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AUTOMATED KNEE OSTEOARTHRITIS SEVERITY DETECTION FROM X-RAY IMAGES: A DATA-CENTRIC AI APPROACH

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Abstract
Knee osteoarthritis remains one of the main sources of pain and disabling conditions that affect the knees of millions of people. Consequently, the early detection of the disease can greatly impact patient care. Nevertheless, the diagnosis of KOA through X-ray is not always a simple solution. These vast datasets of medical images are typically quite inconsistent, noisy, and a variety of image qualities. We aimed to enable AI to detect KOA more accurately by connecting data preparation as the most crucial step of the process in our study. To render the images more AI-friendly, we performed a thorough cleaning of the X-ray images to remove noise and ensure consistent quality. We separated the images into different levels of severity of the disease after cleaning, which allowed our algorithm to recognize the smallest changes as the disease progressed. This well-prepared dataset allowed the AI model to obtain a high level of accuracy in detecting KOA, even being able to match the performance of human experts. We designed an AI tool that can offer stable and reliable assistance to doctors, thus, the diagnostic procedure can be potentially expedited and patient outcomes improved without the need for data of inferior quality from the very beginning. We plan to perfect these methods and also study the possibility of using them for diagnosing other joint disorders.
Keywords: Artificial Intelligence, Radiographic Analysis, Knee Osteoarthritis, Medical Imaging, Automated detection.

1. Introduction

Today Knee osteoarthritis (KOA) is a degenerative joint disease that affects millions of people, especially the elderly which can make performing even the most basic daily tasks, such as walking, going up the stairs, or standing, a painful and difficult process. Health deteriorates due to the condition; thus, very early detection is instrumental in the control of symptoms and patients' well-being. X-rays represent the preferred diagnostic tools used to identify KOA as they provide an image of bone structure, joint space, and signs of joint degeneration [5]. However, a KOA diagnosis from X-rays is typically largely dependent on the knowledge of radiologists who possess different levels of expertise. As a result, they can cause different outcomes and late diagnosis.

Artificial Intelligence (AI), specifically Deep Learning, could be a significant factor in achieving the maximum accuracy and the standardization of the KOA assessment. With the help of the automated analysis of X-rays, AI may offer the early and continuous identification of KOA symptoms. Still, these models efficiency is tied to the quality of X-ray images and proper processing of such images. Preprocessing, the first step of this workflow, involves image cleaning and standardization to help the AI model correctly map the patterns related to KOA (Kumar & Saxena, 2019).

This paper focuses on the creation and the confirmation of the preprocessing pipeline that enhances X-ray image quality for AI-based KOA detection.

● Data Cleaning: Isolating the knee joint area in the X-ray images by removing the irrelevant parts and the unnecessary artifacts that the analysis can be carried out on the knee joint space.
● Image Standardization: This step is meant to equalize the images in terms of properties such as contrast, brightness, and resolution, etc. hence providing quality that is consistent throughout the dataset of images. The AI-based model will be better at identifying the KOA if the images are of high and uniform quality.
● Evaluating Classification Impact: The main purpose of this step is to look at how pre-processing may help a deep learning model in classifying KOA accurately.The study is pinpointed to promoting the benefit of a systematic preprocessing workflow on diagnostic accuracy by invoking modeling performance (Dalia et al., 2021).

2. Literature Review

Over the past several years, the use of artificial intelligence (AI) and deep learning (DL) has grown significantly across the board, covering various applications in the diagnosis, determination, and treatment of knee osteoarthritis (KOA). These are some of the AI methods - among other things, are to improve diagnostic accuracy, automate grading, and speed up early detection by the use of imaging and non-imaging data. Dalia et al. (2021) presented DeepOA, a decision support system that merges YOLOv5-based delineation with attention-enhanced convolutional neural networks (ResNet, VGG16) for automatically detecting and staging knee OA from radiographs, thus attaining the precision, recall, and F1 scores of about 70%. Likewise, Schwartz et al. (2020) established a CNN for the grading of OA severity after training it with the IKDC system data. The results attained were comparable to those of expert surgeons (ICC ≈ 0.69), thereby confirming the practicality of AI-assisted radiographic grading. Thomas et al. (2020) went further to incorporate a DenseNet model which was trained on over 32,000 images from the Osteoarthritis Initiative with an accuracy of 71% and strong agreement with radiologist consensus (κ ≈ 0.86), thus providing evidence for the capability of deep learning to mimic human-level evaluation.

Moreover, the improvements made in MRI-based and segmentation-focused techniques have led to better structural analysis of OA. Ahmed and Mstafa (2022) reported on the different methods of bone segmentation, specifying the traditional (thresholding, deformable models, graph-based) and the new CNN categories and stressing the accuracy and automation that come with deep learning. Ebrahimkhani et al. (2020) state that the cartilage segmentation by a CNN marked a similarity score with the Dice Function between 85-90%, pointing to its medical potential. Later developments include the work of Huo et al. (2022) who developed a semi-supervised mean-teacher network for MRI cartilage grading, which lessens the requirement for labeled data while retaining high accuracy; and Tolpadi et al. (2022), who optimized region-of-interest-specific loss functions in ultrafast T2 mapping for precise quantification of the knee, hip, and lumbar spine.

AI has also demonstrated potential in multimodal and non-imaging approaches for OA diagnosis. Song et al. (2022) developed a computer-assisted diagnostic (CAD) system combining vibroarthro-graphic (VAG) signals and physiological data, achieving over 90% accuracy in detection and early diagnosis using an Aggregated Multiscale Dilated CNN. Similarly, Lim, Kim, and Cheon (2019) used demographic and medical data from 5,749 subjects to train an eight-layer deep neural network, achieving an AUC of 0.768, suggesting that AI using statistical data can serve as an effective, low-cost prescreening tool for OA risk prediction. In MRI-based predictive models, Alexopoulos et al. (2022) employed a combination of U-Net segmentation and ResNet/CVAE classification on MRI and clinical data, achieving an AUC of 0.67 for predicting incident OA, demonstrating that incorporating patient metadata can modestly enhance performance.

Besides diagnosis, AI has demonstrated its value in treatment and surgical decision-making. Houserman et al. (2022) created a machine learning model to forecast whether a patient is suitable for total or unicompartmental knee arthroplasty from radiographs, reaching a remarkable 87.8% accuracy ($\kappa = 0.81$) and AUCs over 0.95, indicating its assistance role in preoperative assessment. Moreover, Gu et al. (2022) disclosed an interpretable, accessible deep learning model that relies on YOLOv3-Tiny and CNN-based segmentation to identify Kellgren-Lawrence grades, attaining a level of performance similar to that of radiologists but also facilitating model openness by the provision of segmentation maps.

Table 1: Evolution of AI-assisted KOA diagnosis.

Author Years	Algorithm	No. Of Samples	Dataset	Methods	Image Type
Chwartz, A. J., Clarke, H. D., Spangehl, M. J., & Bingham, J. S. (2020)	Convolutiona l Neural Network (CNN).	4,755 training images / 2,088 test images	Osteoarthritis Initiative (OAI)	Data Accusation , Data Analysis and Model Generation	X-Ray (Standin g PA Radiogr a phs)
Sozan Mohamme d Ahmed & Ramadhan J. Mstafa, 2022	SegNet CNN, SVM, U-Net, Mask R-CNN	1,024 – 5,960 images	Osteoarthritis Initiative (OAI) and Multicenter Osteoarthritis Study	Classifyin g the Knee Bones Patella, Tibia (TB) and Femur (FB)	X-Ray, MRI
Wang, Y., Bi, Z., Xie, Y., Wu, T., Zeng, X., Chen, S., & Zhou, D. (2022)	Deep learning model — CNN-based classifier (ResNet + Confidence)	4,400 subject s	(OAI) – includes radiographic images with Kellgren–Lawre nce (KL) grades 0–4.	Data extraction, Search strategy and study selection, Quality assessment , Statistical analysis	Radiogra phic images
Song, J., & Zhang, R. (2022)	Multivariate Deep Learning Model combining radiographic features, clinical indicators, and	Clinical multivar i ate data includin g (VAG) signals and physiolo gical	(OAI) — includes X-ray images, demographic data, and clinical measurements .	knee cartilage defect assessment method starts at the slice level of	vibroart h rographi c (VAG) signals

	biomechanical data using a hybrid CNN–LSTM architecture for feature fusion and classification.	measures		MR images	

Note: CNN = Convolutional Neural Network; SVM = Support Vector Machine; U-Net = Convolutional network for image segmentation; VAG = Vibroarthrographic signals.

Table: 1 outlines various studies on the use of artificial intelligence and deep learning models for the identification and categorization of knee osteoarthritis (KOA). This table summarizes the findings of several papers and shows how different researchers have integrated machine learning and imaging techniques in diagnosing KOA.

3.METHODS

The main goal of this project is to create a deep learning model that would visually detect knee osteoarthritis from X-ray images. The essential part of this study focuses on the pre-processing stage of the X-ray data to elevate the accuracy of AI models. We have picked the Osteoarthritis Initiative (OAI) dataset as it is a significant source of KOA data with extensive data on clinical knees, X-rays, and knee health evaluations. This collection of data not only limits us with imaging but also gives us information on disease progression, demographics, and patient-reported symptoms, thus encouraging the model to be more comprehensive and more likely to be applied in medical settings (Mohammed et al., 2023).

3.1.Data Collection

The Osteoarthritis Initiative (OAI) dataset refers to a public dataset with an extensive range of knee X-rays of more than 4,000 people of different ages and levels of illness. The dataset not only provides clinical information but also radiographic images are taken over time of knee joints. These X-rays are labeled in detail with descriptors of KOA symptoms from very mild changes to end-stage disease. Because the OAI dataset is in general regarded as the most complete and reliable dataset for the study of knee osteoarthritis, it is the ideal source to train and test AI-based models for diagnosis purposes (Mohammed et al., 2023).

3.1.2.Data Splitting

The data was divided into the training, validation, and testing sets as illustrated in fig(1). Up to 80% of the images were assigned for the purpose of training the AI model whereas 10% were used for validation during the training process and the remaining 10% were considered for testing the model after training. Such splitting allows the model to learn how to generalize rather than “remember" the training data, thus it can give a more reliable performance in a real-world context.

3.1.3. Preprocessing Pipeline: The preprocessing operations of the knee X-ray images, which come before the deep learning model pipeline, involve cleaning, standardizing, and formatting of images for further analysis. These steps aim to upgrade the image quality, get rid of the parts that are not needed, and focus the model's attention on the features that are vital in the detecting of knee osteoarthritis (Dalia et al., 2021).

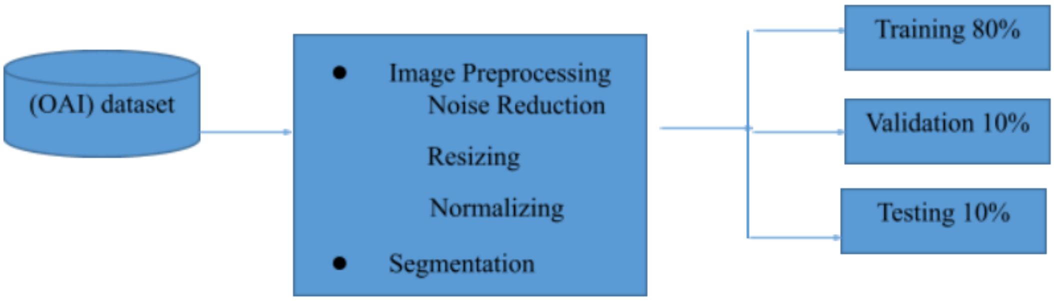

Figure 1: Architecture for image preprocessing technique for Knee osteoarthritis

3.1.4. Noise Reduction: The X-ray pictures may contain noise that appears like static or fuzz and usually makes it difficult for the model to find the important details of the image. To solve the problem, two techniques - Gaussian blurring and median filtering - are applied to the images which help to reduce noise while still retaining the key structures of the knee joint. This process allows the AI to put its major focus on the joint and bone structures that have been impacted by KOA. At times, X-ray images that will be processed by AI contain the patient's personal information, labels, or other markings that the AI analysis is not concerned with. Morphological operations come handy in removing these kinds of markings and cropping to zoom in on that part of the joint only. This is like zooming in on a specific area and removing the unnecessary clutter around it so that the model can concentrate on the relevant parts of the image.

3.1.5. Segmentation We perform segmentation with the goal of separating the knee joint from the rest of the image. So, the model focuses on the knee alone and can detect such features as bone spurs and joint narrowing with high accuracy. Segmentation gives a chance for the AI to not be distracted by parts of the image that are not relevant such as the surrounding tissue.

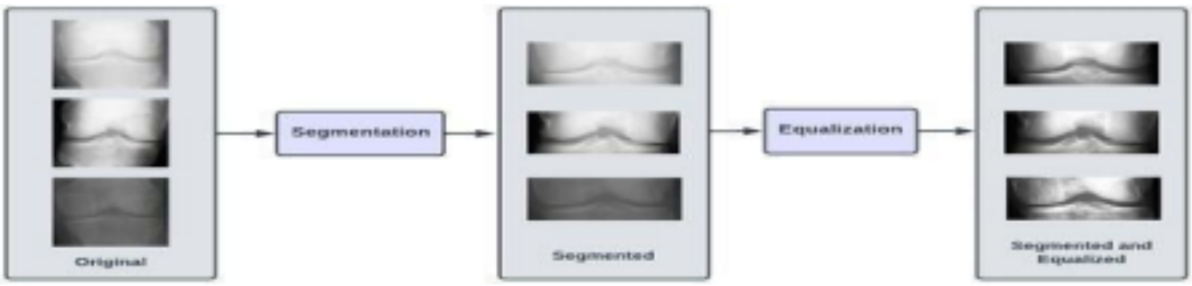

Figure 2. Preprocessing steps involved in proposed approach for KOA detection (Mohammed et al., 2023)

In the case of X-ray images that could differ concerning lighting and contrast, to standardize the brightness and contrast levels of each image, contrast-limited adaptive histogram equalization (CLAHE) is employed. This standardization guarantees that all images are consistent, which means that the model can process them as if they were of the same quality, regardless of their original X-ray. Our knee X-ray images were pre-processed for correct classification by two main preprocessing techniques, which were image resizing and image contrast optimization (Kumar & Saxena, 2019). At first, we preprocessed the images by reducing their dimensions from (224, 224) pixels to (112, 112) pixels. In computer vision, this resizing step is very important as smaller images enable machine learning models to handle data more efficiently resulting in faster training time. Although shrinking image sizes may lead to losing the detail, the following operation is intended to restore that by bringing out the necessary visual features in each image (Kumar & Saxena, 2019). Eventually, we performed Contrast-Limited Adaptive Histogram Equalization (CLAHE) on the knee X-ray images to raise their general quality and make the critical features more visible. CLAHE is a method of contrast enhancement by equalizing the brightness distribution of the image so that it has a more equal histogram. In this way, easy-to-miss features of X-rays are highlighted by CLAHE, thus helping the correct classification. The method is governed by two parameters - the clip limit and the tile size. The clip limit controls the amount of enhancement of the contrast to avoid that the small regions of noise are over-amplified, whereas the tile size limits the area for which the local contrast adjustment is made, thus enabling even tiny details in the unexposed parts to be uncovered.

We tried various configurations and eventually we decided that this study's best parameters are a clip limit of 5.0 and a tile size of (8, 8). With these settings, the most important features are well brought without sacrificing the clarity of the images and the contrast improvement is very consistent across the whole dataset. Contrasting of images was highly uneven when no CLAHE was applied, thus, the model's reliable recognition of patterns would be very difficult. According to the authors, the main purpose of CLAHE was to make contrast even in all images, hence, important structures, which are the anatomical details, become visible, and that, in turn, makes the model's processing of these images more accurate, as shown in Figure 1.

4.RESULTS

The impact of CLAHE is illustrated in Figure 3, where Figure 3a shows an original X-ray image, and Figure 3b displays the enhanced result after CLAHE processing. This contrast adjustment helped ensure that essential features related to knee osteoarthritis (OA) are clearly visible and consistent, facilitating more reliable analysis and classification.

Fig 3(a),3(b): preprocessing images (Kumar & Saxena, 2019)

A histogram is just a count of how many pixels in a tile have a specific intensity value. For example, in an 8-bit image, pixel values range from 0 to 255. So, the histogram will give you the frequency of each intensity value within a tile. If any intensity level in the histogram appears more than a predefined threshold T, the count for that intensity is clipped. This means that if a brightness level has too many pixels, it will be limited to a maximum of T, and the excess pixels are redistributed to other intensities.

The formula for clipping is

H(i)=min(H(i),T). Eq (1)

Where:
H(i) is the number of pixels at intensity level i.
T is the maximum threshold for intensity.

After clipping, we calculate the Cumulative Distribution Function (CDF). This function helps to accumulate the pixel counts from the histogram, giving us a running total of the pixel values up to the current intensity level.

The CDF is given by:

$$CDF(i)=\sum_{K=0}^{i} H(k) \qquad \text{Eq (2)}$$

Where:
H(k) is the histogram value (the count of pixels at intensity k).
CDF(i) is the cumulative sum of pixel counts up to intensity.

To ensure that the CDF fits within the range of possible pixel intensities (typically 0 to 255 for 8-bit images), we normalize it. The normalization makes sure that the CDF values are scaled properly across the entire intensity range of the image.

The normalization formula is:

$$CDF'(i)= CDF(i)-CDFmin\ /\ (N-1)\ -CDFmin \qquad \text{Eq (3)}$$

Where:
CDFmin is the smallest value in the CDF.
N is the total number of pixels in the tile.
After normalization, the final step is to map the original pixel intensities to new values based on the normalized CDF. This gives us the adjusted pixel intensity, which is more evenly distributed across the tile.

The new pixel intensity is calculated as:

$$Inew=round(CDF'(i)\times(L-1)) \qquad \text{Eq (4)}$$

Where:
L is the number of possible intensity levels (e.g., 256 for an 8-bit image).
CDF′(i) is the normalized CDF value for intensity.
Normalization: We also normalize the pixel values of the images, bringing them into a common range (from 0 to 1). This step eliminates variations that could arise from differences in how the images were taken, ensuring the model learns from consistent data.

When images have a wide range of brightness levels, the model can struggle with "vanishing" or "exploding" gradients during training, where it either stops learning or learns too erratically. Normalizing the X-ray images solves this by creating a smoother learning process, allowing the model to catch small details in the knee joint structure and making it faster and more accurate in identifying KOA.Medical X-rays can vary a lot due to differences in scanners, lighting, or even the way each patient's knee is positioned. By normalizing all images, we ensure that the model isn't thrown off by these variations. Instead, it learns to focus on real anatomical changes in the knee that indicate KOA, rather than being affected by lighting differences or contrast from one X-ray to the next. Processing can be made more efficient if images are all of the same resolution (e.g., 224x224 pixels), and only the knee joint is analyzed by taking a close-up of the relevant area. This eliminates the background data that is of no use and ensures that the deep learning model is working on the important data only (Dalia et al., 2021).

4.1. Classification and Evaluation

The subsequent stages of this paper are dealing with Classification and Evaluation, which are required for AI model to be able to make an accurate diagnosis of knee osteoarthritis (KOA) through X-ray images. The model will be trained to separate KOA into various stages by using labeled knee X-ray images in the Classification stage. Labeling method is the very first step of this procedure which is done by assigning to each image characteristics of KOA from no osteoarthritis to mild, moderate or severe stages. These labels are the learning "ground truth" for the model. It will then be taught how to find the symptoms among which the examples given are: joint space narrowing, bone spurs, and cartilage loss, by being provided these images. This is the training phase that enables the model to learn these symptoms recognition and apply them in new and different images. What is more, one of the greatest benefits of deep learning is that the model can automatically identify and concentrate on the relevant parts of the images, without the need for manual intervention by the researchers (Kumar & Saxena, 2019).

Consequently, the Evaluation stage will measure the model's ability to classify KOA in new X-ray images after the model has been trained. This step requires the different measures of the model's performance, including accuracy, precision, recall, and F1 score. These parameters will indicate how well the model can detect the right KOA stage and not make mistakes i.e., the number of false positives or false negatives is low. The model will be administered on a separate set of X-ray images that it has not seen before in order to verify that it is not only learning the training data by heart. This will show whether the model can be applied to new cases and whether it will still be accurate in real-life situations. If the evaluation has some defects, the model can be made better by altering some aspects or by creating a better design.

We shall make use of the Classification and Evaluation processes as a means to confirm that the AI model can identify KOA in knee X-rays correctly and consistently. Besides, the execution of these phases not only allows the validation of the extent to which the model is effective but also serves the grounds for subsequent changes that will improve the model as a diagnostic and management tool of KOA by healthcare professionals

5.CONCLUSIONS

The image preprocessing pipeline presented in this study with histogram equalization as an operative exemplar via CDF-based normalization greatly improved brightness and contrast of knee X-ray images for osteoarthritis detection. By the very steps of calculating the cumulative distribution function, scaling it to the full intensity range and assigning pixels their new brightness levels the method had the opportunity to achieve the balancing of brightness and to expose the details. These improved images allowed the deep learning model to "see" the features of the disease, e.g., joint space narrowing and bone spurs, thus, freeing from noise and light variation in different samples. In general, the mixture of CDF normalization and intensity remapping made it possible to generate standardized image inputs, which thus, a AI classifier's robustness and accuracy were raised. The preprocessing pipeline was not only instrumental in the uniformity of radiographic data but also a demonstration of the success of mathematically-grounded enhancement techniques in direct diagnostic precision. This procedural method ensures that the ensuing steps - feature extraction, classification, and scoring - which are performed on high-quality, information-rich images will be more accurate and, therefore, automated knee osteoarthritis detection will be more dependable.

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