ACKNOWLEDGEMENT

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# ABSTRACT

Arthritis, particularly Rheumatoid Arthritis (RA) and Osteoarthritis (OA), affects millions globally, often causing significant disability. Getting an early and accurate diagnosis is key to managing it well. Unfortunately, many places, especially rural areas, don't have easy access to expert medical evaluations. Traditional diagnosis can be slow, prone to mistakes, and inconsistent, making it hard to pinpoint the type of arthritis or its severity.

To tackle these problems, We developed ArthoAid – Smart Arthritis Detection System, an AI-powered tool designed to help with early detection and management of arthritis. My system uses Machine Learning to categorize patients as healthy, having RA, or having OA based on their clinical data. If someone is identified with OA, a Deep Learning model (specifically a Convolutional Neural Network) then analyzes their knee X-ray images to automatically figure out how severe the condition is. On top of that, ArthoAid recommends expected precaution depending on the diagnosis and severity, making sure patients get the right care quickly.

The platform is built with a simple, affordable, and easy-to-use interface, making it accessible even in remote areas for both patients and healthcare workers. ArthoAid helps cut down on misdiagnoses, saves time, and supports better treatment decisions. By bringing AI into arthritis care, ArthoAid aims to make it smarter, faster, and available to everyone.

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# I : INTRODUCTION

Arthritis, a widespread health issue, causes pain and stiffness in joints, often making everyday activities a struggle for millions worldwide. Two of the most common forms are Rheumatoid Arthritis (RA) and Osteoarthritis (OA). Accurately diagnosing which type a person has is vital for effective treatment. However, this often demands specialized tests and expert medical evaluations, which are not always readily available, especially in rural or underserved areas. This lack of quick and precise diagnosis can unfortunately lead to incorrect or delayed treatment, impacting patients' quality of life

To solve this, we created ArthoAid—an AI-based system that helps detect arthritis using smart computer programs. It first looks at patient information to decide if the person is healthy, has RA, or OA. For OA patients, it uses a special kind of AI called Deep Learning to look at knee X-ray pictures and find out how serious the arthritis is. This helps doctors understand the patient's condition faster and more accurately.

## Problem Specification :

Right now, finding out if someone has arthritis takes a lot of time and sometimes mistakes happen because doctors have to manually check both patient details and X-ray images. In many places, especially rural areas, there aren't enough expert doctors or proper tools available, which delays proper diagnosis and treatment. After getting diagnosed, patients also struggle to properly understand how serious their condition is. So, there is a need for an easy, fast, and reliable system that can detect whether a person has arthritis and how severe it is, using both clinical details and X-ray images. This will help patients get diagnosed earlier and manage their condition better, even in areas with limited medical facilities.

## Motivation :

We decided to build ArthoAid because there are many problems in how arthritis is diagnosed and treated. Some of the main reasons are:

- **More Cases** – Arthritis patients are increasing, so faster and accurate systems are needed.
- **Not Enough Doctors** – Many places don't have enough experts or machines to diagnose properly.
- **Need for Early Help** – Early detection can stop the disease from getting worse.
- **Inaccurate Manual Checks** – X-ray reading can differ from one doctor to another.
- **Reduce Errors** – AI can give stable results and reduce wrong diagnoses.
- **Affordable for All** – Our system is simple and cheap, so it can be used anywhere.

With ArthoAid, we want to improve how arthritis is detected and make healthcare more reachable and better for everyone.

## Objectives :

The main idea behind ArthoAid is to make arthritis detection simple, quick, and reliable using the power of AI. First, the system checks if a person is healthy or if they have Rheumatoid Arthritis (RA) or Osteoarthritis (OA) just by using their clinical information. If someone has OA, it then looks at their knee X-ray and tells how serious the condition is.

This whole process saves a lot of time for both doctors and patients. It cuts down on manual effort and reduces the chances of mistakes in diagnosis. ArthoAid is built to be easy to use—even in small clinics or villages—and it helps healthcare workers make better, faster decisions. We've also kept the system open for future features, like adding regional languages or real-time health tracking.

## Challenges :

- **Getting Quality Data:**
  It was hard to collect clean and clear medical data, especially X-rays, as many were blurry or varied a lot between patients.
- **Training the Model:**
  Teaching the AI to handle different cases needed a lot of fine-tuning to avoid wrong predictions.
- **Making it Easy to Use:**
  We had to design a simple interface so that even non-technical users could easily use the system.
- **Working in Low-Resource Areas:**
  Ensuring the system runs well even with limited devices and poor internet was a big task.
- **Doctor Recommendation:**
  Suggesting doctors needed highly accurate results, which was challenging, so it's not included in the current version.

## Novelty :

ArthoAid brings in new and useful features that most other tools don’t have. Here’s what makes it special:

- **ML + Deep Learning Together** : Most systems use one technique. We used both ML to classify arthritis type and CNN to check how severe OA is using X-rays.
- **Low-Cost and Accessible Design** : We designed the tool to be cheap, simple, and easy so that even people in rural areas can benefit from it.
- **Simple and Future-Ready** : The tool has a clean interface and can support local languages or add more features later.

These unique features make ArthoAid not just smart but also practical and helpful in real-life use.

# II : LITERATURE SURVEY

**1. Tiulpin, A., Klein, S., Bierma-Zeinstra, S., Thevenot, J., & Saarakkala, S. (2018).**

***Automatic Knee Osteoarthritis Diagnosis from Plain Radiographs: A Deep Learning-Based Approach***
*IEEE Transactions on Medical Imaging*
This paper introduced a deep learning model that grades knee X-rays for osteoarthritis using the Kellgren-Lawrence system. This helped us build our OA severity grading part. However, their work only focused on OA and didn't consider other arthritis types like RA.

**2. Bashir, S., Khan, M. A., & Shah, J. H. (2021).**

***Machine Learning Approach for the Detection and Classification of Arthritis***
*Journal of Healthcare Engineering*
This study used machine learning methods like SVM and Decision Trees to detect arthritis based on symptoms and lab reports. This inspired our patient classification system. But their model didn't use any X-ray images or assess how serious the disease is.

**3. Hameed, B. I., et al. (2020).**

***Computer-Aided Diagnosis for Knee Osteoarthritis: A Review***
*Multimedia Tools and Applications*
This paper gave an overview of different OA detection tools, showing how useful computer-based systems can be for early diagnosis. This pushed us to create a complete system. The downside was that their study was mostly theoretical with no working software.

**4. Litjens, G., et al. (2017).**

***A Survey on Deep Learning in Medical Image Analysis***
*Medical Image Analysis Journal*
The discussed deep learning in medical imaging, including methods like CNNs and transfer learning. Their work gave us valuable tips for improving our X-ray model. But it wasn't focused on arthritis, so we had to adapt it for our needs.

**5. Prashanth, R., et al. (2016).**

***Medical Diagnostic Decision Support System Using Machine Learning Algorithms***
*Procedia Computer Science*
This work applied machine learning to predict diseases using symptoms and compared different models. This helped us choose Random Forest for better and

clearer results in classifying arthritis. However, they didn't include imaging or specialize in arthritis.

**6. Tiulpin, A., & Saarakkala, S. (2020).**

***Multimodal Machine Learning for OA Diagnosis***
*IEEE Access*
This recent study combined patient information and knee X-rays for better OA detection. Their hybrid method inspired us to mix both clinical and image data. Still, their system didn't cover RA or suggest any doctors.

**7. He, K., Zhang, X., Ren, S., & Sun, J. (2016).**

***Deep Residual Learning for Image Recognition (ResNet)***
*CVPR Conference Proceedings*
Introduced the ResNet, a powerful deep learning model that works well for image tasks. We used this for our OA severity grading model. But since it wasn't originally made for medical images, we had to fine-tune it carefully.

**8. Hinton, G. E., Osindero, S., & Teh, Y. W. (2006).**

***A Fast Learning Algorithm for Deep Belief Nets***
*Neural Computation*
This work laid the foundation for deep learning by developing Deep Belief Networks. This helped us understand how deep learning works in layers. Their work, however, was very theoretical and not directly used in our system.

**9. World Health Organization (2021).**

***Chronic Rheumatic Conditions Report***
This report highlighted the global burden of arthritis, especially in rural areas with limited healthcare. This encouraged us to create an affordable and accessible tool for early detection. But it only offered insights—not real solutions.

**10. Kaur, S., & Rani, R. (2022).**

***Smart Healthcare using AI and IoT in Rural Areas***
*Journal of AI in Healthcare*
Focused on how AI and IoT can support healthcare in villages using low-cost and offline-friendly tools. This guided us in designing ArthoAid as a simple and usable app for rural health workers. However, their work didn't focus on arthritis detection specifically.

| **Paper** | **What They Did Well** | **What Was Missing** | **How We Used It** |
|---|---|---|---|
| **Tiulpin et al. (2018)** | Used deep learning to grade OA from knee X-rays | Focused only on OA, not RA | Inspired our CNN for OA grading |
| **Bashir et al. (2021)** | Used ML on patient symptoms to detect arthritis | No use of X-ray or severity grading | Helped design our ML-based patient classifier |
| **Hameed et al. (2020)** | Reviewed OA detection tools and stressed early diagnosis | Mostly theory, no real system | Motivated our full, working system |
| **Litjens et al. (2017)** | Explained deep learning for medical images | Didn't cover arthritis in detail | Guided us in image model tuning |
| **Prashanth et al. (2016)** | Compared ML models for symptom-based disease detection | No arthritis focus or image data | Helped pick Random Forest for our system |
| **Tiulpin & Saarakkala (2020)** | Mixed clinical and X-ray data for better OA detection | Didn't include RA or doctor advice | Supported our hybrid model design |
| **He et al. (2016)** | Introduced ResNet for better image learning | Not designed for medical tasks | We used ResNet to boost our X-ray model |
| **Hinton et al. (2006)** | Started deep learning foundations | Too theoretical for direct use | Gave us strong background knowledge |
| **WHO Report (2021)** | Showed the real-world impact of arthritis | No technical solution offered | Inspired us to make a rural-friendly tool |

| Paper | What They Did Well | What Was Missing | How We Used It |
|---|---|---|---|
| **Kaur & Rani (2022)** | Proposed AI for rural healthcare | Didn't target arthritis specifically | Led us to build an offline-capable system |

**Key Gaps Identified :**

- Most existing works focus only on OA or RA, not both.
- Lack of combined analysis of clinical symptoms and **X-ray** imaging.
- Poor accessibility in rural or offline environments.
- Few systems are designed for real-time, end-to-end arthritis detection.

**Our Contribution :**

To address these gaps, our project *ArthoAid* includes:

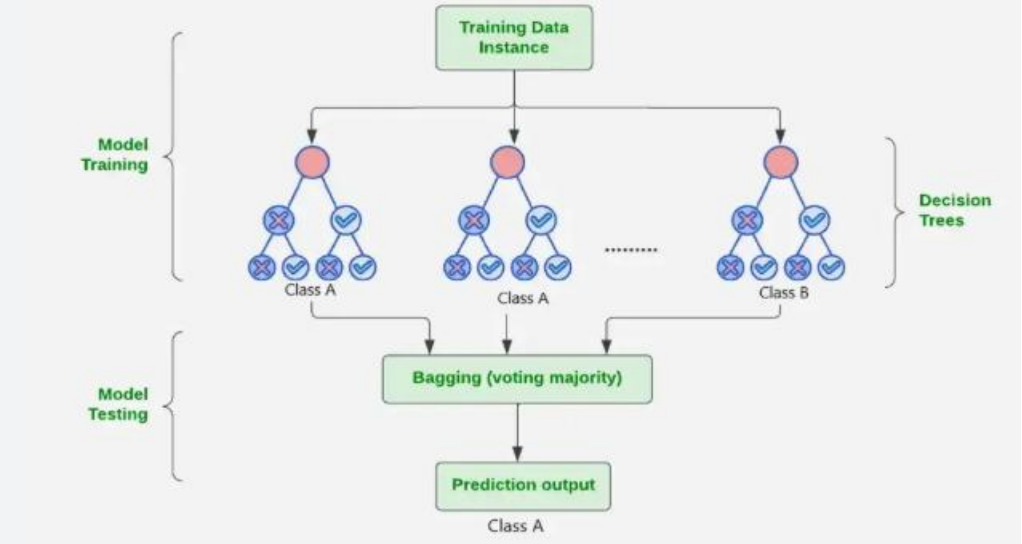
- **ML-based Patient Classification** (Healthy / RA / OA) using clinical data.
- **CNN-based OA Severity Grading** using knee X-rays.
- **An accessible, user-friendly interface**, even for rural health workers.

# III : TECNOLOGIES & TOOLS :

### 1. Random Forest (Machine Learning Model)

• **Definition:** Random Forest is a popular supervised machine learning algorithm that uses multiple decision trees to make accurate and robust predictions. It combines the outputs of many decision trees to improve overall performance and avoid overfitting.

Fig 1: Basic architecture of Random Forest




• **Elaboration:** In our project, Random Forest is used to classify patients based on their input data—like age, symptoms, and medical history—to detect whether they are healthy, have Rheumatoid Arthritis (RA), or Osteoarthritis (OA). Its ability to handle complex data and give reliable results makes it ideal for early diagnosis.

### 2. CNN (Convolutional Neural Network)

• **Definition:** CNN is a type of deep learning model designed especially for analyzing visual data like images. It automatically extracts features from images and learns to recognize patterns without needing manual input.

• **Elaboration:** We use CNN in ArthoAid to analyze knee X-ray images and detect the severity level of Osteoarthritis (OA). It helps identify subtle changes in bone structure that may not be easily visible to the human eye, improving accuracy in grading OA severity.

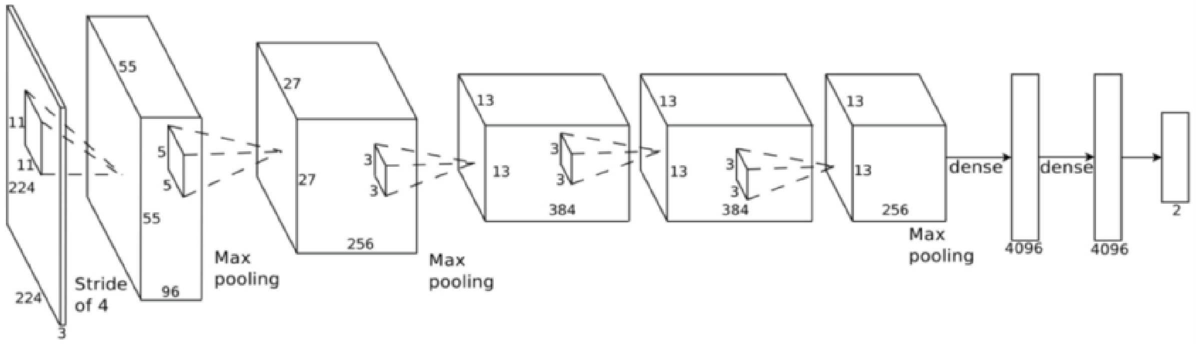



Fig 1: Basic architecture of CNN

### 3. Scikit-learn (Sklearn)

• **Definition:** Scikit-learn is a widely-used Python library that provides simple and efficient tools for data analysis and machine learning, including classification, regression, and model evaluation.

• **Elaboration:** In our project, Scikit-learn is used to implement the Random Forest model and to preprocess patient data. It supports easy integration with other tools and helps train, test, and evaluate our machine learning models quickly and reliably.

### 4. TensorFlow

• **Definition:** TensorFlow is a powerful open-source deep learning framework developed by Google. It provides tools to build, train, and deploy machine learning models efficiently.

• **Elaboration:**
We use TensorFlow to build and train our CNN model for analyzing X-ray images. It handles the complexity of deep learning operations and helps us process image data faster with better accuracy.

### 5. HTML (HyperText Markup Language)

• **Definition:** HTML is the standard language used to create and structure web pages. It defines how content is displayed on a website using tags like headings, paragraphs, images, and forms.

• **Elaboration:** HTML is used in ArthoAid to build the front-end layout where users can upload patient information or X-rays and view the diagnostic results. It forms the backbone of our user interface.

### 6. CSS (Cascading Style Sheets)

• **Definition:** CSS is used to style HTML elements. It controls the look and feel of a website—including fonts, colors, spacing, layout, and responsiveness.

• **Elaboration:** In ArthoAid, CSS helps make our platform visually appealing and easy to navigate. It ensures the interface looks professional and works well on both desktops and mobile devices.

### 7. JavaScript

• **Definition:** JavaScript is a scripting language used to create interactive and dynamic features on websites, such as real-time feedback, animations, and data validation.

• **Elaboration:** We use JavaScript to make our web interface more responsive. For example, it handles client-side form validation and enhances user interaction without reloading the page.

### 8. Flask (Python Web Framework)

• **Definition:** Flask is a lightweight Python web framework used for building web applications. It allows developers to handle web requests, render templates, and manage back-end logic.

• **Elaboration:** Flask is the core of our back-end system. It connects the machine learning and deep learning models with the front end. When users upload data or X-rays, Flask processes the inputs, runs the diagnosis, and returns the results.

# IV : PROPOSED METHOD

## Proposed Model Architecture

### 1. Frontend Layer

**Technologies Used:** HTML, CSS, JavaScript, Flask Templates
This is the face of our application — the part users directly interact with.

**Functionality:**

- Provides a **simple, user-friendly interface** for both patients and doctors.
- Offers pages for:
  - Patient login and registration
  - X-ray and symptom data upload
  - Dashboard to view patient data and results
- Communicates with the backend using HTTP requests to send/receive data.

**Key Features:**

- **Form validation** for safe and clean input.
- **Dynamic pages** tailored to user roles: patient or doctor.
- Mobile- and desktop-friendly UI.

### 2. Backend Layer

**Framework Used:** Flask (Python)
This is the brain of the system, managing all operations behind the scenes.

**Functionality:**

- Handles all **routes and HTTP requests** (e.g., login, register, upload).
- Processes and **validates user data**.
- Connects to the **ML/CNN models** and **database**.
- Controls sessions and role-based access.

### 3. Database Layer

**Database Used:** MySQL (Scalable to PostgreSQL or MongoDB)
This is the memory of the system, keeping everything organized and searchable.

**Entities (Tables):**

- **Users Table:** Stores user info like name, age, symptoms, etc.
- **Reports Table:** Keeps track of uploaded X-rays, predicted conditions, severity, and recommendations

**Functionality:**

- Stores uploaded data securely
- Tracks diagnostic results and decisions
- Enables fast search and retrieval of reports

## 4. Machine Learning Layer

**Technologies Used:**

- **Random Forest (ML):** Classifies users into Healthy, RA, or OA based on input features.
- **CNN (Deep Learning):** Analyzes knee X-ray images and detects OA severity.
- **Libraries Used:** Scikit-learn, TensorFlow, OpenCV, NumPy

**Functionality:**

- Automatically extracts and analyzes key features from data and X-ray images.
- Classifies arthritis type (RA, OA, or Healthy).
- For OA, grades the severity level (Grade 1–4).
- Makes accurate predictions that support early diagnosis.

**Workflow:**

1. User submits symptoms + knee X-ray
2. System preprocesses and feeds data to ML/DL models

3. Classification result and severity grade are generated
4. Forwarded to the doctor dashboard with recommendations

## 5. Integration Layer

**Purpose:** Acts as the connector between all parts of the system.

**Middleware Role:**

- Bridges frontend and backend using **RESTful APIs**
- Controls access based on roles (e.g., patients cannot access doctor data)
- Ensures **data security** and clean HTTP communication (GET, POST)

**API Actions Include:**

- Upload patient info and images
- Fetch prediction results

## Data Acquisition (Clinical + X-Ray)

To build an effective arthritis detection system like **ArthoAid**, the very first step is **collecting high-quality data**. Our system relies on two main types of data:

1. **Clinical Data** – patient information and symptoms.
2. **X-ray Images** – actual knee joint X-ray images to visually detect arthritis.

By combining both, our model gets a more complete view — just like a real doctor would!

---

**i. Clinical Data Collection :**

We collect **basic and symptom-related information** from patients to help identify early signs of arthritis. This includes:

- **Personal Details:** Age, gender
- **Symptoms:** Joint pain, RF, Anti-CCP, ESR, CRP, swelling, Stiffness

This data is used in our **machine learning model (Random Forest)** to classify whether a person is **Healthy**, has **Rheumatoid Arthritis (RA)**, or **Osteoarthritis (OA)**.
It helps the system "learn" how real patients present different forms of arthritis.

**ii. X-ray Image Collection :**

Since OA affects bones and joints visibly, we also use **knee X-ray images** to assess the **severity of Osteoarthritis**.

**Where we get images from:**

- Free online datasets (e.g., from Kaggle)
- Hospital partnerships (with proper consent and anonymization)

**What we need:**

- Clear frontal or side-view knee X-rays
- Preferably labeled with OA severity (Grades 1 to 4)
- Standard image formats (.jpg, .png, or .dcm)

These images are used to train our ***deep learning model (CNN)*** to detect patterns like joint space narrowing, bone deformities, and cartilage loss. The model then grades OA severity — from mild to severe — just by looking at the X-ray.

## Algorithm

The algorithm behind ArthoAid is built to help users easily detect arthritis and get the right medical help. It uses both clinical info and X-ray images to identify if someone is healthy, has Rheumatoid Arthritis (RA), or Osteoarthritis (OA), and guides them step by step.

**Step 1. User Registration**

**Purpose:** Allow new users to create an account in the system.

**Steps:**

- User enters basic details (name, age, gender, contact info, etc.).
- The system stores user information securely for future use.

**Output:** User account created successfully.

---

**Step 2. Login to Dashboard**

**Purpose:** Let users access the arthritis detection system.

**Steps:**

- User logs in using their credentials.
- Dashboard opens with options for data input and diagnosis.

**Output:** User successfully logged in and ready to proceed.

---

**Step 3. Enter Clinical Details**

**Purpose:** Collect symptoms and basic medical history.

**Steps:**

- User fills out a form with information like:
    - Joint pain level
    - Swelling
    - Stiffness
    - RF
    - Anti-CCP
    - ESR, CRP
    - Age and gender
- Machine Learning model (Random Forest) analyzes this clinical data.
- System predicts whether the person is:
    - Healthy
    - Having Rheumatoid Arthritis (RA)
    - Having Osteoarthritis (OA)

**Output:** Predicted arthritis category displayed.

---

**Step 4. If RA or OA is Detected**

**Step 4.1 If Rheumatoid Arthritis (RA) is Detected:**

**Purpose:** Immediate recommendation for further medical consultation.

**Steps:**

- System shows a message recommending the user to consult a specialist.
- No further steps are required within the system.

**Output:** Doctor consultation advised.

**Step 4.2 If Osteoarthritis (OA) is Detected:**

**Purpose:** Proceed to check severity of OA.

**Steps:**

- System asks the user to upload their knee X-ray image.
- X-ray is passed to the deep learning model for analysis.

**Output:** X-ray image successfully uploaded for evaluation.

---

**Step 5. OA Severity Grading (Using CNN Model)**

**Purpose:** Analyze the knee X-ray to determine how advanced OA is.

**Steps:**

- The Convolutional Neural Network (CNN) processes the X-ray.
- System predicts OA severity level (for example: Mild, Moderate, Severe).
- Severity level is displayed to the user.

**Output:** OA severity result provided.

## Type of Arthritis Detection

Based on the clinical data, the system predicts if the person is **Healthy**, has **Rheumatoid Arthritis (RA)**, or **Osteoarthritis (OA)**.

**If RA is Detected:**
The system simply shows a message asking the user to consult a doctor, since X-rays are not needed for RA detection.

**If OA is Detected:**
The user is asked to upload a **knee X-ray** for further analysis.

**OA Severity Grading:**
The system analyzes the X-ray and tells the user how serious the OA is — it could be **Healthy**, **Doubtful**, **Minimal**, **Moderate**, or **Severe**

# OA Severity Grading Using CNN

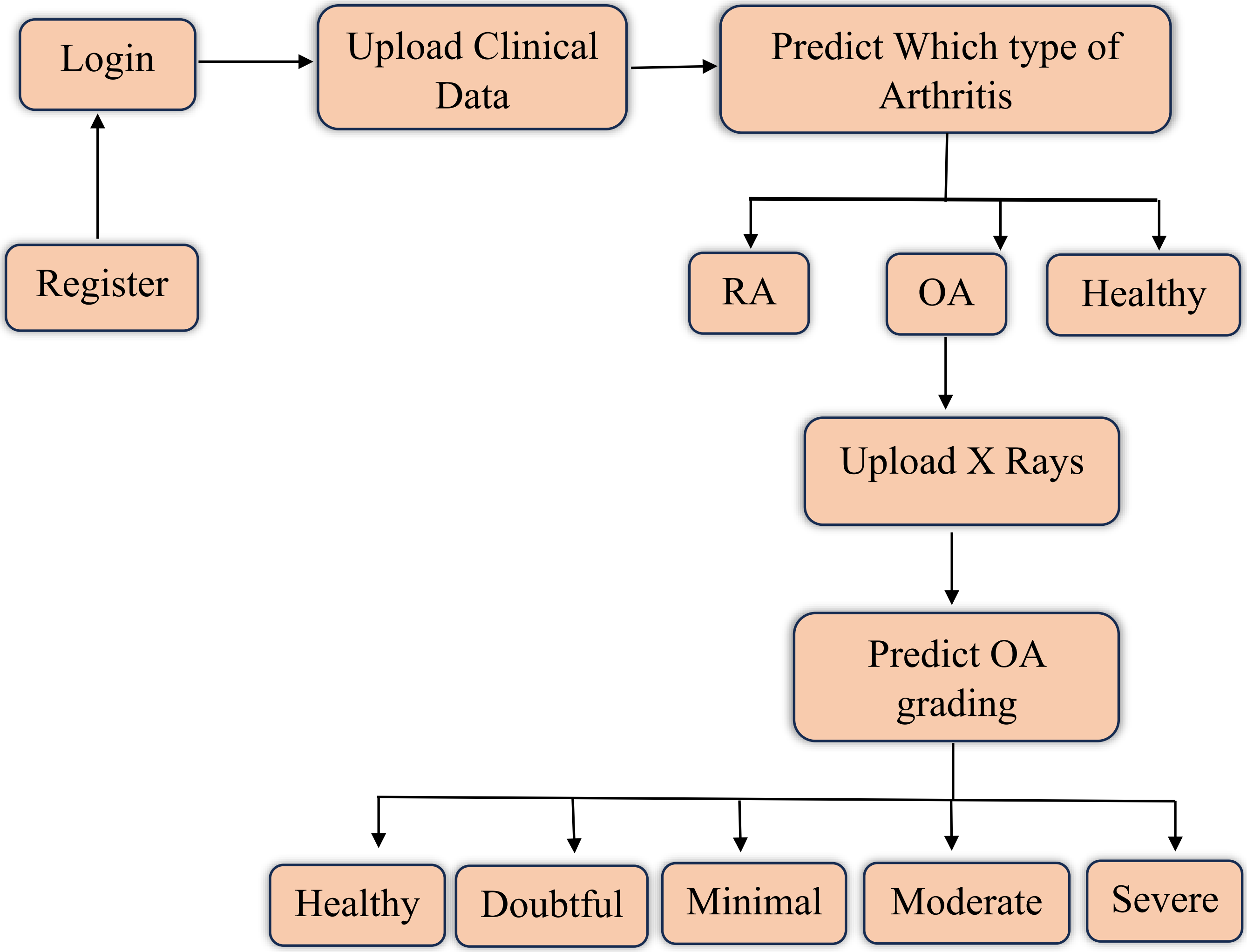
In our project **ArthoAid**, after identifying whether a patient has Osteoarthritis (OA), the next crucial step is to determine **how severe** the condition is. Just like a doctor examines X-rays to decide how much damage has occurred in the knee joint, our system uses **deep learning** — specifically a **Convolutional Neural Network (CNN)** — to perform this task automatically and accurately.

We trained our CNN model on a set of **knee X-ray images** that were already labeled with different OA severity levels (usually from Grade 0 to Grade 4). These labels indicate how much the joint has deteriorated — for example, Grade 0 means healthy joints, while Grade 4 represents severe damage with major joint space narrowing and bone changes. Our model learns from these patterns by identifying visual features such as **joint space narrowing, bone spurs, and irregular shapes** in the bones.

When a new X-ray image is uploaded into the system, the CNN scans it just like a radiologist would — analyzing every detail. Based on its training, it then **predicts the severity level** of OA. This automated grading is not only fast but also reduces human error and helps doctors in making more consistent decisions, especially in remote or rural areas where expert radiologists may not be available.

By including OA severity grading, ArthoAid doesn't just say *if* someone has arthritis — it also tells **how serious** the condition is. This information is incredibly valuable for both patients and doctors to decide on the **next steps in treatment**, whether it's medication, physiotherapy, or surgery.

<u>**Workflow of the Proposed System**</u>




<u>**Testing and Evaluation :**</u>

To make sure our system works well in real-world scenarios, we carefully tested and evaluated it using both clinical data and X-ray images. We divided our dataset into training and testing sets so the model could learn from one part and be tested on completely new data. This helps us check how well it can predict unseen cases.

**1. Testing**

**Objective:**
To verify that ArthoAid works well under different clinical and technical conditions, both in detecting arthritis and grading OA severity.

**Process:**

**i. Test Dataset:**

- We prepared a test dataset with labeled clinical records (age, gender, symptoms, history) and annotated X-ray images for OA grading.
- The data was varied to represent healthy individuals, RA patients, and OA patients across different severity levels.

**ii. Test Cases:**

- **Clinical Classification Testing (ML Model):** Tested how accurately the Random Forest model predicts Healthy, RA, or OA cases using symptom data.
- **X-ray Grading Testing (CNN):** Evaluated how the CNN model performs in classifying OA severity levels from knee X-ray images.
- **Edge Case Testing:** Included incomplete clinical data, noisy X-rays, or poor image quality to test system robustness.
- **Integration Testing:** Verified the end-to-end process: from user input → model prediction → recommendation system.

**iii. Execution:**

- Ran models with test datasets and logged predictions, classification outputs, and confidence levels.

**iv. Results Validation:**

- Compared the model outputs with real patient labels and doctor-approved diagnoses.

**2. Evaluation**

**Objective:**
To measure how well ArthoAid performs using real-world medical evaluation metrics that reflect accuracy, sensitivity, and overall effectiveness.

**Key Metrics Used:**

i. **Precision:**
Measures how many of the arthritis detections or OA severity predictions

were actually correct.
→ *High precision means fewer false diagnoses.*

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}}$$

ii. **Recall (Sensitivity):**
Tells how many real cases of arthritis or OA were correctly identified.
→ *High recall means we're not missing actual patients.*

$$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}$$

iii. **F1 Score:**
Combines precision and recall into a single balanced metric.
→ *Useful for understanding overall reliability.*

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

iv. **Accuracy:**
Measures how often the system correctly classified a patient as Healthy, RA, or OA.
→ *Reflects the overall correctness of predictions.*

$$\text{Accuracy} = \frac{\text{TP} + \text{True Negatives (TN)}}{\text{Total Samples}}$$

v. **Confusion Matrix Analysis:**
Helped us visualize misclassifications—for example, cases wrongly labeled as OA instead of RA.

# V: EXPERIMENTAL RESULT & ANALYSIS

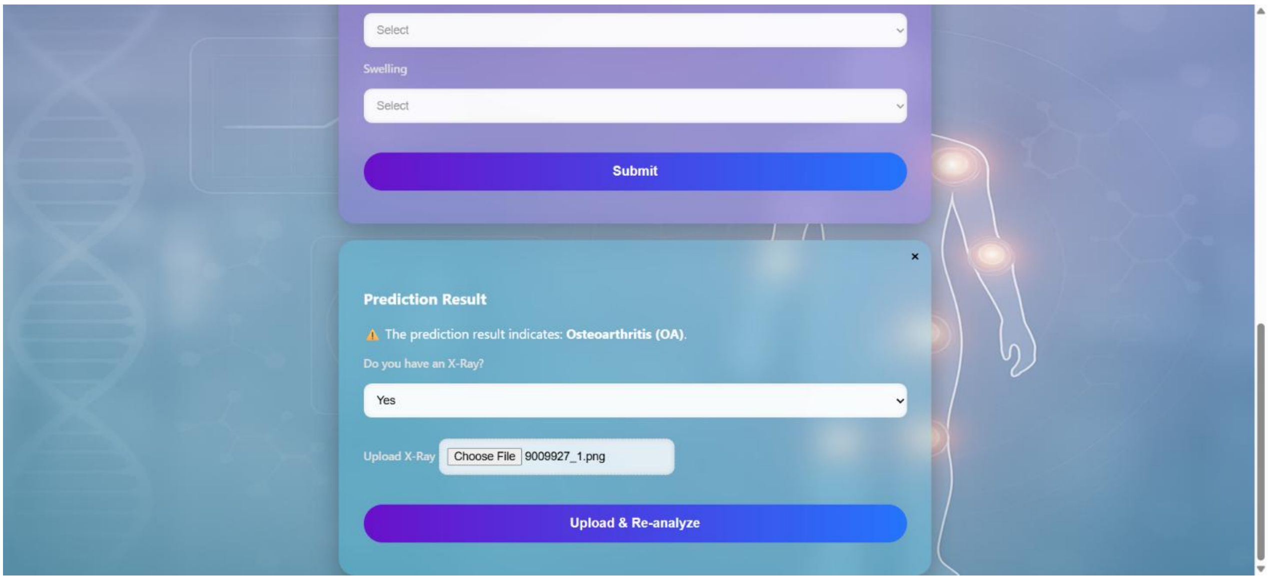
## 1. Input ,Output Results :

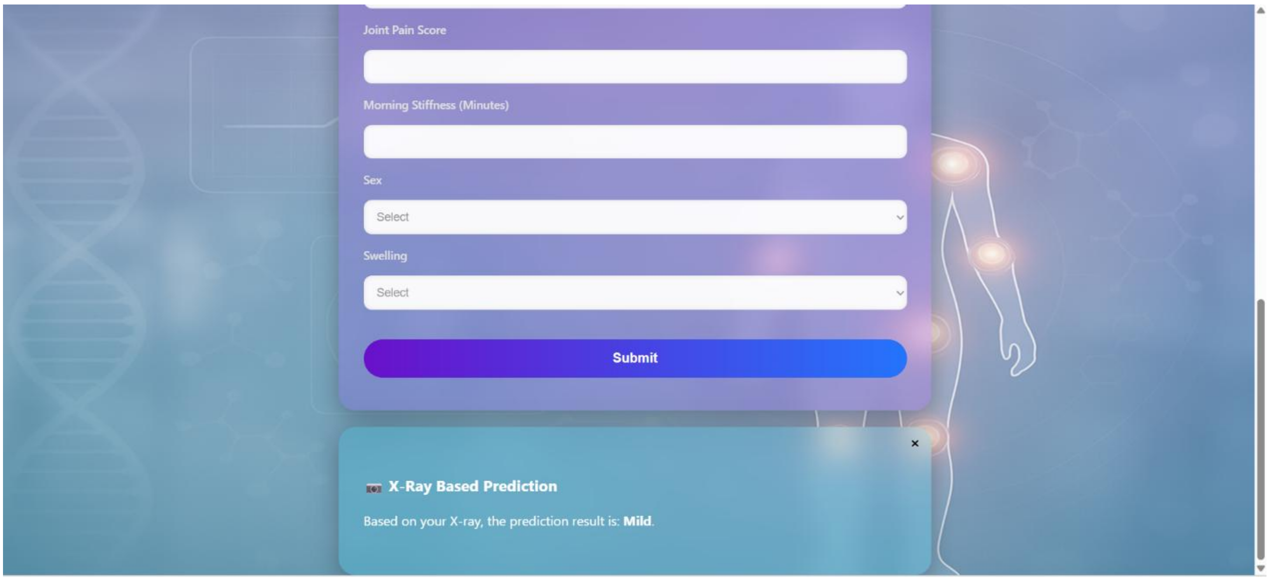
Log in Page:

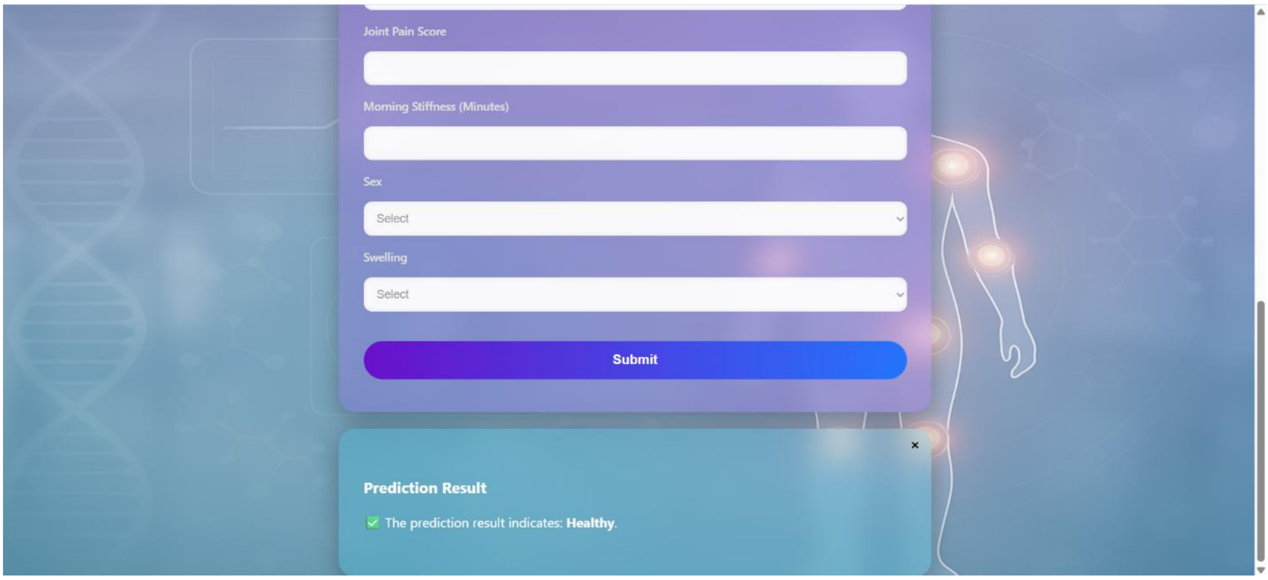

Registration Page:

Dashboard:


Result:






## 2. <u>Analysis Of System</u> :

### Confusion Matrix -1

- **ML (Random Forest ) based arthritis classification**

| Class | Healthy | OA | RA |
|---|---|---|---|
| Healthy | 55 | 3 | 3 |
| OA | 1 | 71 | 0 |
| RA | 3 | 2 | 62 |

**Classification Report:**

| Class | Precision | Recall | F1-Score | support |
|---|---|---|---|---|
| Healthy | 0.93 | 0.90 | 0.92 | 61 |
| OA | 0.93 | 0.99 | 0.96 | 72 |
| RA | 0.95 | 0.93 | 0.94 | 67 |
| Accuracy | - | - | 0.94 | 200 |
| Macro avg | 0.94 | 0.94 | 0.94 | 200 |
| Weighted avg | 0.94 | 0.94 | 0.94 | 200 |

$$\text{Accuracy} = \frac{\text{sum of diagonal elements}}{\text{total samples}}$$

Accuracy = 188/200

= 0.94

**Confusion Matrix -2**

- **CNN-based OA severity detection**

Actual

Predicted

| Class | Class 0 | Class 1 | Class 2 | Class 3 | Class 4 |
|---|---|---|---|---|---|
| Class 0 | 89 | 5 | 4 | 0 | 2 |
| Class 1 | 12 | 80 | 1 | 4 | 3 |
| Class 2 | 2 | 6 | 90 | 2 | 0 |
| Class 3 | 0 | 3 | 0 | 89 | 8 |
| Class 4 | 2 | 0 | 2 | 4 | 92 |

$$\text{Accuracy} = \frac{\text{sum of diagonal elements}}{\text{total samples}}$$

Accuracy = 440/500

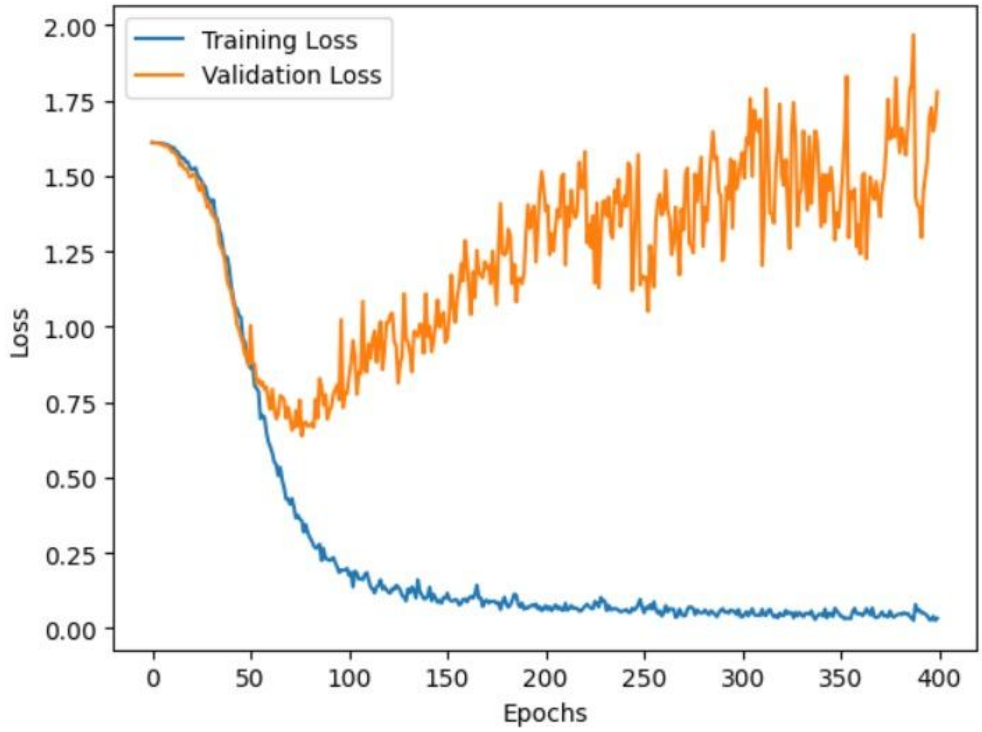
= 0.88

Weighted Precision ≈ 0.880

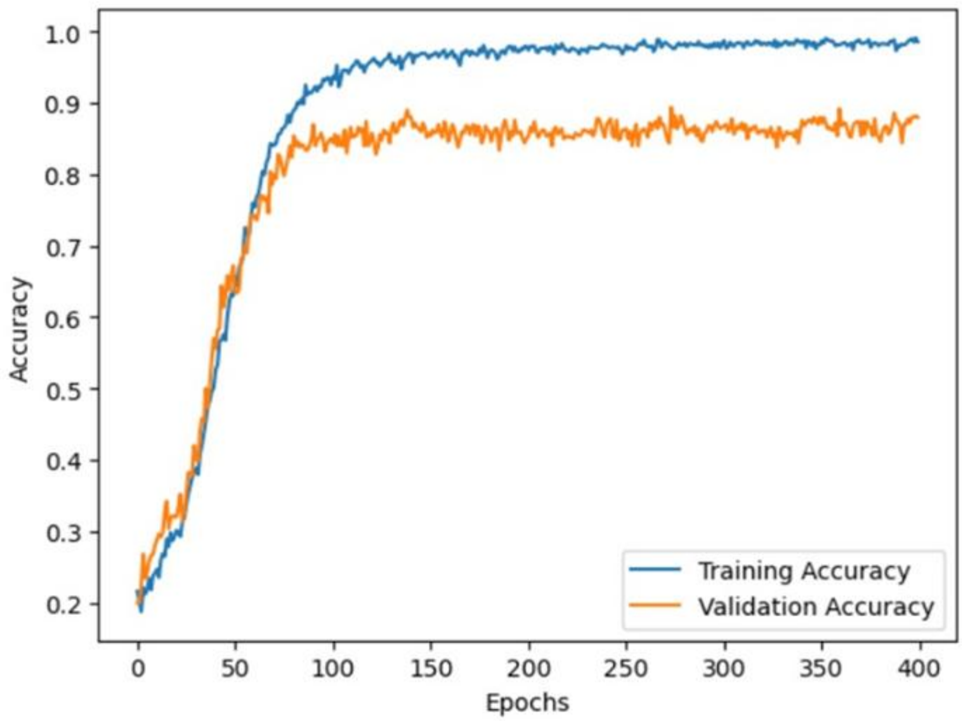
Weighted Recall ≈ 0.880

Weighted F1-Score ≈ 0.880

➢ **CNN-based OA severity detection validation Graph:**




➢ **Accuracy Graph of CNN-based OA severity detection :**



# VI : FUTURE ENHANCEMENTS

1. **Smarter AI Models for Arthritis Detection :**

We plan to use more advanced AI tools like transformers or combined models that can learn better from both symptoms and X-rays. This will make the system even more accurate at detecting different types of arthritis.

2. **RA Severity Detection :**

Currently, we do not have enough clinical and imaging data related to Rheumatoid Arthritis (RA) to train the model for severity detection. Due to this limited data, our system can only detect whether RA is present or not but cannot assess its severity. In the future, if we are able to collect a larger and more diverse dataset for RA patients, we plan to develop and add a severity grading system, which will help patients and doctors better understand how serious the condition is and guide proper treatment.

3. **Talk to Doctors Directly in the App :**

We want to add a feature where patients can talk to doctors through video calls or chats after they get their results. This will make it easier to get quick advice, especially in remote areas.

4. **Mobile App for Easy Rural Healthcare Access :**

A versatile mobile application will help isolated villagers and inhabitants of underserved rural areas with restricted access to medical clinics. Through the upload of diagnostic scans and receipt of timely professional evaluations, issues may be addressed remotely. Moreover, an offline functionality allows for usage even where internet connectivity proves unreliable.

5. **Prospective Integration with Wearable Technology :**

Looking ahead, ArthoAid could synchronize with smartwatches and physical activity trackers. By monitoring steps taken, sleep logged, or daily exertion levels, it might facilitate a more holistic perspective of user wellness over time.

6. **Cloud-Based System :**

By shifting to cloud platforms like AWS, ArthoAid can run faster, store more data securely, and allow doctors and patients to use it from anywhere.

7. **Connect with Hospital Records :**

We want ArthoAid to link with hospital systems so doctors can see patient history easily and patients don’t have to explain everything again every time.

# VII: CONCLUSION

Our project, **ArthoAid**, was created to make arthritis detection easier and more accessible, especially for people who may not have quick access to doctors or hospitals. We focused on identifying whether someone is healthy, has Rheumatoid Arthritis (RA), or Osteoarthritis (OA) by using simple clinical information like symptoms, age, and medical history. For patients with OA, we also worked on checking how severe it is by looking at their X-ray images.

We built a system that's easy to use for both patients and doctors. It helps in getting a quick idea of what condition the patient might have and how serious it is. The project can be really helpful in remote areas, where there aren't many specialists available.

We also added features like showing suitable doctors based on the diagnosis, so that patients can get help faster. The whole idea is to support early detection and make the journey to treatment a little smoother.

In short, ArthoAid brings technology and healthcare together in a practical way. It's not meant to replace doctors but to assist them and guide patients in the right direction. With a few more updates in the future, this tool can become even more helpful for people dealing with arthritis.

# VII : REFERENCES

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**ii. Dataset:**


- Clinical data - https://www.kaggle.com/datasets/michaelkevin001/arthritis-clinical-dataset-using-blood-report
- Kaggle: Osteoarthritis Severity Grading datasets for training CNN model. https://www.kaggle.com/datasets/shashwatwork/knee-osteoarthritis-dataset-with-severity