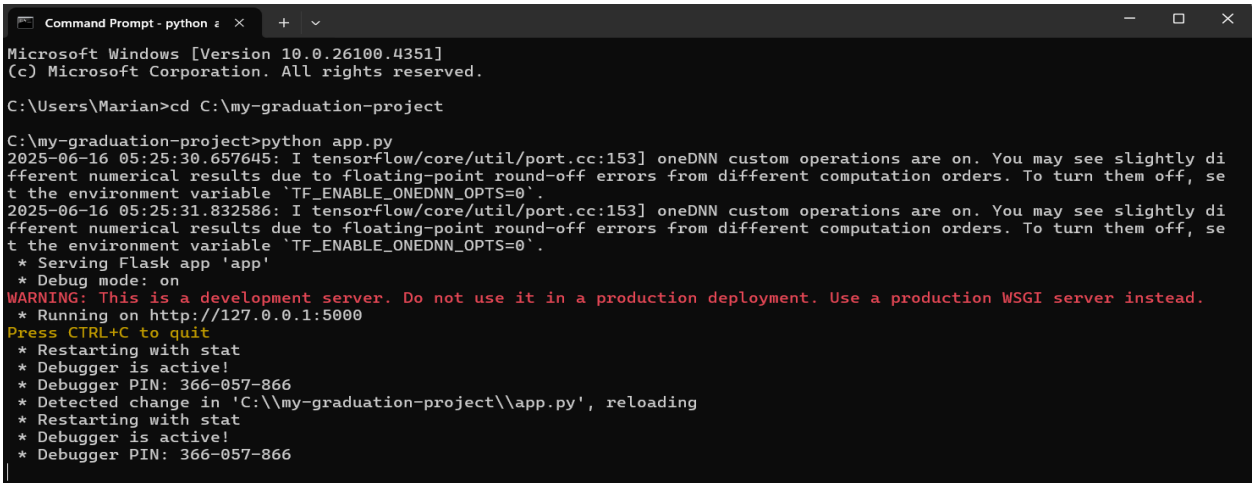
- **Overall Statistics:**
  - Average angle error
  - Average range of motion (ROM)
  - Average normal confidence score

❑ Backend (Firebase & FastAPI):

The backend is a Flask-based API responsible for analyzing sensor data using a pre-trained LRCN (Long-term Recurrent Convolutional Network) model. It determines exercise quality by detecting motion phases and comparing them to ideal movement patterns.

- **Processing Pipeline:**
  - Load model & scalers (EMG scaler, angle scaler)
  - Preprocess EMG and angle data (e.g., filtering, normalization)
  - Create sequences for LRCN model input
  - Predict motion class (normal/abnormal) for each time window
  - Detect phases using knee angle data
  - Calculate stats per phase (ROM, angle errors, confidence)
  - Generate feedback per exercise phase

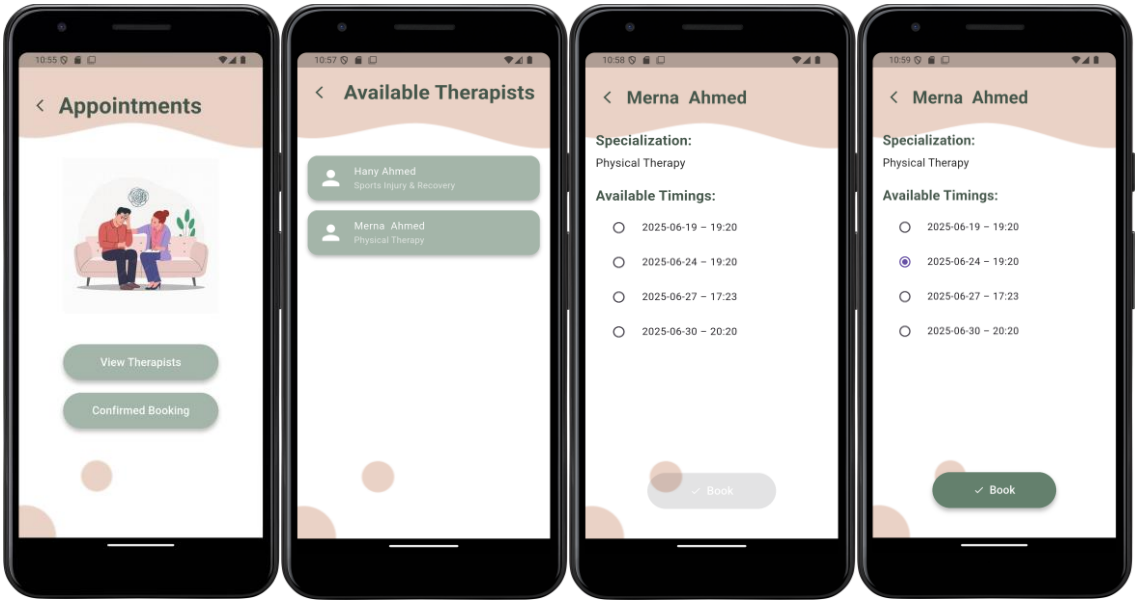




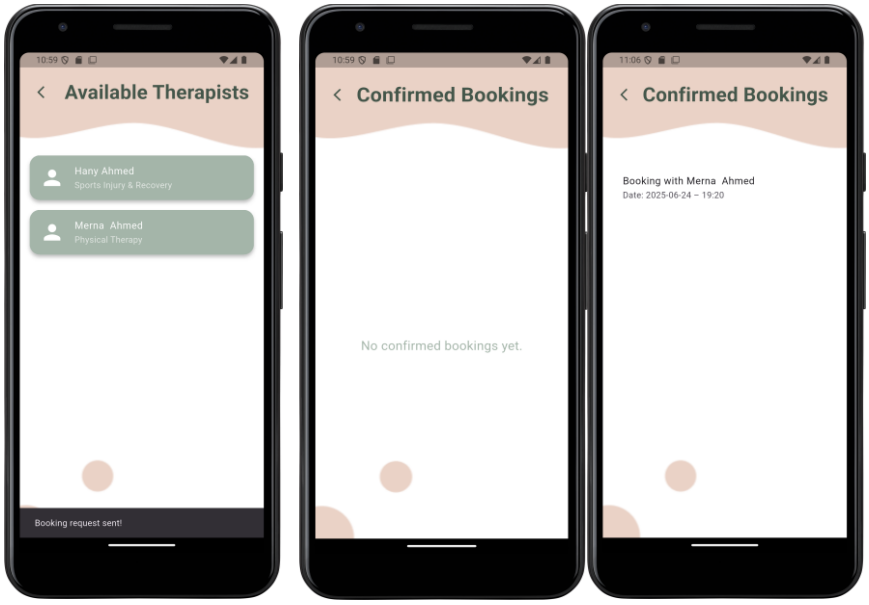
5.1.4 Appointment Booking [frontend + backend]:

❑ Frontend (Flutter – Dart)

- Upon navigating to the **Appointments** section, patients are presented with a dynamically generated list of therapists retrieved from Firestore.
- The screen fetches a list of available therapists from Firestore, showing:
  - Therapist's full name
  - Specialty (Physiotherapy, Sports Rehab)
  - Available time slots (date + time)
- **Slot Selection and Booking:**
  When a patient selects a therapist and a slot, the app:
  - Sends a **booking request**
  - Displays a **confirmation UI** showing: "Request sent – waiting for approval"
  - Prevents duplicate bookings for the same slot
- **My Appointments Section:**
  Patients can view all their current and past appointment requests.
  Each appointment includes:
  - Therapist name
  - Selected time
  - Current status: Pending, Confirmed, or Rejected



Before & After Confirmation from Therapist



❑ Backend (Firebase)

- **Firestore Structure:**
  Collection: therapists
  Each document represents a therapist and contains:
  - fullName: Therapist name
  - specialty: Area of expertise
  - availability: List of time slots with date, time, isBooked (true/false)
- **Data Flow:**

1.When the patient opens the Appointments screen, the app fetches all documents from therapists.
2.Only available time slots (isBooked: false) are shown.
3.Data updates in real-time using Firestore listeners.

- **Security Rules**
  Patients: read-only access
  Therapists: write access to their own availability

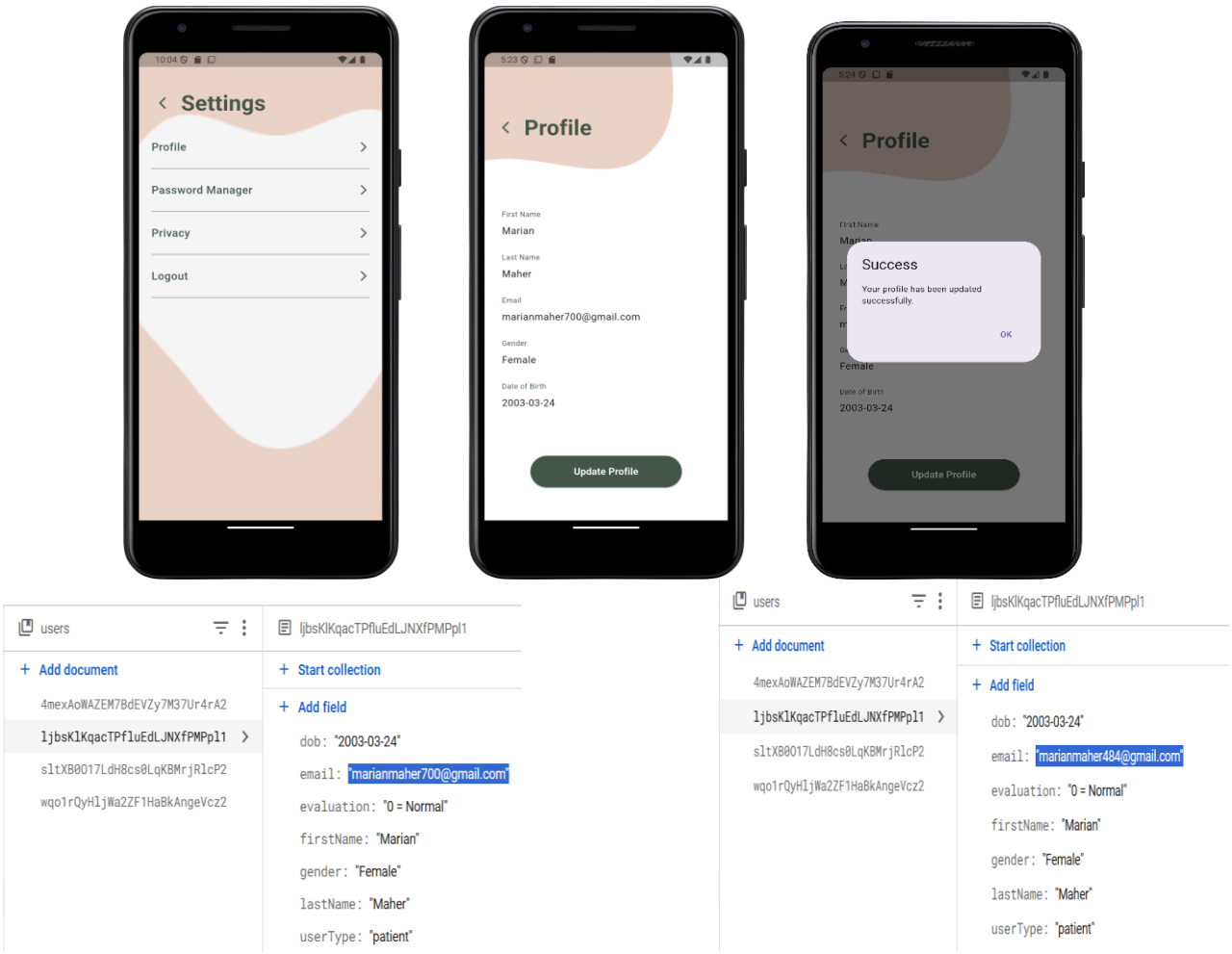
5.1.5 Patient Settings [Frontend + Backend]:

1. Profile:

- Displays the user's personal information:

  (Full Name,Email Address, Gender, Date of Birth)

- Optionally allows editing personal details.
- User data is stored in **Firestore.**
- When the user updates their profile, the corresponding fields in **Firestore** are automatically **updated** using update () operations.



2. Manage Password:

- User enter: (Current Password, New Password, Confirm New Password)
- Validations ensure the new password is strong and matches the confirmation.
- Triggers Firebase re-authentication before password update.
- Uses `reauthenticateWithCredential()` to confirm the old password.
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- Displays the app's privacy policy in a scrollable screen

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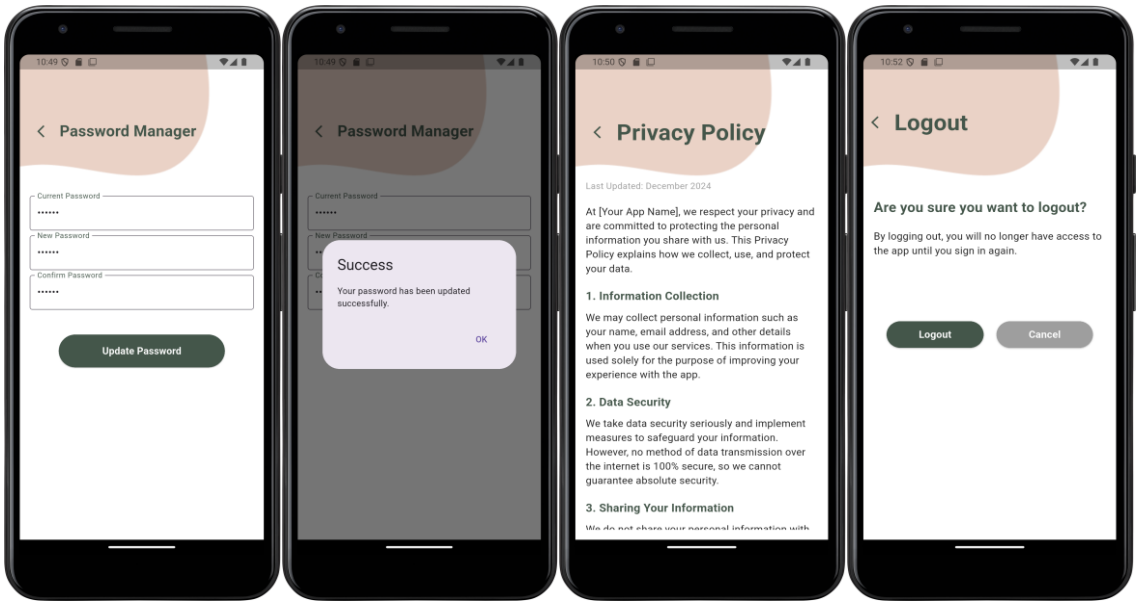


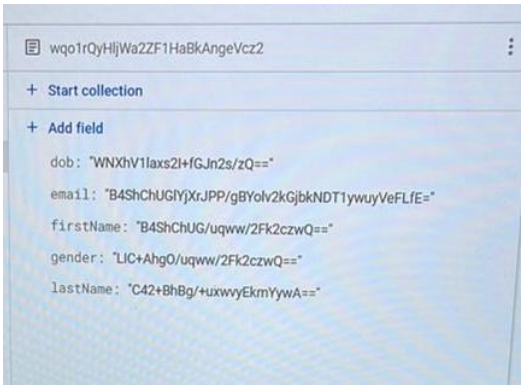
5.1.6 Security results:

The implementation of AES-128 in CBC mode within our Smart Rehabilitation System significantly improved data security, system reliability, and compliance with GDPR and HIPAA. By encrypting EMG signals and personal patient data before sending them to Firebase, we ensured end-to-end protection from edge devices to cloud storage. Synchronizing encryption settings across the ESP32 and Flutter app allowed accurate cross-platform decryption. Firebase was secured with strict rules and device authentication, preventing unauthorized access. Simulated brute-force attacks confirmed the encryption's strength, and the system maintained low-latency performance suitable for real-time physiotherapy monitoring.

Encrypted data of EMG sensor:

Damaged data:

Encrypted data of patient data:



5.2 Therapist-Side Outcomes.

5.2.1 Registration and Authentication [frontend + backend]:

❑ Frontend (Flutter – Dart):

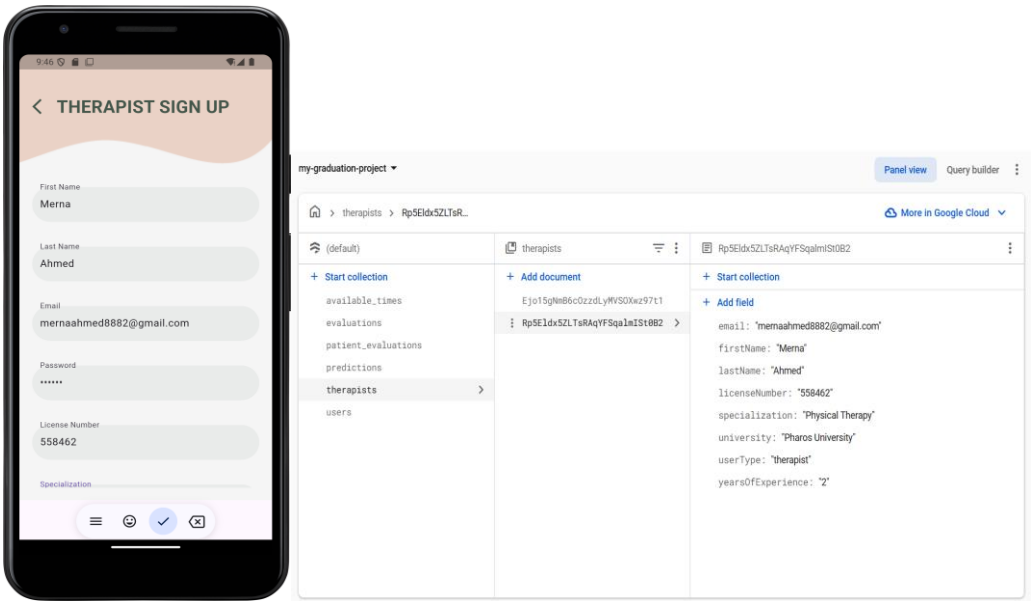
- **Therapist Sign-Up Interface:**
  - The therapist fills the sign-up form with the following fields:

    (First Name, Last Name, Email, Password, License Number, Specialization, Years of Experience, University Name, Signature)

- **Therapist Login Interface:**
  - Email and password authentication via Firebase.
  - On Successful Login
    The app checks the user's role (therapist) and verification status (verified == true) from Firestore.

❑ Backend (Firebase & Blockchain):

- **Firebase Auth**:
  - Handles secure user creation, hashed passwords, and token-based sessions.
- **Firestore**:
  - Stores extended profile info under therapistes/{uid}.
- **Blockchain:**
  - Ensure the signature of therapist .



5.2.2 Therapist Home Page – Appointments Section [Frontend + Backend]:

❑ Frontend (Flutter – Dart):

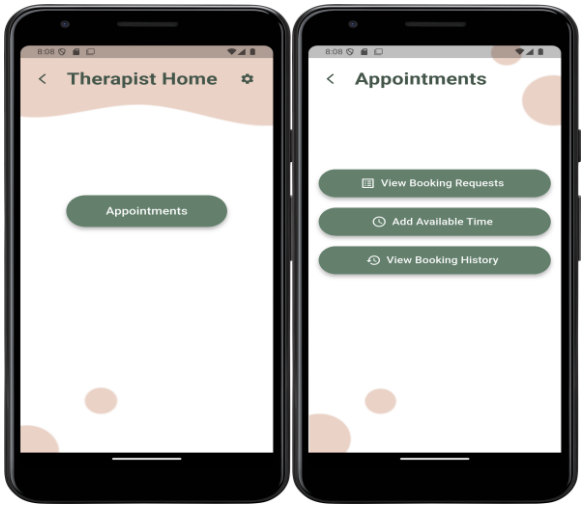
- The Therapist Home Page integrates a complete appointment management system. It allows therapists to manage their availability, respond to patient booking requests, and track confirmed sessions in an intuitive and secure manner.
- Upon logging in, therapists have access to a dedicated **Appointments Section**, which includes three key functionalities:

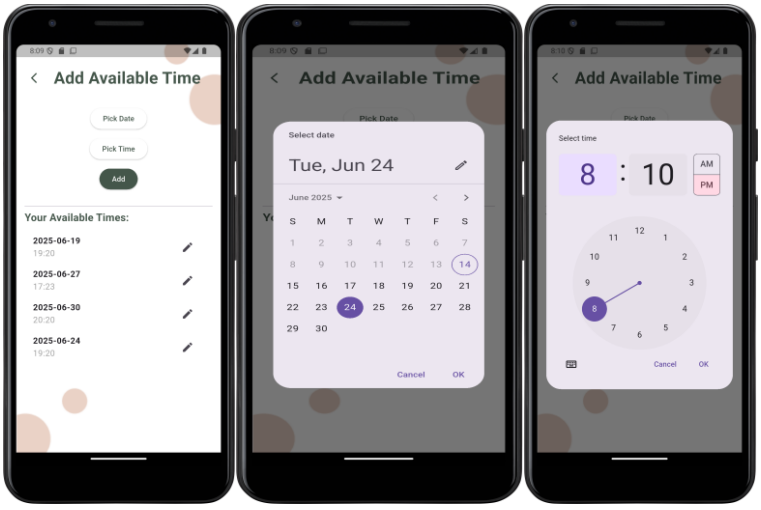
1. **Add Available Time:**
   - UI provides a form with **date and time pickers**.
   - On submission, the slot is added to **Firestore** and becomes visible to patients.

- Slots are marked as available until booked.

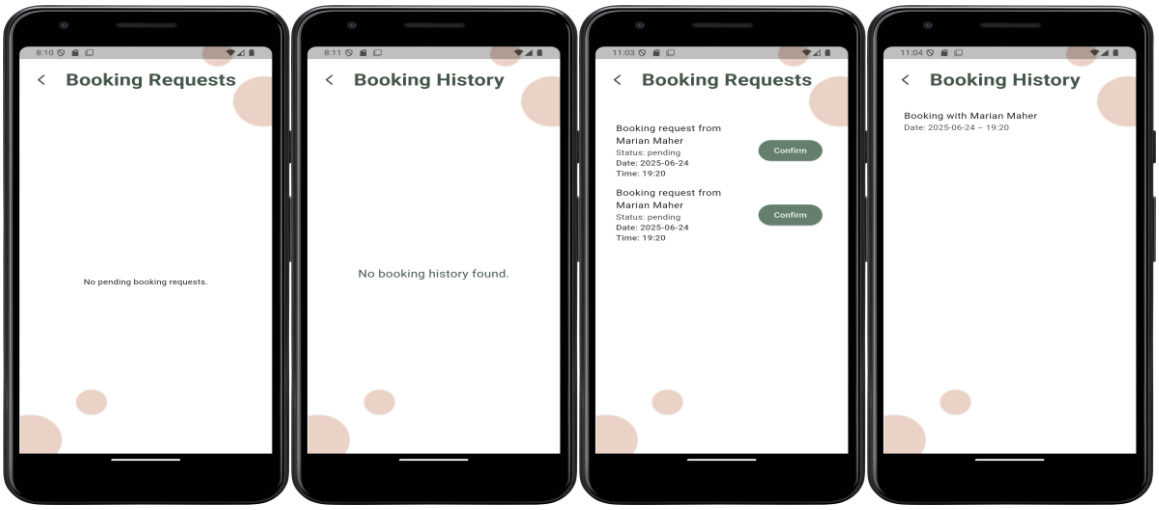
2. **View Booking Request:**
   - Lists all incoming **appointment requests** from patients.
   - Each request displays:
     -Patient's name
     -Requested slot (date & time)
   - Action buttons: **Accept** or **Reject**
   - On accepting a request:
     -The appointment is confirmed.
     -The corresponding time slot is **removed** from the therapist's available list.

3. **View Booking History**
   - Displays a list of all confirmed appointments (past and future).
   - Each entry includes:
     - Patient name
     - Appointment date & time





Before any request from patient **After a request from patient**



❑ Backend (Firebase Firestore):

- Firestore Collections:

  The booking system is structured using two main collections:

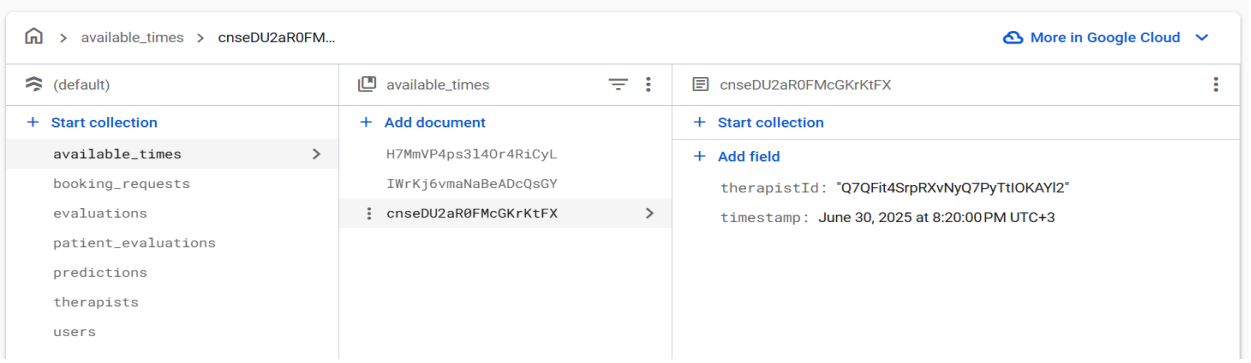
  1. available_times Collection:

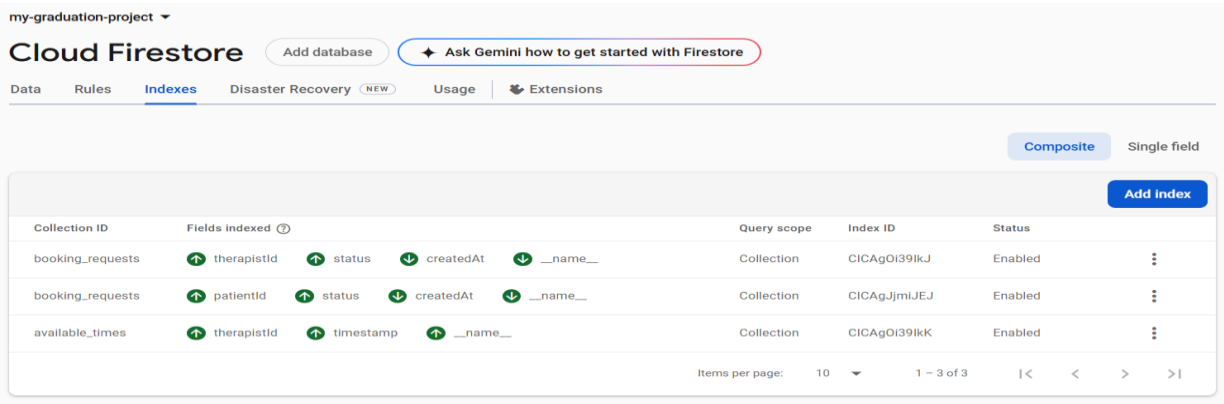
- This collection holds all the available appointment slots offered by therapists.
- Each document includes:
-

Field	Type	Description
therapistId	string	UID of the therapist who added this slot.

timestamp	datetime	Date and time of the available slot.

This collection is queried by patients to view available slots.

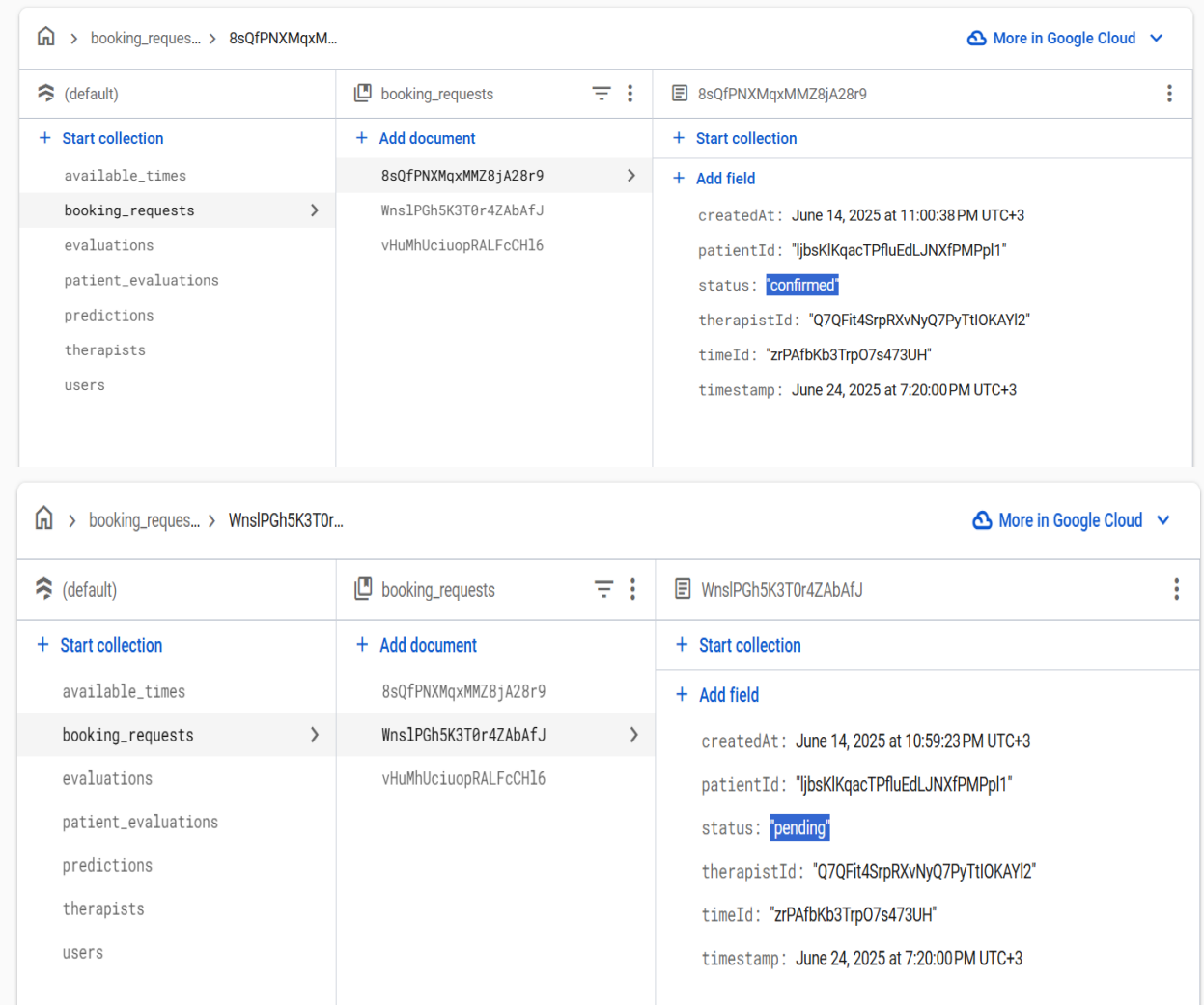




2. booking_requests Collection:

- Stores appointment requests submitted by patients.
- Each document contains:

Field	Type	Description
created At	datetime	Timestamp when the request was made.
Patient Id	string	UID of the patient requesting the session.
Therapist Id	string	UID of the selected therapist.
timestamp	datetime	Date and time of the requested appointment.
status	string	Current status of the request (pending, confirmed, rejected).
Time Id	string	ID of the original available time slot. Used for deletion upon confirmation.



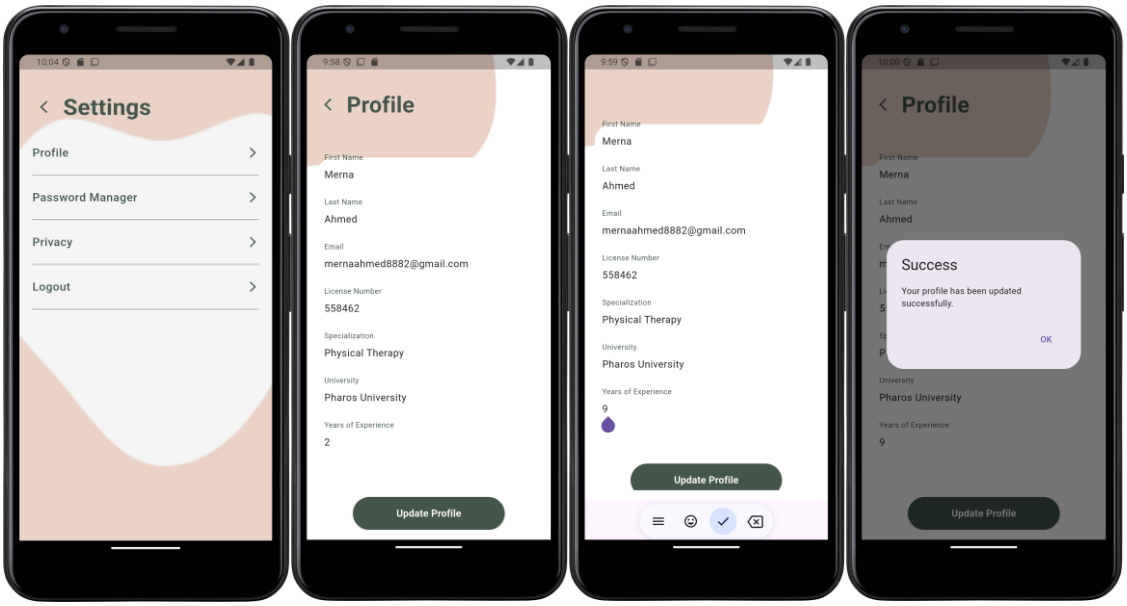
5.2.3 Therapist Settings – [Frontend + Backend]:

1. Profile:

- Displays the Therapist's personal information:

  (Full Name, Email Address, License Number, Specialization, University, Years of experience)
- Optionally allows editing personal details.
- User data is stored in **Firestore** .

- When the user updates their profile, the corresponding fields in **Firestore** are automatically updated using update () operations.



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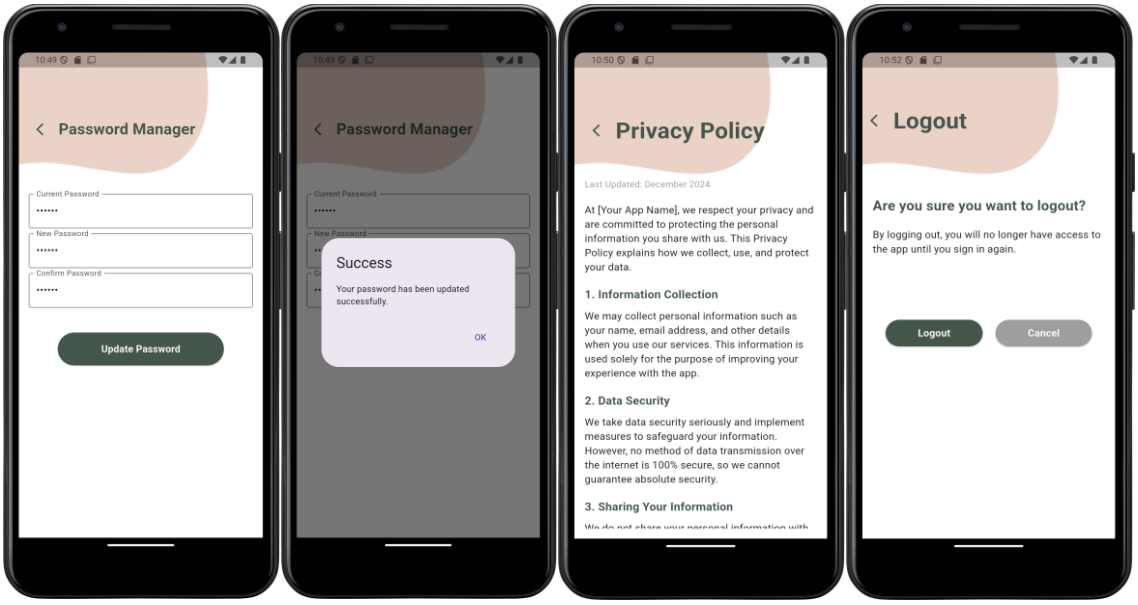
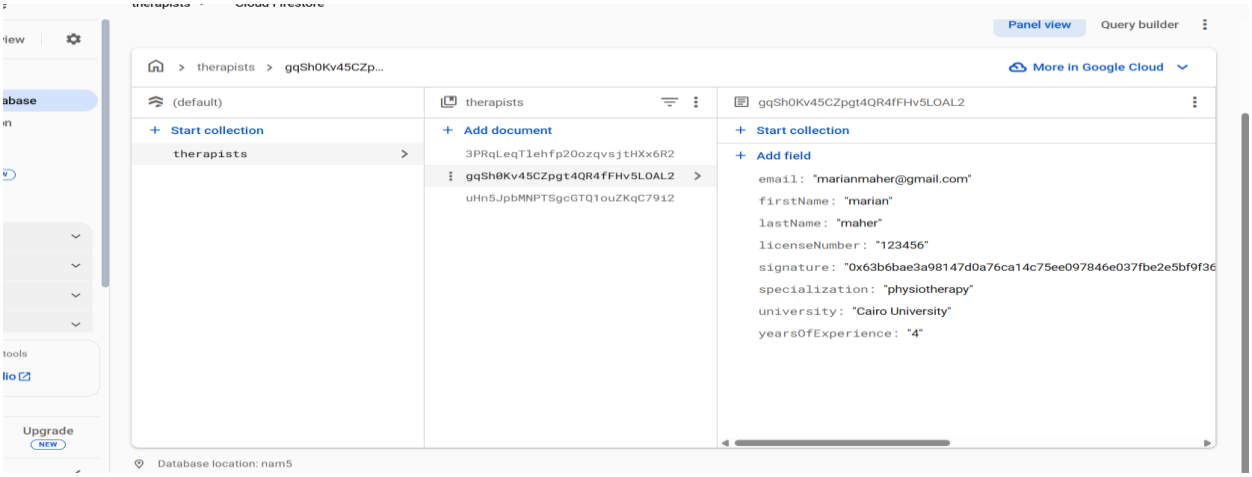


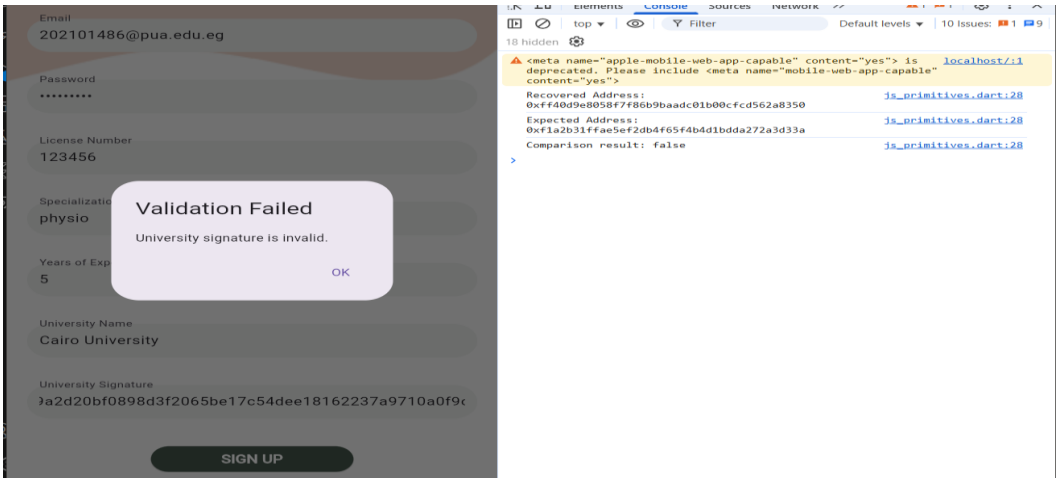
5.2.4 Security results:

The implementation of blockchain-based therapist validation in our Smart Rehabilitation System resulted in a highly secure, transparent, and tamper-resistant registration process. By utilizing digital signatures from trusted universities stored as public keys on the Ethereum Sepolia testnet, we ensured that only accredited therapists could join the platform. This system successfully prevented unauthorized or fraudulent registrations by verifying the authenticity of each therapist's digital signature through off-chain cryptographic techniques. The decentralized nature of blockchain eliminated the need for a central authority, reducing the risk of manipulation or data breaches. Additionally, the integration of this verification process within the Flutter mobile app and Firebase storage maintained a seamless user experience while upholding strict security and compliance standards.

Validated email(therapist):



Unvalidated therapist:



10. Conclusion:

The Smart Rehabilitation System represents a transformative approach to physiotherapy by combining IoT, AI, and secure mobile technologies to deliver intelligent, personalized, and remote care. Through real-time EMG and computer vision-based assessments, the platform ensures accurate diagnosis, adaptive rehabilitation, and continuous monitoring of patient performance. By integrating machine learning for classification, deep learning for movement analysis, and secure blockchain-backed data management, the system not only enhances patient outcomes but also upholds high standards of safety, privacy, and scalability. This innovative solution bridges the gap between patients and therapists, making high-quality rehabilitation accessible, efficient, and future-ready.

11. Future work:

For part of Encryption:

Use of AES-GCM Instead of CBC

- Transition to AES-GCM (Galois/Counter Mode) which provides both confidentiality and authentication (integrity check).
- This mode eliminates the need for separate checksum handling

For part of Blockchain:

QR Code-Based Signature Submission

- Introduce QR code generation for signed therapist data, allowing quick and secure scanning during signup via mobile camera.

Automated University Signer Portal

- Develop a web portal for universities to securely generate and manage digital signatures using their MetaMask accounts. This reduces manual signing.

For part of Mobile Application as a Patient:

Integration of Pre-Built IMU and ECG AI Models into the Mobile Application
Artificial Intelligence models for both IMU (Inertial Measurement Unit) and ECG (Electrocardiogram) signal analysis have already been successfully developed and validated independently. However, their integration into the mobile application remains a future milestone due to the following challenges:

- **Multimodal Data Synchronization:** Differences in sampling rates and data formats make real-time fusion technically challenging.
- **Unified Feedback System:** Combining motion and physiological data requires advanced logic to deliver accurate, context-aware insights to patients and therapists.

To further enhance the system's clinical utility, several improvements are envisioned:

- **Multi-Channel EMG Expansion**: Integrate additional EMG channels to capture more detailed muscle activity with its joints ito mprove joint angle prediction accuracy.
- **Personalized Calibration**: Implement subject-specific model fine-tuning to improve prediction accuracy across varied patient profiles.
- **Cross-Population Validation**: Extend validation to diverse age groups and injury types for broader clinical applicability and generalization.
- **Real-Time Feedback Enhancement by joint angles**: Optimize latency and extend the real-time feedback system to more exercises with customizable performance thresholds.

For part of Mobile Application as a Therapist:

Therapist–Patient Chat & Live Video Consultation

Enable secure real-time communication between patients and therapists through a built-in chat system and optional video consultation, helping therapists monitor progress and give live feedback remotely.

Chapter 9: Literature Review

9.1 Literature Review

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شكر وتقدير

."نتقدم بخالص الشكر والامتنان لكل من قدم لنا الدعم والإرشاد طوال فترة تنفيذ مشروع تخرجنا **"نظام التأهيل الذكي**

في المقام الأول، نُعرب عن بالغ امتناننا لكل من **الأستاذ الدكتور سعد درويش، والدكتورة سحر غانم، والمهندسة إسراء همشري،** على إشرافهم القيم، وتشجيعهم المستمر، وملاحظاتهم البنّاءة في جميع مراحل المشروع. لقد كان لتوجيهاتهم وخبراتهم الدور الأساسي .في بلورة الفكرة وتنفيذها بنجاح

كما نود أن نشكر **كلية علوم الحاسب والذكاء الاصطناعي بجامعة فاروس** لما قدمته لنا من معرفة وأدوات وبيئة تعليمية محفزة .ساعدتنا على خوض هذا المشروع وإنجازه بالشكل المطلوب

ولا يفوتنا أن نتوجه بجزيل الشكر والتقدير لأعضاء الفريق: **أسماء أحمد أحمد، حبيبة أسامة، فرح نصر جويد، مريم أحمد محمود، .وماريان ماهر صبحي،** على التزامهم وتعاونهم وروح الفريق التي ساهمت بشكل أساسي في تحويل هذه الفكرة إلى حل ذكي ومبتكر

.وأخيرًا، نتقدم بخالص الامتنان لأسرنا وأصدقائنا على دعمهم المعنوي المستمر، وصبرهم، وتشجيعهم لنا طوال رحلتنا الأكاديمية

الملخص

يُعد **نظام التأهيل الذكي** منصة علاج طبيعي عن بُعد، تعتمد على تقنيات استشعار متقدمة، وذكاء اصطناعي، واتصال آمن عبر تطبيقات الهواتف المحمولة، بهدف مراقبة وتعزيز عملية التعافي لدى المرضى. من خلال دمج معالجة الإشارات الحيوية، وتعلم الآلة، والتعلم العميق، والرؤية الحاسوبية، يقدم النظام خطة تأهيل شخصية قائمة على التغذية الراجعة اللحظية تحت إشراف المعالج عن بُعد.

ينقسم النظام إلى مرحلتين أساسيتين:

أولًا: التشخيص والتصنيف
يتم تحليل الإشارات الكهربائية السطحية للعضلات (إس إي إم جي) من عضلة الفاستس ميديااليس لاكتشاف الأنماط العصبية العضلية. ثم يُستخدم نموذج تصنيفي لتحديد ما إذا كانت النشاطات العضلية طبيعية أم غير طبيعية، مما يُمهد لوضع خطة علاجية مخصصة لكل حالة.

ثانيًا: التأهيل الشخصي

للحالات غير الطبيعية: يتم تقديم تمارين دعم موجهة مثل تمرين مد الركبة النهائي. ويقوم نموذج هجين يجمع بين بيانات العضلات الكهربائية وأجهزة الاستشعار الحركية بتقدير زوايا المفصل، وتقييم جودة الحركة، وتقديم تصحيح لحظي لتحسين وظيفة العضلات.

للحالات الطبيعية: يتم ممارسة تمارين لياقة عامة مثل القرفصاء، وتمارين البطن، وتمارين الذراع، باستخدام نظام رؤية حاسوبية بدون استخدام حساسات قابلة للارتداء، مع تقديم تصحيح فوري للأداء وتصوّر مرئي للمستخدم.

ولضمان السلامة، تتم مراقبة النشاط القلبي باستخدام مستشعر تخطيط القلب الكهربائي بشكل مستمر لاكتشاف علامات الإجهاد الزائد أثناء التمارين.

يُستخدم تطبيق موبايل آمن كواجهة للنظام، ويقدم

تقييمات تلقائية

جلسات تمرين شخصية وموجهة

تحليلات أداء

وجدولة مواعيد مع الأخصائي

ويتم تأمين البيانات من خلال تقنية تشفير متقدمة وتسجيل الجلسات باستخدام تقنية البلوكشين عبر بنية تحتية سحابية. يقدم هذا النظام حلاً ذكيًا وقابلًا للتوسع يُعزز من التعافي الصحي ويُسهم في تطوير الرعاية الصحية من خلال إنترنت الأشياء والرؤية الحاسوبية والتحليل الذكي الآمن.