# X-Rays Based Knee Osteoarthritis Diagnosis and Classification

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***Abstract*: Knee osteoarthritis (OA) is a condition that affects the knee joints and is categorized by radiographic changes. Accurate and early diagnosis of through X-rays is crucial for initiating appropriate treatment and slowing the progression of the disease. This project work implements a deep learning based ordinal classification system to uniquely identify and categorize knee osteoarthritis (OA) using single knee X-ray images. The proposed approach leverages the Osteoarthritis Initiative (OAI) dataset and join in several models, including DenseNet161, Xception, VGG19, and ResNet34. Additionally, for detection purposes, we employ advanced YOLO models such as YOLOv6, YOLOv7, YOLOv5x6, and YOLOv5 GhostNet. While initial work involved using DenseNet169 with fine-tuning for classification and comparing Transfer Learning (TL) techniques, our project expands upon this by exploring additional methods to enhance classification performance and by utilizing a broader range of YOLO models for improved detection.**

***Keywords*: detection and classification, knee osteoarthritis, ordinal classification, X-rays.**

## 1. Introduction

The Osteoarthritis (OA) is a complex disease having multiple risk factors, hence its diagnosis, detection, and treatment challenging [1], [2]. Osteoarthritis is a chronic degenerative condition marked by the deterioration of cartilage, resulting in the breakdown of joint. Knee Osteoarthritis (KOA) is a kind of osteoarthritis that distresses the joint of the knee. KOA presents symptoms such as discomfort, pain firmness, oedema, and restricted knee joint mobility. Contributing factors include age, sex, hereditary qualities, race, overweightness, injury, vitamin D deficit, and way of life [1]-[4]. KOA has varying grades of severity from healthy knee to severe. Recent studies indicate that the global prevalence of KOA is 16% [5]. World Health Organization (WHO) states that KOA remains more prevalent in women (18.0%) compared to men (9.6%) and primarily affects individuals over the age of 60 [1].

Diagnosis of knee osteoarthritis typically relies on Magnetic Resonance Imaging (MRI), symptoms, and radiographs Nevertheless, infancy of Osteoarthritis is frequently difficult to detect. Furthermore, there exists weak correlation among the severity of pain, dysfunction and the severity of Osteoarthritis as indicated through imaging. These highlights need for more effective diagnostic techniques to identify Osteoarthritis in its early stages. Osteoarthritis related biomarkers could offer a solution [1]. The X-rays are commonly used to evaluate symptoms then diagnose Knee Osteoarthritis [1], [3]. Distinguishing features observed in radiographs include Joint Space Narrowing (JSN), bone deformities and growth development, JSN denotes the damage of cartilage among joints, osteophytes are hard lumps that form on joints or bones [3].

The Kellgren and Lawrence (KL) grading system is a classifying technique utilized for grading KOA the severity based on radiographs [6], [7]. This system assigns ordinal numbers to classify the severity levels. In automated diagnosis and classification, various imaging modalities are analysed using techniques from image processing and computer vision, such as image enhancement, segmentation, texture analysis, and shape analysis [3], [8], [9]. Image segmentation is useful for detecting and localizing knee joints in images, while texture and shape features are extracted for use in machine learning classifiers. Deep Learning approaches such as Convolutional Neural Networks (CNNs), are important also popular in computer vision and image analysis tasks. Popular CNN like ResNet [10], VGG [11], and DenseNet [12] have been employed for various tasks in classification. Approaches like Transfer learning allows for leveraging existing architectures and their learned weights to reduce computational costs [13]. A deep learning network pre-trained on ImageNet can be utilized as a feature extractor or fine-tuned to adapt to a specific dataset [11]. These advanced approaches are increasingly being applied to KOA classification.

Recent advancements in deep learning have significantly impacted the field of medical imaging, through the use of Convolutional Neural Networks (CNNs). These networks have gained prominence due to their effectiveness in handling computer vision and image analysis tasks. Prominent CNN such as ResNet [10], VGG [11], and DenseNet [12] have been applied to various classification challenges. Transfer learning is a valuable technique in this context, allowing the utilization of pre-trained networks to extract features or fine-tune networks for specific datasets, thereby reducing computational requirements and improving performance [13]. In the context of KOA, these advanced CNN architectures are increasingly being employed for classification tasks.

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## 2. Literature Survey

A comprehensive review by Iqbal et al. [4] highlights the complex nature of knee osteoarthritis, emphasizing the variety of factors that contribute to knee osteoarthritis and the need for a comprehensive approach to diagnosis and treatment. The review accentuates the paramount of considering a broad range of risk factors when evaluating and managing KOA. Similarly, the work of Teoh et al. [5] explores imaging features relevant for diagnosing and prognosticating KOA. Their review focuses on manual grading methods and the integration of machine learning approaches, demonstrating the potential for improved diagnostic accuracy through advanced imaging techniques and computational methods.

Saini et al. [7] conducted a comparative study on automated classification and grading methods for KOA using radiographic imageries. Their study emphasizes the effectiveness of various automated approaches in enhancing the accuracy of KOA classification and grading. This research underscores the growing role of automated systems in medical diagnostics and their potential to improve the reliability of disease assessment.

In another study, Anifah et al. [8] investigate the use of self-organizing maps combined with Gabor kernels and contrast-limited adaptive histogram equalization for classifying osteoarthritis. Their approach showcases the potential of combining various image processing techniques to enhance classification accuracy and provide a more detailed analysis of OA-related features.

Furthermore, Brahim et al. [9] developed a decision support tool aimed at early KOA detection using X-ray imaging and machine learning techniques. Their research, utilizing dataset from the Osteoarthritis Initiative, demonstrating the effectiveness of integrating machine learning with traditional imaging modalities to improve early detection and diagnostic accuracy.

Yong et al. [14] contribute to the field by proposing a severity classification method for knee osteoarthritis using an ordinal regression module. Their approach highlights the importance of developing robust classification systems that can accurately reflect the severity of KOA and facilitate more informed clinical decision-making.

Overall, the integration of advanced imaging techniques and machine learning algorithms holds great potential to transform diagnosis and management of knee osteoarthritis. Through improving accuracy and early detection of the disease, these advancements could lead to more effective treatment strategies and better patient outcomes. The continued exploration of innovative approaches and technologies will be crucial in addressing the challenges associated with KOA and enhancing the overall quality of care for affected individuals.

## 3. Methodology

### *A. Proposed Work*

The proposed system utilizes up-to-date deep learning approaches to automatically identification and diagnosing knee osteoarthritis using X-ray images. We intend to train and evaluate our unique models utilizing the Osteoarthritis Initiative (OAI) dataset. To classify, we will join Xception, DenseNet161/169, DenseNet121, VGG19, and ResNet34, and an ensemble Additionally, to further develop the proposed system we will use the Kellgren and Lawrence (KL) grading system for classification. Furthermore, to detect Knee Osteoarthritis we will use state of the art YOLO models like YOLOv5 GhostNet, YOLOv5x6, YOLOv6, YOLOv7. The models will be trained to distinguish and find radiographic potentials of knee osteoarthritis. Therefore, the system needs to give a reliable outcome for early diagnosis and reviewing. As a result, reducing the burden on healthcare systems and personnel.

### *B. System Architecture*

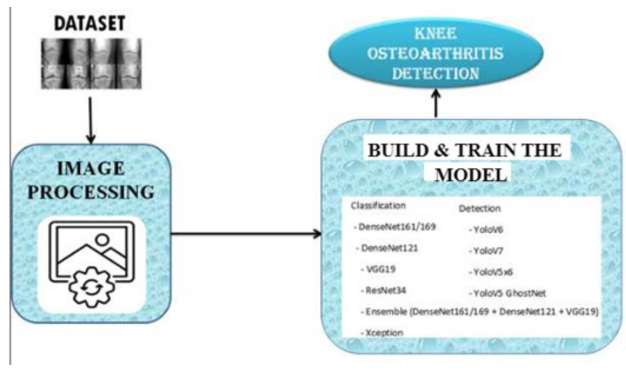


Fig. 1. Proposed architecture

The image outlines a process for knee detection using deep learning techniques. The process includes developing and training several models for classification, such as DenseNet161/169, DenseNet121, VGG19, ResNet34, and an ensemble model combining DenseNet161/169, DenseNet121, and VGG19. For detection tasks, models like YoloV6, YoloV7, YoloV5x6, and YoloV5 GhostNet are employed. These models are applied to processed knee X-ray images to identify and locate signs of osteoarthritis.

### *C. Dataset*

The dataset utilized in this research is sourced from the Osteoarthritis Initiative (OAI) dataset [9]. It consists of 9,786 X-ray images, categorized according to the Kellgren and Lawrence (KL) grading system. The distribution of images among the different grades is as follows: 3,857 images in grade 0, 1,770 images in grade 1, 2,578 images in grade 2, 1,286 images in grade 3, and 295 images in grade 4. Each image is standardized to a resolution of 224 × 224 pixels. Given the substantial class imbalance, the dataset is divided into training, testing, and validation subsets, with the partitioning approach following the methodologies established by previous studies [19][28]. This ensures a balanced evaluation of the model across different severity grades.

### *D. Image Processing*

In image processing for deep learning applications, a range of techniques is employed to augment and prepare images for training models. The ImageDataGenerator from Keras is a commonly used tool that facilitates various image augmentation strategies to enhance the robustness of models. This tool allows for re-scaling images to ensure that pixel values fall within a desired range, typically normalizing them between 0 and 1. Shear transformation, another technique, involves tilting the image along one axis to create a perspective distortion, helping the model generalize better to different orientations. Zooming adjusts the scale of the image to simulate a range of distances, hence refining the network's ability to identify objects at different dimensions. Horizontal flipping is used to create mirrored versions of images, which aids in learning invariant features regardless of their orientation. Additionally, reshaping modifies the dimensions of the image to fit the input requirements of the neural network, ensuring consistency across training samples.

For detection tasks, torch vision provides a suite of tools tailored to image preprocessing and augmentation. These tools facilitate the transformation of images, including resizing, cropping, and normalization, to align with the requirements of object detection models. Techniques such as random horizontal flipping, random vertical flipping, and random cropping are employed to introduce variability and improve model generalization. By combining these augmentation techniques with deep learning frameworks, the models become more robust, capable of handling diverse image conditions and variations effectively.

### *E. Algorithms*

#### *1) DenseNet161/169*

DenseNet161/169 are deep convolutional neural networks featuring dense connectivity patterns, where each layer receives input from all preceding layers. This design improves gradient flow and feature reuse, enhancing model performance on complex tasks. DenseNet161 and DenseNet169 differ primarily in their depth, with DenseNet169 being deeper and potentially offering better feature extraction and representation.

#### *2) DenseNet121*

DenseNet121 is a deep convolutional network with a dense connectivity pattern, which allows each layer to access all preceding layers' features. It has 121 layers, providing a balance between depth and computational efficiency, and is effective in capturing complex image features while mitigating vanishing gradient issues.

#### *3) VGG19*

VGG19 is from the Visual Geometry Group family. It’s known for its simple yet effective design with 19 total layers. This includes sixteen convolutional and three fully connected layers. Despite its depth, VGG19 is computationally intensive but performs well in image classification tasks.

#### *4) ResNet34*

ResNet34 is from the Residual Network series and has 34 layers with well-designed residual connections. Those skip connections help overcome vanishing gradient problems while delivering high accuracy without excessive computational complexity.

#### *5) Ensemble (DenseNet161/169 + DenseNet121 + VGG19)*

The ensemble combines DenseNet161/169, DenseNet121, and VGG19 to leverage the strengths of each architecture. By aggregating predictions from these diverse models, the ensemble approach improves classification accuracy and robustness. This technique benefits from the complementary features learned by each individual model, leading to better overall performance.

#### *6) Xception*

Xception stands for Extreme Inception. Xception is a deep convolutional neural network architecture. This design reduces computational cost while maintaining high accuracy. Xception is effective in capturing complex patterns and features in images, making it suitable for various image classification tasks.

#### *7) YOLOv6*

YOLOv6 is a speedy real-time object detector made to quickly locate objects. It improves on previous versions by refining detection methods while being fast.

#### *8) YOLOv7*

YOLOv7 is an advanced version of the YOLO (You Only Look Once) series, featuring improvements in detection accuracy and speed. It introduces new architectural enhancements and techniques for better object localization and classification. YOLOv7 is optimized for real-time object detection with high precision.

#### *9) YOLOv5x6*

YOLOv5x6 is an enhanced variant of YOLOv5, featuring additional layers and improvements for better performance. It includes modifications to the base YOLOv5 architecture to enhance feature extraction and object detection accuracy, making it suitable for complex and detailed image analysis tasks.

#### *10) YOLOv5 GhostNet*

YOLOv5 GhostNet integrates the GhostNet architecture with YOLOv5 for object detection. GhostNet uses efficient convolutional operations to reduce computational complexity while maintaining accuracy. This combination improves YOLOv5’s efficiency and performance, particularly for real-time object detection tasks with resource constraints.

## 4. Experimental Results

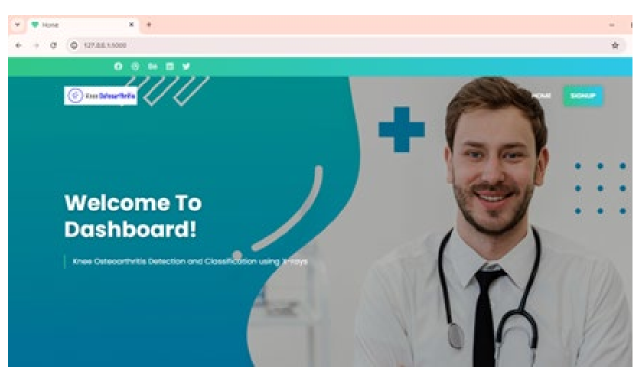


Fig. 2. Home page

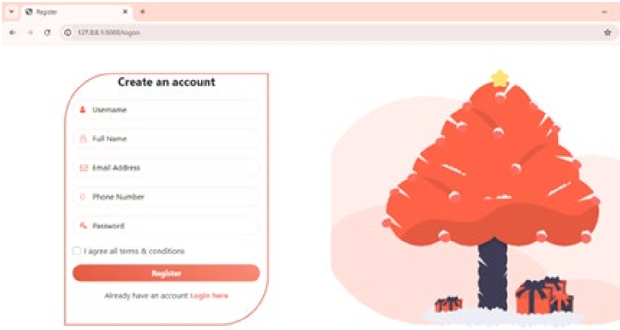


Fig. 3. Registration page

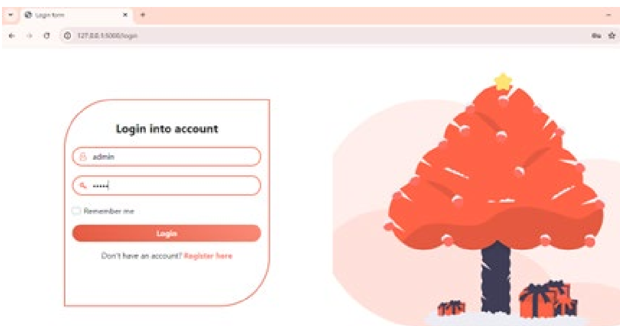


Fig. 4. Login page

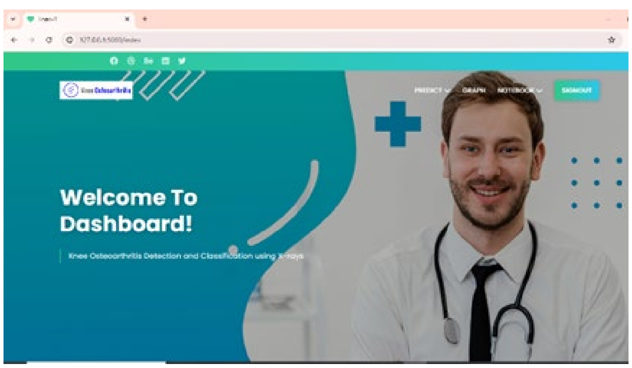


Fig. 5. Welcome page

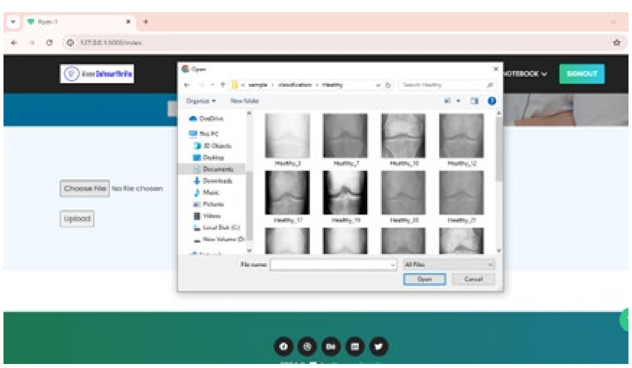


Fig. 6. Upload input image for classification


Fig. 7. Predict result for given input

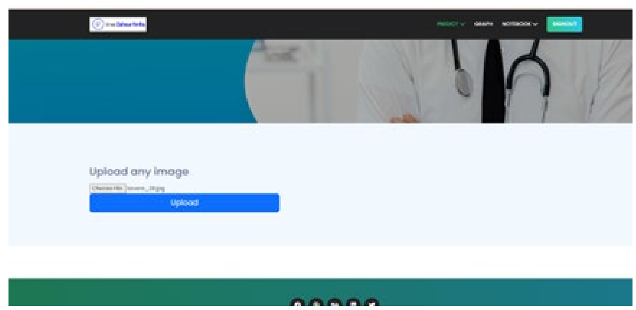


Fig. 8. Upload input image for detection

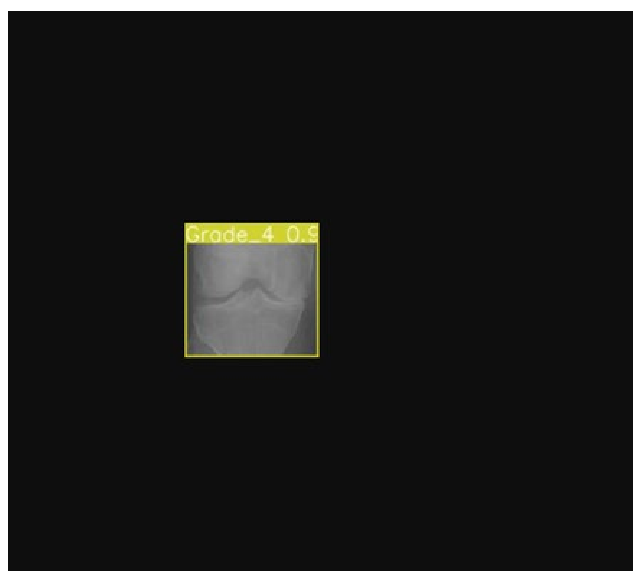

Fig. 9. Final outcome for given input image

Similarly, we can try other cases in same process for classification and detection.

## 5. Conclusion

In this paper, we successfully implemented a deep learning ordinal classification for grading knee osteoarthritis (KOA) using X-ray images. Our approach, integrates state-of-the-art techniques has yielded exceptional results across all Kellgren and Lawrence (KL) grades. By employing an ensemble of fine-tuned models, we have enhanced the performance and accuracy of KOA classification, providing healthcare professionals with a reliable and efficient tool. The application of ordinal classification has notably improved our system's ability to assess the severity of knee osteoarthritis, offering a swift and precise evaluation of input X-rays. This advancement not only aids in early diagnosis but also saves valuable time for healthcare professionals. Our approach presents a viable alternative to traditional methods, facilitating timely and accurate grading of knee osteoarthritis. The significant performance gains demonstrate the effectiveness of deep learning models and advantages of ensemble methods in scientific image analysis.

## 6. Future Scope

Future research efforts will focus on the continued refinement of these models, with an emphasis on evaluating their effectiveness across diverse clinical environments. Notably, ensemble techniques have yielded considerable enhancements across all evaluation metrics. In subsequent studies, we intend to incorporate datasets from a range of clinical settings to further validate the models' robustness and generalizability.

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