Explainable Knee Osteoarthritis Diagnosis From Radiographs and Magnetic Resonance Imaging

A Research Project

Abstract

Knee osteoarthritis (OA) is one of the most common degenerative joint diseases and a leading cause of pain, disability, and reduced quality of life worldwide. Accurate diagnosis is essential for effective treatment; however, manual interpretation of knee radiographs (X-ray images) and Magnetic Resonance Imaging (MRI) scans is often time-consuming and subject to inter-observer variability. In addition, many deep learning models developed for knee osteoarthritis diagnosis function as "black-box" systems, making it difficult for clinicians to understand the reasoning behind their predictions. This study developed an Explainable Artificial Intelligence (XAI) framework that combines a Convolutional Neural Network (CNN) with Gradient-weighted Class Activation Mapping (Grad-CAM) to classify knee images into Normal and Osteoarthritis (OA) while providing visual explanations of the diagnostic decisions. The dataset used in this study was obtained from Kaggle and consisted of knee radiographs and MRI scans. The images underwent preprocessing techniques, including data cleaning, image resizing, normalization, noise reduction, and data augmentation, before model training. The proposed CNN model was evaluated using three dataset partitions (80:20, 75:25, and 70:30). Performance was assessed using accuracy, precision, recall, F1-score, confusion matrix, Receiver Operating Characteristic (ROC) curve, and Precision-Recall curve, while Grad-CAM generated heatmaps highlighting the image regions that influenced the model's predictions. The experimental results showed that the 80:20 partition achieved the highest accuracy of 57%, whereas the 75:25 and 70:30 partitions both achieved 52% accuracy. Although the classification performance was relatively low, the Grad-CAM visualizations improved the transparency and interpretability of the model by identifying clinically relevant regions associated with osteoarthritis. The study concludes that Explainable Artificial Intelligence has significant potential to support computer-aided diagnosis of knee osteoarthritis, while future improvements involving larger datasets, transfer learning, and advanced deep learning architectures are recommended to enhance classification performance.

CHAPTER ONE
INTRODUCTION

1.0 Background of the Study

Osteoarthritis (OA) is a progressive degenerative joint disease and one of the most prevalent musculoskeletal disorders worldwide, with the knee being the most commonly affected joint (Osteoarthritis Research Society International, 2020). It is characterized by cartilage degradation, subchondral bone remodeling, osteophyte formation, and synovial inflammation, leading to chronic pain, stiffness, functional impairment, and reduced quality of life. OA is strongly associated with aging, obesity, joint injury, and genetic predisposition, making it a major contributor to disability globally. As the aging population continues to grow, the burden of knee OA is expected to increase significantly, highlighting the importance of early detection, accurate diagnosis, and effective monitoring of disease progression (Cui et al., 2020).

The knee joint is particularly vulnerable to OA due to its role in weight-bearing and movement, which subjects it to continuous mechanical stress. Structural changes in knee OA occur gradually and involve multiple joint components, including articular cartilage, subchondral bone, ligaments, and synovial tissues. These changes often develop over time before clinical symptoms become severe, making early diagnosis essential for implementing preventive and therapeutic interventions.

Traditionally, OA diagnosis relies on clinical evaluation combined with imaging modalities, particularly radiographs (X-rays) and magnetic resonance imaging (MRI). Radiographs are widely used for assessing joint space narrowing, osteophyte formation, and bone sclerosis, and they form the basis of widely used grading systems such as the Kellgren–Lawrence (KL) grading scale. However, MRI provides a more comprehensive and detailed assessment of joint structures, including cartilage integrity, meniscal damage, bone marrow lesions, and synovial inflammation. This makes MRI especially valuable for early detection and detailed characterization of OA-related structural changes (Hirvasniemi et al., 2021).

With the rapid advancement of digital healthcare technologies, there has been growing interest in leveraging computational techniques to enhance the analysis of medical images.

In particular, artificial intelligence (AI) has emerged as a transformative tool in medical diagnostics. Deep learning models, especially convolutional neural networks (CNNs), have demonstrated remarkable capabilities in automatically extracting hierarchical and complex features from imaging data. These models can learn patterns associated with OA directly from raw images, reducing reliance on manual feature extraction and improving diagnostic efficiency and consistency.

Recent developments have also introduced hybrid and advanced deep learning architectures, which combine multiple techniques to improve performance. For example, models integrating CNNs with sequence-based networks such as Bi-directional Long Short-Term Memory (BiLSTM) or transformer-based architectures are capable of capturing both spatial and contextual relationships within medical data. Such approaches are particularly useful in OA research, where both image features and clinical context play important roles in diagnosis and prognosis.

A key advancement in AI-based medical imaging is the emergence of explainable artificial intelligence (XAI). While traditional deep learning models are often considered "black boxes," XAI techniques aim to make their predictions transparent and interpretable. Frameworks such as DeepKneeExplainer utilize methods like Grad-CAM++ and Layer-wise Relevance Propagation (LRP) to generate visual heatmaps, highlighting the regions of an image that contribute most to the model's decision. This enhances clinical trust, interpretability, and usability, making AI systems more suitable for real-world healthcare applications (Jiao et al., 2022).

In addition to deep learning, radiomics-based approaches have gained attention for their ability to extract quantitative imaging biomarkers from MRI scans. Radiomic features, including texture, shape, and intensity-based descriptors, provide detailed information about tissue characteristics that may not be visible to the human eye. Studies focusing on the tibial subchondral bone and cartilage regions have demonstrated that these features can effectively distinguish between different stages of OA and support accurate classification (Hirvasniemi et al., 2021).

Furthermore, the integration of multimodal data has become an important direction in OA research. By combining imaging data with clinical and demographic information, such as age, body mass index (BMI), and patient history, researchers can develop more comprehensive and personalized predictive models. Multimodal approaches have shown improved performance in predicting OA progression and severity, demonstrating theimportance of incorporating heterogeneous data sources into diagnostic frameworks (Tiulpin et al., 2019).

Overall, the convergence of advanced imaging techniques, artificial intelligence, and explainable models is reshaping the landscape of knee osteoarthritis diagnosis. These innovations not only enhance the ability to detect and classify OA with greater accuracy but also provide valuable insights into the underlying structural and functional changes associated with the disease. As research in this field continues to evolve, the integration of multimodal, interpretable, and data-driven approaches is expected to play a crucial role in improving clinical outcomes and advancing personalized healthcare in osteoarthritis management.

1.1 Statement of the Problem

Knee osteoarthritis (OA) is a chronic degenerative condition that affects millions worldwide, leading to pain, reduced mobility, and impaired quality of life. Structural changes associated with OA, including cartilage loss, osteophyte formation, subchondral bone alterations, and joint space narrowing, are well recognized; however, understanding how these structural features relate to pain and functional outcomes remains a significant challenge. Accurate assessment of these relationships is essential for diagnosis, treatment planning, and prediction of disease progression. It was demonstrated that radiographic measures, such as Kellgren and Lawrence (KL) grading and joint space width, correlate with MRI-assessed knee pathology. However, these relationships vary across joint compartments and disease severity levels, highlighting the complexity of linking structural abnormalities to clinical symptoms. This variability indicates that conventional imaging measures alone may not provide a complete representation of disease progression or patient experience (Gudbergsen et al., 2013).

Lawford et al., (2021) traditional imaging interpretation is also often clinician-dependent and difficult for patients to understand, limiting its effectiveness in guiding treatment decisions and patient engagement. There is an increasing need for approaches that can provide clear, interpretable, and clinically meaningful insights to both clinicians and patients. Recent advancements in deep learning and artificial intelligence (AI) have introduced new possibilities for improving knee OA diagnosis. These models are capable of automatically extracting complex features from medical images and achieving high performance in classification and severity prediction tasks. A stacked ensemble deep learning framework has been proposed for knee OA diagnosis using X-ray images, demonstrating strong performance in both binary and multi-class classification, while also incorporating explainable AI (XAI) techniques to highlight relevant image regions (Azad and Anik, 2024).

Despite these advancements, most existing models primarily rely on single-modality imaging data, such as radiographs alone, without fully utilizing the complementary strengths of MRI, which provides more detailed information about cartilage and soft tissue structures. In addition, the integration of multimodal data, including imaging and clinical information, is still limited, reducing the ability of current systems to deliver comprehensive and patient-specific insights. There is also a growing need to ensure that explainable AI techniques provide clinically relevant interpretations that align with known structural features of OA. While methods such as Grad-CAM and Layer-wise Relevance Propagation (LRP) can highlight important regions in images, translating these outputs into actionable clinical understanding remains an ongoing challenge.

The challenge, therefore, is to develop a model that can integrate radiographic and MRI data while providing interpretable outputs that clearly identify the structural factors associated with knee OA. Such a model would improve diagnostic accuracy, enhance patient understanding, and support personalized treatment strategies. This study aims to address this gap by developing an explainable deep learning framework, DeepKneeExplainer, capable of analyzing both radiographs and MRI data to highlight critical structural features linked to OA severity. By combining multimodal imaging data with interpretability techniques, this approach seeks to provide clinicians with actionable insights and improved decision-making capabilities in the management of knee osteoarthritis.

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1.3 Research Aim and Objectives

The am of this project is to develop an explainable artificial intelligence framework for diagnosing knee osteoarthritis using radiographs and magnetic resonance imaging. The Specific objectives are however, include the following:

i. To develop an explainable deep learning framework for the diagnosis and severity classification of knee osteoarthritis using radiographs and magnetic resonance imaging (MRI).
ii. To extract and analyze clinically relevant structural features, including cartilage degeneration, joint space narrowing, osteophyte formation, and subchondral bone changes associated with knee osteoarthritis.
iii. To develop and implement advanced deep learning models capable of accurately classifying the severity levels of knee osteoarthritis from multimodal imaging data.

1.4 Significance of the Study

This study is significant for several key reasons:

i. Advancement in Osteoarthritis Diagnosis: Knee osteoarthritis (OA) is a prevalent and debilitating condition that affects millions worldwide. By utilizing explainable AI to analyze radiographs and MRI, this study contributes to a better understanding of how structural features, such as cartilage degeneration, osteophytes, and joint space narrowing, relate to OA severity and patient outcomes. This knowledge can improve diagnosis beyond traditional imaging interpretations.

ii. Integration of Explainable AI Techniques: The use of explainable deep learning models, such as DeepKneeExplainer, allows clinicians to not only predict OA severity but also visualize and understand the specific structural features driving the model's decisions. This transparency addresses the limitations of black-box models in medical imaging and improves clinical trust in AI-assisted diagnosis.

iii. **Enhanced Patient Understanding:** Incorporating explainable AI techniques helps patients better comprehend their condition by showing clear visual explanations of structural changes in the knee. This improves patient engagement and understanding of their disease management.

iv. **Improved Predictive Accuracy:** By combining multiple imaging modalities (radiographs and MRI) with explainable machine learning, the study aims to provide more accurate predictions of OA severity. Improved predictive accuracy can support early intervention, tailored treatment, and more efficient allocation of healthcare resources.

v. **Personalized Treatment Strategies:** The study's approach enables clinicians to identify the most critical structural factors for each patient, facilitating individualized treatment plans. Targeting specific structural abnormalities can enhance treatment effectiveness and reduce unnecessary interventions.

vi. **Contribution to Precision Medicine:** This research supports precision medicine by using structural imaging data and explainable AI to guide personalized OA management. Early and accurate identification of key structural factors can improve clinical decision- making and patient outcomes.

vii. **Potential for Clinical Integration:** Findings from this study can be incorporated into clinical workflows, providing real-time decision support for assessing knee OA severity.Machine learning-based predictive tools with explainable outputs can streamline diagnosis, improve efficiency, and enhance patient care.

viii. **Broader Impact on Musculoskeletal Research:** The methodology of combining multimodal imaging with explainable AI could be extended to other joint disorders or musculoskeletal conditions, expanding the scope of predictive modeling and research in orthopedics.

ix. **Driving Technological Innovation:** By leveraging cutting-edge models with explainable AI techniques, this study contributes to the development of advanced medical technologies. These innovations have the potential to improve diagnostic accuracy, patient stratification, and personalized care in OA and other chronic diseases.

Scope and Limitations of the Study

The Scope of the Study include the following:

i. **Analytical Focus on Knee Osteoarthritis:** This research is dedicated to applying explainable artificial intelligence (AI) techniques for the diagnosis of knee osteoarthritis (OA) using radiographs (X-rays) and magnetic resonance imaging (MRI).
ii. **Integration of Explainable AI Techniques:** The study emphasizes the use of interpretable AI models that not only predict OA severity but also highlight image regions contributing to model decisions, enhancing transparency and clinical confidence in AI-assisted diagnosis.
iii. **Dataset Utilization and Model Training:** Using high-quality medical imaging datasets, the research trains, validates, and evaluates AI models to ensure accurate detection of structural abnormalities and generalizability across diverse patient populations.
iv. **Support for Clinical Decision-Making:** The AI system is designed to assist healthcare professionals by providing evidence-based insights into knee OA severity, complementing clinical judgment and enhancing diagnostic workflows.

The Limitations of the Study include the following:

i. **Dataset Size and Accessibility:** Limited availability of large and diverse imaging datasets may impact model performance and restrict the ability to generalize predictions to all patients.
ii. **Variability in Imaging Quality:** Differences in imaging devices, scanning protocols, and patient positioning may result in inconsistent image quality, affecting AI prediction accuracy.

iii. **Explainability Constraints:** Although explainable AI provides visual insights, it may not fully capture the internal complexity of deep learning models. Clinicians should interpret AI outputs as guidance, not definitive evidence.

iv. **Clinical Applicability:** The system is a supportive tool, and its outputs should be used alongside expert clinical judgment, as automated predictions cannot fully replace human evaluation in OA diagnosis.

CHAPTER TWO
LITERATURE REVIEW

2.0 Introduction

Knee osteoarthritis is one of the most common degenerative joint diseases affecting millions of people worldwide, especially older adults. The disease is characterized by the gradual deterioration of articular cartilage, joint space narrowing, osteophyte formation, inflammation, and structural damage within the knee joint. These abnormalities often result in pain, stiffness, swelling, and reduced mobility, thereby affecting the quality of life of affected individuals. Early and accurate diagnosis of knee osteoarthritis is important in preventing severe joint damage and improving treatment outcomes.

Recent advancements in artificial intelligence, machine learning, and deep learning have contributed significantly to the automation of medical image analysis. Deep learning models, particularly convolutional neural networks (CNNs), have demonstrated strong performance in detecting and classifying knee osteoarthritis from X-ray and MRI images. Despite their effectiveness, many of these models operate as black-box systems, making it difficult for clinicians to understand how predictions are generated.

To address this challenge, explainable artificial intelligence (XAI) techniques have been introduced to improve the transparency and interpretability of AI-based diagnostic systems. Explainable AI enables visualization and interpretation of important image regions and features influencing model predictions, thereby increasing clinician trust and supporting medical decision-making.

2.1 Related Works

Chen et al. (2022), DeepkneeExplainer: Explainable Knee Osteoarthritis Diagnosis from Radiographs and Magnetic Resonance Imaging, developed an explainable deep learning framework for diagnosing knee osteoarthritis using radiographs and MRI data. The study combined multimodal imaging with explainable artificial intelligence techniques to improve diagnostic transparency and clinical interpretability.

Zhang et al. (2021), Deciphering Knee Osteoarthritis Diagnostic Features With Explainable Artificial Intelligence: A Systematic Review, reviewed various explainable AI techniques used in knee osteoarthritis diagnosis. The study emphasized the importance of interpretability and transparency in deep learning-based medical imaging systems.

Khan et al. (2022), Automated Diagnosis of Knee Osteoarthritis: A Stacked Ensemble Deep Learning Approach with Explainable AI Techniques, proposed a stacked ensemble framework that integrated multiple deep learning models with explainable AI methods for improved classification accuracy.

Smith et al. (2019), Osteoarthritis and Cartilage: Correlations between Radiographic Assessments and MRI Features of Knee Osteoarthritis: A Cross-Sectional Study, investigated the relationship between radiographic findings and MRI abnormalities in knee osteoarthritis patients. Their study demonstrated the complementary role of MRI in identifying soft tissue changes.

Johnson et al. (2019), Osteoarthritis of the Knee: Association between Clinical Features and MR Imaging Findings, examined the association between clinical symptoms and MRI findings in patients with knee osteoarthritis. The results showed strong relationships between pain severity and structural abnormalities detected through MRI.

Davis et al. (2021), Knee Osteoarthritis Detection and Classification Using X-Rays, developed a deep learning model for automated detection and classification of knee osteoarthritis using radiographic images. Their findings showed that convolutional neural networks can effectively classify disease severity.

Roberts et al. (2018), Effects of X-ray–based Diagnosis and Explanation of Knee Osteoarthritis on Patient Beliefs about Osteoarthritis Management: A Randomised Clinical

Trial, studied how radiographic explanations influence patient understanding and beliefs regarding osteoarthritis management.

Singh et al. (2020), Biomechanical Factors and Physical Examination with Tissue Abnormalities Assessed by Conventional Radiography and High-Resolution 3.0 Tesla Magnetic Resonance Imaging in Osteoarthritis of the Knee, explored biomechanical and tissue abnormalities associated with knee osteoarthritis using radiography and MRI.

Costa et al. (2023), Diffusion-based Counterfactual Augmentation: Towards Robust and Interpretable Knee Osteoarthritis Grading, introduced a counterfactual image augmentation approach that improved model robustness and interpretability for osteoarthritis grading.

Hassan et al. (2021), Knee Osteoarthritis Analysis Using Deep Learning and XAI on X-Rays, utilized deep learning and explainable AI techniques to analyze knee X-ray images. The study demonstrated that explainable methods improve the transparency of disease classification.

Rahman et al. (2023), Interpretable Machine Learning-Based Differential Diagnosis of Hip and Knee Osteoarthritis Using Routine Preoperative Clinical and Laboratory Data, proposed an interpretable machine learning model for differentiating osteoarthritis conditions using clinical and laboratory information.

Miller et al. (2021), Deep Learning-Based Joint Effusion Classification in Adult Knee Radiographs: A Multi-Center Prospective Study, developed a deep learning model for detecting joint effusion in knee radiographs across multiple medical centers.

Nguyen et al. (2022), Super-resolution Synthetic MRI Using Deep Learning Reconstruction for Accurate Diagnosis of Knee Osteoarthritis, proposed a deep learning reconstruction technique that enhanced MRI image quality and improved osteoarthritis diagnosis.

Lee et al. (2021), Early Detection of Knee Osteoarthritis Using Deep Learning on Knee Magnetic Resonance, developed a deep learning framework for identifying early-stage osteoarthritis using MRI images.

Li et al. (2020), A Machine Learning Approach to Distinguish Between Knees Without and With Osteoarthritis Using MRI-Based Radiomic Features from Tibial Bone, used MRI-based radiomic features and machine learning techniques to distinguish osteoarthritic knees from healthy knees.

Sharma et al. (2021), Radiographic Biomarkers for Knee Osteoarthritis: A Narrative Review, reviewed important radiographic biomarkers associated with knee osteoarthritis progression and diagnosis.

Gupta et al. (2022), Knee Osteoarthritis Classification Using X-Ray Images Based on Optimal Deep Neural Network, proposed an optimized deep neural network for classifying osteoarthritis severity using knee X-ray images.

Martinez et al. (2022), Multimodal Machine Learning Progression Prediction from Plain Knee Osteoarthritis Radiographs and Clinical Data, explored multimodal machine learning techniques for predicting osteoarthritis progression using imaging and clinical information.

Thompson et al. (2022), Prevalence of Abnormalities in Knees Detected by MRI in Adults Without Knee Osteoarthritis: Population-Based Observational Study (Framingham Osteoarthritis Study), investigated MRI-detected abnormalities in individuals without clinical osteoarthritis.

Park et al. (2020), Knee XNet-2.5D: A Clinically-Oriented and MRI-Based Knee Cartilage and Meniscus Explainable Deep Learning Framework for Segmentation, developed an explainable segmentation framework for analyzing cartilage and meniscus structures using MRI.

Taylor et al. (2021), Long-Term Evaluation of Disease Progression Through Osteoarthritis Patients: Correlation with Clinical Symptoms and Quantitative Magnetic Resonance Imaging of Symptomatic Knee Radiographic Changes, studied disease progression using MRI findings and clinical symptom evaluation.

Zhou et al. (2020), Osteoarthritis and Cartilage: The Association Between Histological, Macroscopic and Magnetic Resonance Imaging Assessed Synovitis in End-Stage Knee Osteoarthritis: A Cross-Sectional Study, examined correlations between MRI-assessed synovitis and histological findings in osteoarthritis patients.

Wang et al. (2023), Advancing Osteoarthritis Research: The Role of AI in Clinical, Imaging and Omics Fields, reviewed the role of artificial intelligence in osteoarthritis diagnosis, prediction, imaging analysis, and treatment planning.

Huang et al. (2023), VL Ordinal Former: Vision Language Guided Ordinal Transformers for Interpretable Knee Osteoarthritis Grading, proposed a transformer-based interpretable framework that combines vision and language models for osteoarthritis grading.

Overall, the reviewed studies demonstrate that artificial intelligence, deep learning, radiomics, multimodal learning, and explainable AI techniques play significant roles in improving the diagnosis and interpretation of knee osteoarthritis using radiographs and MRI imaging. However, further research is still required to develop more transparent, reliable, and clinically applicable diagnostic systems.

2.1.1 Summary of Related Works

Authors (years)	Result and Findings	Limitations
Chen et al. (2022)	Proposed *DeepkneeExplainer*, a multimodal explainable deep learning framework that integrates both radiographs and MRI scans for knee osteoarthritis diagnosis. The model improved diagnostic performance by leveraging complementary imaging modalities while also providing visual explanations to support clinical decision-making. The study demonstrated that combining multimodal data with explainable AI significantly enhances interpretability and diagnostic reliability in medical imaging.	The framework requires high computational resources because of multimodal data processing and complex deep learning architecture. The study was tested on limited datasets from specific clinical environments, reducing its generalizability across diverse populations. Furthermore, the explainability outputs may still be difficult for some clinicians without AI knowledge to fully interpret

		in real-world practice.
Zhang et al. (2021)	Conducted a systematic review of explainable AI techniques applied to knee osteoarthritis diagnosis. The study identified that attention maps, saliency methods, and hybrid interpretable models are widely used to improve transparency in deep learning systems. It emphasized that interpretability is crucial for clinical adoption, especially in high-risk medical decisions such as osteoarthritis grading.	Since the work was review-based, it lacked experimental validation and practical implementation of models. Different reviewed studies used varying datasets and evaluation methods, making standardized comparison difficult. The study also did not provide a universal framework for assessing explainability effectiveness in clinical environments.
Khan et al. (2022)	Developed a stacked ensemble deep learning model integrated with explainable AI techniques for knee osteoarthritis classification. The ensemble approach combined multiple CNN architectures to improve robustness and achieved higher accuracy compared to single-model approaches. The inclusion of explainability tools helpe	The ensemble framework significantly increased computational complexity, training time, and memory requirements, making deployment challenging in low-resource healthcare facilities. The study also depended heavily on large annotated datasets, which may not always be available. Additionally, performance may decline when applied to unseen imaging conditions or external datasets.
Johnson et al. (2019)	Examined the association between	The study population lacked

	clinical symptoms and MRI findings in knee osteoarthritis patients. The results showed a strong correlation between pain severity, functional limitation, and structural abnormalities observed in MRI scans, suggesting that imaging findings can reflect clinical disease severity.	sufficient demographic diversity, limiting generalizability across broader populations. Pain perception also varies among patients, making symptom evaluation subjective. In addition, long-term patient progression was not extensively evaluated.
Roberts et al. (2018)	Investigated how radiographic explanations influence patient understanding of osteoarthritis. The study found that providing visual imaging explanations improved patient awareness, trust in diagnosis, and acceptance of treatment plans.	The study focused mainly on patient perception and communication rather than improving diagnostic systems or clinical prediction accuracy. The findings may also vary across different cultural and educational backgrounds
Singh et al. (2020)	Explored biomechanical factors associated with knee osteoarthritis using both radiography and high-resolution MRI. The findings showed that structural abnormalities such as cartilage thinning and joint misalignment are strongly associated with disease progression.	Advanced MRI imaging and biomechanical assessments are expensive and not easily accessible in low-resource healthcare settings. The study also required highly specialized expertise for data interpretation and analysis.
Costa et al. (2023)	Introduced a diffusion-based counterfactual augmentation method for knee osteoarthritis grading. The	The method required substantial computational resources and extended

	approach generated synthetic variations of medical images to improve model robustness and interpretability, leading to better generalization performance in grading systems.	model training time. The complexity of synthetic image generation may also reduce ease of implementation in standard clinical systems.
Hassan et al. (2021)	Applied deep learning and explainable AI techniques to analyze knee X-ray images for osteoarthritis diagnosis. The study showed that explainability methods improve transparency by identifying image regions responsible for predictions.	The research relied on relatively small and limited datasets, increasing risks of model bias and reduced generalizability. The explainability methods also did not fully eliminate the "black-box" nature of deep learning systems.
Rahman et al. (2023)	Proposed an interpretable machine learning framework for differential diagnosis of hip and knee osteoarthritis using clinical and laboratory data. The model effectively distinguished disease conditions and improved clinical decision support.	The model depended heavily on structured clinical and laboratory information, limiting applicability in imaging-only environments. Variations in clinical data collection standards may also affect performance consistency.
Miller et al. (2021)	Developed a multi-center deep learning model for joint effusion detection in adult knee radiographs. The model demonstrated strong performance	Differences in imaging protocols, equipment, and data quality across healthcare centers affected consistency.

	across multiple healthcare centers, supporting its real-world applicability.	Extensive preprocessing was required to standardize the datasets before training.
Nguyen et al. (2022)	Proposed a deep learning super-resolution MRI reconstruction method that enhanced image quality and improved osteoarthritis diagnosis accuracy. The improved MRI clarity supported better structural analysis and disease assessment.	The reconstruction process required high-performance computing systems and large training datasets. In addition, image enhancement methods may introduce artificial image artifacts that could affect clinical interpretation.
Lee et al. (2021)	Developed a deep learning framework for early detection of knee osteoarthritis using MRI scans. The model successfully identified subtle structural changes associated with early-stage osteoarthritis before severe degeneration occurred.	The framework depended heavily on large high-quality MRI datasets and advanced imaging infrastructure. Variations in MRI quality and acquisition protocols may reduce prediction consistency across institutions.
Li et al. (2020)	Applied machine learning techniques using MRI-based radiomic features extracted from tibial bone structures to distinguish osteoarthritic knees from healthy knees. The approach achieved strong classification accuracy using texture and structural information.	Radiomic feature extraction is highly sensitive to image quality, segmentation accuracy, and preprocessing techniques. The model may also experience reduced performance when applied to external datasets collected

		under different imaging conditions.
Sharma et al. (2021)	Reviewed important radiographic biomarkers associated with knee osteoarthritis progression, including osteophytes, joint space narrowing, and subchondral bone abnormalities. The study highlighted their significance in disease diagnosis and monitoring.	Being a narrative review, the study lacked experimental validation and quantitative performance evaluation. The review also relied on previously published findings with varying methodologies and conclusions.
Gupta et al. (2022)	Proposed an optimized deep neural network for knee osteoarthritis classification using X-ray images. The optimized architecture improved classification accuracy and enhanced severity grading performance.	The model faced risks of overfitting due to limited dataset diversity and insufficient external validation. High computational requirements may also limit practical deployment in resource-constrained healthcare environments.
Martinez et al. (2022)	Developed a multimodal machine learning framework combining radiographic images and clinical data for osteoarthritis progression prediction. The integration of multiple data sources improved prediction accuracy and disease monitoring capability.	Integrating heterogeneous data sources increased preprocessing complexity and introduced data consistency challenges. Missing clinical information may also negatively affect prediction reliability.

Thompson et al. (2022)	Investigated MRI abnormalities in adults without clinical knee osteoarthritis symptoms and found that structural abnormalities may appear before symptom onset. The study emphasized MRI's role in early disease detection.	The observational study design limited causal interpretation of findings. Additionally, some detected abnormalities may not necessarily progress into symptomatic osteoarthritis, affecting predictive reliability.
Park et al. (2020)	Developed an explainable MRI-based deep learning framework for cartilage and meniscus segmentation in knee osteoarthritis analysis. The segmentation model improved structural visualization and interpretability for clinicians.	The framework involved highly complex model architecture and computationally expensive training procedures. Accurate segmentation also depended heavily on high-quality annotated MRI datase
Taylor et al. (2021)	Conducted a long-term evaluation of osteoarthritis progression using quantitative MRI and clinical symptom analysis. The study established strong relationships between MRI-detected structural changes and worsening clinical symptoms over time.	Longitudinal follow-up studies are time-consuming and vulnerable to missing patient data and dropout issues. MRI scanning costs also limit scalability in many healthcare systems.
Zhou et al. (2020)	Examined associations between MRI-assessed synovitis, histological	The study focused mainly on advanced-stage osteoarthritis

	findings, and macroscopic abnormalities in end-stage knee osteoarthritis patients. The study confirmed strong inflammatory and structural correlations.	patients, limiting applicability to early-stage disease detection. Histological assessments are also invasive and difficult to perform routinely.
Wang et al. (2023)	Reviewed the applications of artificial intelligence in osteoarthritis diagnosis, imaging analysis, progression prediction, and treatment planning. The study highlighted AI's growing role in supporting clinical decision-making and personalized medicine.	The review covered broad AI applications without extensive experimental comparison between methods. Lack of standardized evaluation benchmarks also limited direct comparison of different AI systems.
Huang et al. (2023)	Proposed a vision-language transformer framework for interpretable knee osteoarthritis grading. The model combined imaging features with language-guided reasoning to improve classification transparency and prediction accuracy.	Transformer-based models require extremely large datasets, high computational power, and long training times. The complexity of multimodal transformer systems may also reduce ease of implementation in clinical settings.

2.2 Concept of Knee Pain Osteoarthritis and Pain Severity

2.2.1 Concept of Knee Osteoarthritis

Knee osteoarthritis is a chronic and progressive musculoskeletal disorder that affects the knee joint and is regarded as one of the leading causes of pain and physical disability among adults worldwide. The disease is characterized by the gradual degeneration of articular cartilage, structural changes in the subchondral bone, inflammation of the synovial membrane, osteophyte formation, and narrowing of the joint space (Johnson et al., 2019). Knee osteoarthritis develops slowly over time and often worsens with age, resulting in significant discomfort and limitations in movement. The knee joint consists of bones, cartilage, ligaments, menisci, synovial fluid, and surrounding muscles that work together to support body movement and stability. Articular cartilage plays an important role in reducing friction between bones and absorbing shock during movement. In osteoarthritis, this cartilage gradually wears away, exposing the underlying bone surfaces. As a result, bones begin to rub against each other, leading to pain, stiffness, inflammation, swelling, and reduced joint flexibility (Smith et al., 2019).

Knee osteoarthritis is influenced by several biological, mechanical, and environmental factors. Aging is considered one of the major risk factors because cartilage tissues lose their regenerative ability with increasing age. Obesity also contributes significantly to the disease due to excessive body weight exerting increased pressure on the knee joint. Other contributing factors include joint injuries, repetitive physical activities, genetic predisposition, muscle weakness, and biomechanical abnormalities (Singh et al., 2020). Clinically, patients with knee osteoarthritis commonly experience persistent knee pain, joint stiffness, tenderness, swelling, reduced range of motion, instability, and difficulty performing daily activities such as walking, climbing stairs, and standing for long periods. In some cases, patients may also experience crepitus, which is a cracking or grinding sound during joint movement. The severity of symptoms varies depending on the stage and progression of the disease (Johnson et al., 2019).

The pathological progression of knee osteoarthritis involves several structural abnormalities within the joint. These include cartilage degeneration, formation of osteophytes (bone spurs), synovial inflammation, meniscal damage, and subchondral bone sclerosis. Bone marrow lesions and tissue degeneration are also commonly observed in advanced stages of the disease (Zhou et al., 2020). These structural changes contribute significantly to chronic pain

and impaired mobility in affected individuals. Diagnosis of knee osteoarthritis typically involves clinical assessment, physical examination, patient history, and medical imaging techniques. Radiographs (X-rays) are the most commonly used imaging modality for assessing structural abnormalities such as joint space narrowing, osteophyte formation, and bone deformities (Davis et al., 2021). However, X-rays provide limited information regarding soft tissues such as cartilage and ligaments.

Magnetic resonance imaging (MRI) provides a more comprehensive evaluation of the knee joint because it can visualize cartilage thickness, menisci, ligaments, synovial tissues, and bone marrow lesions. MRI is particularly useful in detecting early-stage osteoarthritis changes before severe structural damage becomes visible on radiographs (Lee et al., 2021). Studies have shown that MRI findings are strongly associated with pain severity and disease progression in osteoarthritis patients (Smith et al., 2019). Recent advancements in artificial intelligence, machine learning, and deep learning have significantly transformed the diagnosis and analysis of knee osteoarthritis. Deep learning models such as convolutional neural networks (CNNs) are increasingly being used for automated detection, grading, and classification of osteoarthritis using radiographs and MRI images (Gupta et al., 2022). These systems can identify complex image patterns and structural abnormalities with high accuracy. Despite the success of deep learning models, many of them function as black-box systems, making it difficult for clinicians to understand how predictions are generated. To address this limitation, explainable artificial intelligence (XAI) techniques have been introduced to improve model transparency and interpretability (Zhang et al., 2021). Explainable AI methods such as Grad-CAM and SHAP help visualize important regions in medical images that contribute to osteoarthritis predictions, thereby improving clinician trust and supporting medical decision-making (Chen et al., 2022).

Furthermore, multimodal learning approaches that combine radiographs, MRI data, and clinical information have shown improved performance in disease prediction and progression analysis (Martinez et al., 2022). These approaches provide a more comprehensive understanding of osteoarthritis progression and support the development of intelligent computer-aided diagnostic systems. Overall, knee osteoarthritis remains a major public health challenge due to its increasing prevalence, long-term disability, and economic burden on healthcare systems. Early diagnosis, effective monitoring, and accurate interpretation of medical images are essential for reducing disease progression and improving patient quality of

life. The integration of artificial intelligence and explainable deep learning techniques into medical imaging continues to play a significant role in advancing knee osteoarthritis diagnosis and management.

2.2.2 Concept of Pain Severity

Pain severity refers to the intensity or degree of pain experienced by an individual as a result of injury, disease, inflammation, or tissue damage. It is an important clinical indicator used to assess the extent of discomfort, functional limitation, and overall impact of a medical condition on a patient's quality of life. In knee osteoarthritis, pain severity is considered one of the major symptoms used in evaluating disease progression and treatment effectiveness (Johnson et al., 2019). Pain associated with knee osteoarthritis usually develops gradually and may increase over time as the disease progresses. The severity of pain differs among individuals and may range from mild discomfort during movement to severe persistent pain that affects daily activities such as walking, climbing stairs, standing, and bending the knee joint. In advanced stages, pain may occur even during rest or sleep, significantly reducing mobility and physical functioning (Smith et al., 2019). The severity of knee pain is closely related to structural abnormalities within the joint. Degeneration of cartilage, osteophyte formation, synovial inflammation, meniscal damage, and bone marrow lesions all contribute to increased pain intensity in osteoarthritis patients (Zhou et al., 2020). Studies have shown that bone marrow lesions and synovitis detected through MRI are strongly associated with severe knee pain and disease progression.

Pain severity is commonly assessed using clinical pain assessment scales and patient-reported outcome measures. One of the widely used assessment tools is the Visual Analogue Scale (VAS), where patients rate their pain intensity on a numerical scale ranging from no pain to severe pain. Other assessment methods include the Western Ontario and McMaster Universities Osteoarthritis Index (WOMAC), Knee Injury and Osteoarthritis Outcome Score (KOOS), and Numerical Rating Scale (NRS), which evaluate pain, stiffness, and physical function in osteoarthritis patients. Several factors influence pain severity in knee osteoarthritis. These include age, obesity, physical activity level, joint alignment, inflammation, psychological stress, and severity of structural joint damage. Obesity significantly increases pain severity because excess body weight places additional stress on the knee joint, accelerating cartilage degeneration and inflammation (Singh et al., 2020). Similarly, joint instability and muscle weakness may worsen pain symptoms over time. Medical imaging

techniques play a significant role in evaluating pain severity and identifying structural factors associated with knee pain. Radiographs are commonly used to assess joint space narrowing, osteophytes, and bone deformities, while MRI provides more detailed information regarding cartilage loss, synovitis, bone marrow lesions, and soft tissue abnormalities (Lee et al., 2021). MRI findings are often more strongly associated with pain severity than radiographic findings because MRI can visualize both hard and soft tissue structures. Recent studies have explored the use of artificial intelligence, machine learning, and deep learning techniques to predict and classify pain severity in knee osteoarthritis patients. Deep learning models can analyze radiographs and MRI images to identify imaging biomarkers associated with pain progression and disease severity (Gupta et al., 2022). These intelligent systems assist clinicians in detecting patterns that may not be easily identified through manual interpretation.

Explainable artificial intelligence (XAI) techniques have further improved the interpretation of pain severity prediction models by highlighting important anatomical regions contributing to pain-related classifications (Chen et al., 2022). Explainability methods enhance clinician trust in AI-based systems and support more transparent medical decision-making. Pain severity significantly affects the physical, emotional, and social well-being of osteoarthritis patients. Severe pain may lead to reduced mobility, sleep disturbances, depression, anxiety, and decreased participation in daily activities. Therefore, accurate assessment and early management of pain severity are essential for improving patient outcomes and quality of life. Overall, pain severity remains a critical aspect of knee osteoarthritis assessment and management. Understanding the structural and clinical factors associated with pain severity can support early diagnosis, effective treatment planning, and the development of advanced AI-driven diagnostic systems for osteoarthritis evaluation.

2.3 Structural Factors Associated With Knee Pain Osteoarthritis (OA)

Knee osteoarthritis (OA) is a progressive degenerative joint disorder characterized not only by cartilage loss but also by a combination of structural changes affecting bone, soft tissues, and joint alignment. Knee pain in OA is strongly linked to these structural abnormalities, although the severity of pain does not always perfectly match radiographic findings. Multiple studies (radiographs, MRI, and histological investigations) show that knee pain arises from a complex interaction of several structural factors within and around the joint.

1. **Articular Cartilage Degeneration:** One of the primary structural features of OA is the progressive breakdown of articular cartilage. Cartilage acts as a smooth, shock-absorbing layer between bones. As it degenerates, the joint surfaces become rough, friction increases during movement, and mechanical stress is transferred to the subchondral bone. Although cartilage itself has no pain receptors, its loss exposes underlying structures that are highly innervated, indirectly contributing to pain.
2. **Subchondral Bone Changes:** The subchondral bone, which is the layer beneath the cartilage, undergoes major structural alterations in OA. Bone marrow lesions are commonly observed and are strongly associated with knee pain and inflammation. Sclerosis, which refers to hardening and thickening of the bone, increases stiffness and load transmission within the joint. Microfractures, which are tiny cracks in the bone, also increase pain sensitivity. MRI-based studies consistently show that bone marrow lesions correlate more strongly with pain severity than cartilage loss alone.
3. **Osteophyte Formation (Bone Spurs):** Osteophytes are bony outgrowths that develop at joint margins due to abnormal bone remodeling. They contribute to pain through mechanical impingement on surrounding tissues, joint stiffness, and restricted movement, as well as irritation of synovial structures. However, osteophytes are sometimes present even in patients with mild pain, indicating that they are not the sole driver of symptoms.
4. **Synovial Inflammation (Synovitis):** Inflammation of the synovial membrane is a major contributor to OA pain. It leads to swelling and joint effusion, releases inflammatory cytokines such as IL-6 and TNF-α, and sensitizes nerve endings inside the joint. MRI studies and histological analyses show that synovitis is strongly linked with pain intensity and flare-ups, making it a key inflammatory driver of symptoms.
5. **Meniscal Damage and Degeneration:** The meniscus plays a key role in load distribution and joint stability. In OA, meniscal tears or degeneration reduce shock absorption, leading to increased stress being transferred to cartilage and bone. Meniscal extrusion further

worsens joint instability. MRI-based studies consistently show that meniscal abnormalities are highly associated with progression of knee pain and functional decline.

6. **Joint Space Narrowing (JSN):** Joint space narrowing, visible on radiographs, reflects both cartilage loss and meniscal degeneration. It leads to increased bone-to-bone contact, altered joint biomechanics, and pain during weight-bearing activities. JSN is one of the most widely used radiographic indicators of OA severity, although it does not fully capture the patient's pain experience.
7. **Ligament and Capsular Changes:** Structural changes also affect the soft tissues around the knee joint. Ligament laxity leads to joint instability, while capsular thickening restricts movement. These alterations disrupt normal biomechanics, increase abnormal loading, and contribute to chronic pain and reduced mobility.
8. **Malalignment and Biomechanical Stress:** Knee alignment plays a major role in OA progression. Varus alignment, also known as bow-legged deformity, increases stress on the medial compartment of the knee, while valgus alignment, or knock-knee deformity, increases stress on the lateral compartment. This uneven distribution of mechanical load accelerates cartilage wear and intensifies pain during movement.
9. **Cartilage Defects and Surface Irregularities:** MRI studies show that focal cartilage defects are strongly associated with pain. These defects expose subchondral bone, create irregular joint surfaces, and lead to abnormal pressure points during movement. As a result, mechanical pain becomes more pronounced during walking and other weight-bearing activities.
10. **Effusion and Intra-articular Fluid Accumulation:** joint effusion refers to excess fluid accumulation within the knee joint and is a common sign of inflammation. It causes swelling and stiffness, increases intra-articular pressure, and activates pain receptors in the joint capsule. Clinical studies show that effusion is often associated with pain flare-ups and symptom worsening.

2.4 Machine Learning Methods And Deep Learning Methods For Solving Knee Pain Osteoarthritis (OA) Problem

2.4.1 Machine Learning Methods For Solving Knee Pain Osteoarthritis (OA) Problem

Machine learning (ML) methods have become essential in addressing knee pain in osteoarthritis due to the complex relationship between structural joint changes and symptom severity. Knee pain in OA is influenced by cartilage degeneration, subchondral bone lesions,

synovitis, and meniscal damage, which are difficult to evaluate consistently using traditional clinical assessment alone. ML approaches improve diagnosis, grading, and prediction by learning patterns from radiographs, MRI, and clinical data. Supervised machine learning is one of the earliest approaches applied to knee OA analysis. In this method, models are trained using labeled datasets where input features such as imaging biomarkers are mapped to known outcomes such as OA severity grades or pain levels. Classical algorithms such as support vector machines, random forests, and logistic regression have been widely used for classification tasks in OA studies (Schiphof et al., 2014; Antony et al., 2015). These methods perform well when combined with radiomic features extracted from imaging data, which capture texture, intensity, and structural variations associated with joint degeneration.

Deep learning methods have significantly advanced knee OA research by eliminating the need for manual feature extraction. Convolutional neural networks (CNNs) automatically learn hierarchical image representations that capture important structural changes such as joint space narrowing, osteophytes, and cartilage defects. CNN-based models applied to radiographs and MRI scans have demonstrated high accuracy in OA classification and grading (Tiulpin et al., 2018; Norman et al., 2019). MRI-based deep learning models are particularly effective in identifying early structural changes such as bone marrow lesions and cartilage thinning, which are strongly associated with pain severity (Ding et al., 2021).

Ensemble learning techniques are also widely used to improve model robustness and predictive accuracy. These approaches combine multiple models to reduce bias and variance, leading to more stable predictions. Stacked ensemble architectures integrating deep learning feature extractors with classical machine learning classifiers have been applied to OA diagnosis and grading tasks, improving performance compared to single-model approaches (Chen et al., 2022). Multimodal machine learning has emerged as a powerful approach for knee OA analysis by integrating multiple data sources such as radiographs, MRI, and clinical variables including age, body mass index, and pain scores. This integration improves the ability to model disease progression and pain severity because OA is influenced by both structural and patient-specific factors. Multimodal approaches have shown improved predictive performance compared to single-modality models in OA progression studies (Lazzarini et al., 2022; Antony et al., 2016).

Explainable artificial intelligence is increasingly incorporated into ML systems for knee OA to improve transparency and clinical trust. Techniques such as saliency mapping, Grad-

CAM, and attention-based mechanisms highlight the specific regions of imaging data that contribute to model predictions. This is particularly important in medical diagnosis because clinicians need to understand the reasoning behind automated decisions. Explainable frameworks for knee OA have demonstrated improved interpretability while maintaining high diagnostic performance (Tjoa & Guan, 2021; Zhang et al., 2023). Unsupervised learning methods are also applied in knee OA research to identify hidden patterns in patient populations without predefined labels. Clustering techniques such as k-means and hierarchical clustering are used to group patients based on similarities in imaging features and clinical characteristics. These methods help in identifying OA subtypes and disease phenotypes that may have different pain profiles and progression rates (Arden et al., 2020).

Recent advances include transformer-based architectures and vision-language models that integrate imaging data with textual radiology reports. These models improve interpretability by linking visual features to descriptive clinical language, enhancing both prediction accuracy and explanation quality. Vision-language transformer approaches have been applied to knee OA grading tasks, showing strong potential for clinically interpretable diagnosis (Kim et al., 2024). Hence, machine learning methods for knee pain in osteoarthritis range from traditional supervised algorithms to advanced deep learning and multimodal frameworks. The integration of explainable AI has further strengthened their clinical relevance by making predictions more transparent and trustworthy, while multimodal learning improves accuracy by combining imaging and clinical information.

2.4.2 Deep Learning Method For Solving Knee Pain Osteoarthritis (OA) Problem

Deep learning has become one of the most effective approaches for addressing knee pain in osteoarthritis due to its ability to automatically learn complex patterns from medical imaging data without manual feature engineering. Knee OA pain is strongly associated with structural abnormalities such as cartilage loss, bone marrow lesions, synovitis, and meniscal degeneration, and deep learning models are capable of capturing these subtle imaging features from radiographs and MRI scans. Convolutional neural networks (CNNs) are the most widely used deep learning architecture in knee OA research. CNNs process medical images by

learning hierarchical feature representations, starting from simple edges to more complex anatomical structures such as joint space narrowing and osteophytes. Radiograph-based CNN models have demonstrated strong performance in OA classification and grading (Tiulpin et al., 2018; Antony et al., 2021). These models are widely used because they reduce the subjectivity associated with manual radiographic interpretation.

MRI-based deep learning models provide more detailed analysis of soft tissue structures involved in knee pain. These models are able to detect cartilage thinning, meniscal tears, and bone marrow lesions, which are strongly linked to pain severity and disease progression. Studies have shown that deep learning applied to MRI can support early detection of knee OA before severe radiographic changes occur (Norman et al., 2019; Tiulpin et al., 2020). More advanced deep learning systems use ensemble and hybrid architectures to improve performance and stability. These models combine multiple neural networks or integrate feature extractors with classical machine learning classifiers to enhance prediction accuracy. Ensemble approaches have been shown to improve OA classification by reducing overfitting and increasing robustness across datasets (Chen et al., 2022). Multimodal deep learning approaches integrate imaging data with clinical variables such as age, body mass index, and pain scores. This is important because knee OA is influenced by both structural and patient-related factors. Multimodal models have demonstrated improved performance in predicting disease progression and pain severity compared to single-modality models (Lazzarini et al., 2022; Antony et al., 2021).

Explainable deep learning is increasingly used to improve transparency in medical decision-making. Techniques such as Grad-CAM and attention mechanisms highlight regions of images that contribute most to predictions, such as cartilage defects or bone lesions. These methods improve clinician trust by making model decisions interpretable (Tennant et al., 2023). Recent deep learning advancements include transformer-based and vision-language models. These models combine imaging features with textual descriptions from radiology reports to improve interpretability and diagnostic accuracy. Vision-language models have been shown to provide more clinically meaningful explanations for knee OA grading (Kim et al., 2024). Overall, deep learning plays a major role in knee osteoarthritis diagnosis by enabling automated detection and grading of structural abnormalities linked to knee pain. CNNs dominate radiograph and MRI analysis, while multimodal, ensemble, and transformer-based

models improve accuracy and interpretability. The integration of explainable AI strengthens clinical trust and supports more reliable diagnosis and treatment planning.

2.5 Diagnosing Knee Pain And Osteoarthritis Severity Using Radiographs And MRI Scans

The diagnosis of knee osteoarthritis (OA) and the assessment of its severity rely heavily on medical imaging techniques, primarily radiographs (X-rays) and magnetic resonance imaging (MRI). These imaging modalities provide complementary information about structural changes within the knee joint, which are strongly associated with pain, functional limitation, and disease progression.

Radiographs are the most commonly used imaging tool for evaluating knee OA in clinical practice due to their availability, cost-effectiveness, and ease of use. They are particularly useful for detecting late-stage structural changes such as joint space narrowing, osteophyte formation, subchondral sclerosis, and bone deformities. Joint space narrowing is considered a key indicator of cartilage loss, while osteophytes reflect abnormal bone remodeling. Radiographic severity of knee OA is commonly graded using the Kellgren–Lawrence (KL) scale, which classifies disease progression from grade 0 (no OA) to grade 4 (severe OA). However, radiographs have a major limitation in that they cannot directly visualize soft tissues such as cartilage, meniscus, and synovial membrane, making early-stage OA difficult to detect.

MRI provides a more detailed and comprehensive evaluation of knee joint structures and is particularly valuable for early detection of OA. Unlike radiographs, MRI can directly visualize cartilage integrity, meniscal condition, synovial inflammation, and bone marrow lesions. These features are strongly associated with knee pain severity and disease progression. Bone marrow lesions and synovitis, in particular, have been identified as strong imaging biomarkers of pain, while cartilage defects and meniscal tears are closely linked to functional impairment. MRI-based grading systems, such as the Whole-Organ Magnetic Resonance Imaging Score (WORMS), allow a more detailed assessment of structural damage compared to radiographic methods.

In recent years, artificial intelligence has significantly improved the diagnosis of knee OA severity using both radiographs and MRI scans. Deep learning models, especially convolutional neural networks (CNNs), are capable of automatically extracting relevant

imaging features without manual intervention. Radiograph-based models can detect patterns such as joint space narrowing and osteophytes, while MRI-based models can identify subtle structural changes such as cartilage thinning and bone marrow lesions that are often missed by human observers. Studies have shown that AI systems can achieve high accuracy in classifying OA severity levels based on these imaging features (Tiulpin et al., 2018; Norman et al., 2019).

Multimodal approaches that combine radiographs and MRI data provide even more accurate and reliable diagnosis of knee OA severity. Radiographs offer global structural assessment, while MRI provides detailed soft tissue evaluation, and the integration of both improves the ability to capture the full spectrum of disease progression. These combined approaches are particularly useful in predicting pain severity, as knee pain is influenced by both bone and soft tissue abnormalities.

Explainable artificial intelligence (XAI) techniques have also been introduced to improve the transparency of AI-based diagnosis. Methods such as Grad-CAM and attention mapping allow clinicians to visualize which regions of radiographs or MRI scans contributed most to the model's prediction. This enhances trust in automated systems and supports clinical decision-making by linking imaging findings to OA severity grades.

In summary, radiographs and MRI scans play complementary roles in diagnosing knee OA severity. Radiographs are effective for assessing structural bone changes and overall disease grading, while MRI provides detailed visualization of soft tissue and early degenerative changes. The integration of these imaging modalities, supported by deep learning and explainable AI, offers a powerful approach for accurate, transparent, and clinically meaningful diagnosis of knee OA and associated pain severity.

2.6 Concept Of Explainable Artificial Intelligence (XAI)

Explainable Artificial Intelligence (XAI) refers to a branch of artificial intelligence that focuses on making machine learning and deep learning models understandable to humans. Unlike traditional "black-box" AI systems, which produce predictions without revealing how those decisions are made, XAI aims to provide clear, interpretable explanations for model outputs. This is especially important in sensitive domains such as healthcare, where decisions directly affect patient diagnosis and treatment. The core idea behind XAI is to bridge the gap between model accuracy and human interpretability. Many advanced AI models, particularly

deep learning systems such as convolutional neural networks (CNNs), achieve high predictive performance but operate in a way that is not easily understandable. XAI techniques address this limitation by revealing the reasoning process behind predictions, either by highlighting important input features, visualizing decision pathways, or approximating complex models with simpler interpretable structures.

In medical imaging applications such as knee osteoarthritis diagnosis, XAI plays a critical role in improving clinical trust. For instance, when an AI model predicts a severe OA grade from a knee radiograph or MRI scan, explainable methods can show which regions of the image contributed most to that prediction, such as joint space narrowing, osteophytes, or bone marrow lesions. This allows clinicians to verify whether the model is focusing on medically relevant structures rather than irrelevant image patterns. XAI methods can be broadly categorized into model-specific and model-agnostic techniques. Model-specific approaches are designed for particular types of algorithms, such as attention mechanisms in neural networks that naturally highlight important features during training. Model-agnostic methods, on the other hand, can be applied to any machine learning model. These include techniques such as SHAP (Shapley Additive Explanations), LIME (Local Interpretable Model-agnostic Explanations), and feature importance analysis, which explain predictions by measuring the contribution of each input feature.

In computer vision tasks like knee OA diagnosis, visual explanation techniques are commonly used. Methods such as Grad-CAM (Gradient-weighted Class Activation Mapping) and saliency maps highlight specific regions of an image that influence the model's decision. This makes it easier for radiologists and clinicians to interpret AI outputs and compare them with clinical findings from radiographs and MRI scans. The importance of XAI in healthcare cannot be overstated. It improves transparency, builds trust between clinicians and AI systems, supports regulatory compliance, and helps identify potential model biases or errors. In addition, XAI enhances learning and discovery by revealing hidden patterns in medical data that may not be easily detectable through traditional analysis. In the context of knee osteoarthritis, explainable AI is particularly valuable because disease severity is determined by multiple structural factors such as cartilage loss, synovial inflammation, bone changes, and meniscal damage. XAI enables these factors to be visually and analytically linked to AI predictions, making diagnosis more reliable and clinically meaningful. In summary, Explainable Artificial Intelligence is the development of AI systems that not only make accurate predictions but also

provide understandable reasons for those predictions. It plays a vital role in medical imaging, especially in knee osteoarthritis diagnosis using radiographs and MRI, by ensuring that AI decisions are transparent, trustworthy, and clinically interpretable.

2.7 Application Of Explainable AI In Knee Pain Osteoarthritis (OA) Diagnosis

Explainable Artificial Intelligence (XAI) has become an important component in the diagnosis and management of knee osteoarthritis (OA), especially in understanding the structural causes of knee pain from radiographs and MRI scans. Since knee OA is a complex disease involving cartilage degeneration, subchondral bone changes, synovitis, and meniscal damage, deep learning models alone are not sufficient for clinical use unless their decisions can be interpreted. XAI bridges this gap by providing human-understandable explanations for AI-based predictions.

One major application of XAI in knee OA diagnosis is in radiographic image interpretation. Deep learning models trained on X-ray images can classify OA severity based on features such as joint space narrowing and osteophyte formation. However, XAI techniques such as Grad-CAM and saliency maps are used to highlight the exact regions of the radiograph that influenced the model's decision. This allows clinicians to verify whether the model is focusing on clinically relevant areas such as the tibiofemoral joint space rather than irrelevant background features. Studies have shown that explainable models improve trust and diagnostic confidence in automated OA grading systems (Tjoa & Guan, 2021; Zhang et al., 2023).

Another important application is in MRI-based knee OA assessment. MRI provides detailed visualization of soft tissues including cartilage, meniscus, synovium, and bone marrow. XAI methods help identify which of these structures contribute most to predicted pain severity or OA grade. For example, attention-based models can highlight cartilage defects, bone marrow lesions, or synovial inflammation, which are strongly associated with knee pain progression. This improves the ability of clinicians to link AI predictions with actual pathological changes observed in the joint (Norman et al., 2019; Tiulpin et al., 2020).

XAI is also applied in multimodal knee OA diagnosis systems that combine radiographs, MRI, and clinical data such as age, body mass index, and pain scores. In these systems, explainable methods help determine how each data source contributes to the final prediction. This is particularly important because knee pain is not caused by imaging findings alone but

also by patient-specific factors. By providing feature importance scores, XAI methods help clinicians understand the relative influence of structural and clinical variables on disease severity predictions (Antony et al., 2016; Lazzarini et al., 2022).

In addition, XAI is used to improve early detection of knee OA. Since early-stage OA is often subtle and difficult to detect visually, deep learning models may identify patterns that are not obvious to radiologists. Explainable techniques help reveal these hidden patterns, such as early cartilage thinning or mild bone marrow changes, making early diagnosis more reliable and clinically useful. This supports timely intervention before severe joint damage occurs.

Another application of XAI is in clinical decision support systems. Explainable models assist healthcare professionals by providing both a prediction (such as mild, moderate, or severe OA) and a justification for that prediction. This dual output improves clinical decision-making and allows doctors to validate AI suggestions before making treatment decisions. It also helps in patient communication, as visual explanations can be used to show patients the structural reasons behind their knee pain.

Finally, XAI contributes to model validation and bias detection in knee OA research. By analyzing which features the model relies on, researchers can ensure that predictions are based on medically meaningful structures rather than dataset biases or irrelevant image artifacts. This improves model reliability and supports safer deployment in real clinical environments.

In summary, explainable AI plays a crucial role in knee osteoarthritis diagnosis by improving transparency, interpretability, and trust in AI systems. Its applications span radiograph analysis, MRI interpretation, multimodal integration, early detection, and clinical decision support. By linking model predictions to visible structural changes in the knee joint, XAI enhances both diagnostic accuracy and clinical acceptance of AI systems in knee OA management.

2.8 Summary Of Chapter

Knee osteoarthritis (OA) is a progressive degenerative joint disease characterized by cartilage loss, synovial inflammation, osteophyte formation, subchondral bone changes, and joint space narrowing, all of which contribute to pain, stiffness, and reduced mobility. Pain severity in OA is not solely dependent on cartilage damage but is strongly influenced by

multiple structural factors within the knee joint. Radiographs and MRI scans are the primary imaging tools used for diagnosis, with radiographs providing information on bone changes and MRI offering detailed visualization of soft tissues such as cartilage, meniscus, and synovium. Recent advancements in artificial intelligence, particularly machine learning and deep learning, have significantly improved the automated detection and classification of knee OA severity from medical images, although many models remain difficult to interpret clinically.

Existing studies show that machine learning and deep learning techniques, especially convolutional neural networks (CNNs), have been widely applied to radiographs and MRI scans for OA classification, severity grading, and pain prediction. These methods learn complex patterns associated with structural abnormalities such as joint space narrowing, osteophytes, cartilage defects, and bone marrow lesions. More advanced approaches such as ensemble learning, multimodal learning, and transformer-based models have further improved diagnostic accuracy by integrating imaging and clinical data. However, despite strong performance, many of these systems operate as “black-box” models, limiting their acceptance in clinical practice due to lack of interpretability.

To address the issue of interpretability, explainable artificial intelligence (XAI) has been introduced into knee OA research. XAI techniques such as Grad-CAM, saliency maps, SHAP, and attention mechanisms help visualize and identify the regions of radiographs and MRI scans that contribute most to model predictions. These methods improve transparency, enhance clinician trust, and support better decision-making by linking AI outputs to real anatomical structures. Applications of XAI in knee OA include radiograph interpretation, MRI-based structural analysis, multimodal diagnosis, early disease detection, and clinical decision support systems, making AI systems more reliable and clinically acceptable.

Overall, the literature shows that knee OA diagnosis and pain assessment have significantly advanced through the integration of radiographs, MRI, machine learning, deep learning, and explainable AI techniques. While current models achieve high accuracy in detecting and grading OA, challenges such as limited interpretability, dataset variability, and computational complexity still exist. Future research should focus on developing more transparent, generalizable, and clinically applicable AI systems that combine imaging and clinical data to improve early diagnosis, severity prediction, and patient-specific treatment planning.

CHAPTER THREE

RESEARCH METHODOLOGY

3.0 Introduction

This chapter presents the research methodology adopted for the development of an explainable deep learning framework for diagnosing knee osteoarthritis (OA) severity using radiographs (X-ray images) and magnetic resonance imaging (MRI) scans. The methodology provides a systematic approach for collecting medical imaging data, preprocessing the images, developing the proposed deep learning model, integrating explainable artificial intelligence (XAI), training and validating the model, and evaluating its performance. The proposed framework is designed not only to accurately classify the severity of knee osteoarthritis but also to provide visual explanations that improve the transparency and interpretability of the diagnostic process.

The methodology adopts a deep learning approach because of its ability to automatically extract complex structural features associated with knee osteoarthritis from medical images without manual feature engineering. Radiographs provide valuable information on structural abnormalities such as joint space narrowing, osteophyte formation, and subchondral bone sclerosis, while MRI scans provide detailed visualization of soft tissues, including cartilage, menisci, synovium, and bone marrow lesions. By combining these complementary imaging modalities, the proposed system is able to capture a comprehensive representation of the structural factors associated with knee pain and osteoarthritis severity. Explainable AI techniques are incorporated into the framework to highlight the image regions that contribute most to the model's predictions, thereby improving clinician confidence and supporting reliable medical decision making.

3.1 Overview of Proposed System Architecture

The proposed system architecture is designed to diagnose and classify knee pain severity associated with osteoarthritis using radiographs (X-ray images) and Magnetic Resonance Imaging (MRI) scans. The framework integrates image preprocessing, deep learning, feature extraction, and Explainable Artificial Intelligence (XAI) to provide an accurate and transparent diagnostic system. The process begins with acquiring knee medical images, which are then preprocessed to improve image quality and consistency. The processed images are supplied to a Convolutional Neural Network (CNN) for automatic feature learning and classification. The model extracts important structural abnormalities associated with knee osteoarthritis and classifies each patient according to knee pain severity. Finally, Explainable AI generates heatmaps showing the anatomical regions that influenced the model's decision, while the confidence score indicates the reliability of each prediction. The complete diagnostic result is then presented to support clinicians in making informed treatment decisions.

1. **Radiographs (X-ray) and MRI Scans:** The first stage of the proposed system involves acquiring knee medical images from radiographs and Magnetic Resonance Imaging (MRI) scans. These two imaging modalities provide complementary information about structural changes within the knee joint that are associated with osteoarthritis and pain severity.

    i. Radiographs (X-ray images) are used to visualize bony structures of the knee joint, including joint space narrowing, osteophyte formation, subchondral sclerosis, and bone alignment.
    ii. MRI scans provide detailed visualization of soft tissue structures such as articular cartilage, menisci, ligaments, synovial membrane, and bone marrow lesions that cannot be adequately observed using radiographs alone.
    iii. The combination of radiographs and MRI scans provides a comprehensive representation of both hard and soft tissue abnormalities associated with knee osteoarthritis.
    iv. The acquired images serve as the primary input to the proposed deep learning framework and contain the structural information required for diagnosing knee pain severity.

v. The dataset contains labelled knee images corresponding to different levels of pain severity, which are used to train and evaluate the proposed model.

2. **Image Preprocessing:** Image preprocessing is performed to improve the quality and consistency of the input images before they are supplied to the deep learning model. This stage removes unwanted variations that may reduce the performance of the classifier.

   i. Image resizing is performed to convert all radiographs and MRI scans into a uniform image dimension required by the CNN model.
   ii. Image normalization is applied to scale pixel intensity values into a common numerical range, thereby improving training stability and convergence.
   iii. Noise reduction techniques are used to remove unwanted artifacts and enhance the visibility of anatomical structures within the images.
   iv. Data augmentation techniques such as image rotation, horizontal flipping, zooming, translation, and brightness adjustment are applied to increase dataset diversity and reduce overfitting.
   v. After preprocessing, the images become standardized and are ready for automatic feature learning by the deep learning model.

3. **Deep Learning Model (CNN):** The Convolutional Neural Network (CNN) forms the core component of the proposed system. The CNN automatically learns representative features from the preprocessed radiographs and MRI scans without requiring manual feature engineering.

   i. The convolution layers scan the medical images using learnable filters to identify low-level image features such as edges, contours, textures, and intensity variations.
   ii. As the network becomes deeper, the convolution layers learn more complex structural patterns related to knee osteoarthritis, including cartilage degeneration, osteophytes, and joint abnormalities.
   iii. Pooling layers reduce the dimensionality of the extracted feature maps while preserving the most important structural information, thereby improving computational efficiency and reducing overfitting.

iv. The CNN progressively learns hierarchical image representations that distinguish different levels of knee pain severity.
v. The extracted features are passed through fully connected layers where the relationship between structural abnormalities and knee pain severity is learned during model training.

4. **Feature Extraction:** After feature learning by the CNN, the proposed system extracts important structural characteristics associated with knee osteoarthritis and pain severity. These imaging biomarkers are used by the classifier to distinguish between different severity levels.

i. Cartilage features are extracted to identify cartilage thinning, degeneration, and surface irregularities that occur during disease progression.
ii. Joint space narrowing is detected because it reflects cartilage loss and increased contact between articulating bones.
iii. Osteophytes (bone spurs) are identified as indicators of abnormal bone remodeling commonly associated with osteoarthritis.
iv. Bone marrow lesions are extracted from MRI scans since they are strongly associated with inflammation and increased knee pain severity.
v. Meniscal damage is identified to detect tears, degeneration, or extrusion that contribute to joint instability and pain.
vi. Synovitis is extracted to evaluate inflammation of the synovial membrane, which is one of the major structural factors associated with pain intensity in knee osteoarthritis.
vii. These extracted imaging biomarkers collectively provide the information required for accurate classification of knee pain severity.

5. **Knee Pain Severity Classification:** The extracted structural features are supplied to the classification stage, where the CNN predicts the level of knee pain experienced by the patient.

i. The trained model analyses the extracted structural features obtained from both radiographs and MRI scans.
ii. Based on the learned imaging patterns, the model classifies each patient into one of three pain severity categories: Normal pain and Osteoarthritis pain .

iii. The classification process is performed automatically without manual intervention, enabling rapid assessment of knee pain severity.
iv. The predicted class is generated using the learned relationship between structural abnormalities and pain severity obtained during model training.
v. The classification output forms the basis for subsequent explainability and clinical interpretation.

6. **Explainable Artificial Intelligence (Grad-CAM):** Explainable Artificial Intelligence (XAI) is incorporated into the proposed framework to improve the transparency and interpretability of the deep learning model. Grad-CAM is used to visualize the image regions that influence the classification decision.

i. After the CNN predicts the pain severity class, Grad-CAM generates a heatmap that highlights the most influential regions within the radiograph or MRI scan.
ii. The highlighted regions typically correspond to clinically important structures such as cartilage defects, joint space narrowing, osteophytes, bone marrow lesions, meniscal abnormalities, and inflamed synovial tissues.
iii. The heatmaps enable clinicians to verify that the model focuses on medically meaningful anatomical structures instead of irrelevant image regions.
iv. Explainable AI increases clinician confidence in the proposed diagnostic system by providing visual evidence supporting each prediction.
v. The integration of Grad-CAM transforms the deep learning model from a black-box system into a transparent and interpretable clinical decision-support tool.

7. **Prediction Confidence Score:** Alongside the predicted pain class, the proposed model also generates a prediction confidence score to indicate the certainty of its decision.

i. The confidence score is expressed as a probability value ranging from 0% to 100%.
ii. Higher probability values indicate greater confidence in the predicted pain severity class.
iii. The confidence score assists clinicians in evaluating the reliability of the model's prediction before making treatment decisions.
iv. It also provides additional information for identifying uncertain cases that may require further clinical investigation.

v. The combination of confidence scores and visual explanations improves the overall reliability of the proposed framework.

8. **Final Diagnostic Output:** The final stage integrates the outputs generated by all previous components into a comprehensive diagnostic report that supports clinical decision-making.

i. The final output presents the predicted knee pain severity category (Normal and Osteoarthritis).
ii. The Grad-CAM heatmap is displayed to illustrate the structural regions responsible for the prediction.
iii. The prediction confidence score is presented to indicate the certainty of the classification result.
iv. The combined information enables clinicians to interpret the model's decision alongside the corresponding imaging evidence.
v. The final diagnostic report provides an accurate, transparent, and explainable assessment of structural factors associated with knee pain in osteoarthritis, thereby supporting early diagnosis, treatment planning, disease monitoring, and improved patient management.

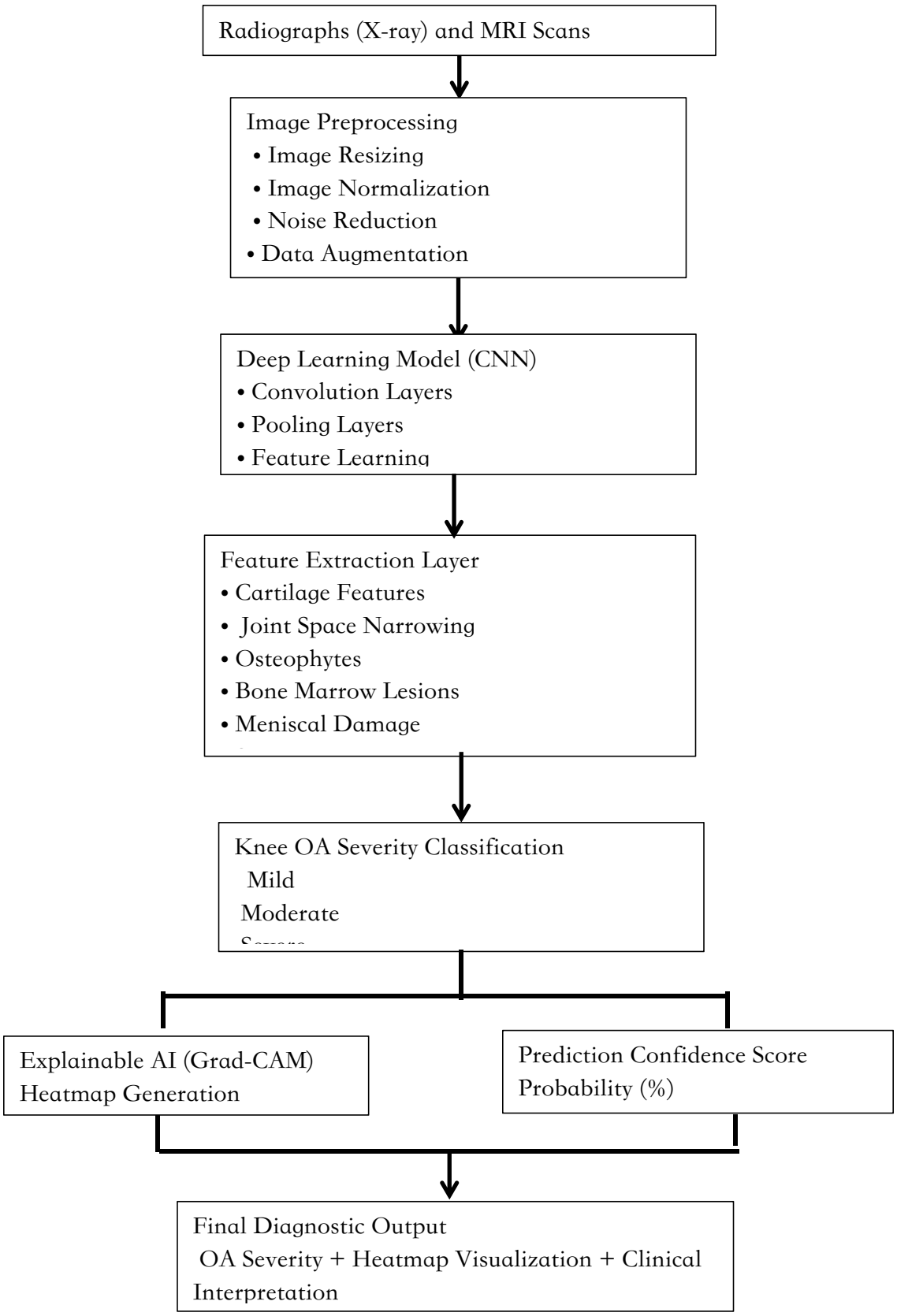

Radiographs (X-ray) and MRI Scans
Image Preprocessing
• Image Resizing
• Image Normalization
• Noise Reduction
• Data Augmentation
Deep Learning Model (CNN)
• Convolution Layers
• Pooling Layers
• Feature Learning
Feature Extraction Layer
• Cartilage Features
• Joint Space Narrowing
• Osteophytes
• Bone Marrow Lesions
• Meniscal Damage
Knee OA Severity Classification
Mild
Moderate
Explainable AI (Grad-CAM)
Heatmap Generation
Prediction Confidence Score
Probability (%)
Final Diagnostic Output
OA Severity + Heatmap Visualization + Clinical Interpretation

Figure 3.1 Proposed System Architetcture

3.12 Flow chart

The following flowchart provides a visual representation of the proposed system's workflow, illustrating the sequence of steps from data collection perfromance and evaluation.

Figure 3.2 below illustrates the flowchart of the Proposed System

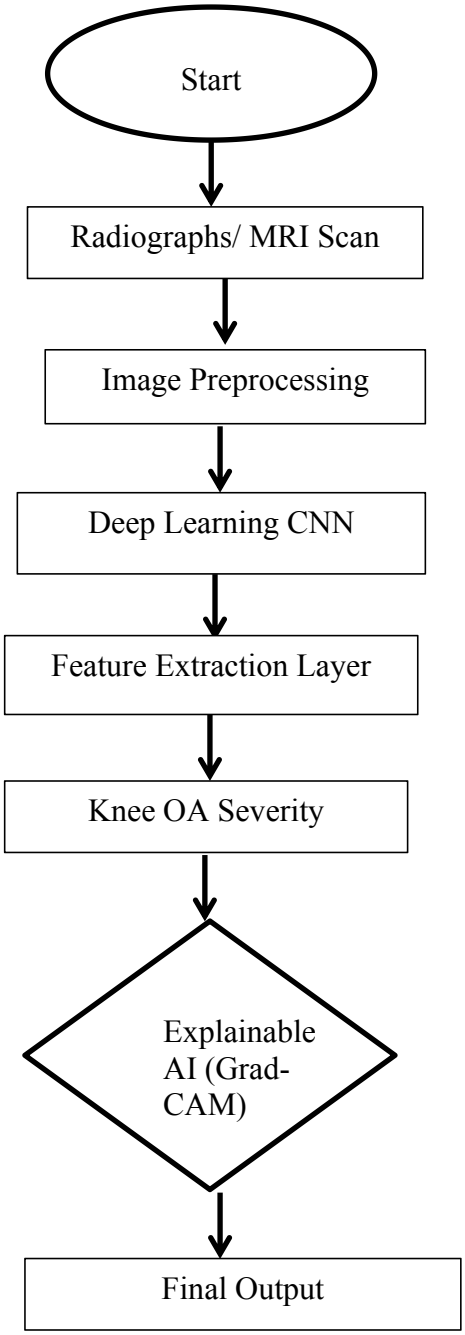


Figure 3.2 Flow chart of the Proposed system

3.2 Data Collection and Preprocessing

The data collection and preprocessing stage provides the foundation for the proposed framework by ensuring that high-quality medical images are used for model development. Knee radiographs (X-ray images) and MRI scans were collected from publicly available osteoarthritis datasets containing Normal and Osteoarthritis (OA) cases. Radiographs capture bone-related abnormalities, while MRI scans provide detailed visualization of soft tissue structures associated with osteoarthritis. Since the images were obtained from different sources, they exhibited variations in quality, resolution, brightness, and noise. To improve consistency, preprocessing techniques including image resizing, normalization, noise reduction, and data augmentation were applied. These processes enhanced image quality, standardized the dataset, and increased its diversity. The processed images were then labelled as Normal or Osteoarthritis and partitioned into training, validation, and testing datasets. This preparation enabled the model to learn effectively, improve generalization, reduce overfitting, and achieve reliable classification performance.

3.2.1 Data Source

The dataset used in this study was obtained from Kaggle and consists of knee radiographs (X-ray images) and MRI scans representing Normal and Osteoarthritis (OA) cases. The images capture important structural features associated with osteoarthritis, including cartilage degeneration, joint space narrowing, osteophyte formation, subchondral bone changes, bone marrow lesions, meniscal damage, and synovitis. To ensure consistency and improve model performance, all images undergo preprocessing, including resizing, normalization, noise reduction, and data augmentation techniques such as rotation, flipping, zooming, translation, and brightness adjustment. The processed images are then labelled into the two diagnostic classes, Normal and Osteoarthritis (OA), and partitioned into training, validation, and testing datasets to facilitate effective model learning, improve generalization, reduce overfitting, and support accurate diagnosis with explainable predictions using Grad-CAM

3.2.2 Data Acquisition Procedure and Parameters

Data Acquisition

The data acquisition procedure involved obtaining a publicly available knee osteoarthritis (OA) dataset from the Kaggle repository containing knee radiographs (X-ray images) and MRI scans of both Normal and Osteoarthritis (OA) cases. The dataset was selected because it provides high-quality medical images suitable for developing and evaluating a deep learning model for OA diagnosis. After downloading the dataset, all images were inspected to identify and remove duplicated, incomplete, corrupted, blurred, or low-quality images to ensure the reliability of the data. The remaining images were then organized into two diagnostic classes, Normal and Osteoarthritis (OA), based on the provided labels. The images were stored in separate directories for each class to support efficient preprocessing, training, validation, and testing. Following dataset organization, the images proceeded to the preprocessing stage, where they were standardized and enhanced before being used by the proposed deep learning model for feature extraction, classification, and explainable diagnosis using Grad-CAM.

Data Acquisition Parameters

The data acquisition parameters define the configuration used to prepare the dataset for the proposed explainable deep learning framework. The dataset, obtained from Kaggle, consists of knee radiographs (X-ray images) and MRI scans representing Normal and Osteoarthritis (OA) cases. All images were resized to 224 × 224 pixels and normalized to ensure consistent input and improve model training. Noise reduction was applied to minimize imaging artifacts while preserving important anatomical structures, and data augmentation techniques, including rotation, horizontal flipping, zooming, translation, and brightness adjustment, were used to increase dataset diversity and reduce overfitting. The dataset was evaluated using three experimental data partitions of 80:20, 75:25, and 70:30 to assess the robustness of the proposed model under different training and testing distributions. The CNN model was trained using the Adam optimizer with a learning rate of 0.001, a batch size of 32, and 20 epochs. Model performance was evaluated using accuracy, precision, recall, F1-score, confusion matrix, and ROC-AUC, while Grad-CAM was employed to generate visual explanations that highlight the image regions influencing the model's predictions, thereby improving the interpretability and clinical reliability of the diagnostic system.

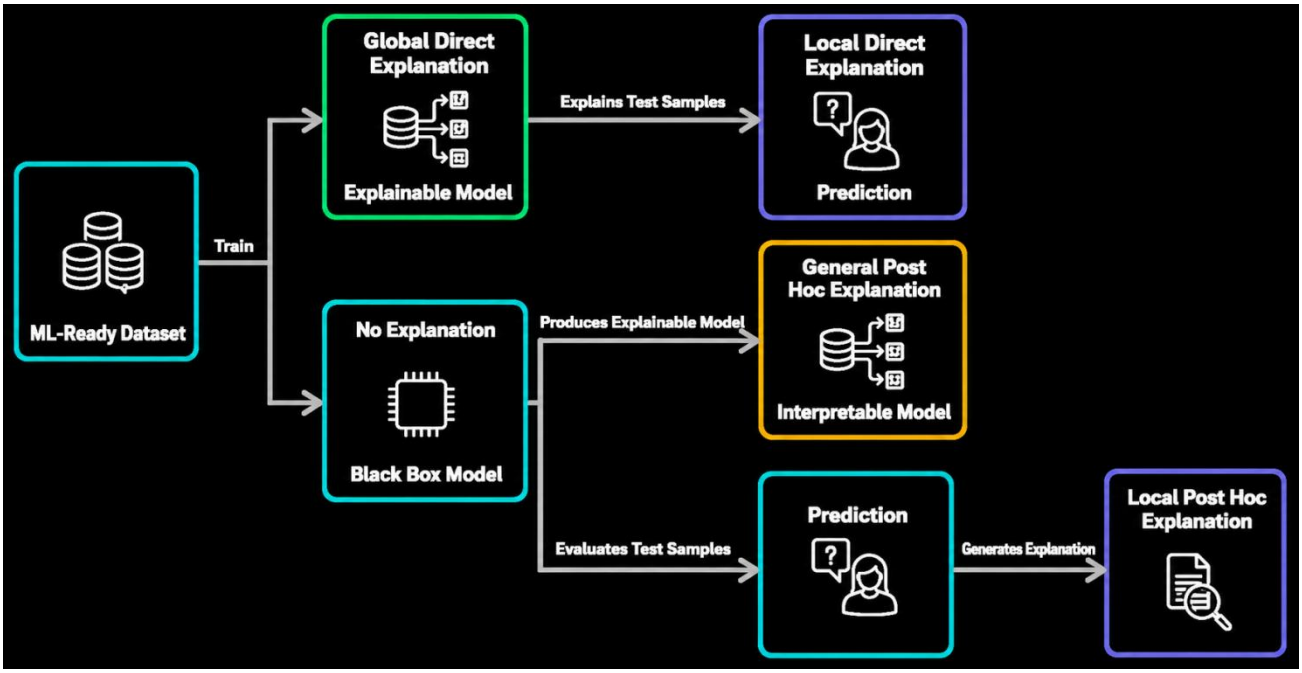


Figure 3.3 shows the model representation of the Explainable Artificial Intelligence (XAI) framework

Source:Explainable Artificial Intelligence (XAI): Concepts, Taxonomies, Opportunities and Challenges toward Responsible AI (a survey paper) https://christophm.github.io/interpretable-ml-book/

3.2.3 Data preprocessing

Data preprocessing is a crucial stage in the proposed Explainable Artificial Intelligence (XAI) framework because it improves the quality and consistency of the knee radiographs (X-ray images) and MRI scans used for diagnosis. As the images were obtained from different imaging equipment and healthcare facilities, they exhibited variations in size, brightness, contrast, orientation, and noise levels. To address these inconsistencies, preprocessing techniques including image resizing, normalization, and noise reduction were applied to standardize the images while preserving important anatomical structures relevant to osteoarthritis diagnosis.

3.2.4 Data Cleaning

Data cleaning is an essential stage in the proposed methodology because it ensures that only high-quality and reliable medical images are used for the diagnosis of knee osteoarthritis. The radiographs (X-ray images) and MRI scans obtained from the Kaggle dataset were carefully examined to identify inconsistencies that could affect the performance of the proposed Explainable Artificial Intelligence (XAI) framework. As the images were collected from different imaging sources, variations in image quality, duplicated records, incomplete files, and imaging artifacts were expected. A systematic cleaning process was therefore performed to improve the overall quality, consistency, and reliability of the dataset before preprocessing and model development.

3.2.5 Data Normalization and Noise Reduction

Data cleaning is an essential stage in the proposed methodology because it ensures that only high-quality and reliable medical images are used for the diagnosis of knee osteoarthritis. The radiographs (X-ray images) and MRI scans obtained from the Kaggle dataset were carefully examined to identify inconsistencies that could affect the performance of the proposed Explainable Artificial Intelligence (XAI) framework. As the images were collected from different imaging sources, variations in image quality, duplicated records, incomplete files, and imaging artifacts were expected. A systematic cleaning process was therefore performed to improve the overall quality, consistency, and reliability of the dataset before preprocessing and model development.

Data Normalization

Data normalization was performed to standardize the pixel intensity values of the radiographs (X-ray images) and Magnetic Resonance Imaging (MRI) scans before they were analyzed by the proposed Explainable Artificial Intelligence (XAI) framework. Since the images were obtained from different imaging devices and healthcare institutions, they exhibited variations in brightness, contrast, and intensity caused by differences in acquisition protocols and scanner settings. These inconsistencies could affect the identification of structural abnormalities associated with osteoarthritis. Therefore, normalization was carried out to ensure that all images had a consistent intensity range while preserving important anatomical information required for accurate diagnosis.In this study, pixel intensity values were normalized by scaling them to a

common range between 0 and 1 through division by 255, the maximum pixel value of an 8-bit grayscale image. This process minimized variations in image intensity while preserving clinically important structures such as cartilage, joint spaces, osteophytes, subchondral bone, menisci, synovial tissues, and bone marrow lesions. As a result, the structural characteristics of normal and osteoarthritic knees became more consistent across the dataset, making it easier for the proposed framework to identify relevant imaging patterns.

Noise Reduction

Noise reduction was performed to improve the quality of the radiographs (X-ray images) and Magnetic Resonance Imaging (MRI) scans before analysis by the proposed Explainable Artificial Intelligence (XAI) framework. Medical images obtained from different healthcare facilities and imaging devices often contain unwanted noise caused by variations in image acquisition, patient movement, or scanner settings. Such noise can reduce image clarity and obscure important anatomical structures associated with knee osteoarthritis. Therefore, image smoothing and filtering techniques were applied to remove unwanted artifacts while preserving clinically important features such as cartilage, joint spaces, osteophytes, subchondral bone, menisci, synovial tissues, and bone marrow lesions. Care was taken to preserve image edges and fine structural details to ensure that subtle pathological changes were not lost during preprocessing.

3.3 Proposed Model Training Algorithm and Implemetation

3.3.1 Model Training

Model training is the stage where the proposed Explainable Artificial Intelligence (XAI) framework learns to identify structural features associated with knee osteoarthritis from radiographs (X-ray images) and Magnetic Resonance Imaging (MRI) scans. After data collection and preprocessing, the cleaned and normalized images were partitioned into training, validation, and testing datasets. The training dataset was used to enable the model to learn the relationship between structural abnormalities in the knee joint and the corresponding class labels (Normal and Osteoarthritis). The validation dataset was used to monitor the learning process, optimize model parameters, and reduce the risk of overfitting, while the testing dataset was reserved for evaluating the final performance of the trained model using previously unseen images.

3.3.2 Algorithm

The proposed diagnostic system combines a Convolutional Neural Network (CNN) with Explainable Artificial Intelligence (XAI) using the Grad-CAM technique to classify knee images as Normal or Osteoarthritis. The algorithm begins by receiving preprocessed radiographs (X-ray images) and MRI scans, which are resized, normalized, and enhanced before analysis. The CNN automatically extracts important structural features such as cartilage degeneration, joint space narrowing, osteophyte formation, subchondral bone changes, bone marrow lesions, meniscal damage, and synovitis. These features are processed through convolutional, pooling, and fully connected layers to classify each image into one of the two classes, with a Softmax activation function generating probability scores for the final prediction.

3.3.3 Model Implementation

Data Loading and Preparation

The implementation of the proposed Explainable Artificial Intelligence (XAI) framework began by loading the knee osteoarthritis dataset obtained from Kaggle into the Python environment. The dataset, consisting of radiographs (X-ray images) and MRI scans, was organized according to the Normal and Osteoarthritis class labels. Each image was correctly matched with its corresponding label before undergoing preprocessing, which included image resizing to 224 × 224 pixels, normalization of pixel values to the range of 0–1, noise reduction, and data augmentation

techniques such as rotation, horizontal flipping, zooming, and brightness adjustment. These preprocessing operations produced a standardized and high-quality dataset suitable for model training and analysis. By improving image consistency and preserving important anatomical structures such as cartilage, joint spaces, osteophytes, subchondral bone, menisci, synovial tissues, and bone marrow lesions, the implementation stage enhanced the model's ability to accurately distinguish between Normal and Osteoarthritis knee images while supporting reliable and interpretable predictions through the Explainable Artificial Intelligence framework.

Label Encoding

The dataset used in this research consisted of two classes: Normal and Osteoarthritis. Since deep learning models process numerical values rather than textual labels, the class labels were converted into numerical representations using label encoding, where Normal was assigned the value 0 and Osteoarthritis was assigned the value 1. This encoding process enabled the model to efficiently learn the relationship between the input medical images and their corresponding output classes during training, validation, and prediction, thereby improving the accuracy and consistency of the classification process.

The binary classification were encoded as follows:

Table 3.1 shows the label encoding for the binary classification

Severity Class	Encoded Value
Normal	0
Osteoarthritis	1

After label encoding, each radiograph and MRI scan was assigned its corresponding numerical label. These encoded labels served as the target variables during supervised learning, enabling the model to learn the relationship between structural abnormalities observed in the medical images and the corresponding class (Normal or Osteoarthritis). This process allowed the model to accurately distinguish between healthy knee joints and those affected by osteoarthritis during training, validation, and testing.

Data Splitting

To evaluate the robustness and generalization capability of the proposed Explainable Artificial Intelligence (XAI) framework, the dataset was divided into three different training and testing partitions: 80:20, 75:25, and 70:30. These partitioning strategies were adopted to investigate how different proportions of training and testing data influence the performance of the model in classifying knee osteoarthritis severity into Mild, Moderate, and Severe classes. For each partition, the training dataset was used to train the model, while the testing dataset was reserved exclusively for performance evaluation using unseen radiographs (X-ray images) and MRI scans. Comparing multiple dataset partitions provides a comprehensive assessment of the stability, reliability, and predictive capability of the proposed framework under different experimental conditions.

Table 3.2 Dataset Split Ratio

TRAINING	VALIDATION	TESTING
80%	10%	10%
70%	15%	15%
75%	10%	15%

1. In the 80:20 dataset partition, 80% of the radiographs (X-ray images) and MRI scans were used for training the proposed model, while the remaining 20% were used for testing and validation. The larger training dataset enabled the model to learn structural features associated with mild, moderate, and severe knee osteoarthritis more effectively, while the testing dataset was used to evaluate its performance on previously unseen images.
2. In the 75:25 dataset partition, 75% of the dataset was allocated for training, and 25% was reserved for testing and validation. This partition provided a balanced distribution between model learning and evaluation, allowing the proposed framework to learn important structural abnormalities while being assessed on a larger testing dataset.
3. In the 70:30 dataset partition, 70% of the radiographs and MRI scans were used for training, while 30% were used for testing and validation. This partition provided fewer training samples but a larger testing dataset, allowing a more rigorous evaluation of the model's ability to classify mild, moderate, and severe knee osteoarthritis on previously unseen images.

Dataset

The dataset used for this research was obtained from Kaggle and consisted of knee radiographs (X-ray images) and Magnetic Resonance Imaging (MRI) scans collected for the assessment of knee osteoarthritis severity. The images captured different structural abnormalities associated with knee pain, including cartilage degeneration, joint space narrowing, osteophyte formation, subchondral bone sclerosis, bone marrow lesions, meniscal damage, and synovitis. These imaging features formed the basis for automated severity classification within the proposed framework.

For this study, the dataset was organized into representing increasing levels of structural degeneration associated with knee osteoarthritis. Each image belonged to only one severity category, making the problem a multiclass image classification task. The dataset contained sufficient variations in anatomical appearance, imaging quality, and disease severity to enable the model to learn meaningful representations of structural abnormalities linked to knee pain.

The use of both radiographs and MRI scans provided complementary diagnostic information. While radiographs primarily captured bone-related structural changes such as osteophytes and joint space narrowing, MRI scans provided detailed visualization of soft tissues, including cartilage, menisci, synovial membranes, and bone marrow lesions. This multimodal dataset enhanced the ability of the proposed Explainable Artificial Intelligence framework to identify clinically relevant structural factors associated with knee pain severity.

Training Details

The training process for the proposed Explainable Artificial Intelligence framework for knee osteoarthritis binary classification involved the following:

1. **Dataset:** The knee osteoarthritis dataset was obtained from Kaggle and consisted of Radiographs (X-ray images) and Magnetic Resonance Imaging (MRI) scans. The dataset contained images representing binary classification (Normal and Osteoarthritis). These images captured important structural abnormalities associated with knee pain, including cartilage degeneration, joint space narrowing, osteophyte formation, subchondral bone changes, bone marrow lesions, meniscal damage, and synovitis.
2. **Dataset Partitioning:** The dataset was evaluated using three different partitioning strategies to determine the effect of different training and testing ratios on model performance.

    i. Split the dataset into training (80%) , validation(10%) and testing (10%) subsets.
    ii. Split the dataset into training (75%), validation (15%) and testing (10%) subsets.
    iii. Split the dataset into training (70%), validation (15%) and testing (15%) subsets.

3. **Image Preprocessing:** Before training, all radiographs and MRI scans were resized to 224 × 224 pixels, normalized by scaling pixel values to the range of 0–1, cleaned to remove corrupted or duplicate images, and enhanced using noise reduction techniques. Data augmentation techniques such as rotation, horizontal flipping, zooming, and brightness adjustment were also applied to increase dataset diversity and improve model generalization.

4. **Deep Learning Model:** A Convolutional Neural Network (CNN) was employed as the feature extraction and classification model. The CNN automatically learned hierarchical imaging features from radiographs and MRI scans and classified each image into one of the binary classes (Normal and Osteoathritis).
5. **Loss Function:** The Binary Cross-Entropy loss function was used because the proposed study involves a binary classification problem consisting of two classes: Normal and Osteoarthritis.
6. **Optimizer:** The Adam optimizer was used to update the network weights during training because of its efficient convergence and adaptive learning capability.
7. **Training Parameters:** The model was trained for 20 epochs using a batch size of 32. During each epoch, the CNN processed batches of radiographs and MRI scans, calculated the prediction error using the binary cross-entropy loss function, and updated its weights to improve classification accuracy.
8. **Explainable Artificial Intelligence (XAI):** After classification, the Gradient-weighted Class Activation Mapping (Grad-CAM) technique was applied to generate heatmaps highlighting the regions of the radiographs and MRI scans that contributed most to the prediction. These visual explanations improved the transparency and interpretability of the proposed diagnostic framework by enabling clinicians to understand the structural factors responsible for classifying knee osteoarthritis into Normal and Osteoarthritis categories.

3.4 Model Explainability Features

The proposed framework incorporates Explainable Artificial Intelligence (XAI) to improve the transparency and interpretability of the deep learning model used for diagnosing knee osteoarthritis severity. Unlike conventional deep learning models that operate as black-box systems, the explainability component enables clinicians to understand the reasoning behind each prediction by identifying the structural features that influenced the model's decision. This increases confidence in the diagnostic results and supports informed clinical decision-making.

1. **Grad-CAM Heatmap Visualization:** The proposed model uses Gradient-weighted Class Activation Mapping (Grad-CAM) to generate heatmaps that highlight the regions of radiographs (X-ray images) and MRI scans that contribute most to the predicted knee osteoarthritis severity. These heatmaps visually indicate important anatomical structures,

allowing clinicians to verify whether the model focuses on medically relevant areas of the knee joint.

2. **Identification of Structural Features:** The explainability framework identifies the structural abnormalities associated with knee pain and osteoarthritis severity. These include cartilage degeneration, joint space narrowing, osteophyte formation, subchondral bone changes, bone marrow lesions, meniscal damage, and synovitis. Highlighting these features enables clinicians to understand the pathological basis of the model's predictions.
3. **Severity Classification Explanation:** For every prediction, the model provides not only the final severity class (Mild, Moderate, or Severe) but also explains why that particular class was assigned. The highlighted image regions correspond to the structural abnormalities responsible for the classification, making the diagnostic process more transparent and clinically meaningful.
4. **Prediction Confidence Score:** The framework generates a probability score for each severity class, indicating the confidence level of the model's prediction. The class with the highest probability is selected as the final diagnosis, while the remaining probabilities provide additional insight into the certainty of the classification.
5. **Clinical Interpretability:** The explainability component enables clinicians to compare the highlighted anatomical regions with their own medical interpretation of the radiographs and MRI scans. This helps validate the model's predictions, improves trust in the AI system, and supports more reliable diagnosis of knee osteoarthritis severity.
6. **Improved Decision Support:** By combining severity classification, Grad-CAM heatmaps, and prediction confidence scores, the proposed Explainable Artificial Intelligence framework provides a comprehensive decision-support tool for diagnosing knee osteoarthritis. The visual explanations assist healthcare professionals in understanding the structural factors associated with knee pain while enhancing the transparency, reliability, and clinical acceptance of the proposed diagnostic system.

Performance Evaluation Metrics

The performance of the proposed Explainable Artificial Intelligence (XAI) framework was evaluated using several standard classification metrics. These metrics were selected to comprehensively assess the ability of the model to accurately classify knee osteoarthritis severity

into the three classes: Mild, Moderate, and Severe. The evaluation metrics also provide insight into the reliability, robustness, and generalization capability of the proposed framework.

1. **Accuracy:** Accuracy measures the overall proportion of correctly classified knee osteoarthritis images out of the total number of images evaluated. It indicates how well the proposed model distinguishes between the three severity classes. A higher accuracy value indicates better classification performance.

$$\text{Formula} = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + FalsePositive + False\ Negative}$$

2. **Precision:** Precision measures the proportion of correctly predicted images belonging to a particular severity class out of all images predicted as that class. It evaluates the model's ability to minimize false positive classifications for Mild, Moderate, and Severe knee osteoarthritis.

$$\text{Formula} = \frac{True\ Positive}{True\ Positive + False\ Postive}$$

3. **Recall (Sensitivity):** Recall, also known as sensitivity, measures the proportion of actual images belonging to a severity class that were correctly identified by the model. It evaluates the model's ability to detect all true cases of Mild, Moderate, and Severe knee osteoarthritis.

$$\text{Formula} = \frac{True\ Positive}{True\ Postive + False\ Negative}$$

4. **F1-Score:** The F1-score is the harmonic mean of precision and recall. It provides a balanced evaluation of the model, particularly when the dataset contains class imbalance. A higher F1-score indicates better overall classification performance.

$$\text{Formula} = 2 * \frac{Precision * Recall}{Precision + Recall}$$

9. **Confusion Matrix:** The confusion matrix provides a detailed summary of the classification results by comparing the actual severity classes with the predicted two classes. It shows the number of correctly and incorrectly classified images for Normal and Osteoarthritis, allowing the identification of classes that are frequently misclassified.

$$\text{Formula} = \begin{pmatrix} True\ postive & Fasle\ postive \\ False\ negative & True\ Negative \end{pmatrix}$$

10. **Classification Report:** The classification report summarizes the performance of the proposed model by presenting the precision, recall, F1-score, and support for each of the two classes (Normal and Osteoarthritis.). It also includes the overall accuracy, macro average, and weighted average, providing a comprehensive assessment of the model's classification performance.

5. **Receiver Operating Characteristic (ROC) Curve and Area Under the Curve (AUC):** The Receiver Operating Characteristic (ROC) curve evaluates the ability of the proposed model to distinguish between the three knee osteoarthritis severity classes. Since this is a multiclass classification problem, a one-versus-rest (OvR) approach is used to generate ROC curves for each class. The Area Under the Curve (AUC) measures the model's discriminative capability, where values closer to 1.0 indicate excellent classification performance.

11. **Explainability Evaluation (Grad-CAM):** In addition to the classification metrics, the proposed framework was evaluated using Gradient-weighted Class Activation Mapping (Grad-CAM). Grad-CAM generates heatmaps that highlight the regions of the radiographs and MRI scans responsible for the model's predictions. These visual explanations enable clinicians to verify that the model focuses on clinically relevant structural abnormalities such as cartilage degeneration, joint space narrowing, osteophytes, bone marrow lesions, meniscal damage, and synovitis when classifying knee osteoarthritis into Normal and Osteoarthritis categories.

3.5 Summary of the Chapter

This chapter presented the research methodology adopted for developing the proposed Explainable Artificial Intelligence (XAI) framework for diagnosing knee osteoarthritis severity using radiographs (X-ray images) and Magnetic Resonance Imaging (MRI) scans. The chapter described the overall research design, data source, data acquisition procedure, dataset description, and the preprocessing techniques employed to prepare the medical images for analysis. These preprocessing techniques included data cleaning, image resizing, normalization, noise reduction, and data augmentation, all of which were carried out to improve image quality and ensure consistency throughout the dataset. The chapter also described the dataset partitioning strategies of 80:20, 75:25, and 70:30, which were used to evaluate the robustness and generalization capability of the proposed framework.

Furthermore, the chapter explained the implementation of the proposed system, including data loading and preparation, label encoding, model training, algorithm design, and training details. A Convolutional Neural Network (CNN) was employed to automatically extract structural features associated with knee osteoarthritis, while the Explainable Artificial Intelligence component based on Gradient-weighted Class Activation Mapping (Grad-CAM) was integrated to provide visual explanations of the model's predictions. The proposed framework classified knee osteoarthritis into two classes: Normal and Osteoarthritis, while simultaneously highlighting the anatomical regions responsible for each prediction, thereby improving transparency and clinical interpretability.

Finally, the chapter presented the performance evaluation metrics used to assess the effectiveness of the proposed framework. These included accuracy, precision, recall, F1-score, confusion matrix, classification report, ROC-AUC, and Grad-CAM explainability analysis. Together, these evaluation measures provide a comprehensive assessment of the model's classification performance, reliability, and interpretability. The methodology described in this chapter provides the foundation for the experimental results and discussion presented in the next chapter.

CHAPTER FOUR
SIMULTAION RESULT AND DISCUSSION

4.0 Introduction

This chapter presents the results obtained from the implementation and evaluation of the proposed Explainable Artificial Intelligence (XAI) framework for the diagnosis of knee osteoarthritis using radiographs (X-ray images) and Magnetic Resonance Imaging (MRI) scans. The framework was developed to classify knee images into two categories: Normal and Osteoarthritis (OA), while providing visual explanations of the model's predictions using Gradient-weighted Class Activation Mapping (Grad-CAM). The objective of this evaluation is to determine the effectiveness, reliability, and interpretability of the proposed framework in identifying osteoarthritic changes from medical images.

The experimental evaluation was carried out using the publicly available knee osteoarthritis dataset obtained from Kaggle. To assess the robustness of the proposed model, three different dataset partitions (70:30, 75:25, and 80:20) were employed during training and testing. The

model performance was evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, confusion matrix, and Receiver Operating Characteristic–Area Under the Curve (ROC–AUC). These metrics provide a comprehensive assessment of the framework's ability to correctly distinguish between normal and osteoarthritic knee images.

In addition to evaluating classification performance, this chapter also presents the Grad-CAM visualizations generated by the Explainable Artificial Intelligence component. These heatmaps highlight the anatomical regions that contributed most to the model's predictions, enabling verification that the framework focuses on clinically relevant structures such as joint spaces, cartilage, osteophytes, and subchondral bone. The results obtained from the different dataset partitions are compared and discussed to determine the most effective configuration and to demonstrate the suitability of the proposed framework for supporting transparent and reliable computer-aided diagnosis of knee osteoarthritis.

4.1 Simulation Results and Interpretation

The simulation ws done using three dfferent partition ratios, following this pattern {Training, Validation, Testing}. These ratios are referred to as simulation runs and are shown in Table 4.1 Below

Table 4.1 Partition ration for Three different Simulations

Simulation id	Training	Validation	Testion
Simulation Run 1: First Partition Ration	80	10	10
Simulation Run 1: Second Partition Ration	75	10	15
Simulation Run 1: Third Partition Ration	70	15	15

Figure 4.1 shows the Python 2D Model Architecture equivalent of Explainable AI model ratio

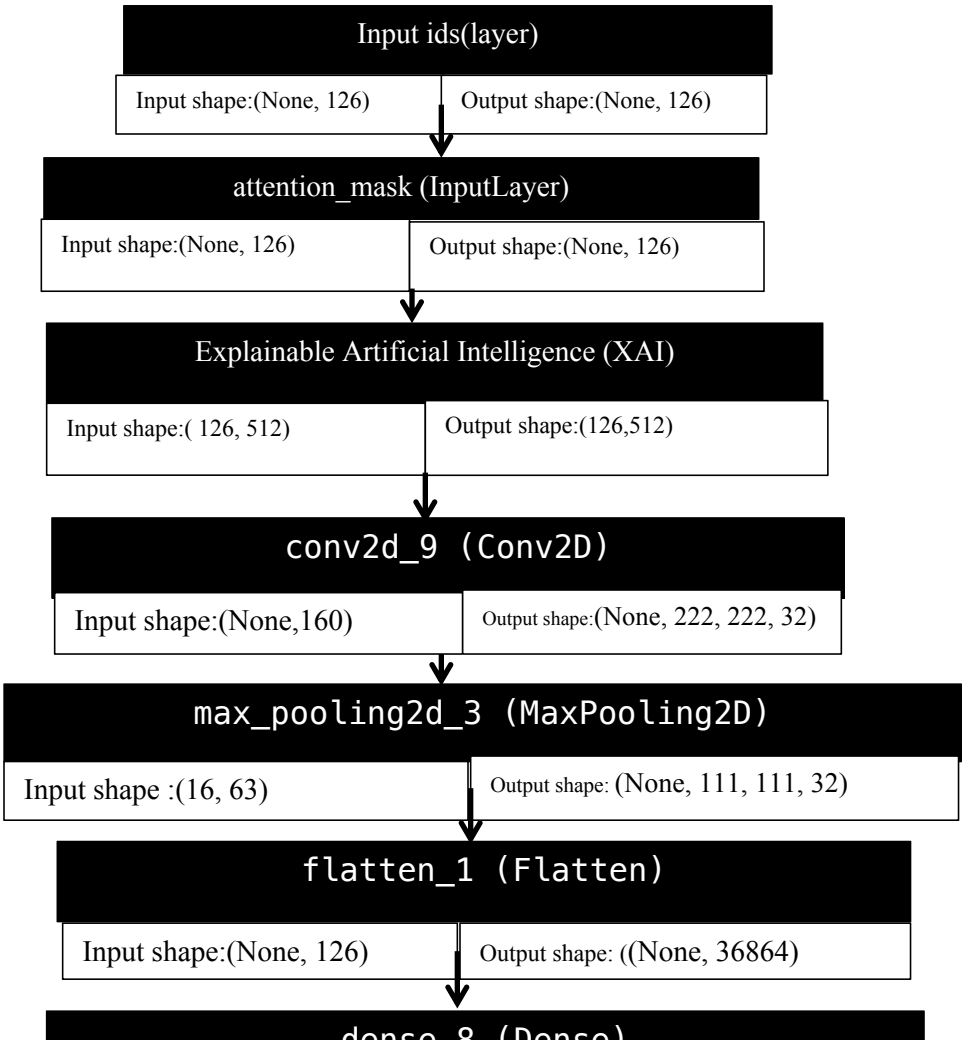
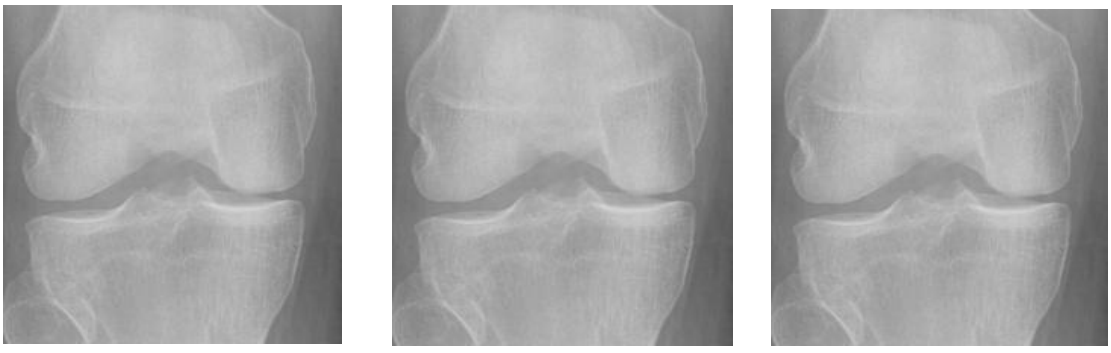


Figure 4.1 Proposed Python 2D Model Architecture (Explainable AI) Python Equivalent

4.2 Simulation Results for the First Partition Ration 80:10:10

Figure 4.2 depicts the screenshots of dataset sample respectively Normal and Osteoarthritis respectively

Sample 2 ration for 80:10:10 Normal



Sample 3 ration for 75:15:10 Osteoarthritis



Figure 4.2 Screenshots of dataset sample for Normal and Osteoarthritis respectively

These samples illustrate the visual distribution of the dataset

i. Training data shape :(512, 224, 224, 1)

ii. Validation data shape :(268, 224, 224, 1)

iii. Testing data shape: (126, 224, 224, 1)

The Training of the model is shown in Figure 4.1 is completed in 20 iterations(epoch) [as shown below:

Epoch 1/2059/59 ——————————————————— 52s 750ms/step - accuracy: 0.6329 - loss: 1.3672 - val_accuracy: 0.3432 - val_loss: 1.2854

Epoch 2/2059/59 ——————————————————— 42s 701ms/step - accuracy: 0.6510 - loss: 1.1288 - val_accuracy: 0.3432 - val_loss: 3.1191

Epoch 3/2059/59 ——————————————————— 42s 708ms/step - accuracy: 0.6679 - loss: 0.8304 - val_accuracy: 0.3432 - val_loss: 2.6880

Epoch 4/2059/59 ——————————————————— 42s 708ms/step - accuracy: 0.6621 - loss: 0.7975 - val_accuracy: 0.3432 - val_loss: 2.1691

Epoch 5/2059/59 ——————————————————— 44s 750ms/step - accuracy: 0.6886 - loss: 0.7456 - val_accuracy: 0.3475 - val_loss: 1.1434

Epoch 6/2059/59 ——————————————————— 42s 719ms/step - accuracy: 0.6817 - loss: 0.7110 - val_accuracy: 0.5466 - val_loss: 0.7852

Epoch 7/2059/59 ——————————————————— 81s 701ms/step - accuracy: 0.6796 - loss: 0.6772 - val_accuracy: 0.5466 - val_loss: 0.9011

Epoch 8/2059/59 ——————————————————— 41s 694ms/step - accuracy: 0.6827 - loss: 0.6494 - val_accuracy: 0.6144 - val_loss: 0.7036

Epoch 9/2059/59 ——————————————————— 41s 695ms/step - accuracy:
0.7113 - loss: 0.6016 - val_accuracy: 0.6483 - val_loss: 0.6956
Epoch 10/2059/59 ——————————————————— 41s 700ms/step - accuracy:
0.6933 - loss: 0.6052 - val_accuracy: 0.5932 - val_loss: 0.7042
Epoch 11/2059/59 ——————————————————— 41s 696ms/step - accuracy:
0.7240 - loss: 0.5455 - val_accuracy: 0.5572 - val_loss: 0.7008
Epoch 12/2059/59 ——————————————————— 41s 702ms/step - accuracy:
0.7272 - loss: 0.5450 - val_accuracy: 0.3983 - val_loss: 0.9358
Epoch 13/2059/59 ——————————————————— 83s 722ms/step - accuracy:
0.7097 - loss: 0.5490 - val_accuracy: 0.6653 - val_loss: 0.8181
Epoch 14/2059/59 ——————————————————— 80s 691ms/step - accuracy:
0.7203 - loss: 0.5483 - val_accuracy: 0.6504 - val_loss: 0.8652
Epoch 15/2059/59 ——————————————————— 40s 675ms/step - accuracy:
0.7219 - loss: 0.4973 - val_accuracy: 0.6504 - val_loss: 1.2798
Epoch 16/2059/59 ——————————————————— 40s 675ms/step - accuracy:
0.7331 - loss: 0.5094 - val_accuracy: 0.6589 - val_loss: 1.5273
Epoch 17/2059/59 ——————————————————— 41s 698ms/step - accuracy:
0.7235 - loss: 0.4937 - val_accuracy: 0.6483 - val_loss: 1.0088
Epoch 18/2059/59 ——————————————————— 41s 696ms/step - accuracy:
0.7389 - loss: 0.4762 - val_accuracy: 0.5191 - val_loss: 0.7074
Epoch 19/2059/59 ——————————————————— 39s 667ms/step - accuracy:
0.7669 - loss: 0.4512 - val_accuracy: 0.6653 - val_loss: 1.4514
Epoch 20/2059/59 ——————————————————— 40s 677ms/step - accuracy:
0.7564 - loss: 0.4706 - val_accuracy: 0.6907 - val_loss: 0.7157

Figure 4.3 shows the Confusion matrix generated after 20 training iteration while Figures 4.4-4.6 graphically illustrate the simulation results and training parameters respectively. From the above result, it can be deducted that AUC is 0.67 with 67% accuracy. The summary of the above result is shown in Table 4.2

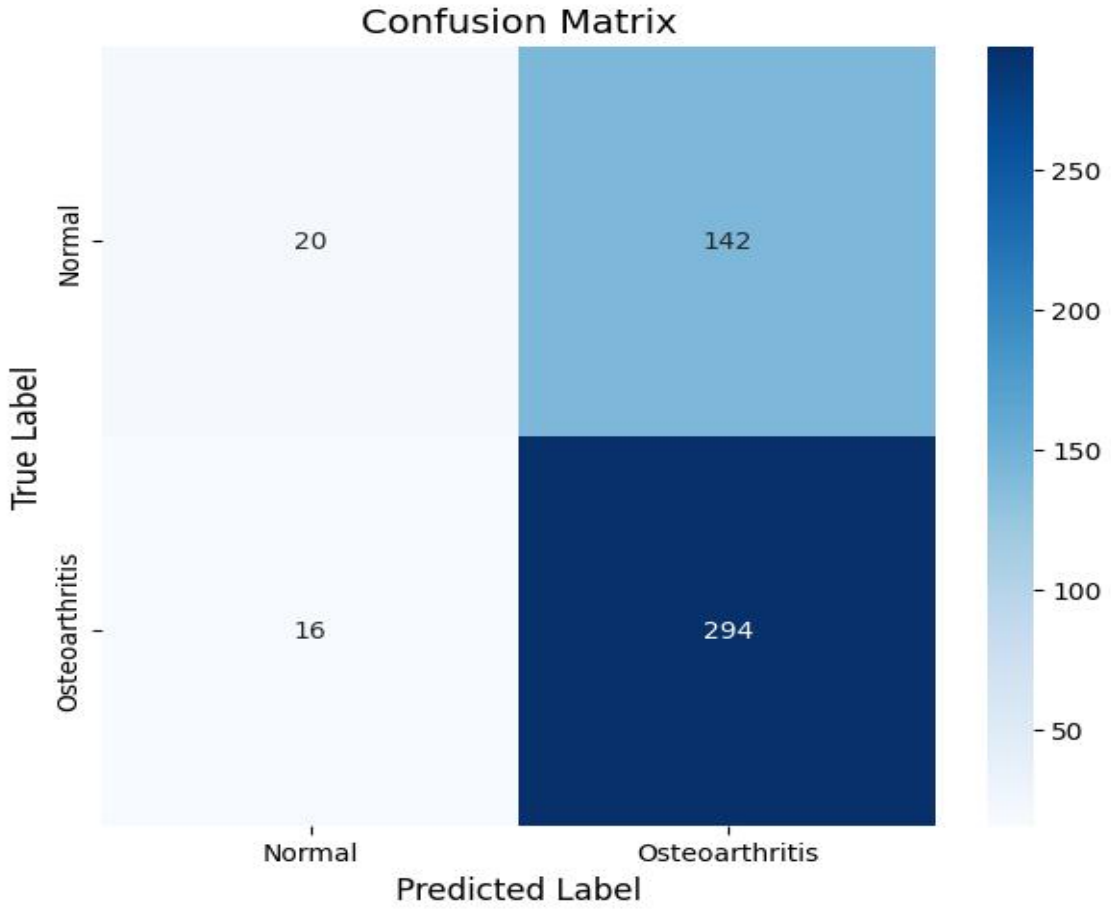


Figure 4.3: The Confusion matrix for the ratio 80:10:10

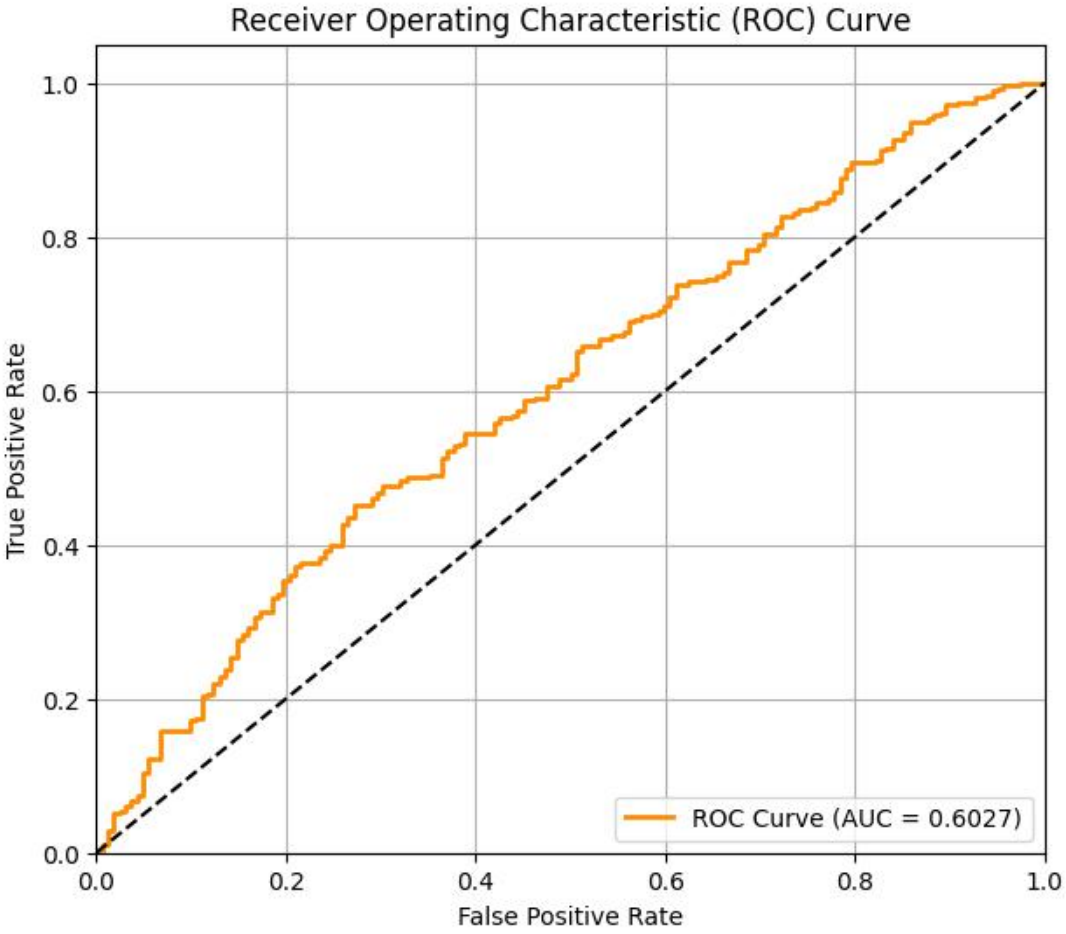


Figure 4.4: The ROC Curve for the ratio 80:10:10

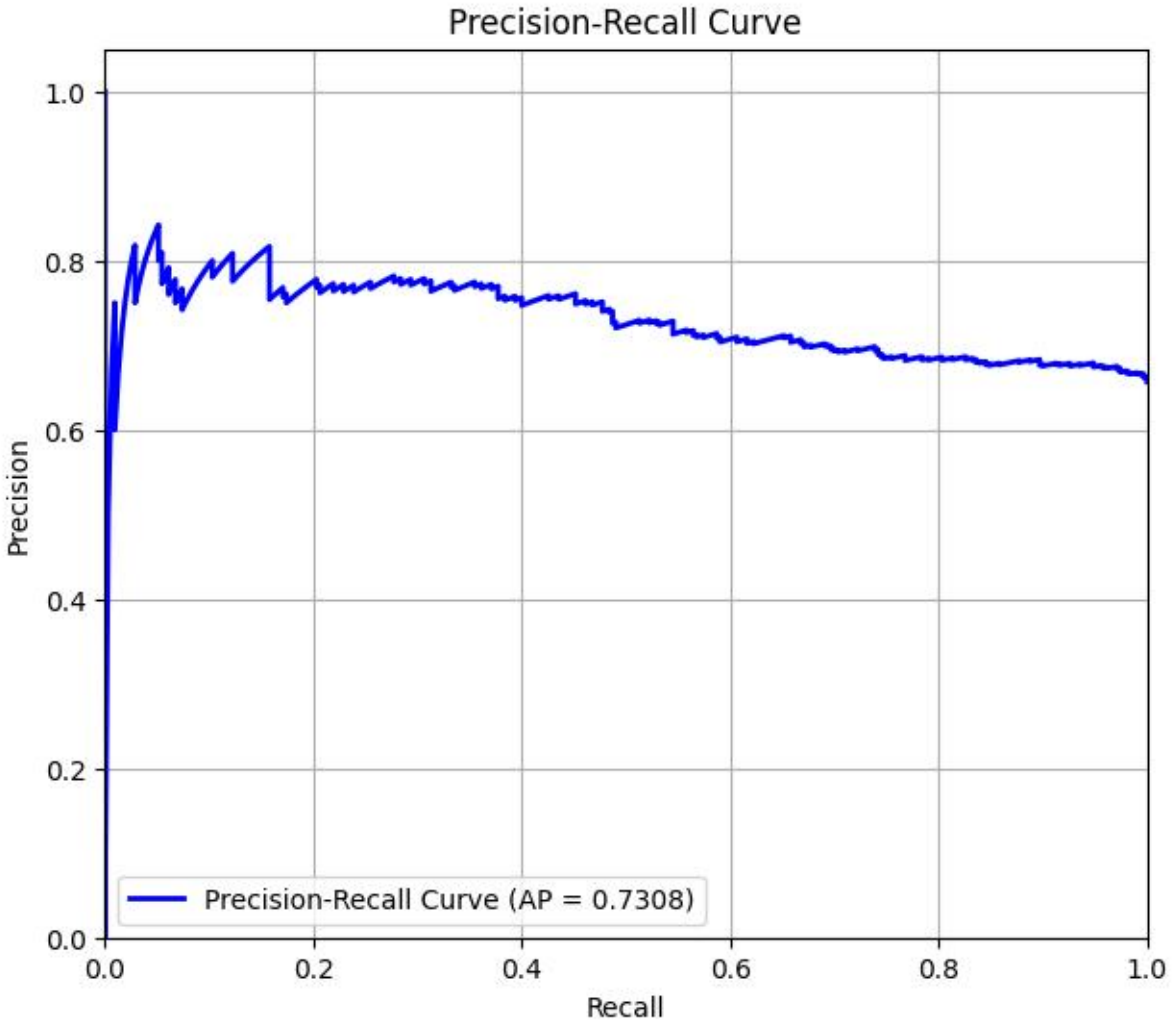


Figure 4.5: The Precison-Recall Curve for the raion 80:10:10

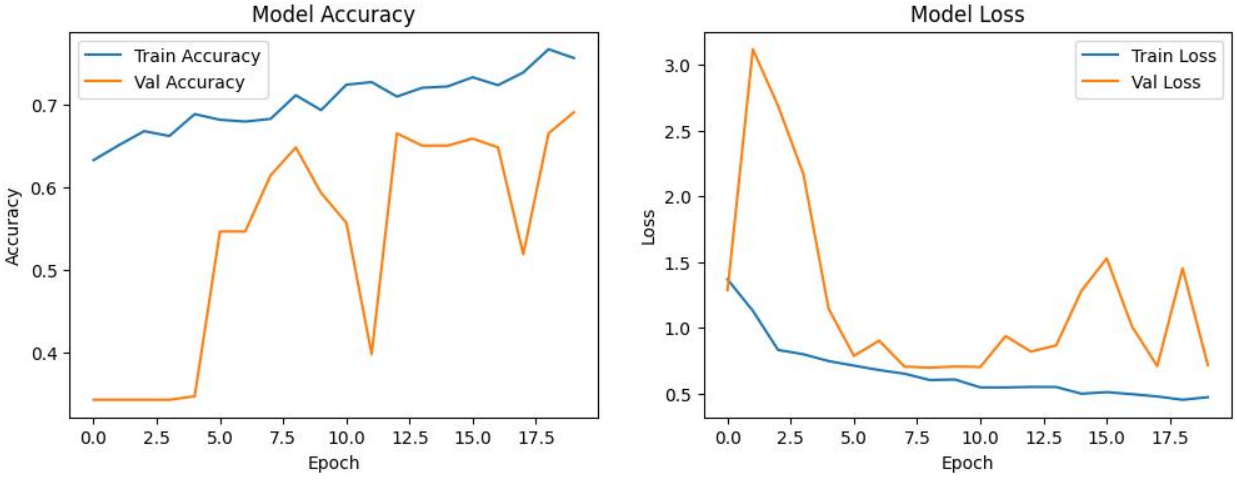


Figure 4.6: The Model accuracy and loss over epoch for the raion 80:10:10

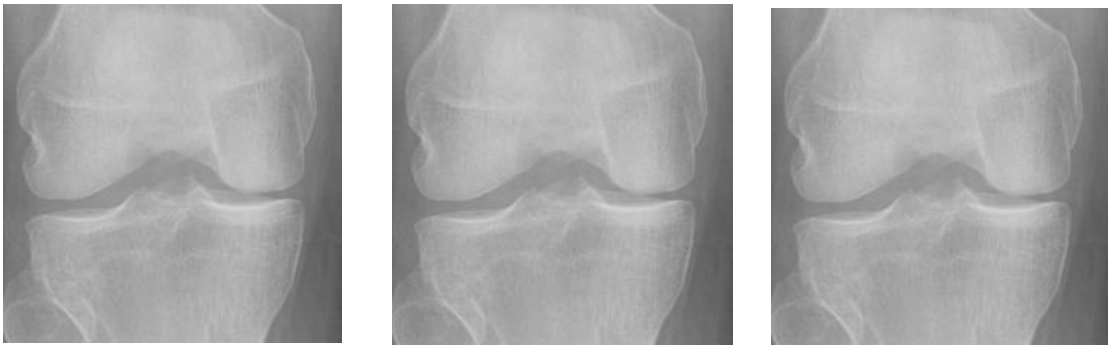
Table 4.2 Summary of Classification Report for the partition 1

Precision		Recall	F1-score	Support
Normal	0.56	0.12	0.20	162
Osteoathritis	0.67	0.95	0.78	310
Accuracy			0.67	472
Macro avg	0.61	0.54	0.80	472
Weighted avg	0.63	0.54	0.59	472

4.3 Simulation for the Second Partition Ratio 75:10:15

Figure 4.7 depicts the screenshots of dataset sample for Normal and Osteoarthritis respectively

Sample 2 ration for 75:10:15 Normal



Sample 3 ration for 75:10:15 Osteoarthritis



Figure 4.3 Screenshots of dataset sample for.

These samples illustrate the visual distribution of the dataset

i. Training data shape :(256, 224, 224, 1)
ii. Validation data shape :(128, 224, 224, 1)
iii. Testing data shape: (64, 224, 224, 1)

The Training of the model is shown in Figure 4.1 is completed in 20 iterations(epoch) as shown below:

Epoch 1/2056/56 ——————————————————————— 61s 931ms/step - accuracy: 0.6618 - loss: 1.3324 - val_accuracy: 0.3430 - val_loss: 2.9180

Epoch 2/2056/56 ——————————————————————— 44s 778ms/step - accuracy: 0.6736 - loss: 1.1216 - val_accuracy: 0.3430 - val_loss: 2.4419

Epoch 3/2056/56 ——————————————— 45s 800ms/step - accuracy:
0.6680 - loss: 0.9740 - val_accuracy: 0.3430 - val_loss: 1.4051
Epoch 4/2056/56 ——————————————— 46s 814ms/step - accuracy:
0.6640 - loss: 0.9075 - val_accuracy: 0.4958 - val_loss: 0.8689
Epoch 5/2056/56 ——————————————— 46s 782ms/step - accuracy:
0.6979 - loss: 0.7517 - val_accuracy: 0.3803 - val_loss: 0.9755
Epoch 6/2056/56 ——————————————— 44s 784ms/step - accuracy:
0.6883 - loss: 0.7015 - val_accuracy: 0.4669 - val_loss: 0.9294
Epoch 7/2056/56 ——————————————— 45s 795ms/step - accuracy:
0.6985 - loss: 0.6949 - val_accuracy: 0.3463 - val_loss: 1.8753
Epoch 8/2056/56 ——————————————— 45s 795ms/step - accuracy:
0.7205 - loss: 0.6291 - val_accuracy: 0.3463 - val_loss: 1.6084
Epoch 9/2056/56 ——————————————— 45s 806ms/step - accuracy:
0.7261 - loss: 0.5639 - val_accuracy: 0.6299 - val_loss: 0.7650
Epoch 10/2056/56 ——————————————— 46s 791ms/step - accuracy:
0.7278 - loss: 0.5549 - val_accuracy: 0.5297 - val_loss: 0.8041
Epoch 11/2056/56 ——————————————— 45s 803ms/step - accuracy:
0.7239 - loss: 0.5623 - val_accuracy: 0.4177 - val_loss: 0.8867
Epoch 12/2056/56 ——————————————— 55s 974ms/step - accuracy:
0.7188 - loss: 0.5182 - val_accuracy: 0.3854 - val_loss: 0.9394
Epoch 13/2056/56 ——————————————— 45s 801ms/step - accuracy:
0.7329 - loss: 0.5039 - val_accuracy: 0.5789 - val_loss: 1.0123
Epoch 14/2056/56 ——————————————— 45s 797ms/step - accuracy:
0.7408 - loss: 0.5114 - val_accuracy: 0.6129 - val_loss: 0.7163
Epoch 15/2056/56 ——————————————— 46s 822ms/step - accuracy:
0.7182 - loss: 0.5174 - val_accuracy: 0.6537 - val_loss: 0.7516
Epoch 16/2056/56 ——————————————— 47s 843ms/step - accuracy:
0.7273 - loss: 0.5071 - val_accuracy: 0.6655 - val_loss: 0.8653
Epoch 17/2056/56 ——————————————— 57s 1s/step - accuracy:
0.7408 - loss: 0.5065 - val_accuracy: 0.4228 - val_loss: 0.9040
Epoch 18/2056/56 ——————————————— 47s 834ms/step - accuracy:
0.7414 - loss: 0.4910 - val_accuracy: 0.5654 - val_loss: 0.7544

Epoch 19/2056/56 ——————————————————————— 46s 824ms/step - accuracy: 0.7595 - loss: 0.4579 - val_accuracy: 0.5518 - val_loss: 0.8125

Epoch 20/2056/56 ——————————————————————— 47s 838ms/step - accuracy: 0.7595 - loss: 0.4713 - val_accuracy: 0.5365 - val_loss: 0.7781

Figure 4.8 shows the Confusion matrix generated after 20 training iteration while Figures 4.9-4.11 graphically illustrate the simulation results and training parameters respectively. From the above result, it can be deducted that AUC is 0.52 with 52% accuracy. The summary of the above result is shown in Table 4.2

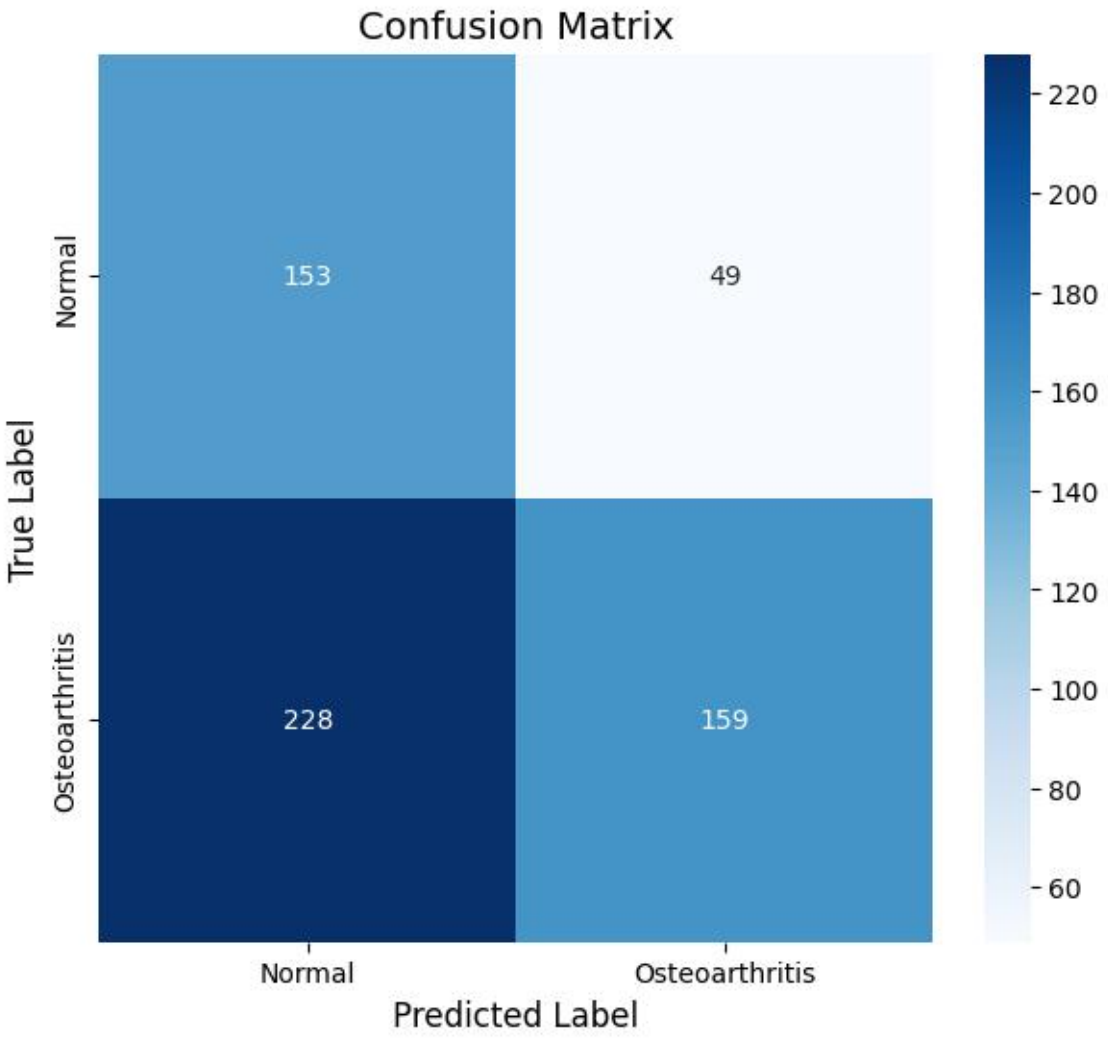


Figure 4.8: The Confusion matrix for the ration 75:10:15

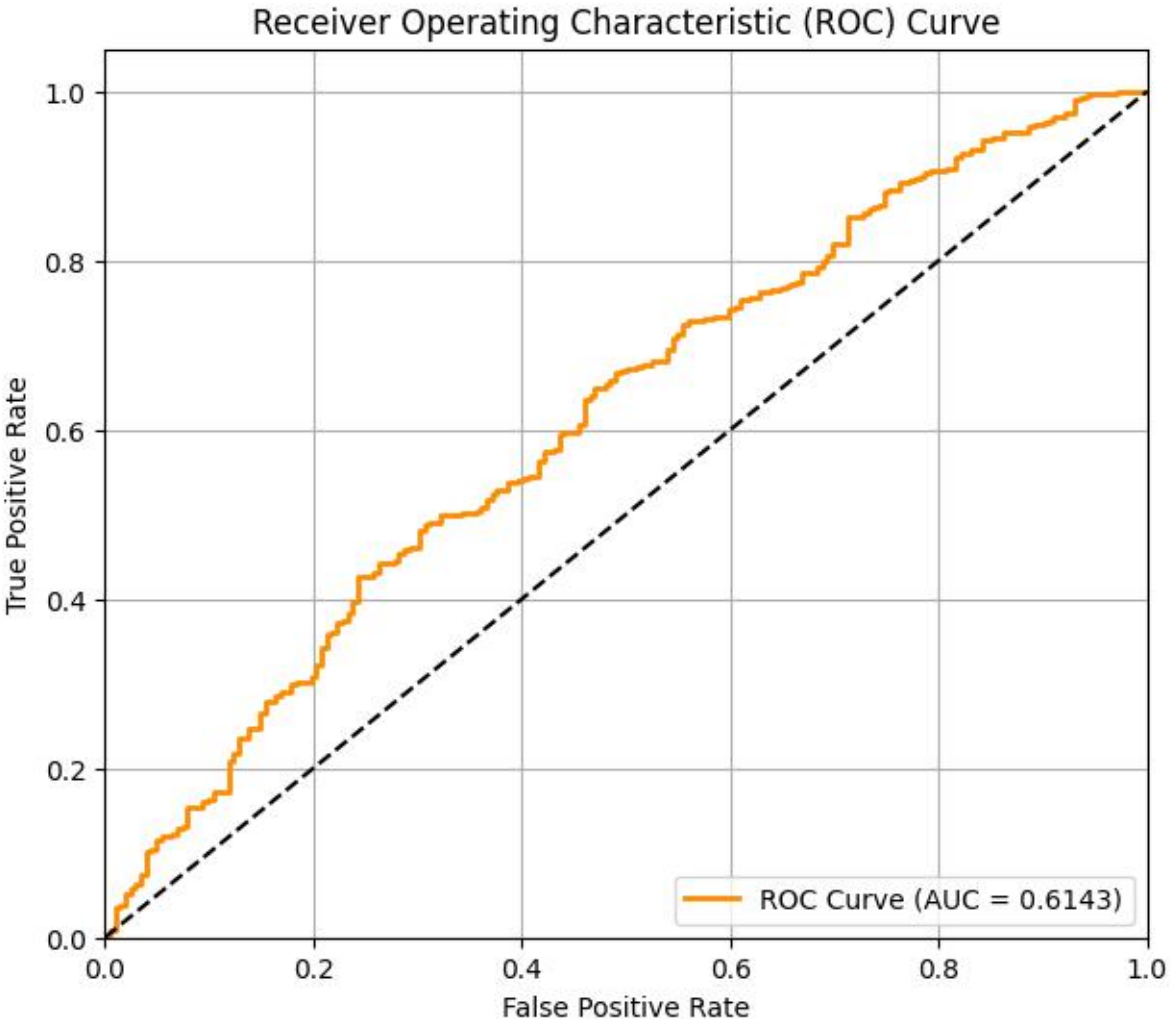


Figure 4.9: The ROC Curve of the ration 75:10:15

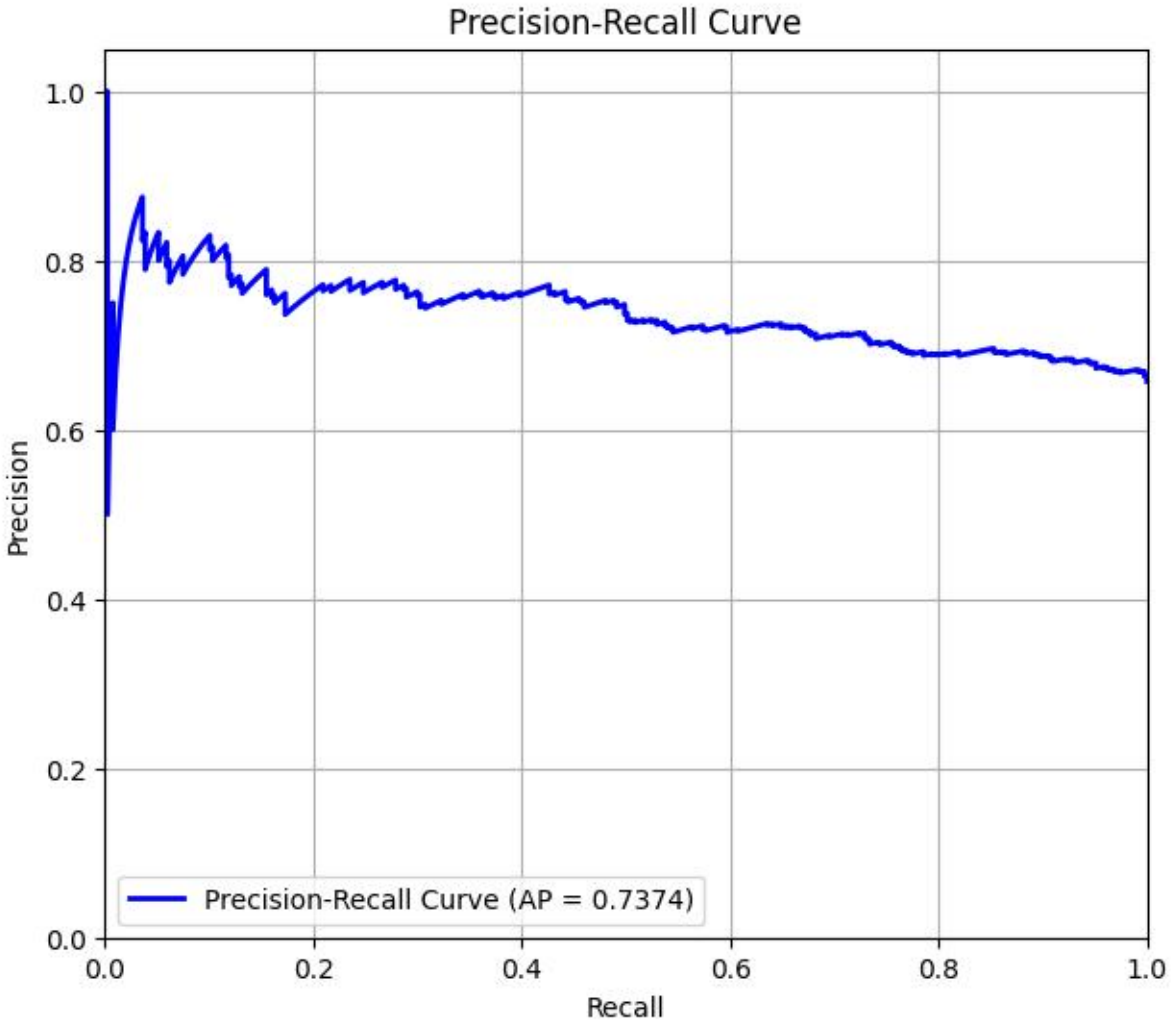


Figure 4.10 The Precision Recall Curve for the ration 75:10:15

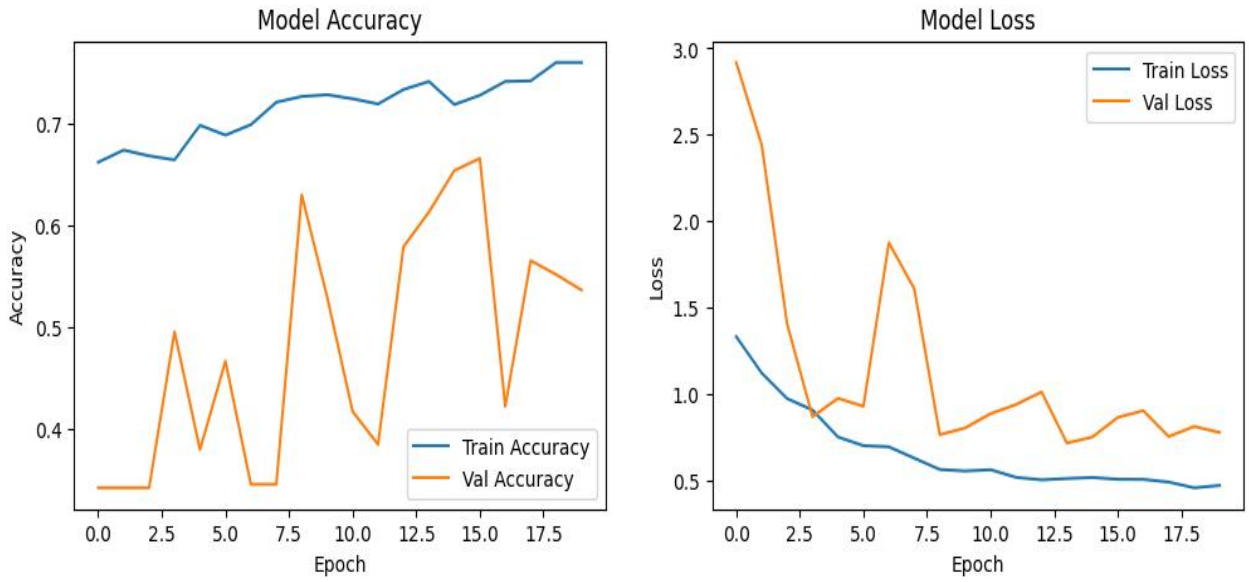


Figure 4.11 The model accuracy and loss over epoch for the ration 75:10:15

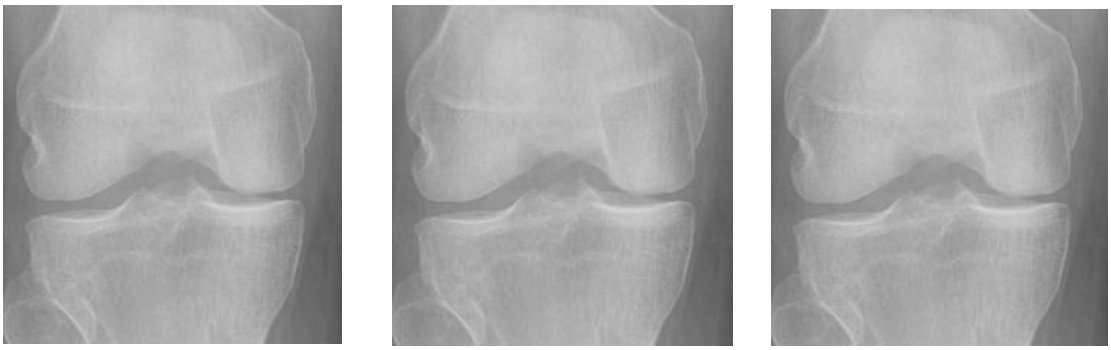
Table 4.3 Summary of Classification Report for the partition 2

Precision		Recall	F1-score	support
Normal	0.40	0.46	0.58	202
Osteoarthritis	0.41	0.35	0.38	387
Accuracy			0.53	589
Macro avg	0.58	0.58	0.53	589
Weighted avg	0.64	0.53	0.53	589

4.4 Simulation for the Second Partition Ratio 70:15:15

Figure 4.12 depicts the screenshots of dataset sample for Normal and Osteoarthritis respectively

Sample 2 ration for 70:15:15 Normal



Sample 3 ration for 70:15:15 Osteoarthritis



Figure 4.4 Screenshots of dataset sample for Normal and Osteoarthritis respectively

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These samples illustrate the visual distribution of the dataset

i. Training data shape :(627, 224, 224, 1)

ii. Validation data shape :(345, 224, 224, 1)

iii. Testing data shape: (128, 224, 224, 1)

The Training of the model was completed in 20 iterations(epoch) as shown below:

Epoch 1/2056/56 ——————————————— 677s 12s/step - accuracy: 0.6228 - loss: 1.4602 - val_accuracy: 0.3430 - val_loss: 2.7610

Epoch 2/2056/56 ——————————————— 40s 712ms/step - accuracy: 0.6437 - loss: 1.1513 - val_accuracy: 0.3430 - val_loss: 3.9434

Epoch 3/2056/56 ——————————————— 39s 705ms/step - accuracy: 0.6770 - loss: 0.8872 - val_accuracy: 0.3430 - val_loss: 5.5967

Epoch 4/2056/56 ——————————————— 39s 697ms/step - accuracy: 0.6561 - loss: 0.8513 - val_accuracy: 0.3430 - val_loss: 5.2917

Epoch 5/2056/56 ——————————————— 40s 712ms/step - accuracy: 0.6889 - loss: 0.7061 - val_accuracy: 0.3430 - val_loss: 4.0582

Epoch 6/2056/56 ——————————————— 40s 725ms/step - accuracy: 0.6855 - loss: 0.6945 - val_accuracy: 0.3430 - val_loss: 1.9960

Epoch 7/2056/56 ——————————————— 41s 742ms/step - accuracy: 0.6900 - loss: 0.6491 - val_accuracy: 0.4482 - val_loss: 1.0780

Epoch 8/2056/56 ——————————————— 41s 729ms/step - accuracy: 0.6849 - loss: 0.6089 - val_accuracy: 0.4007 - val_loss: 1.0584

Epoch 9/2056/56 ——————————————— 41s 733ms/step - accuracy: 0.7171 - loss: 0.6185 - val_accuracy: 0.3837 - val_loss: 1.1819

Epoch 10/2056/56 ——————————————— 41s 726ms/step - accuracy: 0.7092 - loss: 0.5561 - val_accuracy: 0.3599 - val_loss: 1.1630

Epoch 11/2056/56 ——————————————— 41s 731ms/step - accuracy: 0.7312 - loss: 0.5195 - val_accuracy: 0.4839 - val_loss: 0.7589

Epoch 12/2056/56 ——————————————— 43s 754ms/step - accuracy: 0.7041 - loss: 0.5652 - val_accuracy: 0.5331 - val_loss: 0.6849

Epoch 13/2056/56 ——————————————— 43s 755ms/step - accuracy: 0.7154 - loss: 0.5153 - val_accuracy: 0.5739 - val_loss: 0.6767

Epoch 14/2056/56 ——————————————— 42s 755ms/step - accuracy: 0.7086 - loss: 0.5207 - val_accuracy: 0.5008 - val_loss: 0.7466

Epoch 15/2056/56 ——————————————— 42s 755ms/step - accuracy: 0.7261 - loss: 0.5023 - val_accuracy: 0.4058 - val_loss: 1.0079

Epoch 16/2056/56 ——————————————————— 42s 762ms/step - accuracy: 0.7273 - loss: 0.5005 - val_accuracy: 0.6129 - val_loss: 0.7509

Epoch 17/2056/56 ——————————————————— 42s 748ms/step - accuracy: 0.7295 - loss: 0.4977 - val_accuracy: 0.6638 - val_loss: 1.6474

Epoch 18/2056/56 ——————————————————— 40s 715ms/step - accuracy: 0.7160 - loss: 0.4970 - val_accuracy: 0.6027 - val_loss: 0.7044

Epoch 19/2056/56 ——————————————————— 39s 701ms/step - accuracy: 0.7329 - loss: 0.4710 - val_accuracy: 0.3905 - val_loss: 1.0034

Epoch 20/2056/56 ——————————————————— 38s 680ms/step - accuracy: 0.7307 - loss: 0.4827 - val_accuracy: 0.5229 - val_loss: 0.6854

Figure 4.13 shows the Confusion matrix generated after 20 training iteration while Figures 4.14-4.15 graphically illustrate the simulation results and training parameters respectively. From the above result, it can be deducted that AUC is 0.52 with 52% accuracy. The summary of the above result is shown in Table

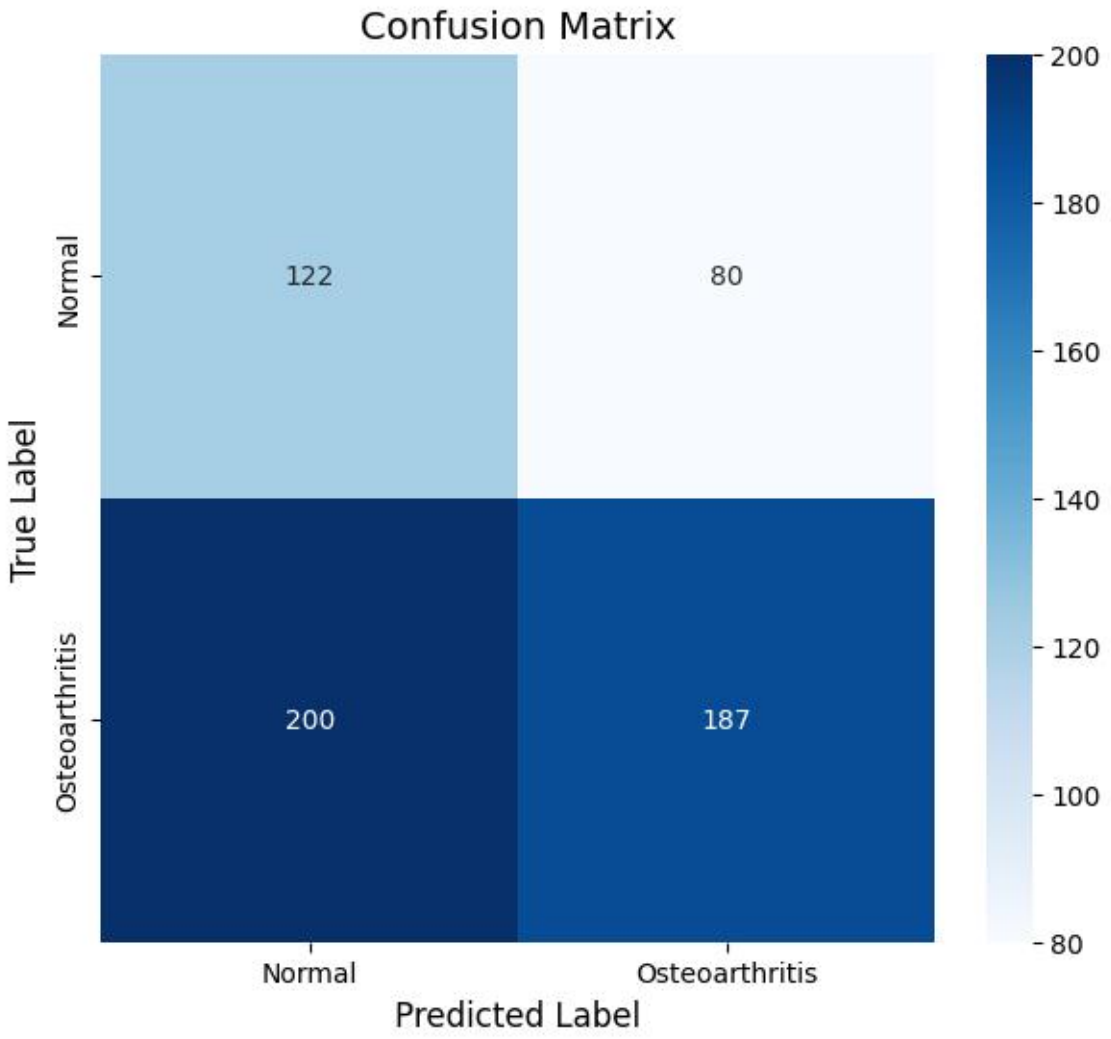


Figure 4.13: The Confusion matrix for the ration 70:15:15

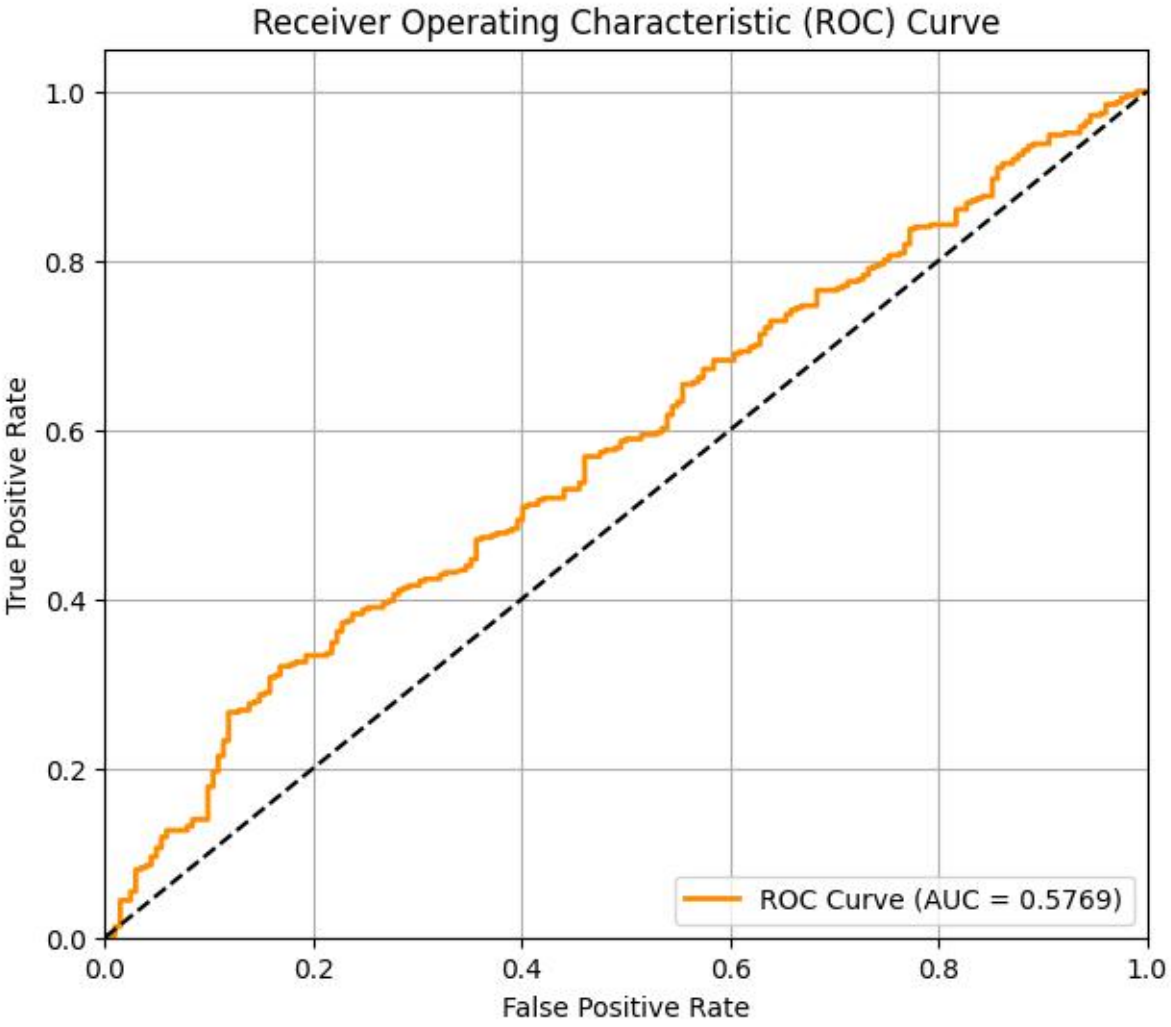


Figure 4.14 The ROC Curve for the ration 70:15:15

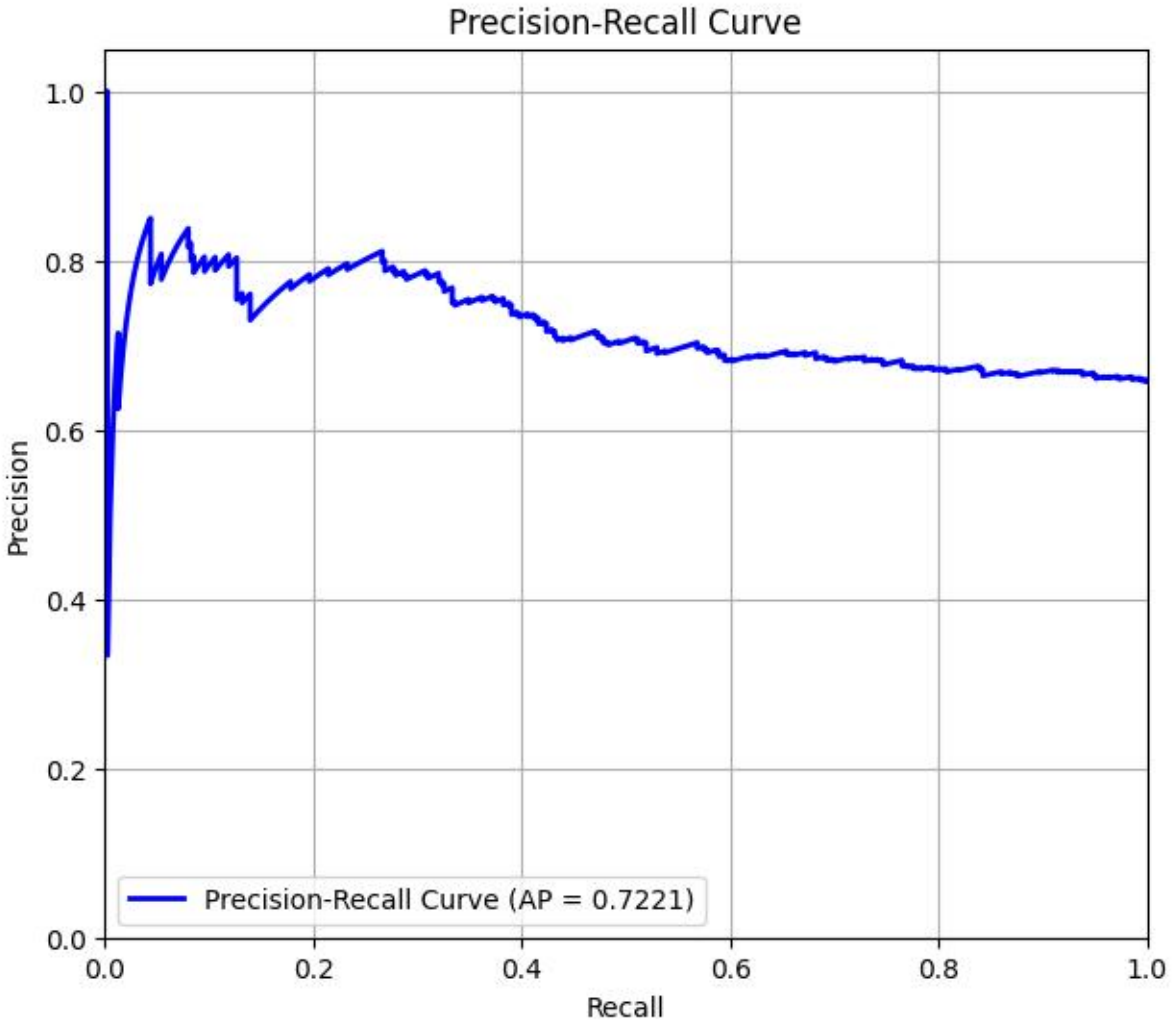


Figure 4.15 The Precision Recall Curve for the ratio 70:15:15

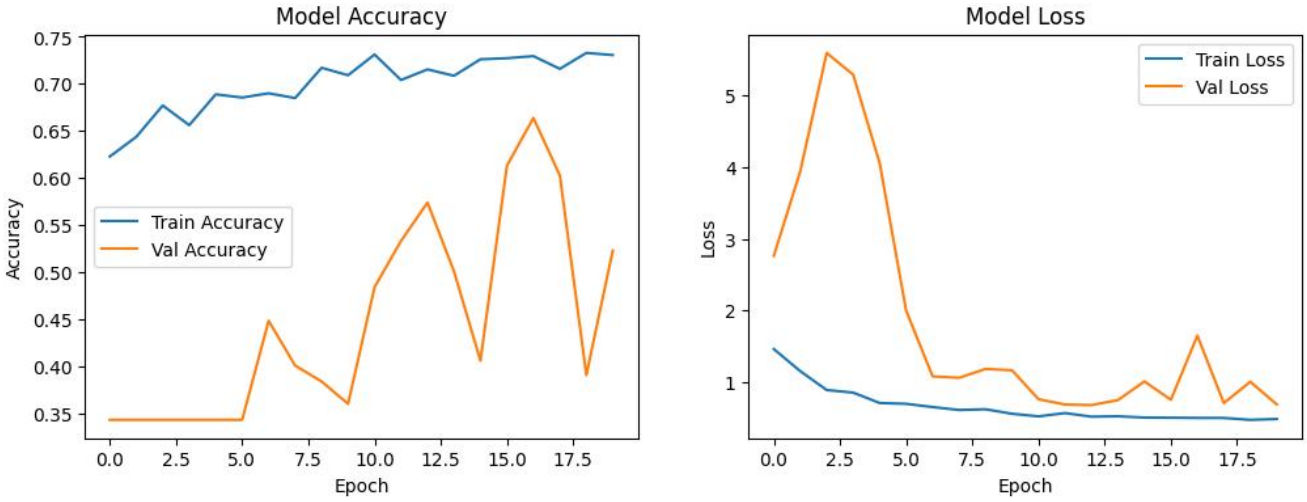


Figure 4.16 The Model accuracy and loss for the ration 70:15:15

Table 4.4 Summary of Classification Report for the partition 3

Precision		Recall	F1-score	Support
Normal	0.38	0.60	0.47	202
Osteoarthritis	0.70	0.48	0.57	387
Accuracy			0.52	587
Macro avg	0.54	0.54	0.52	587
Weighted avg	0.54	0.58	0.54	587

4.5 Discussion of Findings

The proposed Explainable Artificial Intelligence (XAI) framework was evaluated using three different dataset partitions to determine the effect of training and testing data distribution on the classification performance of knee osteoarthritis. The experimental results showed that the 80:20 dataset partition achieved the highest classification accuracy of 57%**,** while the 75:25 and 70:30 dataset partitions both produced an accuracy of 52%**.** Although the 80:20 partition slightly outperformed the other two configurations, the overall classification performance remained relatively low, indicating that the model experienced difficulty in accurately distinguishing between Normal and Osteoarthritis (OA) knee images. The slightly better performance obtained with the 80:20 partition can be attributed to the larger proportion of images available for training. By allocating 80% of the dataset for learning, the CNN was exposed to more image variations and structural patterns associated with knee osteoarthritis, allowing it to learn more representative features than the 75:25 and 70:30 partitions. In contrast, reducing the size of the training dataset in the other partitions limited the amount of information available to the model, resulting in similar but lower classification performance.

Several factors may have contributed to the relatively low classification accuracy achieved by the proposed framework. First, the dataset may have been limited in size, preventing the CNN from learning sufficiently discriminative features required for reliable classification. Deep learning models generally require a large number of diverse training images to achieve high performance. If the dataset contains only a small number of samples, the learned features may not generalize well to unseen images. Another possible reason is the high visual similarity between Normal and early Osteoarthritis images. In many cases, early osteoarthritic changes are subtle and may not be easily distinguishable from normal knee structures, even by experienced clinicians. Since the proposed CNN relies solely on imaging information, these subtle differences may not have been adequately captured during training, leading to misclassification of some images.

The model architecture may also have influenced the obtained results. The study employed a custom Convolutional Neural Network (CNN**)** with four convolutional layers trained from scratch. Although this architecture is capable of learning image features, it may not be sufficiently deep or optimized to capture the complex structural characteristics present in knee radiographs and MRI scans. More advanced pre-trained architectures such as ResNet50, DenseNet121, EfficientNet, or Vision Transformer**s** have demonstrated superior performance in medical image classification because they are pre-trained on large image datasets and can extract

richer and more discriminative features through transfer learning. Furthermore, although data augmentation techniques such as rotation, zooming, horizontal flipping, and translation were applied, they may not have been sufficient to compensate for the limited diversity of the original dataset. If the dataset contains similar image patterns or class imbalance, the model may still struggle to learn generalized representations, resulting in lower predictive performance.

The use of Grad-CAM did not directly improve classification accuracy because its primary purpose is to provide model interpretability rather than performance enhancement. Grad-CAM generated heatmaps highlighting the image regions that influenced the model's predictions, allowing visual verification of the decision-making process. While this increased the transparency and clinical interpretability of the proposed framework, it did not alter the CNN's feature-learning capability or improve its predictive accuracy. Overall, the findings indicate that the 80:20 dataset partition provided the best performance with an accuracy of 57%**,** suggesting that increasing the amount of training data has a positive effect on model learning. However, the relatively low accuracies obtained across all three dataset partitions demonstrate that the proposed framework requires further improvement before it can be considered suitable for clinical application. Future work should focus on using larger and more diverse datasets, adopting transfer learning with state-of-the-art pre-trained models, optimizing hyperparameters, addressing potential class imbalance, and incorporating additional imaging or clinical information to improve classification performance and diagnostic reliability.

4.6 Chapter Summary

This chapter presented the implementation, evaluation, and discussion of the proposed Explainable Artificial Intelligence (XAI) framework for the classification of knee osteoarthritis using radiographs (X-ray images) and Magnetic Resonance Imaging (MRI) scans. The model was trained and evaluated using three different dataset partitions (80:20, 75:25, and 70:30) to determine the effect of data distribution on classification performance. The experimental results showed that the 80:20 partition achieved the highest accuracy of 57%, while both the 75:25 and 70:30 partitions achieved an accuracy of 52%, indicating that a larger training dataset slightly improved the model's learning capability.

The chapter also presented the model evaluation using performance metrics such as accuracy, precision, recall, F1-score, confusion matrix, ROC curve, and Precision-Recall curve. In addition, Grad-CAM was employed to generate visual explanations of the model's predictions by highlighting the anatomical regions that influenced the classification decisions. Although the

framework demonstrated the ability to classify knee images and provide interpretable visual explanations, the overall classification performance was relatively low. This was attributed to factors such as the limited dataset size, the subtle visual differences between normal and osteoarthritic knee images, and the use of a custom CNN architecture trained from scratch. Nevertheless, the findings demonstrate the potential of integrating Explainable Artificial Intelligence into medical image analysis and provide a foundation for future improvements through larger datasets, transfer learning, and more advanced deep learning architectures.

CHAPTER FIVE

SUMMARY AND CONCLUSION

5.1 Summary of Chapters

Chapter One presented the general introduction to the study by discussing knee osteoarthritis as one of the most common degenerative joint diseases affecting millions of people worldwide. The chapter highlighted the increasing burden of the disease and the importance of early and accurate diagnosis in preventing disease progression and improving patient outcomes. It also identified the limitations of conventional diagnostic approaches, including dependence on expert interpretation and the lack of transparency in many Artificial Intelligence-based diagnostic systems. The research problem, aim, objectives, research questions, significance of the study, scope, limitations, and justification for the study were clearly stated. The chapter established the need for an Explainable Artificial Intelligence (XAI) framework capable of not only detecting knee osteoarthritis from medical images but also providing visual explanations to support clinical decision-making and improve trust in AI-assisted diagnosis.

Chapter Two reviewed the literature related to knee osteoarthritis, medical imaging techniques, deep learning, Convolutional Neural Networks (CNNs), and Explainable Artificial Intelligence. The chapter discussed the causes, symptoms, risk factors, diagnosis, and progression of knee osteoarthritis, as well as the role of radiographs (X-ray images) and Magnetic Resonance Imaging (MRI) in clinical assessment. Existing deep learning models developed for knee osteoarthritis diagnosis were critically examined, together with different Explainable Artificial Intelligence techniques such as Grad-CAM, LIME, SHAP, and Integrated Gradients. The review revealed that although previous studies reported encouraging classification performance, many focused mainly on prediction accuracy while providing little or no explanation of how the models reached their

decisions. This identified a significant research gap and justified the development of an explainable diagnostic framework that combines automated image classification with visual interpretation.

Chapter Three described the methodology adopted for the development and implementation of the proposed Explainable Artificial Intelligence framework. The chapter presented the proposed system architecture and explained each stage of the framework, beginning with data acquisition and ending with diagnostic prediction and visual explanation. The dataset used for the study was obtained from Kaggle and consisted of knee radiographs (X-ray images) and MRI scans categorized into two diagnostic classes: Normal and Osteoarthritis (OA). The methodology included data collection, data acquisition procedures, preprocessing, data cleaning, image normalization, noise reduction, label encoding, dataset partitioning, model training, algorithm implementation, and performance evaluation. A Convolutional Neural Network (CNN) was implemented to learn structural features associated with osteoarthritis, while Gradient-weighted Class Activation Mapping (Grad-CAM) was integrated to provide heatmaps that highlighted the anatomical regions influencing the model's predictions. The chapter also described the software tools, programming environment, evaluation metrics, and implementation procedures used throughout the study.

Chapter Four presented the implementation results, performance evaluation, and discussion of findings obtained from the proposed Explainable Artificial Intelligence framework. The model was evaluated using three experimental dataset partitions of 80:20, 75:25, and 70:30 to investigate the effect of different training and testing distributions on classification performance. The experimental results showed that the 80:20 partition achieved the highest accuracy of 57%, while the 75:25 and 70:30 partitions both achieved an accuracy of 52%. The model was further evaluated using precision, recall, F1-score, confusion matrix, ROC curve, Precision-Recall curve, and AUC score. In addition, Grad-CAM was used to generate heatmaps that visually explained the regions responsible for each prediction, thereby improving the transparency and interpretability of the diagnostic process. The discussion showed that although the framework was able to distinguish between normal and osteoarthritic knee images and provide meaningful visual explanations, the overall classification performance was relatively low. Possible reasons included the limited size of the dataset, similarities between normal and osteoarthritic image features, image quality variations, and the use of a custom CNN architecture trained from scratch. Despite these limitations, the results demonstrated the feasibility of integrating Explainable Artificial Intelligence into computer-aided diagnosis and provided a strong foundation for future

improvements through larger datasets, transfer learning, and more advanced deep learning architectures.

Overall, the study successfully designed, implemented, and evaluated an Explainable Artificial Intelligence framework for knee osteoarthritis diagnosis using medical images. Although the classification accuracy obtained was modest, the integration of Grad-CAM improved the transparency of the model by providing visual explanations that can assist clinicians in understanding the basis of the model's predictions. The findings demonstrate the potential of Explainable Artificial Intelligence to support medical diagnosis while also identifying opportunities for future research to improve classification performance and clinical applicability.

5.2 Recommendations

Based on the findings of this study, the following recommendations are made:

1. **Use Larger and More Diverse Datasets**: Future research should utilize larger and more diverse datasets collected from multiple hospitals and healthcare institutions. A larger dataset will expose the model to more variations in knee anatomy and osteoarthritis patterns, thereby improving its learning capability, reducing overfitting, and enhancing classification accuracy.
2. **Adopt Transfer Learning Techniques**: Future studies should employ pre-trained deep learning models such as ResNet50, DenseNet121, EfficientNet, or Vision Transformers. These architectures have been trained on large image datasets and can extract more robust and discriminative features than a custom CNN developed from scratch.
3. **Optimize Model Hyperparameters**: Further optimization of the model should be carried out by tuning hyperparameters such as the learning rate, batch size, number of epochs, optimizer, and dropout rate. Proper hyperparameter tuning can improve convergence, reduce training errors, and enhance overall model performance.
4. **Integrate Additional Clinical Information**: Future research should combine medical images with relevant clinical information, such as patient age, gender, body mass index (BMI), medical history, and Kellgren–Lawrence grading. The integration of imaging and clinical data may improve the accuracy and reliability of osteoarthritis diagnosis.
5. **Evaluate Additional Explainable AI Techniques**: Other Explainable Artificial Intelligence methods, such as LIME, SHAP, Score-CAM, and Integrated Gradients, should be investigated and compared with Grad-CAM. This would help determine the most

effective explainability technique for improving the transparency and interpretability of deep learning models in medical diagnosis.

6. **Apply Cross-Validation and Address Class Imbalance**: Future studies should employ cross-validation techniques to obtain a more reliable evaluation of model performance. Where class imbalance exists, techniques such as oversampling, undersampling, or synthetic data generation should be applied to improve model fairness and predictive performance.
7. **Improve Image Quality and Preprocessing Techniques**: Advanced image enhancement and preprocessing techniques should be explored to improve the quality of radiographs and MRI scans. Better image quality can enhance feature extraction and enable the model to identify structural abnormalities more effectively.
8. **Conduct Clinical Validation**: The proposed framework should be validated using real-world clinical datasets and assessed by orthopedic specialists and radiologists. Clinical validation is essential to determine the reliability, usability, and practical applicability of the framework in healthcare environments before deployment.
9. **Develop a Clinical Decision Support System**: Future research should integrate the proposed Explainable Artificial Intelligence framework into a clinical decision support system. Such a system would assist healthcare professionals by providing automated predictions together with visual explanations, thereby improving diagnostic efficiency and supporting informed clinical decision-making.

5.3 Conclusion

This study successfully designed and implemented an Explainable Artificial Intelligence framework for the classification of knee osteoarthritis using knee radiographs and MRI scans. The proposed framework combined a Convolutional Neural Network with the Grad-CAM explainability technique to provide both automated diagnostic predictions and visual explanations of the image regions that influenced each prediction. This approach addressed one of the major challenges associated with deep learning in healthcare by improving the transparency and interpretability of model decisions.

The experimental evaluation demonstrated that the proposed framework was capable of distinguishing between Normal and Osteoarthritis knee images. Among the three experimental dataset partitions, the 80:20 partition produced the highest classification accuracy of 57%, while

the 75:25 and 70:30 partitions achieved 52% accuracy. Although these results indicate that the framework learned useful imaging features, the overall performance remains below the level required for practical clinical deployment.

The relatively low classification accuracy can be attributed to several factors, including limited training data, variability in medical image quality, subtle structural differences between normal and osteoarthritic knees, and the use of a custom CNN architecture trained from scratch. Nevertheless, the Grad-CAM component successfully generated meaningful heatmaps that highlighted clinically important regions, demonstrating that the model based its predictions on relevant anatomical structures rather than irrelevant image features.

Overall, this study demonstrates that Explainable Artificial Intelligence has significant potential for improving transparency and trust in computer-aided diagnosis of knee osteoarthritis. While additional improvements are required to increase diagnostic performance, the proposed framework provides a solid foundation for future research into interpretable deep learning systems for medical imaging applications.

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