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

Project ID: 25-26J-112

Project Proposal Report

Perera B.B.A.R. – IT22606792

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 Dissertation under my supervision

Signature of the supervisor

(Ms. Jenny Krishara)

Date

2025/08/29

Co-Supervisor,
Ms. Wishalya Tissera

29/08/2025

Abstract

Osteoarthritis (OA) is a degenerative joint disease marked by the gradual breakdown of cartilage and changes in the underlying bone[5]. and is most common in the elderly and is often promoted by joint injuries and mechanical stresses. Knee Osteoarthritis is one of the common disabilities adjusted life years. Although KOA cannot be cured permanently, but the combination of lifestyle changes, medications, physical therapies and sometimes knee transplants can help in managing the condition.

At present, diagnosis and follow-up of KOA are based on X-rays, MRI scans and clinical examination. However, these approaches come with significant drawbacks, they are expensive, they need special equipment, they are scarce (most available only in large hospitals). Furthermore, because of its slow progression, these tools provide a snapshot of the knee's condition at a single point in time, which is not comprehensive. Since KOA is a gradually developing disease that changes over weeks or months, one time imaging fails to give a full picture of how the disease is progressing, especially for older adults and people with mobility challenges. Furthermore, tests are restricted to only one type of data - limiting accuracy of treatment.

To solve these problems, a system with four major components is proposed in this study.

Disease Prediction using X-ray and MRI images.

Clinical, Biomarker and Demographic Data Modelling to improve disease prediction

KOA Severity Grading - clinical data and imaging data (X-ray/MRI)

AI-based VAG-Based Smart IoT Knee Health Monitoring

The system is based on a multi modal deep learning framework, which can learn from patient demographics, clinical symptoms and imaging data to predict KOA progression and severity. The system can offer a more comprehensive and individual perspective of the patient's knee condition. Continuous monitoring can be used to routinely update disease progression and severity and facilitate early intervention and improved long term care. Additionally, the use of explainable AI builds trust by making predictions and decisions more transparent for both healthcare providers and patients.

The result of this research will be a low cost, accessible and real time solution for KOA prediction, monitoring and management, particularly in rural and low resource settings. In this paper, we mainly discussed the Severity Grading Using Clinical and X-ray / MRI Images and individualized treatment planning.

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List Of Abbreviations

Table 1 - List of Abbreviation

Abbreviation	Description
OA	Osteoarthritis
KOA	Knee Osteoarthritis
MRI	Magnetic Resonance Imaging
BMI	Body Mass Index
AI	Artificial Intelligence
KL	Kellgren Lawrence
XAI	Explainable Artificial Intelligence
CNN	Convolutional Neural Network
MLP	Multi Layer Perceptron
CDI	Cartilage Damage Index
Grad-CAM	Gradient weighted Class Activation Mapping

1.Introduction

OA is a joint disease affecting hundreds of millions of people worldwide [1]. An estimated 240 million individuals suffer from symptomatic OA globally, with 10% of men and 18% of women aged 60 and older affected [2]. In Sri Lanka, knee OA (KOA) is particularly prevalent among adult females over 50, with about 21.8% affected, and 29.9% experiencing moderate to severe KOA [3].

KOA is the degenerative form of knee arthritis that is common in the elderly and can result in extreme pain, degeneration of bone joints, joint membranes and ligaments, and deformity of knee joints. KOA does permanent damage to cartilage and surrounding bone structures.

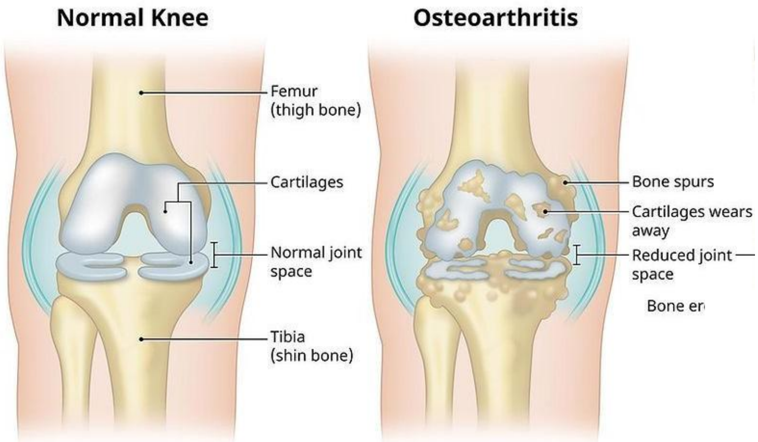

Figure 1– Normal Knee vs Osteoarthritis Knee

KOA severity is often described in stages, ranging from Stage 0 (normal joint health) to Stage 4 (severe OA). In the early stages, symptoms may be minimal, but as the disease progresses, patients experience persistent pain, swelling, stiffness, and loss of joint function.

Figure 2 – Kellgren Lawrence scale

Stage 0 (Normal) - The knee joint appears healthy, with no visible signs of OA. Patients experience no pain or functional impairment, and no treatment is required.

Stage 1 (Minor) - Early signs of OA appear as small bone spur growths, though the cartilage remains largely intact. Patients may not feel noticeable discomfort, and treatment is usually not required unless risk factors (e.g., obesity, family history) are present. Preventive strategies such as regular exercise may be recommended.

Stage 2 (Mild) - X-rays may reveal larger bone spur growth, although joint space remains normal and cartilage damage is limited. Patients may begin to experience mild symptoms such as pain after long activity, stiffness after inactivity, and tenderness during bending or kneeling. Non-pharmacological treatments such as lifestyle modifications, supervised exercise, and physiotherapy are commonly prescribed [4].

Stage 3 (Moderate) - Cartilage damage becomes more evident, and the space between bones starts to narrow. Symptoms intensify, including frequent pain during daily activities, morning stiffness, and joint swelling after extended movement. Over the counter pain relievers or glucocorticoid injections may be recommended if non drug interventions are insufficient[4].

Stage 4 (Severe) - The joint space is greatly reduced, cartilage is nearly destroyed, and movement becomes extremely painful or even impossible. Patients may experience chronic pain, stiffness, and immobility. At this stage, surgical interventions such as bone realignment (osteotomy) or total knee replacement are often the only effective treatment options[4].

Treatment depends on the stage and can involve lifestyle changes, exercise, medications, injections of glucocorticoid, or in advanced stages, surgery like bone realignment and knee replacement.

Although this staging system is significant, the current diagnostic techniques involve extensive use of X-rays, MRI scans and clinical evaluations, all with several shortcomings. These techniques are expensive, need special equipment and know-how and are mainly available in well supplied healthcare centers.

Therefore, there is an increased need for automated objective systems which are able to reliably identify and stage KOA severity. In these systems there would be greater consistency in diagnosis, early intervention, better treatment planning and chronic patient management.

1.1 Background & Literature survey

KOA is becoming more common around the world, leading to a growing need for tools that can help doctors diagnose, predict, and manage the disease more accurately and objectively. Over time, the field has moved from traditional manual checks to advanced AI and machine learning models that use different types of data. This survey looks at important studies in this area, groups them based on their methods, and points out the gaps that still exist gaps that inspire the development of a new, integrated multi-modal system.

A prevailing trend in KOA research is that medical imaging is being utilized for automated diagnosis. Early work by Du, et al. (2018) took it beyond simple classification, and instead predicted KOA progression. The authors used a new CDI based on 36 point locations of knee MR images. By using machine learning models such as Artificial Neural Networks and Random Forests on these biomechanical features, they were able to obtain an AUC of up to 0.785 to predict joint space narrowing. This study was important in showing that quantitative, spatially resolved cartilage could be used to predict disease progression, rather than only diagnose disease status [6].

Based on this, Wang et al. (2022) showed the strength of transfer learning for KOA from MRI. They fine tuned the InceptionResNetV2 architecture and their model reached an impressive accuracy of 96.1% when using an image level data splitting strategy. The work highlighted the potential of deep learning models for deriving verifiable, hierarchical representations of complex medical image data, thereby relieving clinicians of the burdensome task of subjectively gauging the radiology of the medical images [7].

Further developing image based diagnosis, Rameez et al (2024) developed an end-to-end pipeline for X-ray images. Their system contained a CNN for knee joint detection, a binary classifier (MobileNetV2) to detect OA, a custom CNN for KL severity grading and a Random Forest model to suggest treatment depending on the grade, with overall accuracy of 98%. The article is significant because, in it, one tried to connect diagnosis and treatment recommendation in the same framework, but it was still in the field of image analysis [8].

While image-based methods are particularly well suited to diagnostic accuracy, they are static and disconnected from functional, epidemiological and real-world phenomena. Chen et al. (2023) investigated a bimodal approach by combining infrared thermographic imaging with patient health information (e.g. age, BMI, duration of disease). Their study showed that a fusion of these data types represented a significant increase in performance of a decision tree classifier to an accuracy of 85.71% over using either modality alone. This points out the synergy possible with fusion of these different data types to provide a more comprehensive evaluation of KOA severity [9].

Also, in a large scale epidemiological study, Shidore and Jalnekar (2023) tried to identify the risk factors through an in-depth sampling survey of 363 participants. Using statistical methods and ML classifiers (SVM), they found age, BMI, and occupation to be significant risk factors, with 88% accuracy when predicting knee pain. This study offers important information in the demographic and occupational risk factors for KOA, but is intrinsically limited by its subjective self-reported nature [10].

A key issue for medical AI is the black-box nature of deep learning models. Mehta and Kaur (2025) responded to this by introducing a CNN Attention hybrid model to grade KOA severity using X-rays. Their model not only attained a high average accuracy of 92.0%, but also added Grad-CAM visualization of regions of interest including joint space narrowing and osteophytes. Nevertheless, these human-in-the-loop systems significantly increase the clinical interpretability and reliability of the AI-assisted diagnosis by matching the model's decision to well-established clinical indicators [11].

Analysis of these studies shows a clear trajectory and several key unmet needs, highlighting a large gap between high-resolution static clinical imaging and dynamic functional monitoring. Du et al. [6], Wang et al. [7], and Mehta & Kaur [11] have achieved high accuracy for diagnosis and prognosis but are limited to the clinical environment without portability and the ability to continuously monitor patients even during daily activities. The bimodal approach [9] is a step towards integration, but still remains a static evaluation and does not include important biomechanical information such as gait or joint vibrations (VAG signals). The end-to-end pipeline [8] links diagnosis to treatment but does so only based on imaging, and ignores the rich context provided by sensor-based functional data and patient-specific risk profiles as identified by Shidore and Jalnekar [10]. A common lack of constant, real-time monitoring systems. All systems reviewed offer a static analysis, failing to support the dynamic nature of KOA symptoms and functional limitations that change over the course of the day.

This research is fueled by the deficiency in existing gaps of assessment and management of KOA. Based on previous research in multi modal fusion, interpretable AI, and recommendation for treatment, we present a wearable system enabled by edge AI. The system combines precise measurements from a number of sensors (biomechanical, acoustic/VAG and thermal) and clinical risk factors. By combining these aspects, it provides a more comprehensive and continuous approach to managing KOA beyond the hospital's walls, transitioning from one-off diagnoses to continuous, patient specific care.

1.2 Research Gap

KOA is a degenerative joint disease that demands early and precise diagnosis in order to avoid severe disability and enhance patient outcome. Although KOA research has advanced substantially, current grade severity systems are still poor, and fragmented. Existing studies can roughly be divided into two approaches:

1. Image-based grading:

Deep learning models from knee radiographs or MRI images (e.g., Wang et al., 2022; Mehta & Kaur, 2025) have demonstrated encouraging accuracy. However, these approaches are limited to clinical settings, require expensive imaging instruments, and they only provide a static 'snap shot' of the disease. They do not support a continuous monitoring nor capture functional changes over time.

2. Clinical based assessment:

Other studies (e.g., Shidore & Jalnekar, 2023) use patient surveys, statistical risk models or epidemiological factors like age, BMI and occupation. While these provide useful information on population level risks they are subjective, they are retrospective and they are less precise than imaging methods.

This division shows that there is essentially a gap between the existing literature, which mainly employs either image-based or clinical based grading, and the recent advancements where the two are combined. Although attempts (e.g., Chen et al., 2023) have been made to fuse simple health metrics with imaging data, these are still restricted to single point predictions and miss the power of dynamic sensor-based biomechanical data.

Chen et al. (2023) - Predicting Severity of Knee Osteoarthritis Using Bimodal Data and Machine Learning

Mathevon and his colleagues developed a machine learning framework that integrates infrared thermographic images with patient health information (including BMI and age) and uses it to predict the severity of KOA. Their approach was to extract temperature and texture features from thermal images, combine them with clinical metrics and use the SMOTE technique to deal with class imbalance. Of the models tested, they found that a decision tree classifier was the most successful, with 85.71% accuracy, and concluded that bimodal data fusion substantially improves predictive performance over single mode strategies.

Wang et al. (2022) - Classification of Knee Osteoarthritis Based on Transfer Learning Model and Magnetic Resonance Images

They used the InceptionResNetV2 architecture pre-trained on ImageNet to derive features from knee MR images from the OAI-ZIB dataset. Their paper contrasted two optimization methods, SGD and RMSprop, using two data partitioning schemes. The results showed that the model with RMSProp was capable of high performance with up to 96.1% accuracy under image-level splitting, which proved the effectiveness of deep transfer learning for KOA MRI-based diagnosis.

Shidore & Jalnekar (2023) - Unveiling Risk Factors of Knee Osteoarthritis using Statistical and Machine Learning Model

Associations were analyzed using statistical methods including confidence intervals, odds ratios, and ch-square tests and machine learning models including SVM and Random Forest were used for knee pain prediction. They found that age, BMI, sedentary work and heavy physical activity were significant risk factors, and an SVM model predicted the presence of cardiovascular disease with 88% accuracy.

Mehta & Kaur (2025) - Automating Knee Osteoarthritis Severity Grading with CNN-Attention Hybrid Models

They suggested that a hybrid deep learning model (composed of CNN and attention mechanism) can be used to automate the grading of KOA severity from X-ray images using the KL scale. Their model was trained on publicly available datasets from OAI, and it used Grad-CAM visualizations to illuminate diagnostically relevant regions, such as joint space narrowing and osteophytes. The resulting system obtained an average accuracy of 92.0% with benefits not only for its high classification performance but also for its enhanced interpretability for clinical use.

This research fills these gaps by creating a multi modal KOA severity grading system that combines radiographic image features together with continuous biomarkers and clinical data. By incorporating imaging and force sensing modalities, the system will give a more complete picture of KOA progression. Crucially, it is for on device processing, so it can monitor in real-time without any need for continuous internet access.

By breaking away from static diagnosis to dynamic, patient entered management, this fusion based framework provides clinicians with more powerful decision support and provides patients with a means for ongoing, personalized monitoring in the clinic and in their everyday lives.

Feature / Aspect	Wang et al. (2022) MRI	Mehta & Kaur (2025) X-ray	Shidore & Jalnekar (2023)Survey	Proposed System
Primary Data Type	Medical Images (MRI)	Medical Images (X-ray)	Survey / Clinical Data	Multi-Modal (Clinical + Imaging)
Multi-Modal Data Fusion	No +	No +	No +	Yes
Measurement Scope / Environment	Clinical / Lab	Clinical / Lab	Field / Self-Reported	Yes
Continuous Monitoring	No +	No +	No +	Yes
Biomechanical Data	No +	No +	No +	Yes
AI / Analytics	No +	No +	Yes	Yes
Clinical/Patient Use	No +	No +	Yes	Yes
Internet Needed	No +	No +	Yes	Yes
Treatment Suggestions	No +	No +	No +	Yes

Table 2 - Comparison of former research

1.3 Research Problem

KOA is a progressive joint disease that significantly affects mobility and quality of life. Primarily, there is not reliable and automated way to evaluate the severity of the KOA. At present, doctors can make use of mostly X-rays and MRI scans. While these techniques are effective in hospitals, they have a few drawbacks:

Not suitable for regular monitoring: Advanced imaging costs are high, special personnel are needed and the patient must come into the hospital. Furthermore, these methods usually are able to offer only a point-time snapshot thus making it challenging to depict the progressive developments of the disease.

Low availability and use: MRI or high quality imaging facilities may not be available in many resource-constrained or rural settings, leading to delayed or inconsistent diagnosis.

Interpretation by specialist: Severity grading is often interpreted from the opinion of the specialist and can differ from one clinician to another. This inconsistency lowers the reliability and can result in under- or overestimation of severity of the disease.

Given these limitations, a critical void does exist in developing an accurate, accessible and automated solution for KOA severity grading.

This component aims at proposing a multi-modal deep learning solution that combines imaging data (X-rays/MRIs) and clinical information (demographics/biomarkers/medical history, etc.). By fusing these complementary data sources, the system will attempt to,

Provide a more objective and repeatable severity measure than human interpretation.

Increase diagnostic accuracy through the use of both imaging-evident morphologic changes and clinical risk factors.

Provide a solution that is more scalable and decarbonized, with reduced dependence on specialized infrastructure.

Ultimately, this approach will allow for early diagnosis and longitudinal surveillance of KOA progression, with improved patient outcomes and decreased healthcare burden.

2. Objectives

2.1 Main Objective

The main goal of this research is to create a framework for early detection, severity grading, and ongoing monitoring of KOA. The study plans to combine different methods. This includes analysing X-ray and MRI images to predict the disease, using clinical, biomarker, and demographic data to model KOA risk, and applying deep learning techniques to grade disease severity. Additionally, the research will develop a smart IoT-based knee health monitoring system. Together, these elements will provide a practical solution for both diagnosing the condition and monitoring patients over the long term.

2.2 Sub Objectives

1. **New Automated KOA Severity Grading**

   To build a strong classification model that can be used to predict KL grades (0 - 4) based on imaging patterns (x-ray/MRI) as well as clinical/demographic and biomarker data. Make sure grading system minimizes subjectivity and produces reproducible and valid results among patients

2. **Multi Modality Data Integration**

   Design an architecture that will integrate imaging information with non-imaging information (biomarkers, clinical information, demographic information) for better diagnostic accuracy. Assess contribution of each data source (imaging vs clinical) in severity evaluation: to justify added value of integration.

3. **Explainable AI Integration**

   Integrate XAI techniques (e.g., Grad-CAM, SHAP, LIME) into the severity grading framework to deliver accountable and interpretable predictions to clinicians. Draw visual explanations (e.g., drawing on top of X-ray/MRI images which show affected areas) that help doctors to understand why a patient was classified at a particular severity level by the model. Importance of clinical features (e.g., age, bmi, biomarkers) are important but should be ranked and should be presented in an easy to use way so that the confidence in the system can be increased.

4. Help Better Clinical Decision

Provide a decision support system to clinicians that adds severity prediction to the description of contributing factors so that treatment planning and communication with patients can be improved. Since the system is used by healthcare professionals, it is tested for usability to ensure that it will improve diagnosis consistency and monitoring efficiency over offline methods.

3. Methodology

This project followed a step-by step methodology to design, build, and test a system for automatically grading the severity of using both medical images (X-rays/MRI) and clinical data (patient history, demographics, and biomarkers). The overall aim was to create a reliable, interpretable, and easy-to-use tool for healthcare support.

Data Collection and Preparation

Data Sources:
The study took two types of data:

X-ray/MRI Images: knee radiographs were taken from known open datasets such as the OAI.

Patient Details: Age, gender, BMI, pain scores and other health parameters

Preprocessing:

Image Data: All images were resized to the same size (224x224 pixels), normalized to 0-1 range, and augmented (rotations, flips) for better generalization.

Clinical data: Missing values were managed appropriately (imputation or removal), and statistics such as age and BMI were normalized in such a way that no single feature overshadowed the analysis.

Model Architecture

A multi-modal deep learning model was designed with two major branches:

1. Image Branch (CNN): A CNN was automatically applied to key features extracted from knee X-rays such as joint space narrowing and osteophyte formation.

2. Clinical Branch (MLP): A Multi-Layer Perceptron processed clinical data (e.g., BMI, age, pain score) to capture important health-related signals.

3. Feature Fusion and Classification: Each branch's output was fused into a single feature vector. This integration enabled the model to learn associations between image pattern and clinical data, and classify the patient into one of the five KL grades (0-4).

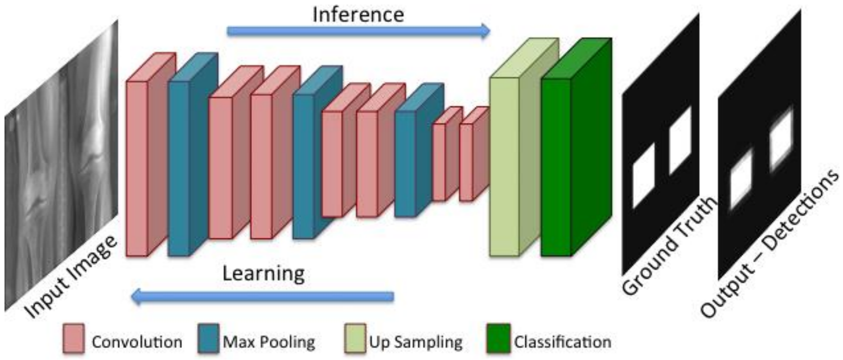

Figure 3 - The-Fully CNN

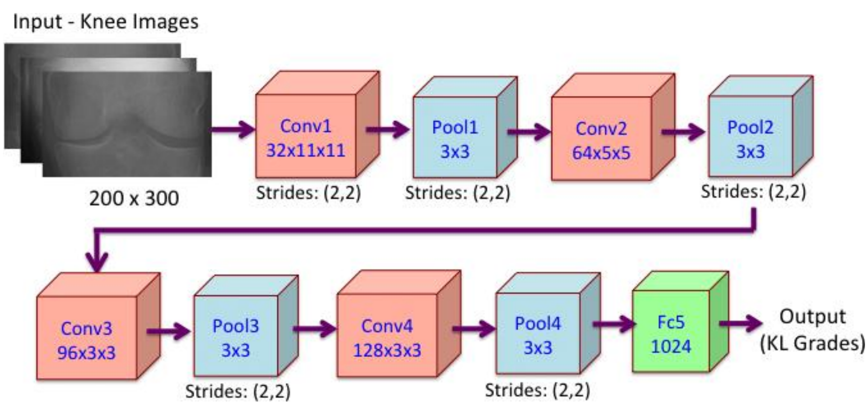

Figure 4 - The Network Architecture

Model Training and Evaluation

Training:

The model will train with the Adam optimizer and categorical cross-entropy loss, suitable for multi class classification. Early stopping was used to avoid overfitting.

Baseline Comparisons:

Image-only model (CNN without clinical data)

Clinical-only model (MLP without images)

Metrics:

Evaluation was carried out using Accuracy, Precision, Recall, F1 Score, and Confusion Matrices. The primary goal was to confirm that combining imaging and clinical data produced better results than using either source alone.

Explainability and Interpretation

To make the model's predictions reliable to doctors:

Moreover, Grad-CAM heatmaps showed the specific regions in the knee image (such as narrowed joint spaces, osteophytes) that contributed to the decision.

SHAP values helped in explaining the contribution of each clinical factor (i.e., age, BMI) in the final prediction.

This step made it important that the system was not a black box but instead provided clear and interpretable results to aid clinical decision-making.

3.1 Requirements Analysis

Objective:

To design, develop, and evaluate a novel deep learning system that automatically grades the severity of KOA by fusing features extracted from radiographic images (X-ray/MRI) with structured clinical patient data and biomarkers, thereby providing a more accurate and clinically interpretable assessment than unimodal approaches.

3.2 Project Requirements

3.2.1 Functional Requirements:

- Preprocess knee radiographic images (X-ray or MRI) as an input to the deep learning model.
- Take in structured clinical data (e.g., Age, BMI, Symptom Duration) and preprocess it before you input it into a neural network.
- Build CNN from scratch and use it for extracting relevant features from images.
- MLP for processing and feature extraction from clinical data
- Combine extracted image with clinical features into combined representation.
- For the fused features, each was assigned to either one of the five KL grades.
- Provide a confidence level, or probability distribution, for the predicted grade.
- be compared with baseline image-only and clinical-only models to demonstrate higher performance
- produce output which may be part of a larger system (API for a web/mobile application)

3.2.2 Non-Functional Requirements:

Accuracy: The model should have competitive classification accuracy (Target: >90% overall, F1-Score >0.85) on a standard dataset.

Interpretability: The model's predictions must be interpretable, for example, using Grad-CAM to identify areas of the image that play a critical role in the decision.

Scalability: The model architecture and training pipeline needs to scale with growing multi-modal data (images + clinical records) without a drastic degradation in training time or classification accuracy.

Reliability: The system must be able to manage input data that are of varying quality and quantity that we would see for different brands of X-ray machines, different imaging protocols, and different methodologies of data entry in the clinical setting.

Security: All patient data such as medical images and structured clinical data must be anonymized when developing and training the model. The system needs to be developed in compliance with data protection legislation, providing that sensitive health data is processed with a level of technical and organizational security measures.

Explainability and Transparency: The model must not be a black box. It shall provide inherent explainability through techniques like Grad-CAM to visually justify its image-based predictions by highlighting regions of interest. Furthermore, the contribution of clinical features to the final prediction must be quantifiable and reportable, for instance, using methods like SHAP.

3.2.3 User Requirements

Patients:

- Want a comfortable and lightweight wearable device for daily use.
- Want to view their knee health status and severity level in real-time through the app.
- Want timely alerts in case of abnormal conditions or worsening KOA severity.
- Want clear and simple explanations of the results (via XAI).

Clinicians:

- Want accurate KOA risk assessment and severity grading reports.
- Want access to long-term patient history, disease progression, and trend analytics.
- Want an explainable system to understand why a prediction was made (XAI for trustworthiness).
- Want integration with hospital systems.

3.2.4 System Requirements

Hardware Requirements

- Wearable device with sensors (vibration/microphone for joint sounds, optional EMG).
- Mobile devices (Android/iOS smartphone or tablet).
- Cloud server (for data storage, training models, and clinician dashboard).
- X-ray/MRI image input sources (integrated with PACS systems).

Software Requirements

- Mobile Application (Android/iOS) for patients.
- Web Dashboard for clinicians (React/Angular + backend APIs).
- Machine Learning Frameworks (TensorFlow/PyTorch/Scikit-learn).
- Data Processing (Python, Pandas, NumPy).
- Database (MySQL/PostgreSQL for structured data, MongoDB for unstructured imaging data).
- Cloud services (AWS/GCP/Azure) for scalable storage and computation.
- Security protocols (SSL/TLS, OAuth 2.0, JWT authentication).

3.3 System Design

3.3.1 Component System Diagram

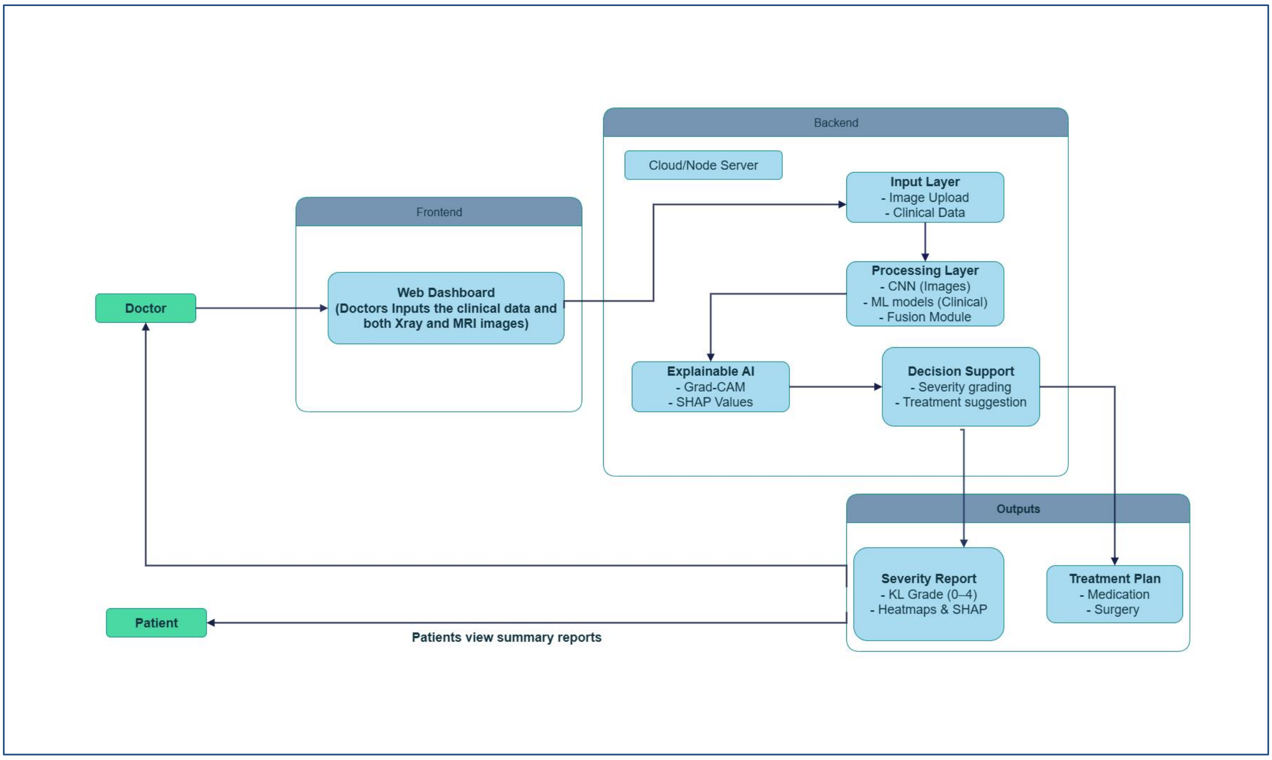

Figure 5 - Component Architecture

3.3.2 Overall System Diagram

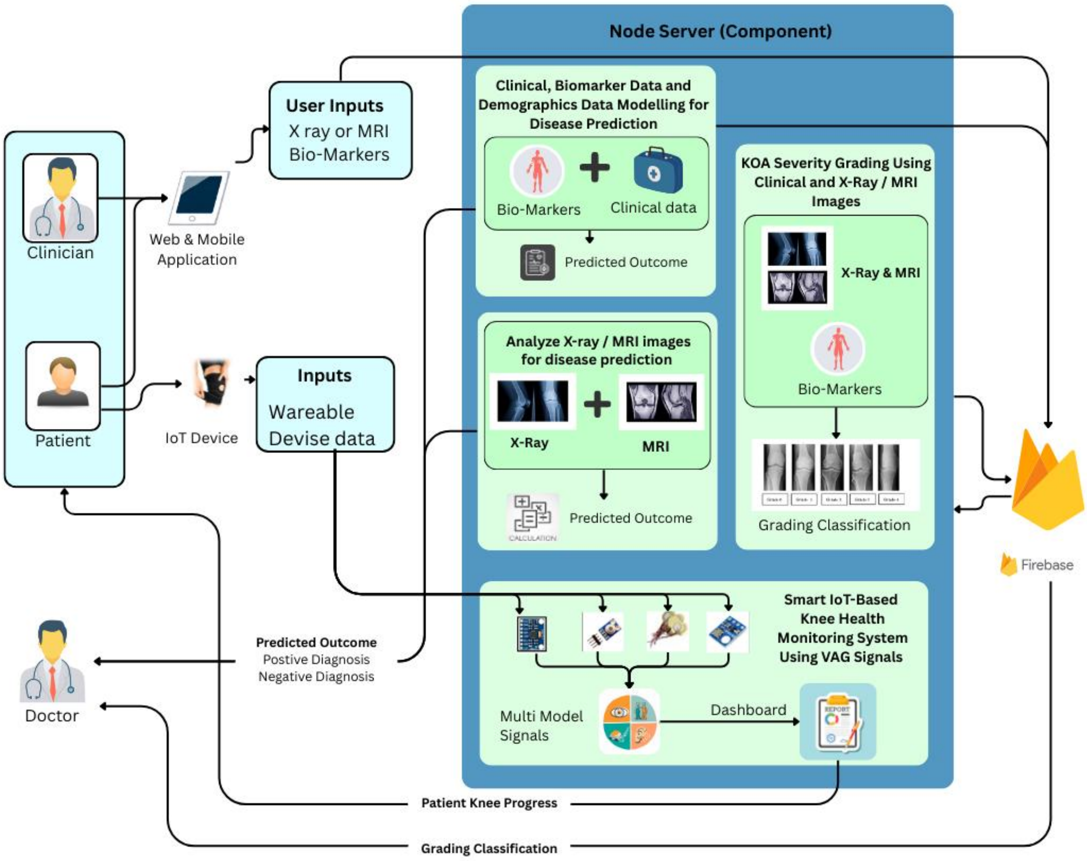

Figure 6 - Overall System Diagram

3.3.3 Component Use Case

Use Case ID	UC01
Use Case Name	Multi-Modal KOA Severity Grading with Explainable AI
Summary	The system automatically grades the severity of a patient's KOA by fusing features from X-ray/MRI images and clinical data. It provides a KL grade (0-4) and an XAI report highlighting the key image regions and clinical factors that led to the decision.
Priority	High
Pre Condition	Patient's X-ray and/or MRI images are uploaded to the system. Patient's structured clinical data (e.g., age, BMI, pain score) is available. The multi modal deep learning model is trained and deployed. The clinician is logged into the system.
Post Condition	A KL grade (0-4) is generated and displayed. An XAI report (e.g., heatmaps, feature importance scores) is provided. The prediction and explanation are stored in the patient's record.
Primary Actor	Clinician (Radiologist, Orthopedic Specialist)
Triger	A clinician requests a severity assessment for a specific patient.
Main Scenario	
Step	Action
1	Clinician selects a patient from their dashboard and navigates to the "KOA Analysis" section.
2	System automatically loads the patient's most recent knee X-ray and MRI images.
3	System retrieves the patient's relevant clinical data (Age, BMI, previous injury history, pain score) from the Electronic Health Record.
4	Clinician clicks the "Grade Severity" button to initiate the analysis.
5	The system preprocesses the images and normalizes the clinical data.
6	The multi modal AI model extracts features from both the images and clinical data, fuses them, and generates a KL grade prediction.
7	The XAI component generates an explanation for the prediction.
8	The results and explanations are saved to the patient's database record for audit trails and future reference.

Extensions	
Step	Action
2a	If images are not available, The system prompts the clinician to upload the required files manually.
3a	If clinical data is incomplete, The system alerts the clinician but proceeds with the analysis using available data, flagging the result as based on partial input.
6a	If model confidence is below a threshold, The system does not display a grade but flags the case for "Expert Review," stating it could not reach a reliable conclusion.

Table 3 - Use Case

3.3.4 Sequence Diagram

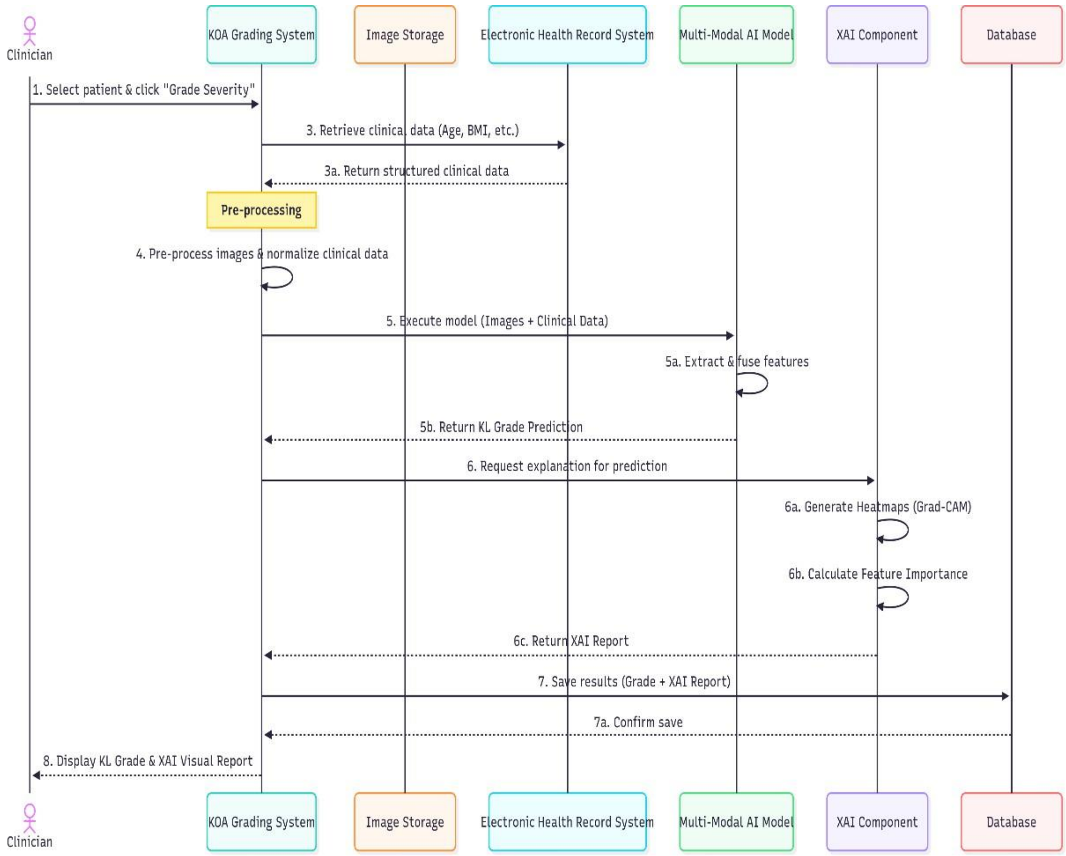

Figure 7 - Sequence Diagram

3.4 Development

The approach of this project will be to have an iterative development methodology. Instead of constructing the entire system all at once, you'll be constructing it in small increments or sprints that are testable prototypes. This is perfect for a research project because it can be evaluated and adjusted at all times depending on results.

Iteration 1: Develop and test the Image-Only Pipeline

Iteration 2: Development and testing of the Clinical-Only Pipeline (MLP)

Iteration 3: Incorporate both pipelines into the Multi Modal Model and fusion

Iteration 4: Refine, test and implement explainability features

Technology Stack & Tools

Python: The main programming language for its broad data science and machine learning libraries.

TensorFlow and Keras: The main deep learning frameworks that are used for developing, training, and testing the custom multi-modal neural network from scratch. Keras is used because it is simple and has an intuitive API.

Pandas: For loading, cleaning and manipulating structured clinical data from CSV files

NumPy: For efficient numerical computing and multi-dimensional array processing (necessary for image data).

OpenCV: Used for image processing (reading, resizing, normalising X-ray and MRI images)

Scikit-learn: For further data preprocessing (e.g. advanced feature scaling) and for computing evaluation measures such as F1 score and confusion matrices.

Matplotlib & Seaborn: To create standard graphs, plots and charts to visualize results, model performance, and data distributions.

Grad-CAM: The main library to implement Grad-CAM to create visualizations in the form of heatmaps that explain the model's predictions for images.

SHAP: Calculates and visualizes the contribution of each clinic characteristic (e.g., BMI, age) to the model's final prediction in a transparent way.

3.4.1 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

3.4.2 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.

3.4.3 User Interface Development

We 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

Test Objective

The objective of the testing phase is to verify and validate that the Multi Modal KOA Severity Grading System works correctly, is reliable, performs efficiently, and produces clear and usable outputs in a clinical setting. Testing will also confirm that combining imaging and clinical data improves accuracy and robustness compared to using a single data source alone.

Test Scope

This plan covers testing for the core software component: the multi modal deep learning model and its supporting data processing pipelines.

In Scope: Data preprocessing modules, custom CNN model, MLP model, fusion mechanism, classification head, evaluation metrics, and explanation generation (Grad-CAM, feature importance).

Out of Scope: Hardware integration, end-user web/mobile application UI and large scale deployment infrastructure.

Unit Testing

Confirm that severity staging rules and thresholds are properly in place.

Grade 0: (Normal): Make sure that normal healthy knee X-rays without osteophytes or joint space narrowing are correctly graded as Grade 0.

Grade 1 (Doubtful): Screening for low-grade osteophytes on a test classification basis. Check that borderline cases are always dealt with.

Grade 2 (Mild): Determine the model is detecting definite osteophytes and possible narrowing of joint space.

Grade 3 (Moderate): Confirm presence of multiple osteophytes, clear joint space narrowing and moderate bone deformity.

Grade 4 (Severe): The system is required to identify large osteophytes, severe joint space narrowing, subchondral sclerosis and bone deformity.

Integration Testing

See if severity staging works well with other modules.

Image Processing Integration: Ensure that feature extracted preprocessed radiographs are associated with the correct KL grade.

Clinical Data Alignment: Make sure that clinical indicators (e.g. pain score, BMI) correlate with image-based KL staging.

Multi Modal Fusion: test that the severity staging results from the combination of imaging and clinical data for final classification.

Performance & Load Testing

Evaluate stability, accuracy and efficiency of severity staging.

Prediction Time: Measure average time make KL grade per patient

Scalability: Batch inference (e.g. 1000+ X-rays) to test system throughput

Resource Usage: See GPU/CPU/RAM usage during staging calculations.

Repeatability: make sure repeated passes on the same input always give the same grade.

Model Validation Testing

Assess the medical accuracy, robustness and reliability of staging predictions.

Baseline Comparison: Compare the staging accuracy with radiologist-labeled ground truth.

Cross Validation: Use K Fold validation to ensure that the performance remains consistent across datasets.

Confusion Matrix Analysis: Point out frequent misclassifications (i.e. confusion between grade 2 vs grade 3).

Robustness Testing - Verify grading on noisy, low resolution, or rotated X-rays

Explainability Verification - Use Grad-CAM/heatmaps to validate the model is attending to clinically relevant areas (e.g. joint space narrowing, osteophytes).

3.6 Work Breakdown Chart

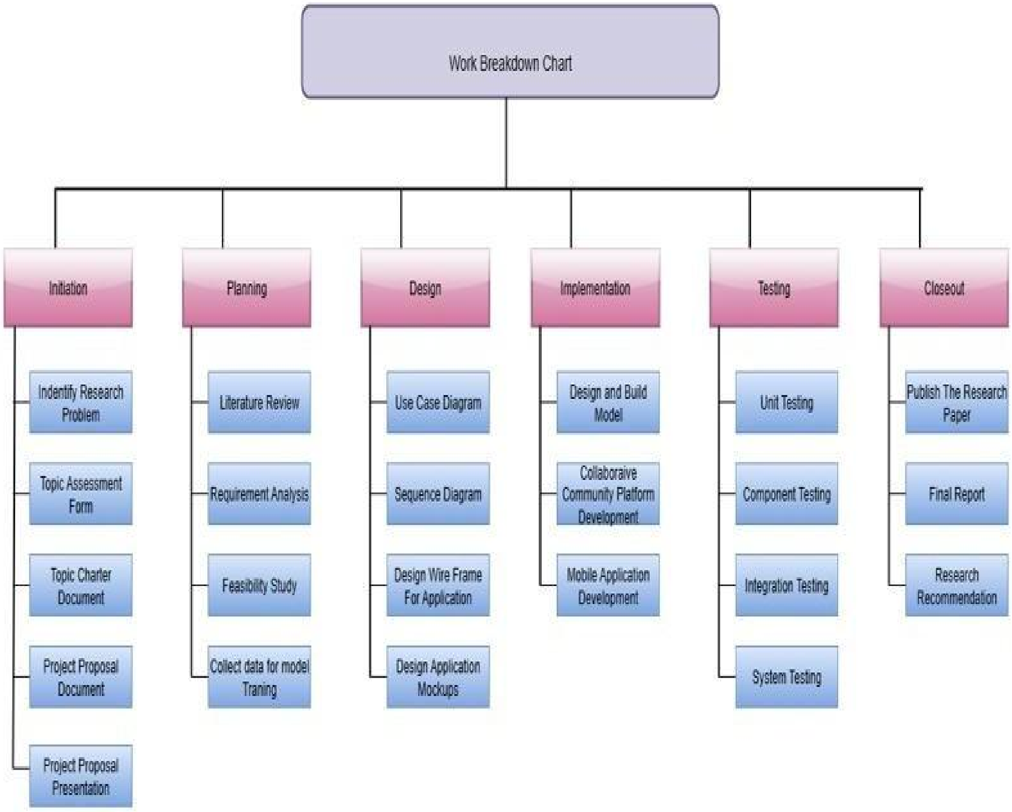

Figure 8 - Work Breakdown Chart

3.7 Gantt Chart

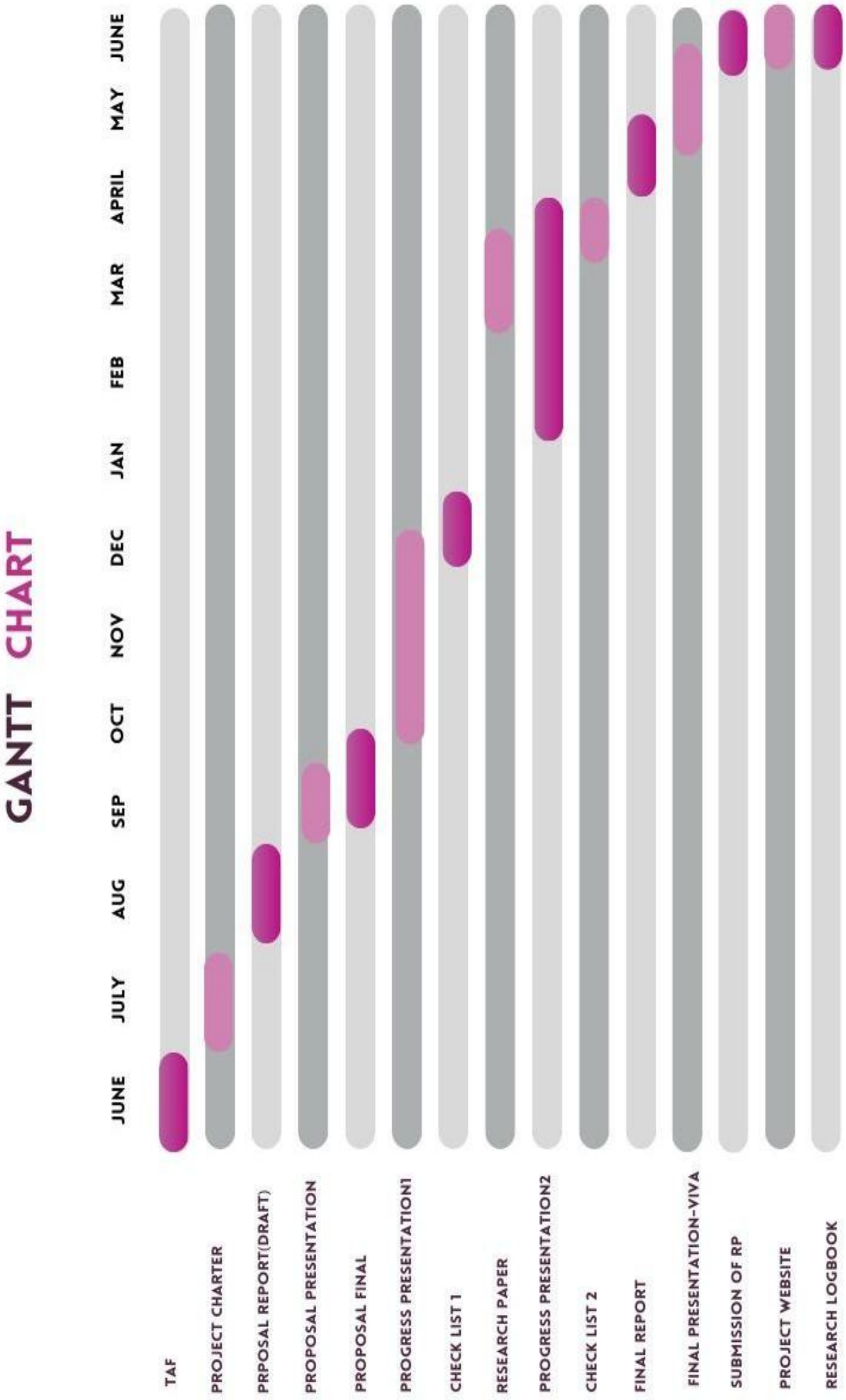

Figure 9 - Gantt Chart

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