KNEE OSTEOARTHRITIS PREDICTION AND PROGRESSION USING MULTI-MODAL DEEP LEARNING.

Project ID: 25-26J-112

Project Proposal Report

Gamage D.M.G.P.K – IT22188472

BSc (Hons) in Information Technology Specializing in Data Science

Department of Information Technology
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Supervisor - Ms. Jenny Krishara

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Declaration

We declare that this is our own work, and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of our knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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The supervisor/s should certify the proposal report with the following declaration.

The above candidates are carrying out research for the undergraduate dissertations under my supervision.

Signature of the Supervisor	Date
....	2025/08/29
(Ms. Jenny Krishara)	
Signature of the Co-supervisor	Date
....	29/08/2025
(Ms. Wishalya Tissera)	

Abstract

KOA is one of the most common degenerative joint disorders, significantly impacting mobility and quality of life, particularly among the ageing population. Traditional diagnostic methods, such as X-ray and MRI imaging, while effective, are costly, limited to hospital environments, and provide only static insights into disease progression. There is a growing need for an affordable, patient-friendly, and continuous monitoring system that enables early detection and supports timely intervention.

This research proposes the development of a Smart IoT-Based Knee Health Monitoring System using VAG signals and biomechanical data. The framework integrates wearable sensors, including accelerometers, gyroscopes, and VAG microphones, to capture subtle knee vibrations and movement patterns during daily activities. Data will be processed in real time using TinyML models deployed on ESP32 microcontrollers, ensuring low-power, on-device inference without constant reliance on cloud resources. The system will provide real-time feedback through a mobile application, enabling both patients and clinicians to track knee health and receive alerts about abnormal conditions.

The study will also incorporate advanced signal processing methods such as Empirical Mode Decomposition and Ensemble EMD to extract key features like RMS amplitude, peak frequency, and spectral entropy, which are essential for detecting KOA-related changes. Anticipated results include improved accuracy in early KOA detection, effective grading of severity, and validation of the system in real-world conditions.

Ultimately, the proposed solution aims to bridge the gap between clinical diagnostics and home-based monitoring, offering an accessible, cost-effective, and scalable healthcare tool. This approach is particularly valuable for rural and low-resource communities, where access to advanced imaging facilities is limited. The system is expected to enhance early intervention, slow disease progression, and improve patients' overall quality of life.

Keywords: Knee Osteoarthritis, Vibroarthrography, IoT, Wearable Sensors, TinyML

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List Of Abbreviations

Abbreviation	Description
KOA	Knee Osteoarthritis
VAG	Vibroarthrography
AI	Artificial Intelligence
VMD	Variational Mode Decomposition
SVM	Support Vector Machine
CT	Computed Tomography
MRI	Magnetic Resonance Imaging
IoT	Internet of Things

EMD	Empirical Mode Decomposition "Empirical Mode Decomposition is a method used to break down complex signals into smaller, simpler parts called Intrinsic Mode Functions"
EEMD	Ensemble Empirical Mode Decomposition "An advanced form of EMD that adds small random noise to the signal and averages the results. This helps avoid mixing of frequencies and gives cleaner, more accurate signal components."
Vicon Optoelectronic Motion System	"A motion capture system that uses infrared cameras and reflective markers to track human or object movements in 3D."

1. Introduction

Arthritis, particularly KOA, is a common degenerative joint disease characterized by pain, stiffness, and reduced mobility caused by cartilage wear in the knee joint. This degradation leads to bones rubbing against each other, resulting in discomfort and permanent damage. KOA affects millions worldwide, especially the elderly, and early detection is essential to manage the condition effectively and delay or avoid surgical interventions [1],[2].

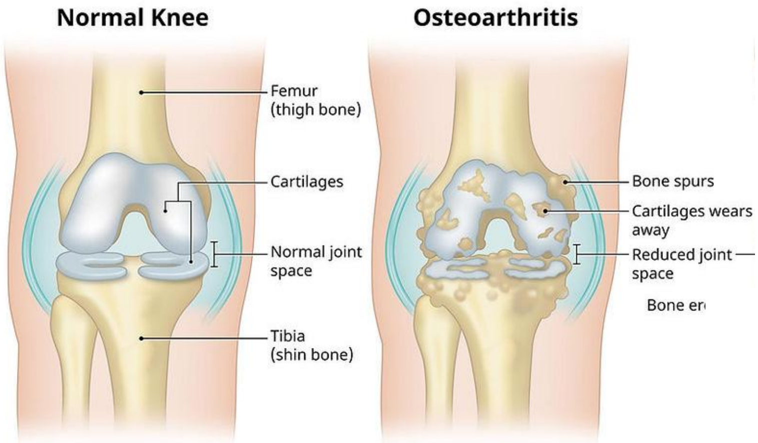

Figure 1 - Normal Knee vs Osteoarthritis Knee

Conventional diagnostic approaches for KOA include imaging techniques such as X-rays, MRI, and CT. While these methods are widely used, they are often expensive, inaccessible outside hospital settings, and not suitable for continuous monitoring [3], [4]. VAG, a non-invasive method, records mechanical vibrations generated by the knee joint during movement. This technique shows promise in early KOA diagnosis by detecting subtle abnormal joint sounds like crepitus and grinding, which are associated with cartilage damage [5].

Signal processing methods are crucial for analysing VAG data. Techniques such as EMD and EEMD have been employed to denoise signals and extract key features. However, these methods suffer from issues like mode mixing and instability, which can limit their effectiveness [6], [7]. Recently, VMD has emerged as a more robust approach to decomposing complex signals and enhancing noise suppression [8].

Machine learning algorithms, including SVM, Random Forests, AdaBoost, and ensemble classifiers, have been applied to classify VAG signals into normal and abnormal categories with accuracies reaching up to 93% [9], [10]. These models typically utilize features from time and frequency domains as well as scalograms and spectrograms. Despite these advances, most research remains limited to offline analysis of recorded signals, with few solutions implementing real-time, wearable monitoring systems.

Previous KOA detection methods focused mainly on clinical tests and offline VAG analysis without combining continuous real-time monitoring with wearable sensor technology. This project aims to address this gap by developing an IoT-based wearable device that continuously captures knee joint vibrations during daily activities and wirelessly transmits the data to a mobile application. The application will employ advanced ML models for real-time processing and provide alerts regarding potential knee problems while tracking disease progression outside of clinical environments [11].

In conclusion, this study builds on prior research by integrating advanced VAG signal processing techniques such as VMD with machine learning into a portable wearable device. This approach facilitates continuous, non-invasive KOA monitoring, making knee health management more accessible, timely, and cost-effective.

1.1 Background & Literature survey

KOA is a common degenerative disease of the joints, characterized by the destruction of cartilage tissue, joint pain, stiffness, and decreased mobility, primarily affecting older adults [1], [2]. Diagnosis and surveillance of KOA at an early stage is key to delaying the development of the disease and enhancing the quality of life of patients [1]. Conventional diagnostic tools primarily rely on the use of imaging tests, such as X-rays, MRI, and CT, which, despite their efficiency, are costly, unavailable in non-hospital-based facilities, and unsuitable for continuous monitoring [3], [4].

VAG is a non-invasive method with the potential to identify KOA through measurements of mechanical vibrations and abnormal articular sounds that occur during motion. Abnormal crepitus and grinding sounds related to cartilage wear can be used as an indicator of early pathological changes by VAG [5]. It is important to process these VAG signals correctly to be able to diagnose reliably. Signal decomposition tools such as EMD and EEMD have been used to filter out noise and extract useful information, but they are limited by problems such as mode-mixing and instabilities [6], [7]. Recently, there has been the introduction of VMD, which provides greater noise robustness and effective extraction of signal components [8].

Machine learning has improved the way VAG signals are classified to identify normal and abnormal situations in joint conditions. Classification accuracy results are above 93% using SVM, Random Forests, AdaBoost, ensemble classifiers using the features of the time and frequency domains, and scalograms and spectrograms [9], [10]. Although these results are encouraging, most of the literature available in the field focuses on offline analysis, and the feasibility of these methods to be applied in real-time monitoring devices is minimal.

The use of wearable sensors and IoT frameworks has seen a recent development that allows constant monitoring of KOA in the real world. Such wearable devices can measure the VAG signals during daily tasks and wirelessly send information to the computer in real time to analyze data with the help of AI algorithms [11], [12]. The use of VMD and machine learning in wearable devices contributes to the reduction of noise, and the accuracy of detection of KOA is improved [12]. Moreover, mobile applications send the necessary alerts and track the long-term development of the disease, which allows patients and healthcare providers to be independent of the clinical setting [13].

However, a significant gap remains in translating these research advances into accessible, non-invasive, and cost-effective wearable devices for continuous KOA monitoring. Most prior research does not fully integrate advanced signal processing, machine learning, and real-time IoT solutions into a cohesive system. Addressing this gap by designing a wearable VAG-based monitoring system will advance personalized knee health management, make KOA detection and monitoring more practical and widespread.

1.2 Research Gap

KOA is a progressive joint disease. It requires ongoing monitoring to prevent severe damage and improve treatment. While several studies have looked at monitoring KOA with wearable devices, sensors, or AI, most existing research has important limitations. These include issues with sensor type, real-time monitoring, accessibility, and ongoing analysis.

Research 1. [15]

This study used a mix of 3D accelerometers, gyroscopes, and reflective markers to examine tibial and femoral accelerations during walking. The system could tell apart healthy knees from those affected by KOA based on differences in joint movement and impact when walking. The approach achieved high accuracy in separating KOA patients from healthy individuals and provided detailed biomechanical data, like joint acceleration and angular motion. However, the system was lab-based and required an expensive VICON optoelectronic motion capture setup, which made it hard to move. Measurements were limited to controlled environments, and there was no option for long-term monitoring or real-time alerts for patients or clinicians.

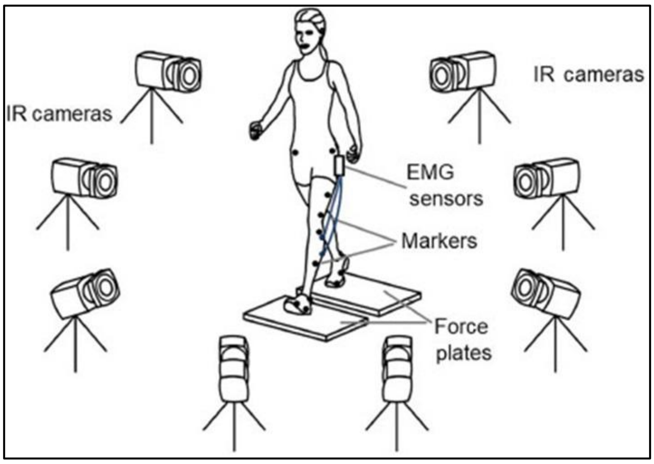

Figure 2 – VICON optoelectronic motion capture
(https://engcourses-uofa.ca/books/ortho/gait-analysis/)

Research 2. [16]

This research created a wearable knee support that included an IMU and force sensors, aimed at monitoring knee angles and gait patterns. The collected data was sent to a cloud platform and displayed through a web application, allowing doctors to track patient progress and manage follow-up appointments remotely. The system's strengths include its portable design, which is suitable for monitoring at home, real-time data collection and visualization, and the combination of both angular motion and force measurements. Limitations arise from its need for constant internet access, which makes monitoring difficult in low-resource areas. Additionally, the system only measures angular movement and force, missing subtle knee vibrations or crepitus (VAG signals), which are vital for early detection. The lack of on-device AI processing also restricts immediate detection of possible joint deterioration.

Research 03. [17]

This study suggested a multi-modal system that brought together X-ray and MRI images, clinical records, demographic data, and real-time knee joint signals. AI models predicted KOA severity and disease progression, and the results were available through mobile and web interfaces. The study's strengths include its broad approach, which integrates imaging, clinical, and real-time sensor data, along with using predictive AI for early intervention support. However, it did not include VAG sensors for capturing subtle knee vibrations. Most data processing depended on cloud computing, limiting use in rural or low-resource areas. Moreover, the system mainly focuses on prediction and classification rather than on continuous, real-time monitoring of knee biomechanics during daily activities.

A review of these studies shows that most current methods either concentrate on precise lab-based measurements or rely on cloud-dependent wearable monitoring. No study has combined VAG signal analysis with wearable IMU and force sensors for continuous, real-time monitoring of KOA. Existing solutions often capture only joint motion or medical imaging and clinical data, missing vital subtle vibration signals needed for early detection of cartilage degeneration. While AI-based prediction exists, edge processing on wearable devices is rarely used, reducing usability in low-resource or rural areas. None of the systems offer instant alerts to patients or caregivers when abnormal knee vibrations or joint changes occur. These gaps emphasise the need for an integrated, real-time, portable, and smart KOA monitoring solution, which this proposed research aims to address.

Feature / Aspect	Research 1	Research 2	Research 3	Proposed System
Sensors / Data	Yes ✅	Yes ✅	Yes ✅	Yes ✅
Measurement Scope / Environment	No ❌	Yes ✅	Yes ✅	Yes ✅
Continuous Monitoring	No ❌	No ❌	No ❌	Yes ✅
AI / Analytics	No ❌	No ❌	Yes ✅	Yes ✅
Wearable / Portable	No ❌	Yes ✅	Yes ✅	Yes ✅
Internet Needed	No ❌	Yes ✅	Yes ✅	Yes ✅
User Alerts	No ❌	No ❌	No ❌	Yes ✅
Data Fusion / Multi-modal	No ❌	No ❌	Yes ✅	Yes ✅
Clinical / Patient Use	No ❌	Yes ✅	Yes ✅	Yes ✅
Scalability / Deployment	No ❌	No ❌	Yes ✅	Yes ✅

Table 1: Comparison of former research.

1.3 Research Problem

Osteoarthritis is one of the most common forms of arthritis worldwide and KOA is a major cause of pain and activity limitation in old people. In 2019, nearly 364.6 million individuals were diagnosed with KOA around the world, which represented approximately 4.9% of the global burden of disease [1], [2]. According to the World Health Organization, OA is the third major cause of mobility limitation in people above 45 years old [14].

The gold standard for the diagnosis of KOA is X-ray and MRI testing and other examinations [3], [4]. Although valuable in the clinical setting, these methods are costly, necessitate specialist interpretation, and afford one static image of the knee. That makes them not suitable for long-term monitoring, particularly to early KOA changes. Furthermore, serial X-rays increase the radiation burden on patients, and frequent visits to the hospital cause a barrier to accessibility for those in rural or resource-poor areas [2], [3]. As a result, most patients resort to intermittent visits or general guidance, and the result is delayed diagnosis and accelerated disease progression [2].

A few wearable and gait analysis systems that presented step count, joint angles, or basic accelerometer readings have been proposed [11], [12]. All these methods are unable to record the vibroacoustic signals (VS), which are known to contain important information about the status of the cartilage [5], [9]. Other systems in the research domain are very cloud-heavy, which can be expensive, require internet connectivity, and are not practical for users with limited resources [12], [13]. As a result, there is currently no fully satisfactory, low-cost, portable, and intelligent KOA monitoring device at present.

There is thus a vast void: a long-term monitoring system that is user-friendly and safe and can pick up minute biomechanical and acoustic signals from the knee before they become a major disease. I introduce a wearable device, which is an IoT device, featuring VAG as well as movement and pressure sensors, which captures the motion of the knee in daily life to resolve this issue. We will process our data on an ESP32 microcontroller with TinyML models, such as real-time, low-power. [11], [12]. The system will communicate with a mobile app or web app over Wi-Fi to enable immediate data feedback to patients and remote disease monitoring by doctors. [13].

The originality of this system consists in integrating VAG analysis with motion sensing and on-device TinyML inference implementation, providing an inexpensive, easy-to-use, and radiation-free means of early KOA detection. With continuous monitoring, this wearable solution may enhance early diagnosis, the patient's self-awareness, and clinical decision-making, particularly in underdeveloped areas where access to sophisticated diagnostic solutions is limited [11], [12], [13].

2. Objectives

2.1 Main Objective

In this study, we propose to create an integrated system for early detection, assessment of severity, and continuous monitoring of KOA. This system integrates and processes clinical records and images (X-ray and MRI) of the patient with knee movement and vibration signals from wearable sensors using machine learning and IoT technologies. The system is targeted at real-time detection, aiming at early and continuous non-invasive user-friendly monitoring of knee joint degeneration to enable timely clinical intervention and long-term patient outcome improvement. Moreover, the system is targeted at and designed for patients from rural and resource-limited settings to provide an affordable and practical solution to continuous monitoring of knee health.

2.2 Specific Objectives

1. Wearable Device Design and Implementation
Create a small, low-power, IoT-based wearable device incorporating Vibroarthrography sensors, accelerometers, gyroscopes, and pressure sensors. It should be of a wearable form with daily wearability and be able to pick up even slight knee vibrations and biomechanical signals.

2. Real-Time Data Acquisition and Processing
Capture real-time knee joint signals during normal daily activities with high fidelity. Employ signal pre-processing techniques such as filtering, denoising, and feature extraction to purify the data for sound analysis.

3. On-Device Machine Learning Integration
Integrate TinyML models performing real-time inference on the ESP32 microcontroller. On-device processing will facilitate knee health status classification without the need for prolonged cloud computing or constant internet connectivity.

4. Mobile/Web Application Interface
Use a mobile and/or web-based application to display real-time monitoring results. The application will provide early notifications and alerts for patients and healthcare professionals for abnormal knee states.

5. Usability Testing and System Validation
Test the device's accuracy, reliability, and responsiveness in real-world situations. Conduct usability testing involving clinicians and patients to validate that the system is intuitive and feasible for long-term use.

6. Long-Term Monitoring and Early Detection
Measure and quantify knee joint vibration and biomechanics longitudinally. Allow early detection of KOA onset and contribute to continuous management of knee health outside hospitals.

3. Methodology

The Smart IoT-Based Knee Health Monitoring System, which relies on VAG signals, will use the Agile Software Development Life Cycle Model. The Agile approach focuses on incremental development, regular feedback, and adaptability. It allows for quick updates and improvements in both hardware and software. This enables precise and user-friendly real-time KOA monitoring.

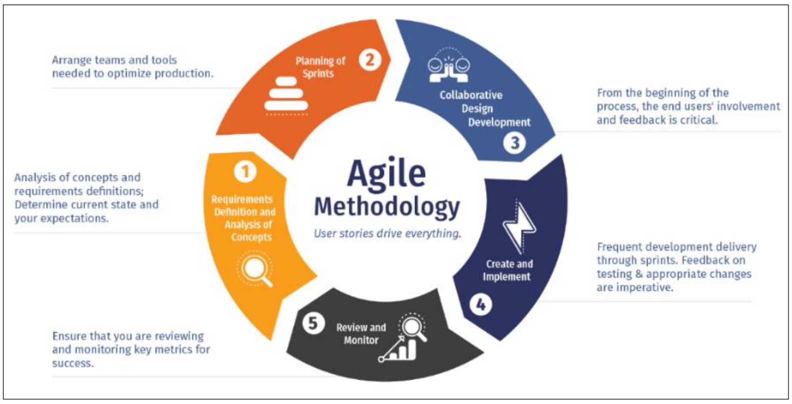

Figure 3 – Agile Methodology

3.1 Requirements Analysis

Identify the medical, technical, and user requirements for the wearable KOA monitoring device and platform.

Sources of Information :

Healthcare Professionals

- **Orthopaedic doctors**: Provide insights into KOA symptoms, clinical diagnostics, and relevant biomechanical parameters.
- **Physiotherapists**: Advise on knee movement patterns, rehabilitation exercises, and monitoring needs.

Patient Feedback

- Surveys and interviews to capture requirements related to comfort, wearability, usability, and preferences for data sharing or visualization.

Published Literature

- Research articles on VAG signal acquisition, accelerometry, gyroscope-based knee monitoring, and IoT-enabled KOA devices.
- Studies such as Turcot et al., 2007; Supalak Amplod et al., 2020; and Kumar & Kishore, 2021.

Public Datasets

- **Knee Health Dataset Using VAG Signals for AI & IoT** (Kaggle, 2021) Kaggle Dataset Link

3.2 Project Requirements

3.2.1 Functional Requirements

- The system should collect real-time VAG, motion, and pressure sensor data from the wearable.
- The system should preprocess and filter the collected signals to remove noise.
- The system should run on-device TinyML models to classify KOA severity.
- The system should transmit processed data via Wi-Fi to a mobile/web application.
- The mobile application visualize sensor data.
- The system should generate alerts for abnormal signals or high KOA risk.
- The system should allow clinicians to view patient history and severity levels.

3.2.2 Non-Functional Requirements

- **Performance:** Real-time inference for KOA detection.
- **Usability:** Simple and intuitive interface for patients and clinicians.
- **Reliability:** Continuous monitoring for at least 8 hours on battery power.
- **Security:** Encrypted communication and secure login to protect patient data.
- **Scalability:** Support for multiple patients and cloud-based expansion.
- **Portability:** Mobile app compatible with Android/iOS, wearable, lightweight

3.2.3 User Requirements

- Patients want a comfortable wearable device for daily use.
- Patients want to view their knee health status in real-time.
- Patients want timely alerts for abnormal conditions.
- Clinicians want accurate KOA risk and severity reports.
- Clinicians want access to long-term patient history and trends.

3.2.4 System Requirements

Software Requirements:

- Firmware for ESP32 (Arduino IDE).
- TinyML framework (TensorFlow Lite Micro).
- Mobile application (Flutter).
- Cloud database (Firebase).

Software	Usage
	Arduino IDE Develop firmware to acquire and process sensor data
	C/C++ programming Program sensor modules, transmission logic
	Firebase Store, log, and manage sensor data for analysis
	REST API Facilitate communication between devices, the database, and the front-end
	Python Data analysis, feature extraction, and model development
	TensorFlow Train and deploy machine learning models for KOA prediction
	Flutter Build a mobile app for real-time monitoring and alerts
	React Develop a web dashboard for visualization, historical data, and notification

Table 2: Software and their usage

Hardware Requirements:

Tools	Usage
	**ESP32 microcontroller** Processes sensor data and communicates with mobile/cloud via Wi-Fi.
	**MPU6050 - (Accelerometer + Gyroscope Sensor)** Tracks knee movement, orientation, and angular velocity
	**GY-906 MLX90614 Contactless Temperature Sensor** Monitors body or device temperature for safety and analysis
	**Piezoelectric discs** Detects abnormal vibrations indicating knee activity
	**BMP180 Digital Barometric Pressure Sensor** Measures force on the knee joint for movement analysis.
	**Lithium Battery Charger Board Circuit Protection** Powers the wearable device and ensures safe charging.
	**Li-Po battery** Lightweight rechargeable power source.

Table 3: Hardware Components and Usage.

3.3 System Design

3.3.1 Use Case Diagram

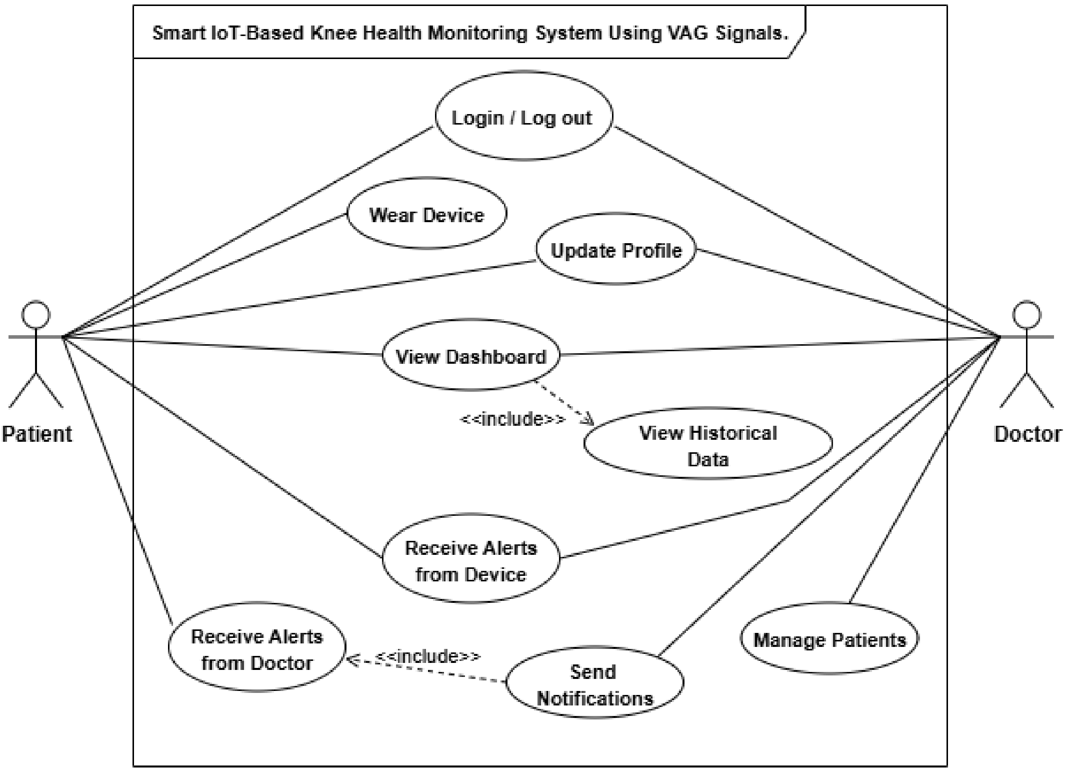

Figure 4 – Use Case Diagram

The IoT-Based Smart Knee Health Monitoring System Use Case Diagram emphasizes the activities between the system, patients, and doctors.

Its main users are the patients who put on the IoT knee device and use the mobile application, and doctors who monitor patient information and provide medical instructions. Patients can use the system to wear the device, record VAG signal data, update their profiles, and access a real-time monitoring dashboard. The dashboard can access and analyse records and is allowed to patients. Patients are also alerted: the device makes them aware of any irregularities in the knee, and the doctor provides them with additional notifications and medical consultation. Doctors can sign in and out, edit their profiles, review patient dashboards and their records, manage patient lists, add and/or delete users, and send patients messages or alerts about the treatment.

3.3.2 Overall System Diagram

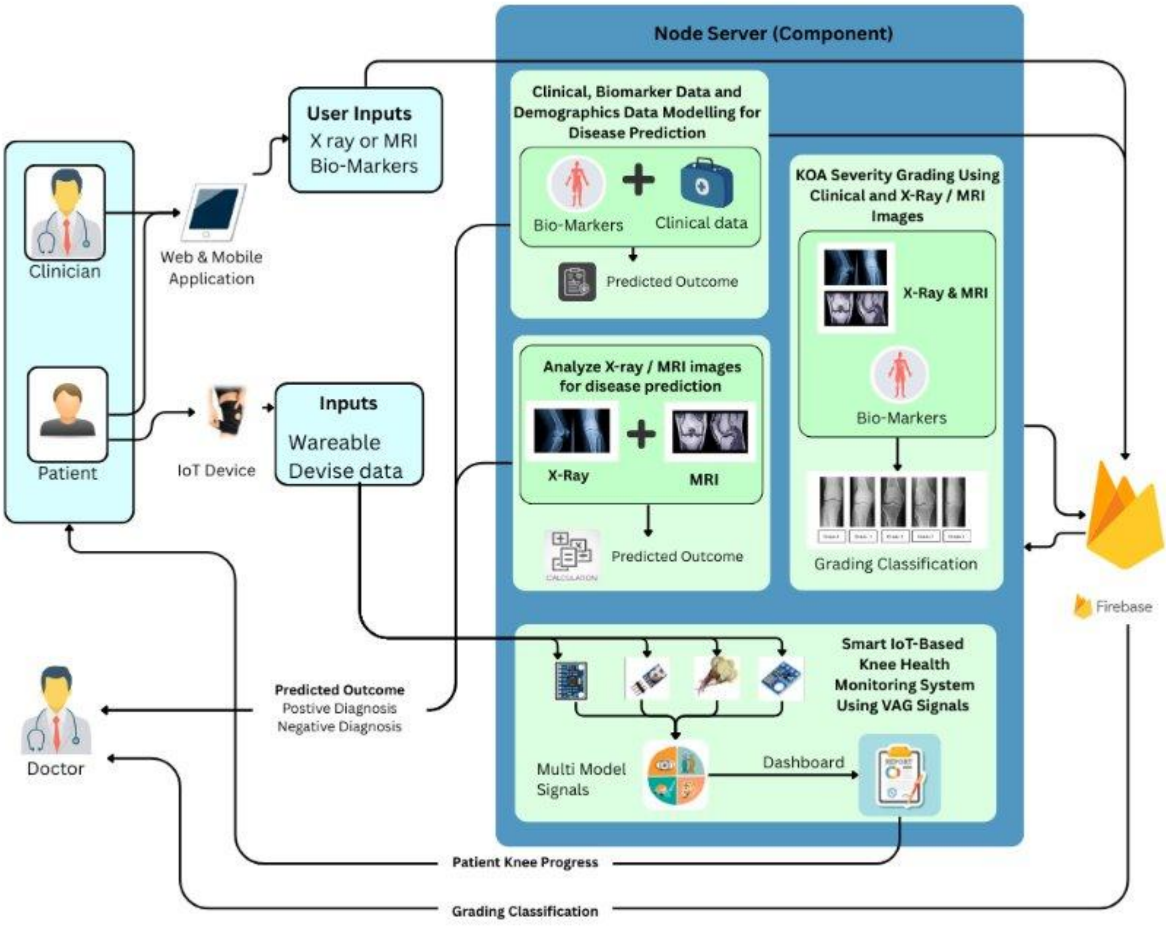

Figure 5 – Overall System Diagram

3.3.3 Component Diagram

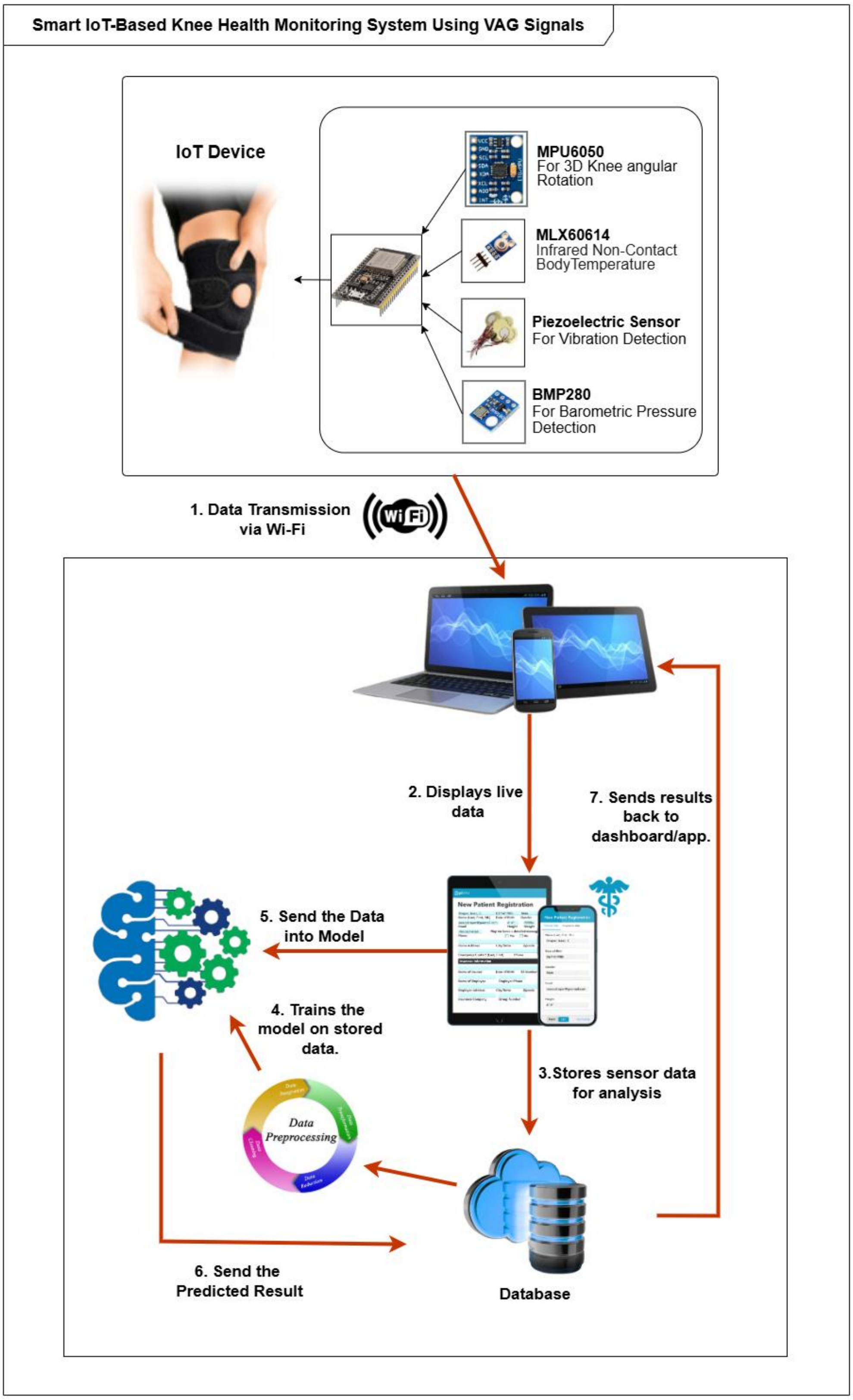

Figure 6 – Component Diagram

3.4 Development

The development phase covered hardware, firmware, cloud, and machine learning integration to implement the IoT-based knee osteoarthritis monitoring system.

3.4.1 Hardware Development

An ESP32 microcontroller acted as the central processing unit in the hardware unit. The following types of sensors were integrated: temperature, pressure, gyroscope, accelerometer, and vibration. Signal conditioning circuits were added to enhance data quality, and portability was offered by a rechargeable Li-Po battery.

3.4.2 Firmware Development

The Arduino IDE will be used to develop the firmware. Pre-processing techniques like noise filtering and feature extraction will be used to lower transmission overhead, and sensor data acquisition modules will record readings at appropriate sampling rates. Data will be sent to the web server via the ESP32's Wi-Fi module.

Technologies - Arduino IDE, C/C++ programming

3.4.3 Web and Database Development

Incoming data streams will be handled by an API and a web server. A web form or mobile interface will show the data, and it will be stored in a central database for review, logging, and analysis.

Technologies - Web server, Database, API

3.4.4 Machine Learning Integration

Features will be extracted from sensor data and used to train a machine learning model in Python to predict KOA severity.

Technologies – Python, TensorFlow / Scikit-learn, etc.

3.4.5 User Interface Development

I will make a mobile app and a web dashboard that will show sensor data, show prediction results, and send alerts. Historical charts and records will help both patients and doctors keep an eye on how their knees are doing.

Technologies – Flutter, Web dashboard framework

3.5 Test Plan

The objective of the test phase will be to confirm the functionality, correctness, reliability, and user interface of the IoT-based knee osteoarthritis monitoring system through thorough testing and verification.

Unit Testing: Each hardware and software component will be tested individually. This will include testing sensor data acquisition (acceleration, vibration, gyroscope, pressure, temperature), ESP32 firmware, database queries, and machine learning model performance.

Integration Testing: Sensor, ESP32, firmware, web server, database, machine learning module, and user interface interactions will be tested for smooth integration, proper communication, and unhindered data flow.

User Testing: A pilot group of patients and clinicians will utilise the prototype device and mobile/web interface. Usability, visualization clarity, and effectiveness of alerts will be measured. Feedback will be collected to finalize the system.

Performance Testing: The system will be tested under various conditions of varying Wi-Fi speeds, battery levels, and unbroken stretches of continuous data collection to check for stability, performance, and scalability. Real-time responsiveness of the predictions and the dashboard visualization will also be evaluated.

3.6 Deployment

The deployment phase will include:

- Deploying an ESP32-based wearable device with sensors to fetch real-time data.
- Deploying the database on a cloud platform
- Releasing mobile and web apps to clinicians and patients.
- Deploying a trained ML model
- Supplying system runs in a real-world setting for pilot testing.

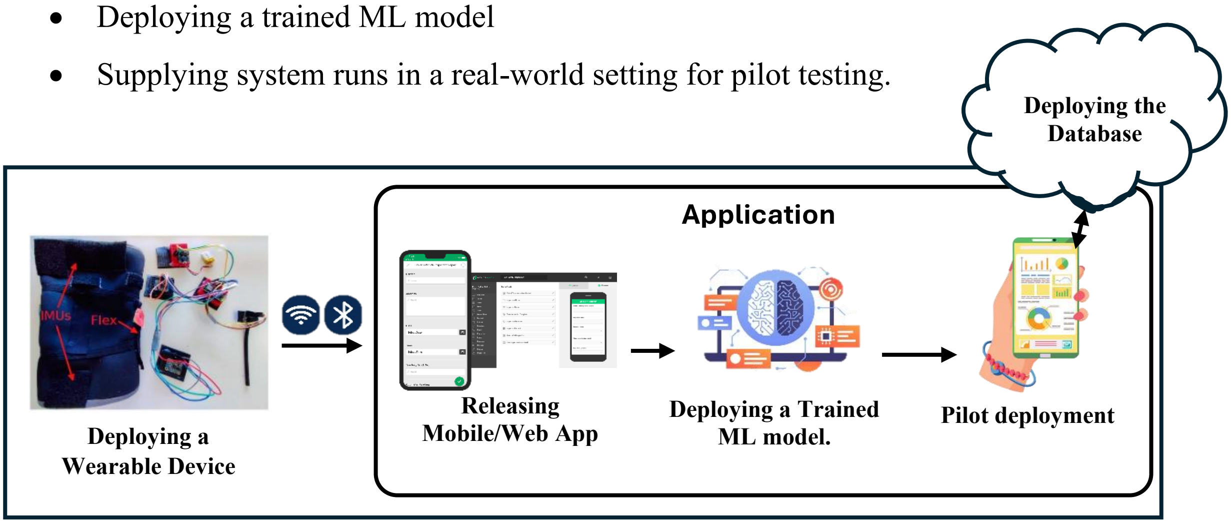

Figure 7 – Deployments of the Proposed Monitoring Components

3.7 Work Breakdown Chart

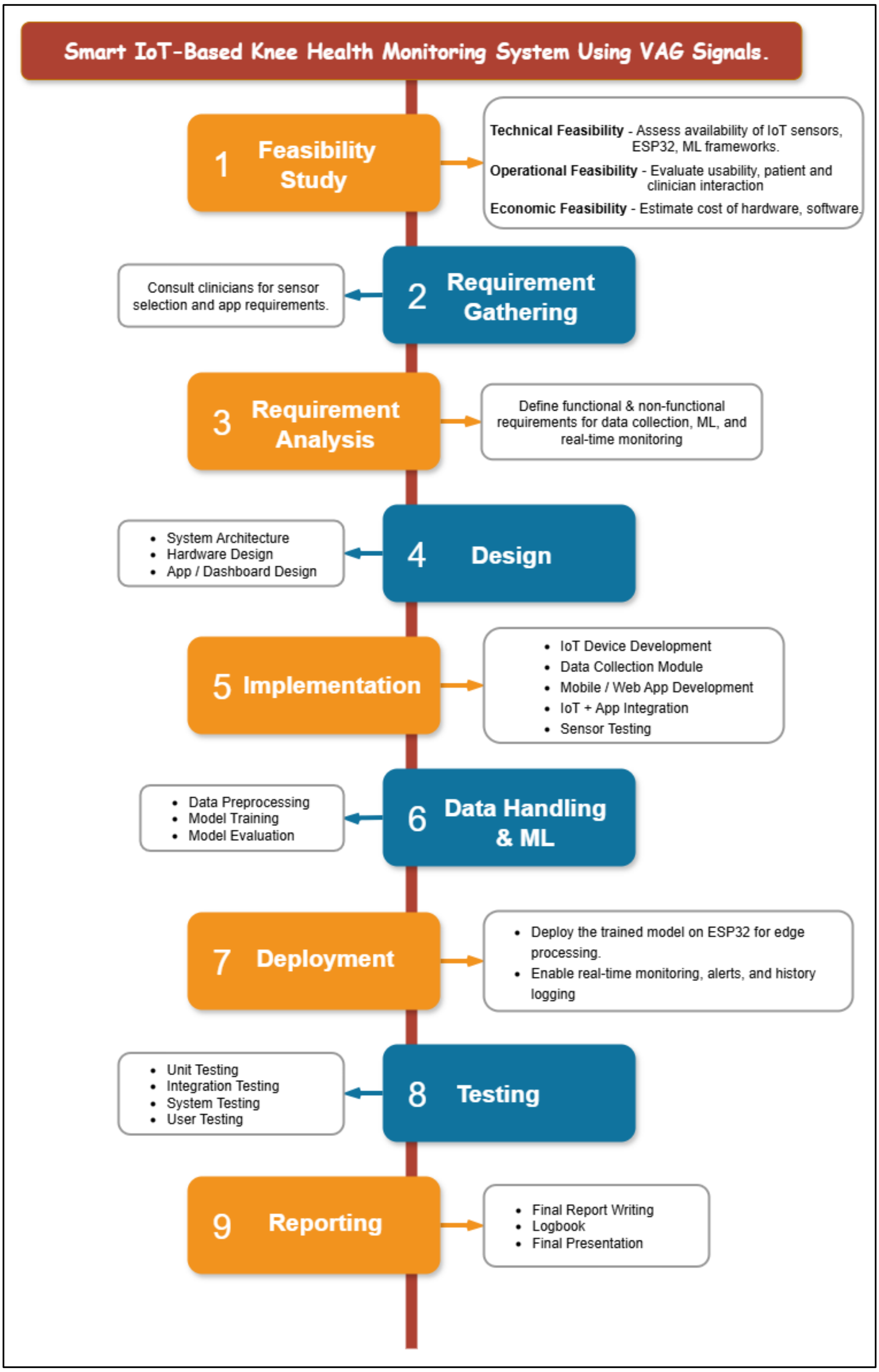

Figure 8 – Work Breakdown Chart

3.8 Gantt Chart

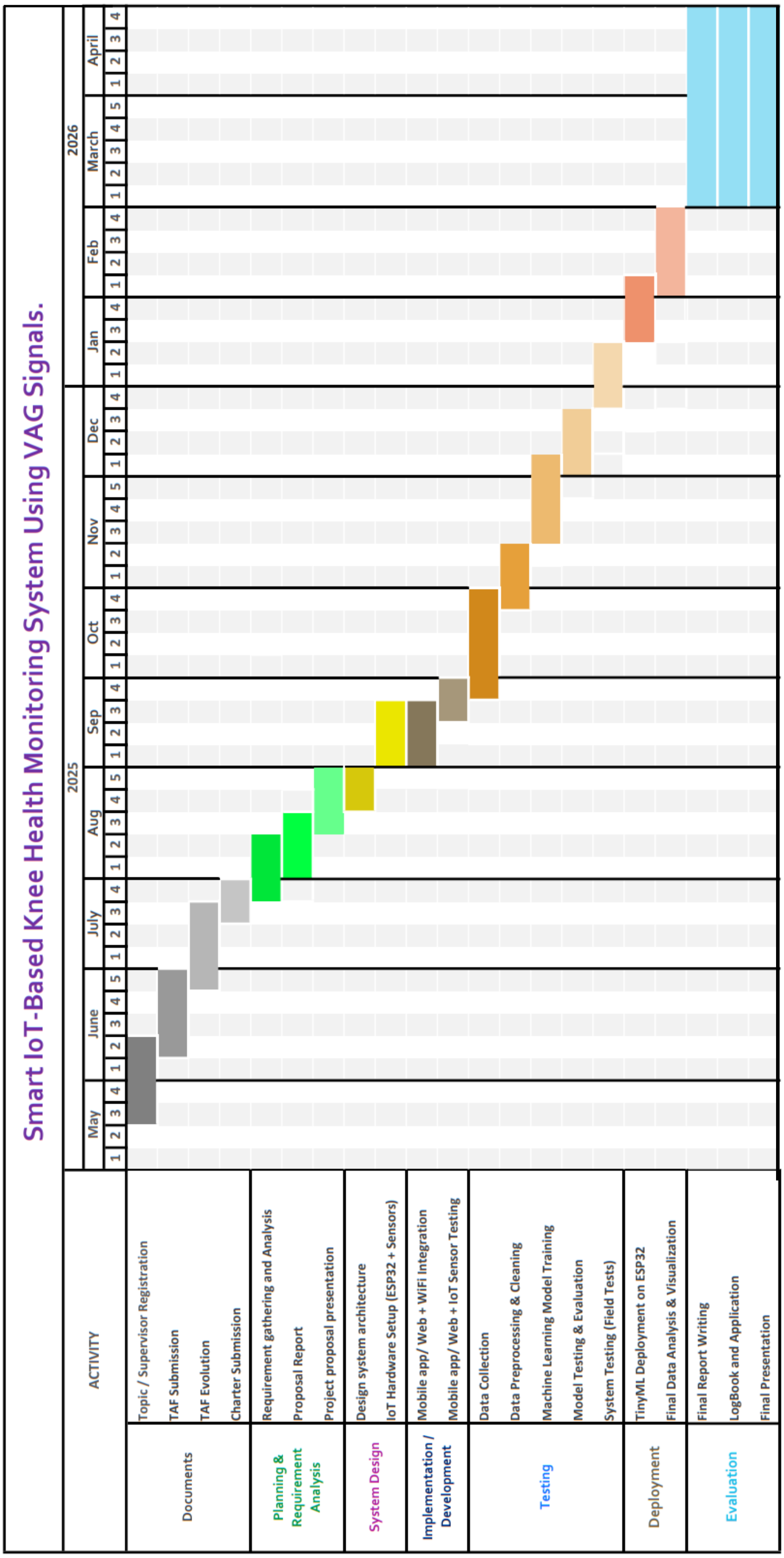

Figure 9 – Gantt Chart

4. Commercialization and Entrepreneurship Potential

4.1 Market Opportunity

KOA is a prevalent degenerative joint disorder affecting millions worldwide, with incidence steadily increasing in ageing populations. Current diagnostic methods, such as MRI and X-ray, are expensive, reliant on hospital infrastructure, and not suitable for ongoing patient monitoring. There is a clear and growing need for portable, affordable, and user-friendly solutions that facilitate early detection and continuous monitoring of KOA, particularly in rural or resource-constrained settings. The proposed wearable IoT-based system directly addresses these challenges by providing real-time feedback, longitudinal disease tracking, and timely alerts for both patients and clinicians.

Relevant market segments include:

- Healthcare Providers & Clinics: Hospitals, physiotherapy centers, and rehabilitation clinics seeking improved patient monitoring tools.
- Elderly Care & Assisted Living Facilities: Institutions aiming to implement continuous KOA symptom monitoring for residents.
- Direct-to-Consumer Market: Individuals interested in non-invasive, home-based knee health assessment.

4.2 Competitive Advantages

The proposed solution distinguishes itself through several key advantages:

1. Wearable & Non-Invasive: In contrast to MRI or X-ray, the device is lightweight, portable, and safe for daily, repeated use.
2. Real-Time Monitoring: It continuously collects VAG, motion, and pressure signals, enabling prompt detection of abnormalities.
3. On-Device AI Processing: Integration of TinyML models on the ESP32 allows low-power, rapid, on-device inference without requiring constant internet connectivity.
4. Mobile/Web Integration: The system delivers immediate feedback and visualizes historical data for both patients and healthcare professionals.
5. Cost-Effective: Production and maintenance costs are significantly lower compared to conventional imaging diagnostics.

4.3 Business Model

A commercial approach can leverage both B2B and B2C strategies:

1. B2B: Devices are supplied to hospitals, clinics, and physiotherapy centers, supported by subscription-based software for data analytics and monitoring dashboards.
2. B2C: The wearable device is sold directly to end-users, with optional subscription tiers for cloud storage, alerts, and personalized data insights.

4.4 Estimated Costs & Pricing

Description	Cost (LKR)
Data Collection & Processing	6,000.00 – 10000.00
IoT Wearable Device	20000.00 – 30000.00
Firebase Blaze Plan (Pay-As-You-Go)	2,400.00 – 2,500.00 / month
	50,000.00 – 65,000.00

Table 4: Estimated Cost

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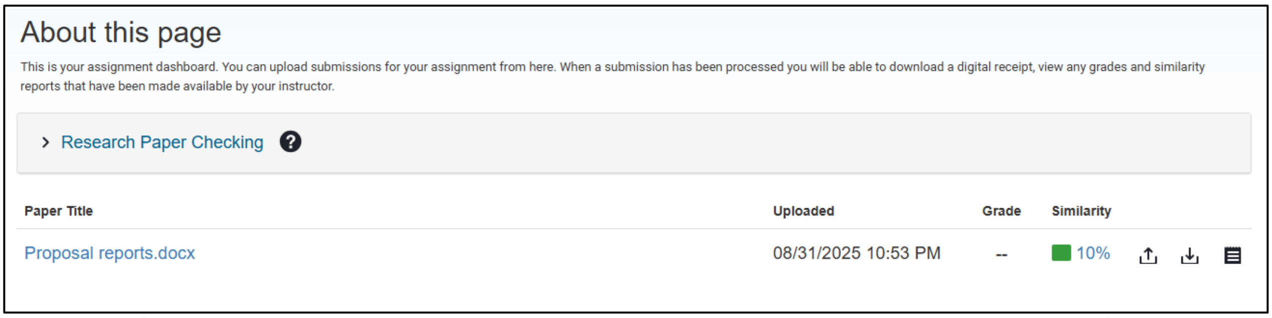

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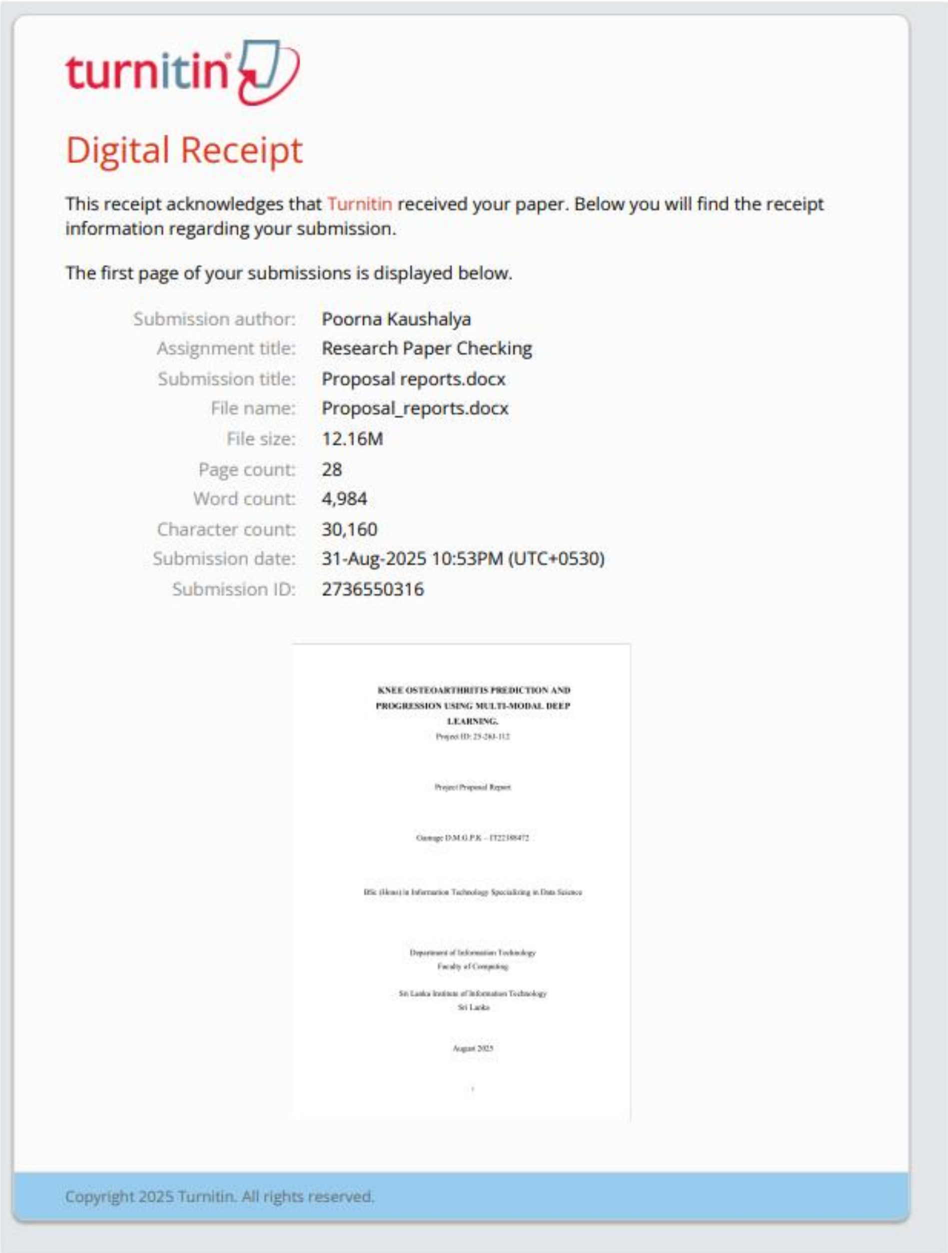

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KNEE OSTEOARTHRITIS PREDICTION AND PROGRESSION USING MULTI-MODAL DEEP LEARNING.

Project Proposal Report

Department of Information Technology
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