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A Transformer-Driven Approach for Knee Osteoarthritis Grading Using Deep Learning

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INDEX TERMS:

Knee osteoarthritis,
deep convolutional generative adversarial network (DCGAN),
knee osteoarthritis grades,
image pre-processing,
compact convolutional transformer,
knee X-ray.

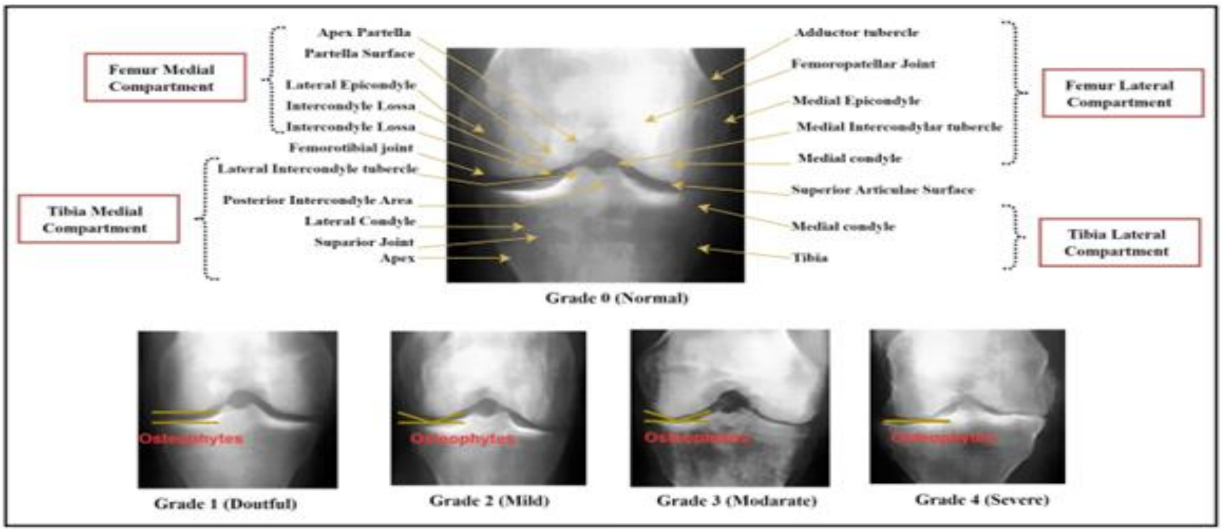
ABSTRACT

Knee osteoarthritis (KOA) is a progressive joint disorder often diagnosed via X-ray imaging due to its accessibility and low cost. The severity is typically assessed using the Kellgren and Lawrence (KL) grading scale. Early detection using this method can slow disease progression through timely intervention. In this study, four datasets were combined and augmented using Deep Convolutional Generative Adversarial Networks (DCGAN), resulting in 110,232 enhanced images. Advanced preprocessing techniques such as adaptive histogram equalization (AHE), fast non-local means filtering, and resizing were applied to improve image quality. A modified Compact Convolutional Transformer model, KOA-CCTNet, was developed and fine-tuned by optimizing multiple hyperparameters to efficiently handle large-scale data and reduce training time. Experimental results showed KOA-CCTNet outperformed state-of-the-art models including ResNet50 (80.77%), MobileNetv2 (79.98%), DenseNet201 (80.23%), InceptionV3 (76.89%), and VGG16 (79.58%), achieving a superior test accuracy of 94.58%. The model maintained high performance even on reduced datasets, offering an effective and scalable solution for KOA grade classification.

I.INTRODUCTION

Knee osteoarthritis (KOA) is a progressive joint condition primarily affecting cartilage and causing pain, stiffness, and reduced mobility. It is commonly diagnosed using X-ray imaging, supported by the Kellgren-Lawrence (KL) grading system, which classifies KOA severity from Grade 0 (normal) to Grade 4 (severe). Early diagnosis is crucial for slowing disease progression, yet subjective symptom assessment and class imbalance in datasets pose challenges.

To address these issues, this study proposes KOA-CCTNet, an enhanced diagnostic framework leveraging a Compact Convolutional Transformer model. Four diverse KOA datasets (Mendeley I & II, Kaggle, AIDA) were combined into a unified data hub with 11,431 images. Dataset imbalance was handled using DCGAN-based augmentation, and image quality was improved using Adaptive Histogram Equalization (AHE) and Fast Non-Local Means (FNLM) filtering.



The example of the Kellgren–Lawrence (KL) scale.

KOA-CCTNet was developed and optimized to improve training efficiency and performance, outperforming conventional CNNs and transformer models like ViT in classification accuracy and training time. It proved effective even on limited and imbalanced medical datasets.

Key contributions include:

1. Creation of a large, diverse KOA dataset from multiple sources.
2. Addressing class imbalance with advanced GAN-based augmentation.
3. Application of robust pre-processing to enhance image quality.
4. Development of KOA-CCTNet, which achieves superior accuracy and efficiency compared to existing models.

The paper follows with a literature review, methodology, experimental results, conclusion, and references.

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Grade	Intensity	Statement
Grade 0	Normal	No radiographic features of KOA are present
Grade 1	Doubtful	Doubtful joint space narrowing and possible presence of small osteophytes
Grade 2	Mild	Definite joint space narrowing and the presence of osteophytes
Grade 3	Moderate	Moderate joint space narrowing, multiple osteophytes and possible bone remodeling
Grade 4	Severe	Severe joint space narrowing, extensive osteophyte formation and possible joint deformity

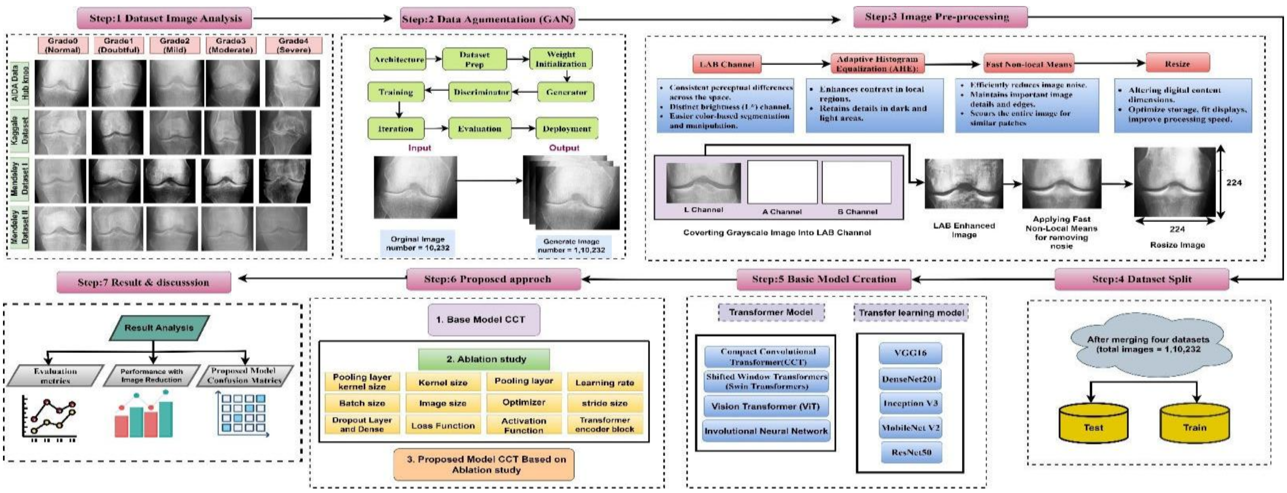
TABLE 1. Knee osteoarthritis (KOA) grade description.

II.LITERATURE REVIEW

Numerous studies have explored deep learning approaches for diagnosing Knee Osteoarthritis (KOA) using X-ray images, highlighting advancements in automated classification based on the KL grading scale.

Ganesh Kumar and Goswami [17] used CNNs with image sharpening to improve classification accuracy to 91.03%, though limited by poor pre-processing. Mohammed et al. [18] applied six pre-trained DNN models, with ResNet101 performing best, achieving up to 89% accuracy. Another study [19] combined Faster RCNN and AlexNet for region detection and severity grading, reaching near 99% accuracy.

El-Ghany et al. [20] utilized DenseNet169, achieving 95.93% accuracy for multi-class KOA classification, surpassing previous benchmarks. Similarly, [21] employed transfer learning with models like ResNet-34 and VGG-19, achieving 98% accuracy and a Kappa score of 0.99.



Workflow diagram

DST-CNN by Nasser et al. [13] introduced a discriminative approach using texture-shape features and achieved 74.08% accuracy, especially effective for borderline cases. Olsson et al. [22] trained a ResNet-based 35-layer CNN on unfiltered data, attaining AUC values above 0.87 across KL grades.

Chaugule et al. [7] developed a DCNN using autoencoders, segmentation, and feature fusion, achieving validation and test accuracies of 95.70% and 96.31%, respectively. Qadir et al. [23] applied BiLSTM with ResNet features, reaching 84.09% accuracy and strong performance across KOA grades.

Yunus et al. [24] proposed a 3D transformation of 2D X-rays using LBP, PCA, and features from AlexNet and Darknet-53, achieving 90.6% accuracy. Their system used ONNX-YOLOv2 for localization with a 0.98 mAP.

Despite varied success, limitations include inconsistent pre-processing, class imbalance, and reliance on small datasets. This study addresses these gaps by integrating multiple datasets, enhancing image quality, and proposing a dedicated deep learning model for robust KOA classification.

III. METHODOLOGY

Our approach starts by integrating four public KOA X-ray datasets, totaling 11,431 images. After removing 1,199 low-quality images, we retained 10,232 for further use. Data augmentation via DCGAN increased the dataset to 110,232 images, ensuring class balance across KL grades. We pre-processed all images by converting to LAB color space, applying Adaptive Histogram Equalization (AHE) for contrast enhancement, denoising with Fast Non-Local Means (FNLM), and resizing to 224×224 pixels.

Experimental Setup

Training was performed using Python with TensorFlow, Keras, and PyTorch on an RTX 3060 GPU system over 200 epochs.

Data Augmentation – DCGAN

DCGAN was used to synthesize realistic knee X-rays, enhancing dataset diversity. The generator and discriminator were trained adversarially to create high-fidelity samples. Output images closely matched original medical images in structure and histogram-based intensity metrics.

Image Pre-processing

- **AHE**: Improved local contrast in low-visibility regions of X-rays.

- **FNLM**: Reduced noise while preserving edges and structure, enabling faster and accurate diagnosis.
- **Verification**: Metrics like MSE, PSNR (>31), SSIM (>0.99), and RMSE (>0.54) confirmed image quality was preserved post-processing.

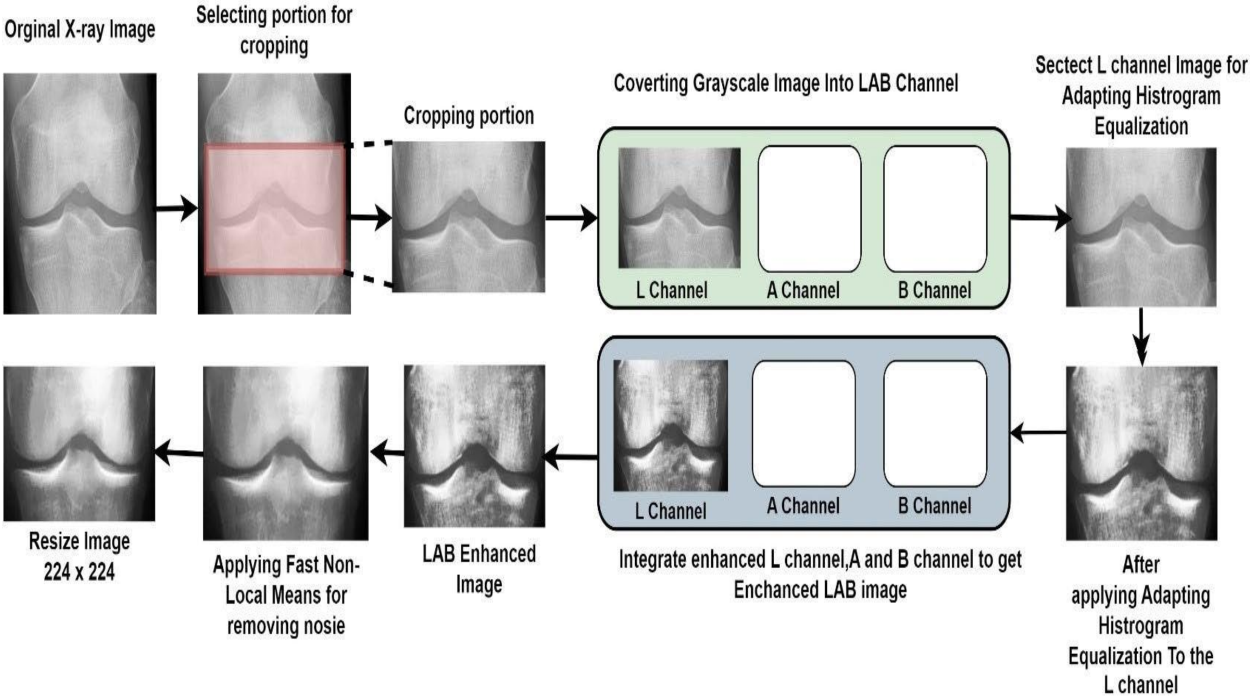


Image pre-processing workflow.

IV. RESULTS

A. Performance Metrics

Various metrics, including accuracy, precision, recall, F1-score, and MCC, were used to evaluate the model's performance. A confusion matrix and accuracy-loss curves are shown in Figure 11C.

B. Transfer Learning Results

Five transfer learning models were tested. While MobileNetV2 achieved the highest accuracy, it was time-consuming. Other models showed slower performance with lower accuracy.

C. Transformer Models Results

Four transformer models were tested, with the CCT model achieving 86.54% accuracy in 225 seconds per epoch. The ViT model had a lower accuracy but was slower. The CCT model was selected for further use due to its speed.

D. Optimal Model Performance

The CCT model outperformed others with 94.4% accuracy, 94.2% F1-score, and excellent specificity (98.53%). The results show strong classification performance with X-ray images.

E. Dataset Augmentation Techniques

Four augmentation methods were applied. DCGAN-generated images achieved the best results, with 94.58% accuracy. Other techniques like elastic deformation and geometric augmentations resulted in lower accuracies.

F. Performance with Reduced Data

The model's accuracy dropped with reduced image sets: 94.58% (100%), 92.26% (75%), 90.15% (50%), and 87.55% (25%).

G. Model Visualization

Figures 12(a) and 12(b) show smooth training/validation accuracy and loss curves, indicating no overfitting. Figure 12(c) illustrates the confusion matrix.

H. Comparison with Existing Work

Our model outperformed prior works, which lacked image augmentation techniques. For example, previous studies achieved accuracies ranging from 69% to 90.6%. Our approach, with large datasets and advanced augmentation (DCGAN), showed superior results in KOA classification.

Accuracy comparison with existing literature

Paper	Name of the dataset	Data Augmentation	Apply image pre-processing techniques	Models	Classification Types	Accuracy
A.S. Mohammed et.al.[18]	1. Osteoarthritis Initiative (OAI)	N/A	N/A	VGG16, VGG19, ResNet101, MobileNetV2, InceptionResNetV2 and DenseNet121	1.Healthy 2.Doubtful 3.Minimal 4.Moderate 5.Severe	Dataset I- 69% (ResNet101) Dataset II- 83% (ResNet101) Dataset III- 99% (ResNet101)
S.Olsson et.al[22]	1. Osteoarthritis Initiative (OAI) (Total Image- 6403)	N/A	Yes	Convolutional Neural Network (CNN)	1.Healthy 2.Doubtful 3.Severe	87% CNN
U. Unus et.al	Mendeley VI (Total image 3795)	N/A	N/A	Open exchange neural network(ONNX) and YOLOv2	1.Normal 2.Doubtful 3.Mild 4.Moderate 5.Severe	90.6% (Their proposed model)
The Current study	1.Kaggle (400 image) 2.Mendeley I (8260 image) 3.Mendeley II (1650 image) 4.AIDA	DCGAN (Generated 110232 augmented images from 10232 images) Total Dataset:	1.Lab Channel 2.Adaptive Histogram Equalization (AHE) 3.Fast Non-Local	Proposed Model KOA-CCTNet	1.Normal 2.Doubtful 3.Mild 4.Moderate 5.Severe	94.58% (for marge dataset of all five grade) 97.10% (Grade-0), 97.25%

	Datahub (1121 image) Marge Dataset (Total image11431. After removing damage images, the final marge dataset contains 10232 raw images)	110232	Means(FNLM) 4.Resize			(Grade-1), 95.50% (Grade-2), 98.26% (Grade-3), 99.26% (Grade-4),

VI.CONCLUSION

Our study's goal was to improve KOA categorization using X-ray pictures employing a big datahub, which is how the KOA-CCTNet framework was created. After analyzing four transformer and five transfer learning models, we decided to choose the CCT model as our core architecture, and this framework is an invention based on that model. Four different sets of X-ray pictures with various quality and resolution made up the varied dataset we curated. Because of the noise and artifacts in these images, we had to use image processing techniques to make all 110,232 of the images in our dataset better. Developing a balanced dataset was our top priority, and we used augmentation techniques to increase its size and improve the model's training effectiveness. This method was essential for handling our image dataset's diversity and guaranteeing thorough training. Nine distinct ablation studies were included in our comprehensive review, which allowed us to optimize the KOA-CCTNet model and solve issues with training time and dataset size. Interestingly, the KOA-CCTNet performed exceptionally well, attaining an accuracy percentage of 94.58%. This high degree of accuracy was preserved even while working with fewer photos, demonstrating the resilience and dependability of the model. Significant contributions to the area are made by our study, such as the creation of a reliable dataset utilizing original augmentation approaches and the improvement of image quality using a variety of pre-processing methods. Additionally, we offered thorough comparisons across several transformer and transfer learning models, ultimately refining the KOA-CCTNet to produce exceptional outcomes.

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