Knee Osteoarthritis Prediction and Progression using Multi-Modal Deep Learning

Project Id: 25-26J-112

Project Proposal Report

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BSc. Special (Hons) in Information Technology (Data Science)

Department of Data Science

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

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------------------------------ 29/08/2025

Ms. Wishalya Tissera

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ABSTRACT.

KOA is a disease that impacts millions of people in the world as it is a chronic degenerative joint disease leading to pain, stiffness, disability, and a significant healthcare liability. Traditional diagnostic tools, including the KL grading scale of radiography, offer practical structural information but cannot detect cartilage degradation that does not appear in the x-rays. At a higher cost but with greater complexity, MRI is not widely introduced in everyday screening. Emerging developments in AI and specifically in deep learning, using CNNs, have demonstrated much potential in automated KOA detection. Nevertheless, most currently available methods are unimodal, incorporating either X-ray or MRI, with a low diagnostic accuracy, decreased generalizability, and low clinical interpretability.

This research suggests a multi-modal deep learning system that combines X-ray and MRI images, with clinical and demographic information to enhance detection of KOA, early diagnosis, and predicting progression. The methodology consists of image preprocessing independent CNN feature extraction in each modality, and feature hybrid fusion by attentive means. Besides, explainable AI methods such as Grad-CAM as a visual localization method and SHAP as a feature contribution analysis are included in the framework, which guarantees transparency and clinical trust. The system will conform to both the non-functional requirements and the functional requirements.

The proposed solution implemented using Python, TensorFlow/Keras, PyTorch, OpenCV, and scikit-learn on GPU-enabled environments, aims to deliver a scalable, interpretable, and clinician-friendly diagnostic support system. This study can advance early disease detection, trusted monitoring, and better management of Knee Osteoarthritis.

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List of Abbreviations

Abbreviations	Description
AI	Artificial intelligence
CNN	Convolutional neural network
CLAHE	Contrast Limited Adaptive Histogram Equalization
Grad-CAM	Gradient-weighted Class Activation Mapping
IoT	Internet of Things
KL grading	Kellgren and Lawrence grading
KOA	Knee Osteoarthritis
MRI	Magnetic resonance imaging
RCNN	Region-based Convolutional Neural Networks
ROI	Region of Interest
SHAP	SHapley Additive exPlanations
VAG	Vibroarthrography

1. INTRODUCTION

KOA refers to a progressive disease of joints where there is a gradual destruction of the articular cartilage and alterations in the environment of the bone structure. It is one of the most notable causes of disability globally whereby out of the individuals more than 40 years old, and millions of people has become disabled already and the cases are projected to increase with aging population and rising prevalence of obesity [4]. KOA is characterized by pain, stiffness and swelling as well as lack of mobility, both of which substantially diminish quality of life and constitute a significant healthcare burden to health systems [1].

Medical imaging is imperative in the diagnosis of KOA and its follow-up. Radiographic, especially X-rays studies, are the most common forms because of their accessibility and the results can be related to the disease process like joint space narrowing and the development of osteophytes [2]. Nevertheless, X-rays mainly identify bone changes and could record cartilage degeneration, which is at an early stage. The MRI, instead, is more detailed in the visualization of bone and soft tissues and allows evaluation of the integrity of the cartilage, bone marrow lesions, and the inflammation of synovium [3]. The assimilation of these imaging modalities yields a better view of the disease situation.

Figure 1 - Knee X-ray of a normal person

Figure 2 - Knee X-ray of a KOA patient

New developments in AI, especially deep learning, has transformed the medical image analysis. CNNs have proved to be very accurate in the identification and classification of KOA severity with the use of X-ray and MRI data [4][5]. However, the current models are usually homing on a single imaging modality and thus, the diagnostic accuracy and stability are low.

This study is intended to close that gap by coming up with a dual-mode deep learning framework to analyze both X-ray and MRI images to detect KOA. Through a synergistic combination of the modalities, the proposed system is positioned to further the diagnostic accuracy, allow an early disease detection, and be implemented in more general multi-modal pipelines specifying the progression of KOA.

Figure 3 - MRI of a healthy knee

Figure 4 - Knee MRI of a KOA patient

1.1 Background & Literature Survey

KOA is chronic degenerative joint-related disease that is typified by progressive cartilage erosion and subchondral remodeling and inflammatory changes in the peridermal area. It has become one of the highest causes of disability across the world with more than millions of individuals being affected by the condition worldwide, not to mention its significant influence on mobility and wellbeing [1]. Internal medicine diagnosis of KOA sequentially involves a potentially dependent use of patient history, clinical tests, as well as radiography and MRI. A radiographic grading scale that is commonly used is the KL scale that has Grade 0 (no OA), Grade 1, Grade 2, Grade 3 and Grade 4 (severe OA) [2], [4]. Where the radiograph is helpful to provide structural information about bone alignment and narrowing of joint spaces , MRI is better used to visualize the involvement of structured tissue, such as cartilage destruction, ligament tears, and inflammation of the synovium [5]. Nevertheless, both modalities are limited in terms of accessibility, cost, and in terms of their capacity to pose surveillance on the progress of the disease .

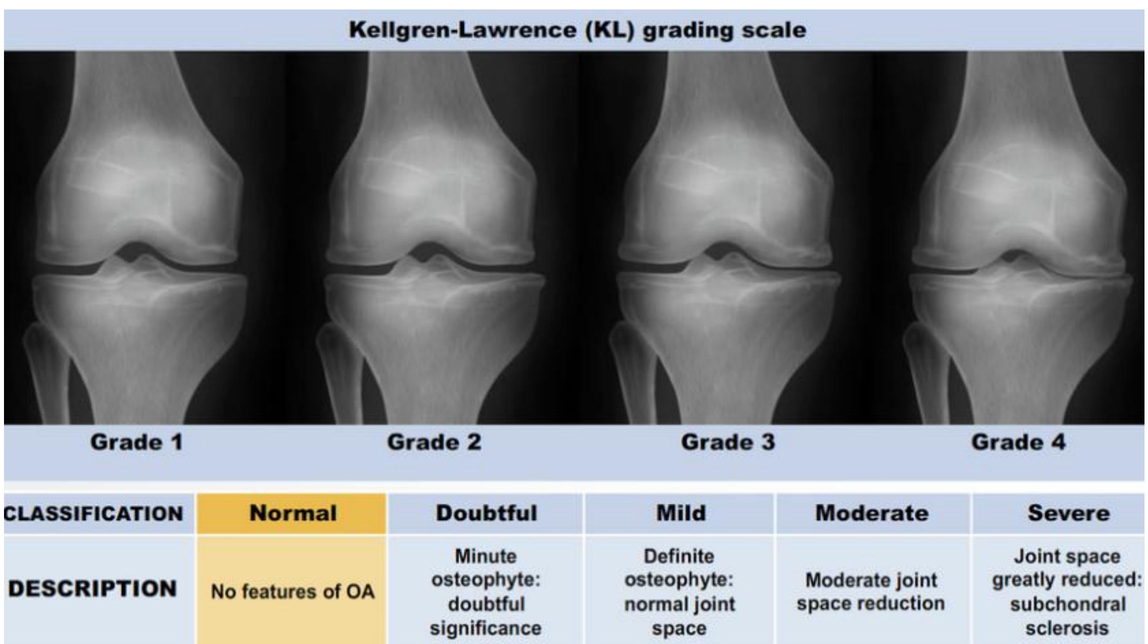


Figure 5 - KL Grading Scale [4]

New technology developments in AI and deep learning have given way into new possibilities in automated KOA detection and prediction of progress of the disease. CNNs showed great performance in categorizing KOA severity simply by looking at X-ray images [6][7]. The results of the study designed by Antony et al. [8] demonstrated the potential of CNN based system to quantify the severity of KOA based on radiographs and performed at a similar level with a trained orthopedic radiologist. In parallel, Balaji et al. [9] significantly attained an automated KOA detection using a R-CNN, which attained a boost in the trained-learned classification detection through use of a ROI extraction. There have also been MRI-based deep learning algorithms, including Du et al. [5], which used simulation data to predict the progression of KOA with high sensitivity based on machine learning techniques applied to MRI data.

Other than unimodal learning, there has been increased usage of KOA assessment through multi-modal deep learning [10][11]. The study by Tiulpin et al. [17] was based on a hybrid architecture, which included MRI and clinical data to predict the KOA adverse outcomes development, proving that the combination of methods and patient factors helps to increase predictive success. Liu et al. [18] went a step further and designed a deep feature fusion framework that used X-ray features leading to a better early-stage KOA prediction in which subtle morphological changes are overlooked by radiologists. This evidence supports the significance of making use of the strengths of different types of data complementary.

Although these have been achieved, there still exist problems in the development of a comprehensive KOA prediction system, which is accessible, and explainable [13], [14]. The available models either deal with non-imaging or imaging data, and thus their use in clinical practice is restricted. Moreover, explainability is also of paramount importance in medical AI systems since medical professionals need to know exactly how decision-making was made to make their trust in models [14]. Other recent explainable AI frameworks have demonstrated potential in visualizing the pathways of a decision in KOA detection, which is likely to reduce the barrier between AI systems and clinical usage.

Finally, it can be concluded that the use of multi-modal datasets, which include X-ray, MRI, clinical, biomarker and biomechanical data, are trending in the literature to help improve the KOA diagnosis and progression prognosis. But its full potential has not been achieved whereby such integration is cost effective, scalable, and real time monitoring framework applicable to both the clinical and remote settings. It is this gap upon which the proposed research has been based.

1.2 Research Gap

KOA is one of the principal causes of disability globally, and, nevertheless, after so many decades of research, accurate early prediction and progression are difficult to achieve. Prior research has addressed different modalities to diagnose the KOA, such as X-ray imaging [4], MRI-based analysis of the cartilage [5], and structured clinical data [12], although each of them is usually viewed individually. The separation restricts the available means of addressing the nature of KOA, which is highly complex and multi-factorial, both structural degradation of joints and physiological risk factors contribute to it.

The ability of deep CNNs to measure KOA severity based on X-ray images has been proven several times in various past studies, including Antony et al. [4]. Nevertheless, X-rays do not show early degeneration of cartilage so well as MRI [5]. Although MRI-based methods like in the study have enhanced the study of soft tissues, they have not been consistently constructed with radiography data in an integrated model of prediction, which leads to disparate accents in diagnosing logic.

One of the major weaknesses of existing literature is the unavailability of multi-modal fusion strategies integrating imaging data and clinical, demographic, and biomarker. Studies such as Tiulpin et al. [10], Teh et al. [11] demonstrate good results in multi-modal learning, yet in this case, reporting the results does not provide real-time tracking and longitudinal modeling of the disease progression. This lack of continuous assessment facilities diminishes the relevance of such systems of personalized healthcare.

According to an AI point of view, the uncertainty quantification and model interpretability has a huge gap in the KOA prediction systems [6], [15]. These models cannot be adopted in the clinical setting since they lack outputs which can be interpreted and confidence levels which can be measured statistically creating the issue concerning clarity and credibility.

Lastly, most of the past research used only static data, which is gathered at one point, with no necessity of long-term continuous observation representing real life world events and that can be transformed into treatment changes happening in the go. The combination of wearable devices that can rely on IoT with predictive analytics of KOA is just getting started. Integration would not only permit early detection but subsequently permit the continued monitoring of the progress, a major key in avoiding disability.

Table 1 shows a tabularized format of the comparison between proposed solutions and some of existing researches.

Product	Focus on bone structure (X-ray)	Focus on soft tissue/cartilage (MRI)	Deep learning-based feature extraction	Fusion of X-ray & MRI insights	Use XAI
Tiulpin et al [10]	✓	x	✓	x	x
Liu et al [11]	x	✓	✓	x	x
Selvaraju at el [16]	x	x	x	x	✓
Chen at el 2025 [12]	x	x	✓	x	✓
Proposed Solution	✓	✓	✓	✓	✓

Table 1 - Comparison of former researches

1.3 Research Problem

Knee Osteoarthritis The progressive degenerative joint disease known as the KOA severely influences the quality of life as well as an increasing global economic burden on health care systems [1]. Early detection and accurate monitoring are the key to successful intervention, but the existing diagnostic technologies are limited and divided. The standard diagnosis is mostly based on X-ray and KL grading scale[2], which, although suitable to detect changes in the structure, do not capture the early changes in cartilage degeneration detectable by MRI [5]. Due to this fact many patients with early KOA may in most cases receive no diagnosis before suffering irreparable harm.

Deep learning has proven to be tremendously successful in automating KOA detection using imaging information in research [8], [9]. Nevertheless, the currently used methods (although there are some multimodal) are unimodal (operating on only one of the following modalities X-ray or MRI) and do not maximize the use of advantages of these modalities. Moreover, non-imaging data including clinical history, biomarkers values, and demographic risk factors that can enhance predictive performance [12] have not been used in a coherent framework fully.

Also, the lack of interpretability and estimation of uncertainties in model predictions of most current KOA AI systems [15], [16] is a decisive caveat to clinical implementation. In high-stakes medical cases, healthcare providers cannot simply trust the prediction results without knowing the justification behind a decision and the level of confidence held by a model.

Thus, the underlying problem of research is the lack of multi-modal deep learning framework that can be clinically applied and has:

- Integrates X-rays, MRI, in a single model.
- Allows early detection.
- Introduces explainable AI and quantification of uncertainty to alleviate doubts and adoption in clinics.

2. OBJECTIVES

2.1 Main Objectives

The main objective is to implement a multi-modal deep learning model that incorporates medical imaging (X-ray and MRI), clinical and demographic information, along with real-time signals collected via IOT-based monitoring system to develop a reliable, interpretable, and clinically applicable tool to early detect and predict the progression of the occurrence of KOA.

2.2 Specific Objectives

The objectives of the study are to develop a dual-modality (X-ray and MRI) image classification methodology based on deep learning to augment the usage of both modalities to classify patients who show Knee Osteoarthritis (KOA) or not, which allows clinicians to be able to detect it earlier to make better clinical decisions.

1. Preprocessing and Region-of-Interests Detection towards a Higher Image Quality and Targeted Knee Joint Analysis

2. The proposed method is to develop a Deep Learning model to provide an accurate KOA detection based on using the X-ray and MRI datasets.

3. Dual-Modality Combination of X-ray and MRI Features to Assess Comprehensively KOA

4. Validation of Model and Performance Assessment

5. Embedding the Explainable AI Methodologies to Promote Clinical Trust and Transparency in Forecasts

3 METHODOLOGY

3.1 System Overview

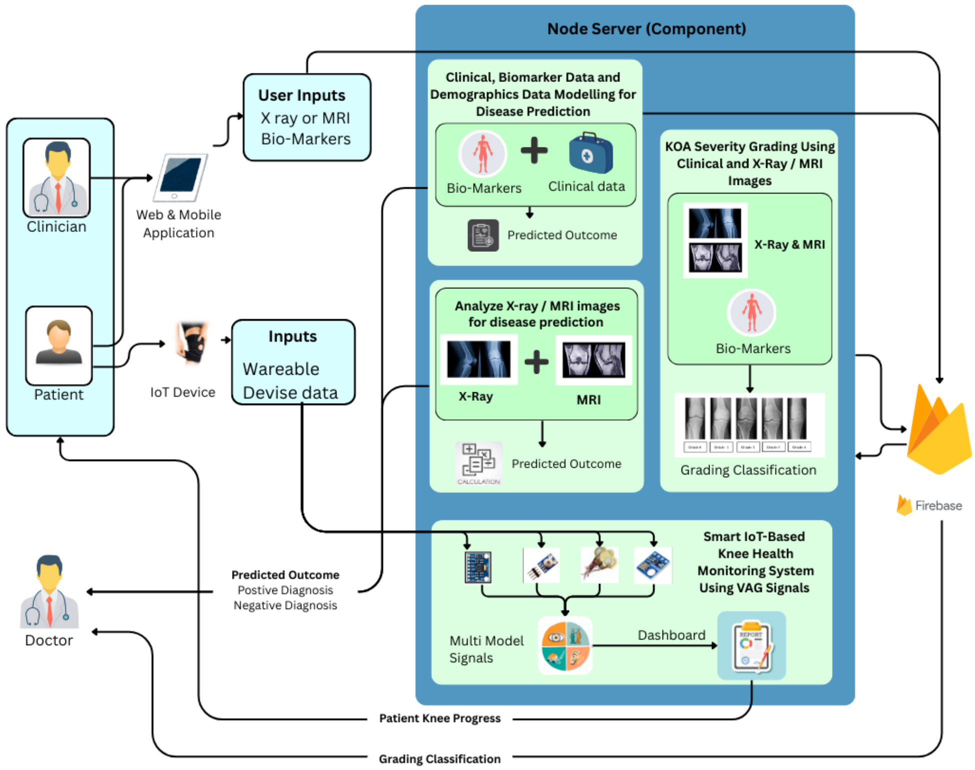


Figure 6 - Overall System Diagram

The proposed system gathers multi-modal data representing varied data sources that provide a wide perspective of KOA risk and evolution. Tabular inputs include demographic, clinical and biomarker information: age, body mass index, mutual history, symptoms and laboratory results. One of the methods used to examine structural bone changes and soft-tissue degeneration is the medical images incorporated in the form of X-rays and MRIs. Moreover, VAG signals under real-time monitoring are measured by IoT based wearable devices which detect vibrations of the knee during movement as important insights to the joint functionalities.

Data of each type is pre-processed and feature engineering before being model trained. Clinical and biomarker data are cleaned and normalized and converted into meaningful machine learnable features. Medical image refinements consist of denoising, contrast and extraction of ROI methods to highlight cartilage and bone architecture. Vibration signals provided by IoT are emitted through Wi-Fi, filtered and denoised in a way that correct representation of mechanical joint activity is achieved.

After pre-processing, data of each modality is trained and tested using the right models. Machine learning algorithms are used to determine KOAs risk factors by processing clinical and biomarker data. Disease diagnosis and the Kellgren-Lawrence severity grade are trained by CNNs on X-ray and MRI. In the meantime, dense neural networks and time-series analysis are considered as methods of detecting abnormal joint mechanics with the use of digital vibration signals of various IoT products. The performance metrics of each model are verified to make sure it promotes reliability.

The output of all the models is then incorporated into a multi-modal fusion layer so that supplementary insights can be integrated. X-ray indicates and MRI shows stated articular degeneration, cartilage and soft-tissue degeneration, clinical and biomarker evidence provided individual risk profile, and VAG provides real-time functional inputs of joint health. Integration is made possible to increase the predictive accuracy of the system by maximizing the merits of each of the modalities.

The pre-processed features and all inputs and all output data are retrieved at a single database location. This facilitates longitudinal monitoring and healthcare providers are able to trace the disease development over a period of time, updating patient records on a constant basis.

The system generated final results are KOA severity grading with the Kellgren-Lawrence scale and binary diagnosis outcomes (positive or negative KOA) and a patient interactive progress dashboard available via web and mobile platforms. The dashboard helps clinicians and patients as it helps visualize disease progression and identify severity trends and generate timely signals and alerts when the situation is deteriorating, and thus, reveals early intervention and tailored treatment planning.

Figure 6 shows the high-level architecture of the proposed application which provides the overview of entire system by identifying the main four components of the system.

3.2 Providing Personalized Activity Suggestions.

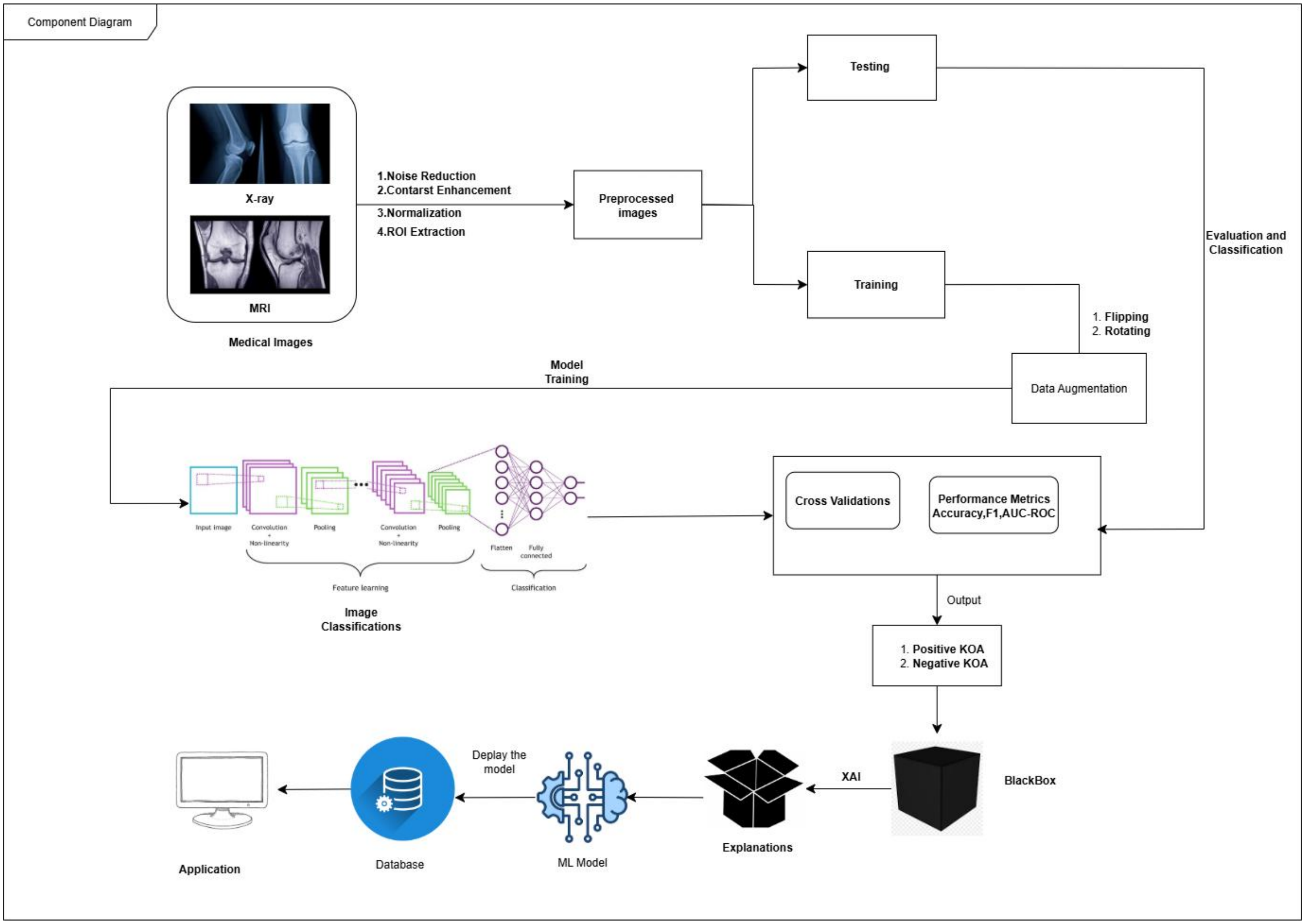


Figure 7 - Provide Personalized Activities

Requirement Gathering.

- Reading internet resources and research papers
- Studying existing systems
- Collect data from Local hospitals and clinics

The following methodology will be carried out to systematically establish the development of a dual-modality deep learning-based KOA detection system by utilizing X-ray images and MRI images. It uses a sequential, yet 6-phase workflow incorporating medical image preprocessing, model development and assessment to provide not only technical soundness but clinical applicability.

1. **Datasets finding and confirmation**

- Publicly accessible repositories including the knee osteoarthritis dataset with the Osteoarthritis knee X-ray dataset and MRI datasets available by open medical archives or collect dataset from local clinics and hospitals.
- Records will be assigned grades based on KL criteria [1] to enable consistency in rating of pictures.
- A sample of the dataset will be examined by the medical professionals (radiologists, orthopedic specialists) to confirm accuracy, diagnose mislabeled cases, and confirm quality diagnosis.

2. **Image Preprocessing and Enhancement**

- Noise Reduction:- Gaussian filtering of the noise and median blurring noise reduction is avoided on the images and the edges are preserved.
- Contrast Enhancement:-CLAHE to bring out the structures.
- Normalization-To standardize input values to train deep learning models by normalizing the pixel intensities values to [-1,1] value range.
- ROI Extraction: It is possible to detect the location of the knee joint (e.g. in a model based on Faster R-CNN) and crop and center the joint region to exclude parts of the anatomy that are irrelevant to the task.

3. **Development of Deep Learning Models**

- Individual CNN models of Each Modality
    - X-ray model: Modeled to show changes that are related to the bones e.g., joint space narrowing and osteophyte formation.
    - MRI model: It is used with the aim of detecting cartilage thickness, meniscus tear, and soft-tissue degeneration.

- Transfer Learning-: Utilizing high feature extraction potential through training of the pre-trained architecture models, ResNet50, EfficientNet-B4, or DenseNet121.
- Hyperparameter Optimization-: the process of optimizing the learning rate, batch size, optimizer type and network depth can be a grid search or can be performed using Bayesian optimization.

4. Multimodal Feature Fusion

- Create a late-fusion or hybrid-fusion algorithm that combines capabilities of both images because of the complementary nature of their strengths in diagnostic capabilities.
- Use experimentation with attention-based fusion layers, to give priority to the features that are useful in terms of giving accurate classification.

5. Model evaluation and tests.

- Compare the outputs with those of the models classical machine learning measures (accuracy, sensitivity, specificity and precision and F1- score).
- AUC-ROC, confusion matrix uses in the estimation of reliability of diagnosis.
- Cross-Validation-: k-fold cross-validation will be used to generalize the models.
- Testing on a different (external) test data set of a different source to figure out what robustness is.

6. Explainability and interpretability

- Grad-CAM to elaborate significant areas of interest in an image that acted on the prediction.
- SHAP can be used to identify how the features at regional or pixel level contribute to pixel decision.

Tools and Frameworks

Programming Language	Python	Main language for deep learning, medical image analysis, and integration. Large community support and libraries for AI.
Deep Learning Frameworks	TensorFlow / Keras	Easy-to-use high-level API, fast prototyping, supports CNNs, transfer learning, and explainability modules.
	PyTorch	Flexible for research, dynamic computation graphs, widely used in academic AI/medical imaging research.
Image Processing & Preprocessing	OpenCV	For image preprocessing (noise reduction, ROI extraction, contrast enhancement).
	scikit-image	Additional preprocessing utilities for filtering, transformations, and edge detection.
Machine Learning Utilities	scikit-learn	For evaluation metrics (accuracy, sensitivity, ROC-AUC), data preprocessing, and baseline ML models.
Visualization and Explainability	Matplotlib / Seaborn	Plot performance graphs, ROC curves, confusion
	Grad-CAM	To visualize important regions in X-ray/MRI contributing to model predictions.
	SHAP	For feature-level interpretability and confidence explanation.
Development Environment	Jupyter Notebook / Google Colab	Experimentation, prototyping, and visualization in one framework

3.3 Work Break Down Structure

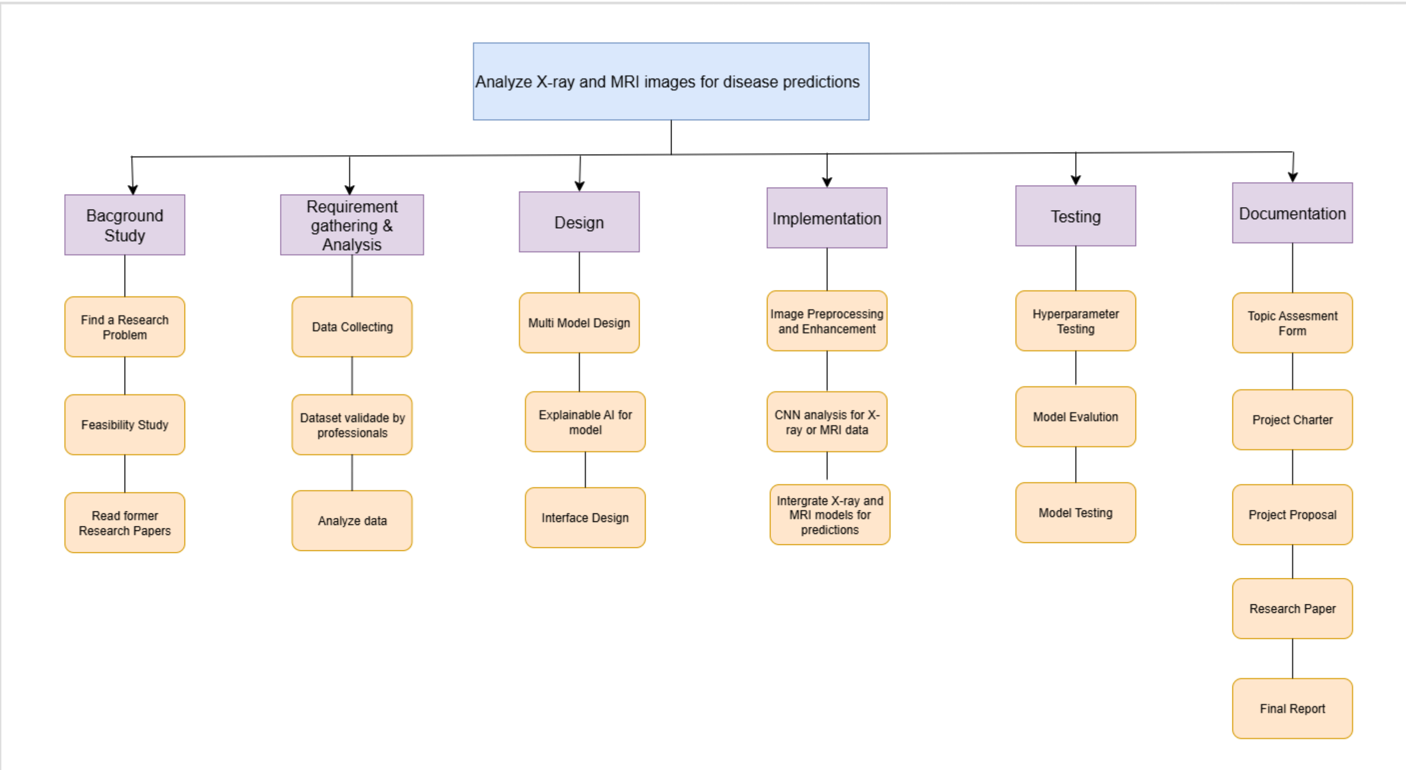


Figure 8 - Work Breakdown Structure

The project work breakdown structure is developed in form of six major steps. background study, requirement gathering and analysis, design, implementation, testing and documentation. Background study is aimed at the definition of the research problem, feasibility evaluation, and literature review. The reliability of the data provided by the requirement gathering and analysis process ensures that they collect medical image datasets, verify them with the professionals, and prepares them in a format useful in developing the model.

Developing a multi-modal framework and integrating explainable AI methods, designing the user interface, and creating CNN-based models to analyze X-rays and MRI are all tasks of the design and implementation phases. The aspects on which testing is centered are hyperparameter optimization and testing of model accuracy. The documentation phase is associated with preparation of reports, proposals, and research publication. Combined, these staged steps offer a formal way in which solid and clinically viable disease forecasting through medical imaging is accomplished.

3.5 Gantt Chart

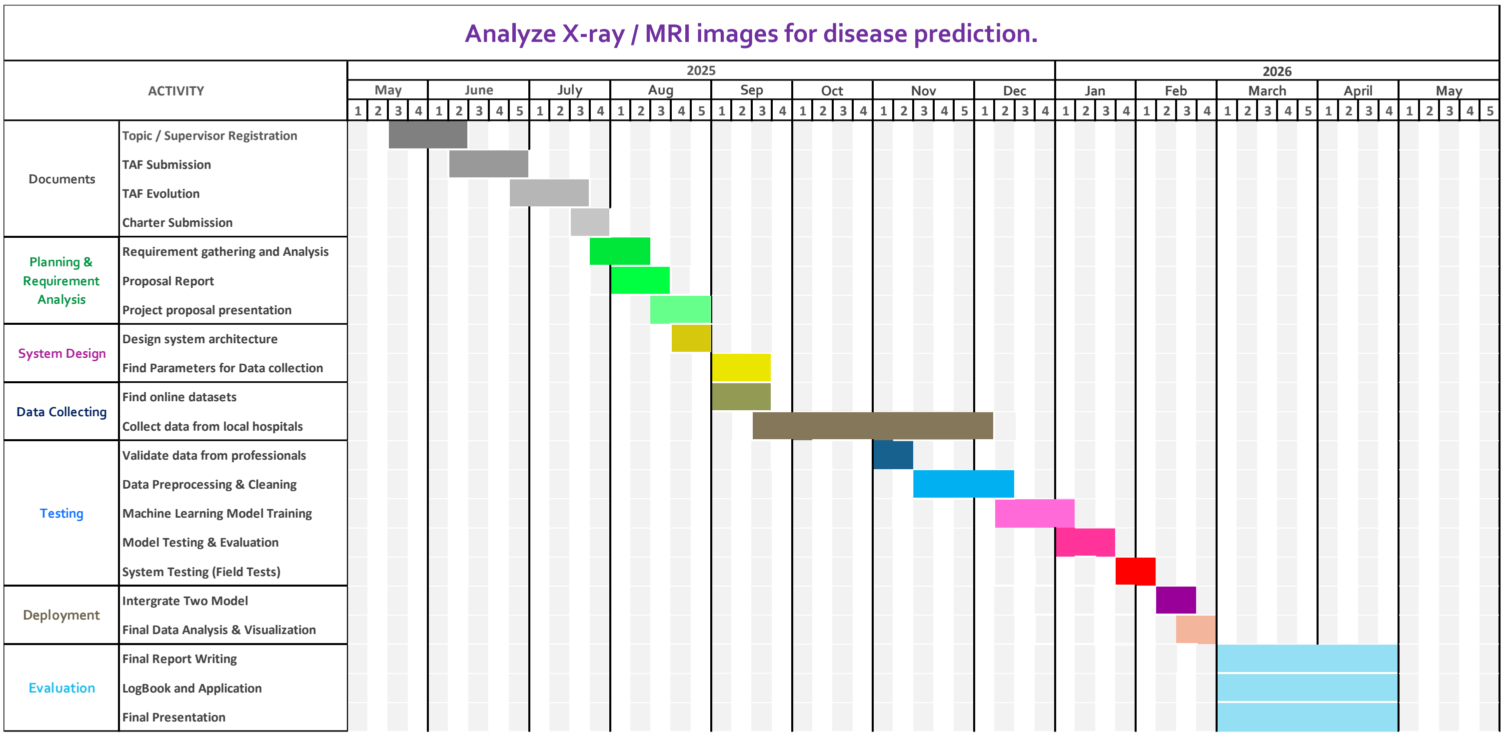


Figure 9 - Gantt Chart

4. DESCRIPTION OF PERSONAL AND FASCILITIES

4.1 Functional Requirements

1. Data entry and capture

    - Support common file formats of X-ray and MRI images in knee (JPEG, PNG).
    - Admit batch uploads of images to use in training, and single-image input to use in inference.
    - Verify that uploaded images are correct on modality and resolution.

2. Image Preprocessing

    - Align Image dimensions and intensities automatically (actually it is only intensity values).
    - Carry out noise-reduction, contrast-enhancement and ROI extraction.

3. Deep Learning Processing Model

    - Store and train individual CNNs, run on X-ray and MRI inputs.
    - Extract features on each of the modalities and then classify independently.
    - Realize late/hybrid fusion to juxtapose outputs of multiple modes to make the final decisions.

4. Prediction Output

    - Making KOA status Positive (KOA present) or Negative (KOA absent).
    - Include a probability / confidence score of each prediction.
    - Create heat-maps of areas that contribute to the prediction

5. Model Evaluation

    - Report performance measures (accuracy, sensitivity, specificity and AUC-ROC).

4.2 Non-Functional Requirements

1. Precision and Reproducibility

   - Minimal classification accuracy.
   - Sensitivity to minimize a false negative.

2. Performance

   - The processing time on GPU architecture of single-image prediction.
   - Provide the support of parallel processing of several images.

3. Scalability

   - Allow more simultaneous processing of images
   - The ability to add new imaging modalities as the future demands
   - Modular design of the model updates.

4. Usability

   - Easy, clinician friendly interface.
   - Personalized visual outputs (heatmap) on decision interpretability.

5. Security and Compliance

   - Guidelines to the handling of medical data.
   - Storage of sensitive patient information encrypted.

5. Commercialization and Entrepreneurship Potential

5.1 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.

5.2 Competitive Advantages

The proposed solution distinguishes itself through several key advantages:

Wearable & Non-Invasive: In contrast to MRI or X-ray, the device is lightweight, portable, and safe for daily, repeated use.

Real-Time Monitoring: It continuously collects VAG, motion, and pressure signals, enabling prompt detection of abnormalities.

On-Device AI Processing: Integration of TinyML models on the ESP32 allows low-power, rapid, on-device inference without requiring constant internet connectivity.

Mobile/Web Integration: The system delivers immediate feedback and visualizes historical data for both patients and healthcare professionals.

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:

B2B: Devices are supplied to hospitals, clinics, and physiotherapy centers, supported by subscription-based software for data analytics and monitoring dashboards.

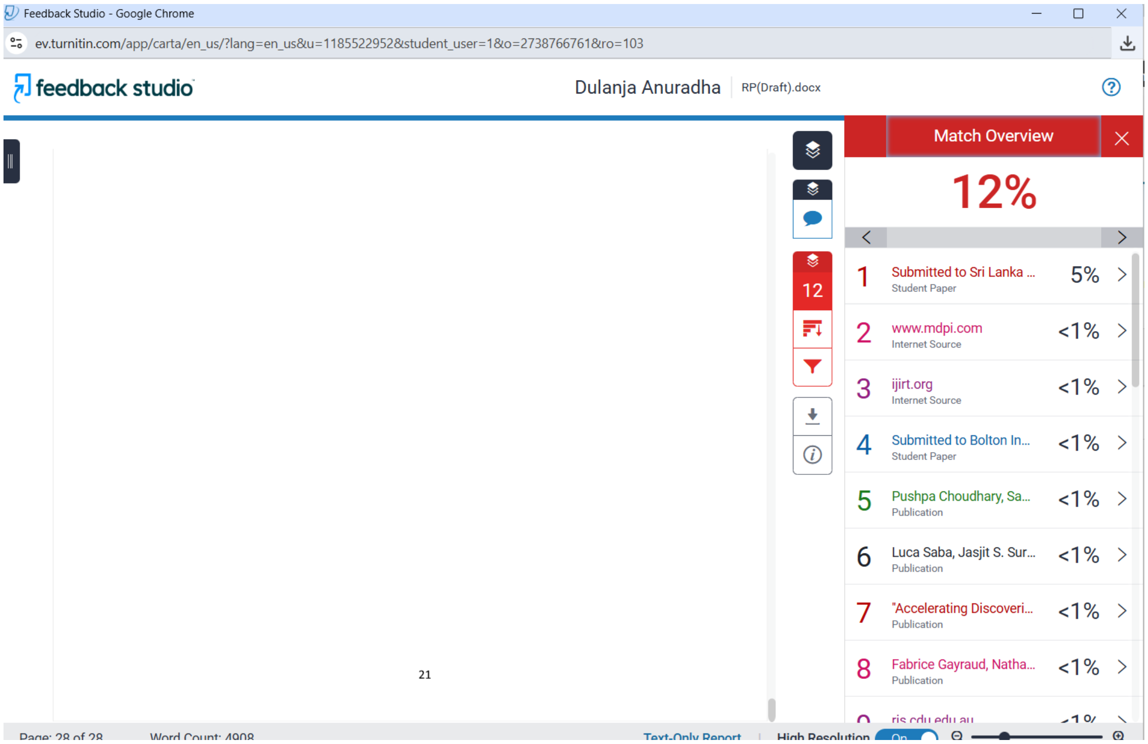
B2C: The wearable device is sold directly to end-users, with optional subscription tiers for cloud storage, alerts, and personalized data insights.

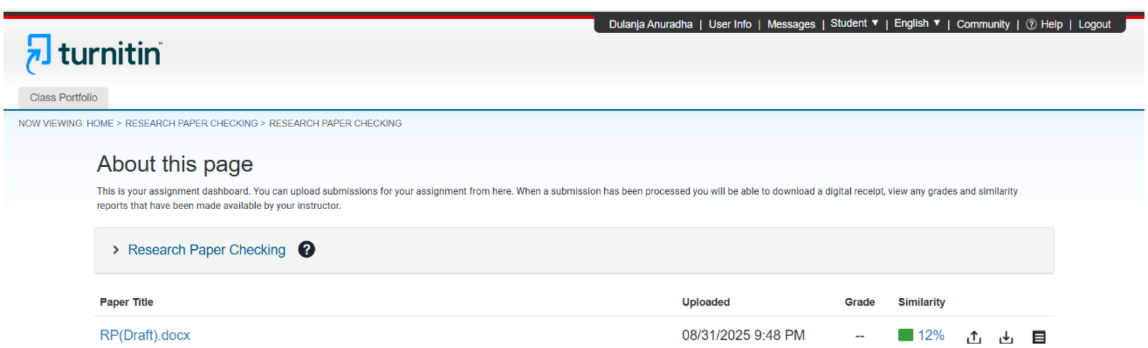
4.4 Estimated Costs & Pricing

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 2 Estimated Cost

6. APPENDICES





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