Deep Learning-Based Framework for Automated Classification of Knee Osteoarthritis Severity and Detection of Joint Space Width in X-Ray Imaging

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Abstract. Knee osteoarthritis (OA) is a universal degenerative disease that affects millions of people worldwide, mainly in older adults, and often leads to chronic pain and reduced quality of life. Effective management of diseases, both by preventing disease progression and initiating specific therapeutic strategies, relies upon timely and accurate diagnosis. In this paper we propose a new framework for the analysis of digital X-ray images that uses a deep learning approach for detection and classification of knee OA. The tasks being investigated include: quantifying the Knee Joint Space Width (JSW), a relevant marker of OA, and estimating its severity with the prominent Kellgren-Lawrence (KL) score. We need to identify JSW in X-ray images, for which we use the YOLOv8 model, which is optimal for fast and accurate detection and highlighting of JSW region in X-ray images. We employ a VGG16 neural network, augmented by transfer learning, to classify the circumstances following the detection of the JSW. To define the grade of severity of OA according to KL scores. That is, this automated system can aid clinicians by offering reliable diagnostics, increasing the value of OA progression assessments, and allowing for more timely and effective interventions. Incorporating state-of-the-art deep learning models, our framework seeks to improve patient management and clinical accuracy.

Keywords: Knee osteoarthritis severity classification, Deep Learning, YOLOv8, VGG16, KL grading.

1 Introduction

Osteoarthritis (OA) of the knee is a common degenerative joint disease where there is progressive degenerative loss of cartilage in the knee joint that causes pain, stiffness, and/or decreased mobility which negatively impacts the quality of life of millions, especially in older adults. According to the World Health Organization (WHO), more than 300 million people worldwide suffer from Osteoarthritis, and the knee joint is one of the commonly affected joints. Knee osteoarthritis (OA) is one of the leading causes of disability among older adults, and its incidence increases with age; hence, timely and accurate diagnosis is essential for efficient and targeted therapy. and improved quality of life. Historically, physicians have diagnosed knee OA by interpreting radiological images manually using the well-accepted Kellgren-Lawrence (KL) grading system. A total of 5 severity levels of the knee OA are defined based on the presence of visual markers including joint space narrowing,

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osteophyte formation structural changes taking place in the joint as well as degradation of articular cartilage. thickening of the synovial membrane, and the development of osteophytes. With cartilage breakdown, the underlying bone becomes exposed and may become sclerotic (hardened), a process that can change its texture and density. Although also on words! it is time consuming, subjective and can vary between different radiologist. The variation in assessments like these can lead to delays in proper diagnoses and appropriate patient care. Automated diagnostic technologies have arisen in recent years to meet these challenges.

State of the art of these systems utilize classical image processing methods like edges detection and templates matching in order to quantify characteristics like joint space width(JSW) from x rays images. In response to these challenges, we propose a new deep learning-based approach for diagnosing and classifying knee osteoarthritis using digital X-ray images. We propose an automated approach that utilizes modern CNNs to automatically perform two important tasks: i) obtain the JSW region that plays a vital role in OA assessment and ii) provide a severity score based on the KL grading system. In particular, we utilize the YOLOv8 model for the fast and accurate detection of the joint space width (JSW) area in X-ray images

Subsequently, VGG16 model processes the extracted features, and predicting OA severity with transfer learning method. Such an automated system could transform the management of knee OA and in doing so support clinicians in achieving more accurate and reliable diagnoses, lead to earlier interventions and better patient outcomes. Section II serves as literature survey review of the work. Section III describes the methodology, including its characteristics and operation. The analysis of the system is covered in Section IV with results and discussion. Finally, section V concludes with the main findings and future implications.

2 Literature survey

Osteoarthritis (OA) is a progressive degenerative condition that profoundly impacts joint function, leading to diminished mobility and a reduced quality of life. In response to the growing prevalence of OA, numerous studies have been dedicated to developing effective techniques for its early detection and classification, aiming to enhance therapeutic interventions and improve patient prognosis. This review consolidates the latest advancements, approaches, and methodologies within this field, offering a comprehensive overview of current diagnostic tools, treatment strategies, and research trends designed to optimize the management of OA and mitigate its long-term effects on affected individuals.

Anifahetal. [1] presented a technique combining Contrast Limited Adaptive Histogram Equalization grade the severity. The approach yielded high correctness in predicting early KOA stages, with classification rates of 93.8% for KL for each OA is grade 0, indicating no visible 70% to grade 1, signifying doubtful; 4% to grade 2, which marks minimal; 10% to grade 3, identifying moderate; and 88.9% to grade 4, representing severe OA. Although accurate in identifying both mild (grade 0) and advanced stages (grade 4), the method showed lower efficacy in identifying intermediate stages, particularly grade2.

In their study, Chen et al. [2] worked the YOLOv2 for automated recognition of knee joints in X-ray images, exploring a variety of classification networks fine-tuned to identify KOA severity, including VGG, ResNet, and DenseNet. Their model's Mean

Absolute Error (MAE) was 0.344, and its maximum exactness was 69.7%. This research provided insights into fully automated knee joint detection and emphasized the network's flexibility across different architecture choices, showcasing moderate correctness in early-stage OA detection.

Thomas et al. [3] established a CNN to grade osteoarthritis using a large radiograph dataset consisting of 32,116 training images, 4,074 tuning images, and 4,090 testing images. This model attained a percentage of 71% F1 score of 70% indicates a balanced performance of the model, where it effectively manages both precision and recall. This means the model accurately discerns 70% Of the pertinent cases.The F1 score reflects the model's overall ability to accurately classify data, with a score of 70% demonstrating reasonable effectiveness in the given task. underscoring its strength in learning features related to KOA severity. The study illustrated how large datasets contribute to effective model training and highlighted the potential of CNNs in addressing variability across X-ray images of knees affected by different OA severities.

Another study [4] applied ResNet combined with a Convolution Block Attention Module (CBAM) for knee OA grading, leveraging the Initiative (OAI) X-ray image dataset. The model's quadratic kappa score was 0.88, its MSE was 0.36, and its total veracity was 74.81%. For KL grade 1, the classification authenticity was 48.66%, whereas for KL grade 4, it was 90.21%. Notably, these results suggest that while the model effectively identifies severe OA (grades 3 and 4), further refinements could improve classification in intermediate stages.

A different approach examined the impact of including clinical information in KOA classification, where researchers [5] The research examined a convolutional neural network (CNN) architecture integrated with six Squeeze-and Excitation Residual Network (SE-ResNet) modules. Using a private dataset with 3,464 training images, 516 testing images, and 386 validation images, the team conducted two experiments. The first utilized only imaging data, achieving AUC values of 0.91, 0.80, 0.69, 0.86, and 0.96 across KL grades 0 to 4. The second incorporated both imaging and clinical data, yielding improved AUCs of 0.97, 0.85, 0.75, 0.86, and 0.95 for each grade. Findings indicated that KL grade 2 was particularly challenging to predict due to high variability within this grade. This study illustrated that additional clinical data improved model performance, offering a more comprehensive approach to KOA severity prediction.

In another investigation [6], U-Net was used to localize left and right knee joints within radiographs from the OAI dataset, followed by classification using Dense Net with demographic data, including age, gender, and BMI. With 25,873 training images, 7,779 validation images, and 5,941 test images, the model achieved sensitivities of 83.7% for normal, 70.2% for mild, 68.9% for moderate, and 86.0% for severe OA, with specificities of 86.1% (normal), 83.8% mild cases, 97.1% moderate cases, and 99.1% severe cases. KL grade 1 was excluded from the analysis due to classification challenges, and inter-observer reliability varied between 0.51 and 0.89, indicating inconsistencies, especially in borderline KOA stages. This study highlighted the importance of differentiating adjacent KL grades, as these were often misclassified.

Finally, ResNet-34 was used to identify KL grade and predict OA progression using a transfer learning approach [7]. The study combined both knee radiographs and patient info (eg, age, ethnicity, BMI and gender) from 728 OAI participants to predict KOA severity and development. Indeed, this transfer learning approach also yielded AUC scores of 0.93, 0.80, 0.88, 0.96, and 0.99 for KL grades 0–4 respectively. The degree of velocity and bone surface roughness variance being reported and its influence on some

measures of predictive reliability further indicates that significant improvements in prediction robustness could be achievable for challenging OA stages sourcing transfer learning models with pre-trained architectures.

Genetic markers have been studied to enhance OA screening, especially in high-risk groups. [8] Badshah et al. analyzed genetic markers in the Pakistani populace, focusing on features that aid in early diagnosis. The results can lead to the invention of specialized diagnostic instruments and matching treatment approaches for patients with similar genetic backgrounds. The findings reiterate the utility of genetic profiling for osteoarthritis management, and emphasizes the need for population-specific studies due to differences in genetic variants across populations. These insights guarantee the relevance of findings and lead to a more efficient health strategy specific to zone and ethnic needs.

With the advancement of image analysis and machine vision, innovative methods for osteoarthritis diagnosis are emerging. Gornale et al. A method for osteoarthritis detection using knee X-ray image analysis was proposed in [9]. In their work, important features were extracted and analyzed from X-ray images using machine vision techniques, with a notable increase in osteoarthritic change identification accuracy. The implication is clear — a combination of automated systems for prompting disease warning systems may help reduce diagnostic variance through assisting earlier detection. This research highlights the potential for computational tools to support physicians in making more accurate and timely osteoarthritis diagnoses.

Imaging and machine learning had a significant impact on knee OA diagnosis and prognosis. Teoh et al. [10] discussed imaging approaches, such as manual grading and machine learning methods, used to detect critical disease features. The study also noted that machine learning can automate feature identification and improve the prediction accuracy. The review identifies the respective strengths and potential limitations of traditional and computational approaches, and provides insights for the translation of these advanced technologies into routine clinical workflows. Utilizing machine learning highlighted transformative potential within these findings that could facilitate higher diagnostic accuracy, decrease subjectivity, and more personalized intervention to osteoarthritis treatment, conducive to more focused and reliable healthcare solutions moving forward.

3 Methodology

In summary, a proposed method to detect and classify knee OA employs an efficient procedure by utilizing state-of-art deep learning algorithms to enhance diagnostic accuracy and to advance the quality of care provided to patients. We first obtain a wide range of knee x-ray images from a trusted source. The dataset comprise variety of conditions of the knee with varying qualities of images ensuring that model can be able to work in real-life scenarios. Joint Space Width (JSW) Area Detection. The next objective is to detect the JSW region which is an important characteristic of OA. For this purpose, the YOLOv8 model is employed which typically achieves fast and clear object detection. The model is trained on x-ray images labelled to highlight the JSW regions. Fig. 1 Presents a overall proposed methodology for knee osteoarthritis classification.

3.1 Data Collection

Data collection forms the backbone of this study. High-quality X ray images datasets were collected from public repositories, such as Kaggle. Data collection is a crucial step in developing an effective diagnostic system for OA. Digital X-ray images of knee joints were sourced from multiple reliable repositories, including publicly available medical imaging databases and institutional archives. These datasets were selected to ensure a diverse representation of knee conditions, including healthy joints and varying stages of OA. Efforts were made to include data from patients of different ages, genders, and ethnicities to enhance the model's generalizability. Images were also gathered from a range of imaging equipment and techniques, capturing variations in resolution, quality, and positioning, which reflect real-world clinical scenarios.

3.2 Preprocessing

Data preprocessing is the first step to ensure that actually, the dataset has the ideal structure to apply for further analysis or modelling. The raw MRI scans were standardized using a set of transformations. All the images are uniformly resized into 224 by 224 pixels because, like all other Vision Transformers, it utilizes a standard dimension for a resolution. Intensity normalization accounted for variations in scanner settings and ensured comparability of the values in pixel intensity. Preprocessing is a crucial step in preparing medical images for analysis, particularly when applying deep learning models to tasks like identifying and classifying osteoarthritis. Preprocessing techniques were carefully implemented to standardize and enhance the quality of knee joint X-ray images, ensuring the models performed at their best. These steps are crucial in enhancing the level of detail and robustness of deep learning algorithms Finally, the preprocess data was divided into training (70%), validation set of 15%, and testing set of 15% to allow for training and evaluation of the proposed models without overfitting.

3.3 Knee Joint Space Width (JSW) Region Detection using YOLOv8

In this sub-module, detection and localization of Knee JSW (joint space width) region present in knee X-ray image is achieved with aid of YOLOv8 model, a high-performance deep learning mode. Initially, manual annotation of the knee of the Radiographic images is performed for the JSW region. These annotations serve as the ground truth used to train the model, allowing it to learn how to accurately predict and localize the JSW during inference. Once annotated, the dataset is transformed into the form which is understood by YOLOv8 using the tools such as Robo flow which simplifies the data preprocessing and make it compatible with the model. This method uses a process of concatenating four images together during training time, allowing the model to learn object detection from various conditions (i.e. whether the object was at a different point in space) and whether the surrounding pixels have been varied. Note that the mosaic augmentation is performed 'online', i.e. in the current epoch. This enables the model to generalize better to new, unseen images, enhancing its robustness. All these improvements and techniques combined make it possible for the YOLOv8 model to reach high performances on detecting and localizing the JSW region, which is one of the most relevant features to diagnose the knee osteoarthritis.

3.4 Knee Osteoarthritis Classification using VGG16

In this module, OA is usually categorized on the basis of its severity, which is vital for controlling the appropriate treatment alternatives and intervention schemes. Deep learning methods are therefore implemented, a well-known and used is the VGG16. This process is facilitated using the enhanced VGG16 convolutional neural network

model. The knee X-ray images pre-processed to identify the Knee Joint Space Width (JSW) through the YOLOv8 model are then provided as input to the VGG16 model. The model is fine-tuned for disease classification, which estimates OA severity according to the Kellgren Lawrence (KL) grading criteria, which classifies OA into five grades according to the KL scoring system: 0 (no OA), 1 (doubtful), 2 (mild), 3 (moderate) and 4 (severe). This allows for an accurate diagnosis and therapy planning.

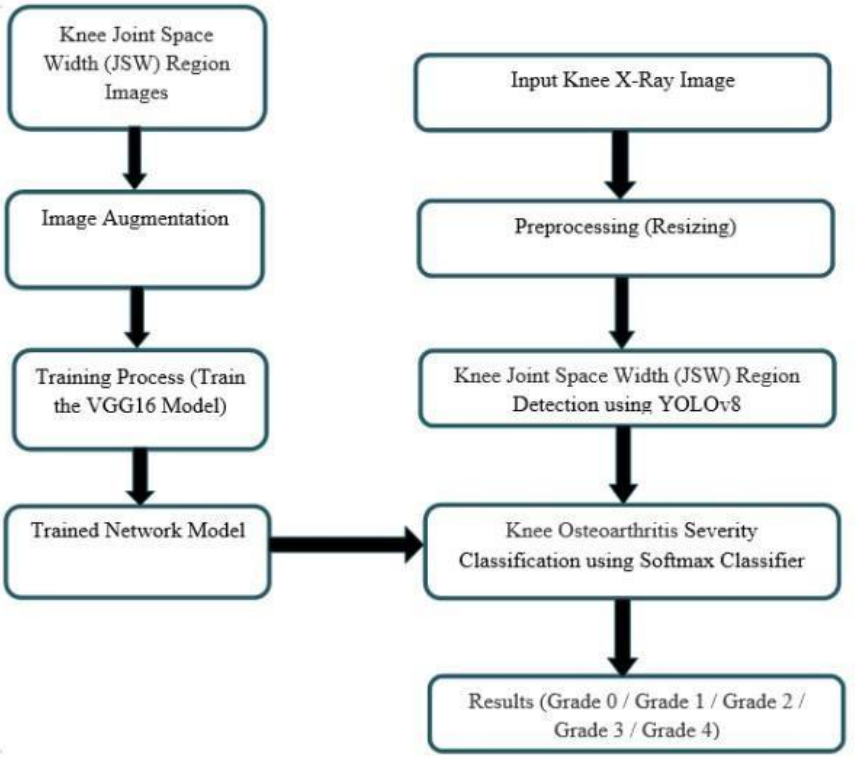

Fig. 1. Overall proposed methodology for knee osteoarthritis classification.

4 Result and discussion

This framework illustrates the outcomes of the evaluation of knee (OA) diagnosis and classification. The VGG16 model performance in the classification of OA severity was evaluated. These metrics provide a measure of how well the model detects and classifies various stages of OA. Besides classification evaluation, the prediction performance of the YOLOv8 model in recognizing the Knee Joint Space Width (JSW) region was also evaluated. The main indices for evaluation of the JSW detection were meaning Average Perfection (mAP) and perfection and revisiting, reflecting the JSW region volume position and the overall detail found in knee X-ray images via the model.

These findings provide insights into the performance of the deep learning knee OA, emphasizing their potential role in clinical decision support. The dataset used in this work, which included images at five different severity grades, was drawn from a public repository on Kaggle. The summary of YOLOv8 performance and metrics (mean Average Sharpness (mAP), correctness, and reminding metrics) for each dataset is listed in Table 1, confirming that it is effective at detecting the Knee Joint Space Width

(JSW) region. The results of these experiments show that the YOLOv8 model was able to successfully localize the JSW region in knee X-ray images, with a high MAP score of 0.995 with respect to an Intersection over Union (IOU) threshold (the IOU criterion or IOU cut-off). This could be represented as the input overlap ratio threshold value, or the IoU 0.5 overlap threshold. The outcomes of this extensive process are shown in Fig 2, including the input image, the identified JSW area, and the end classification output. 2. These quantitative performance metrics are summarized in Table 2 which provides important insights into the performance of the VGG16 model.

VGG16 achieved an accuracy of 92.5%, precision of 90.8%, recall of 91.3%, and f1-score of 91.0 %}. The ROC curve analysis illustrated in Fig. 3 shows a diagram charting the performance in the classification of rigidity for different threshold settings. The AUC of our analysis was 0.9427, which indicated a strong capacity of our model in distinguishing among the(OSD) different severity levels of knee OA. This analysis takes this a step further, confirming that the proposed approach to learning is able to accurately determine and categorize the severity of knee OA, and reinforces its possible application in the clinical setting to assist with timely and appropriate treatment decision-making.

Table 1. Performance metrics

Metrics	Performance
MAP	0.995
Precision	0.988
Recall	1.000

Table 2. Performance analysis of the VGG16 model for knee OA classification

Metrics	**Performance**
Accuracy	0.9153
Recall	0.9143
Precision	0.9236
F1-score	0.9123

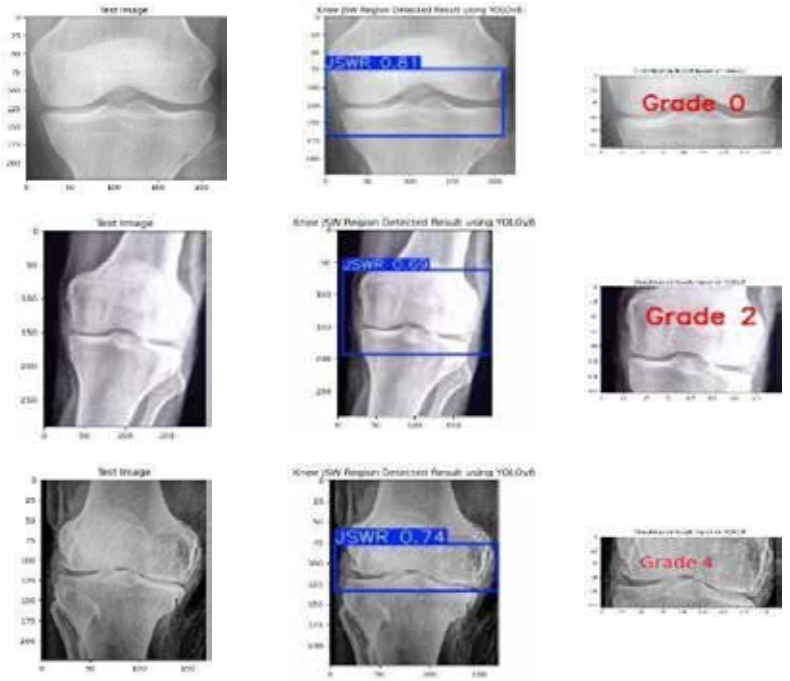

Fig. 2. Knee OA Severity Classification Results.

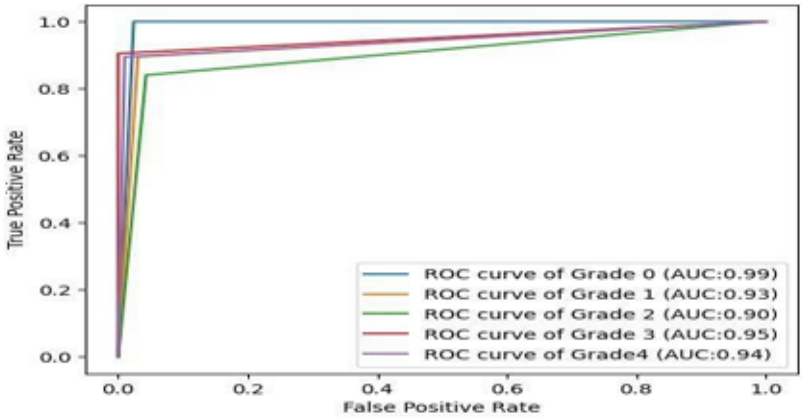

Fig. 3. ROC curve analysis for knee OA classification using VGG16 model.

5 Conclusion

This work proposed a deep-learning-based enhanced approach for the identification and classification of osteoarthritis (OA) images in the digital X-ray images based on artificial intelligence (AI). Using the capabilities of YOLOv8 model, the JSW area which is an important factor of the severity of OA was successfully localized. The YOLOv8 algorithm proved to be robust by identifying the JSW correctly with mAP score of 0.995. Moreover, the VGG16 model was employed to perform transfer learning for the classification of knee OA severity stages following Kellgren Lawrence (KL) algorithm grading system scoring structure. Secondary Deep Learning (DL)

architecture experimented with is VGG16 and it produced phenomenal metrics of performance: authenticity of 91.53%, memory of 91% exactness of 92% and F1 score of 91%. ROC curve analysis confirmed the discriminative capacity of the model to distinguish the levels of knee OA severity. Such approach has important implications for patient outcomes and timely interventions in the clinic. Future efforts will focus on generalization of the complete dataset, optimizations for models, and consideration of additional imaging modalities to enhance the reliability of knee OA classification.

Disclosure of interest. The authors have no competing interests to declare that are relevant to the content of this article.

References

1. L. Anifah, I. K. E. Purnama, M. Hariadi, and M. H. Purnomo, "Osteoarthritis classification using self -organizing map based on Gabor kernel and contrast-limited adaptive histogram equalization," Open Biomed. Eng. J., vol. 7, no. 1, pp. 18–28, Feb. 2013.
2. P. Chen, L. Gao, X. Shi, K. Allen, and L. Yang, "Fully automatic knee osteoarthritis severity grading using deep neural networks with a novel ordinal loss," Computerized Med. Imag. Graph., vol. 75, pp. 84–92, Jul. 2019.
3. K. A. Thomas, L. Kidzinski, E. Halilaj, S. L. Fleming, G. R.Venkataraman, E. H. G. Oei, G. E. Gold, and S. L. Delp, "Automated classification of radiographic knee osteoarthritis severity using deep neural networks," *Radiol., Artif. Intell.*, vol. 2, no. 2, Mar. 2020, Art. no. e190065.
4. B. Zhang, J. Tan, K. Cho, G. Chang, and C. M. Deniz, "Attention-based CNN for KL grade classification: Data from the osteoarthritis initiative," in Proc. IEEE 17th Int. Symp. Biomed. Imag. (ISBI), Apr. 2020, pp. 731–735.
5. H. Kim, K. J. Lee, D. Choi, J. I. Lee, H. G. Choi, and Y. S. Lee, "Can additional patient information improve the diagnostic performance of deep learning for the interpretation of knee osteoarthritis severity," J. Clin. Med., vol. 9, no. 10, p. 3341, Oct. 2020.
6. B. Norman, V. Pedoia, A. Noworolski, T. M. Link, and S. Majumdar, "Applying densely connected convolutional neural networks for staging osteoarthritis severity from plain radiographs," J. Digit. Imag., vol. 32, no. 3, pp. 471–477, Jun. 2019.
7. K. Leung, B. Zhang, J. Tan, Y. Shen, K. J. Geras, J. S. Babb, K. Cho, G. Chang, and C. M. Deniz, "Prediction of total knee replacement and diagnosis of osteoarthritis by using deep learning on knee radiographs: Data from the osteoarthritis initiative," Radiology, vol. 296, no. 3, pp. 584– 593, Sep. 2020.
8. Y. Badshah, M. Shabbir, H. Hayat, Z. Fatima, A. Burki, S. Khan, and S. U. Rehman, "Genetic markers of osteoarthritis: Early diagnosis in susceptible Pakistani population," J. Orthopaedic Surgery Res., vol. 16, no. 1, pp. 1–8, Dec. 2021.
9. S. S. Gornale, P. U. Patravali, and R. R. Manza, "Detection of osteoarthritis using knee X-ray image analyses: machine vision based approach," Int. J. Comput. Appl., vol. 145, no. 1, pp. 20–26, 2016.
10. Y. X. Teoh, K. W. Lai, J. Usman, S. L. Goh, H. Mohafez, K. Hasikin, P. Qian, Y. Jiang, Y. Zhang, and S. Dhanalakshmi, "Discovering knee osteoarthritis imaging features for diagnosis and prognosis: Review of manual imaging grading and machine learning approaches," J. Healthcare Eng., vol. 2022, pp. 1–19, Feb. 2022.

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