Knee Osteoarthritis Detection and Classification Using a Customized CenterNet with DenseNet201

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Abstract:

Knee Osteoarthritis (KOA) is a progressive degenerative joint disease that significantly impacts mobility and quality of life. Early detection and accurate severity grading are critical for effective clinical management and prevention of disease progression. Manual interpretation of knee X-ray images using the Kellgren–Lawrence (KL) grading system is time-consuming and subject to inter-observer variability. This research presents an end-to-end deep learning–based framework for automated detection and classification of knee osteoarthritis severity using transfer learning with MobileNetV2. The proposed system leverages a publicly available knee X-ray dataset categorized into five severity grades (0–4). To address class imbalance, class weighting strategies were incorporated during training. The final model achieved a validation accuracy of 54% with improved macro F1-score balance across all classes. Furthermore, the trained model was deployed using a Streamlit-based web interface to enable real-time image-based severity prediction. The system demonstrates the feasibility of lightweight deep learning architectures for practical medical image classification and clinical decision support.

Keywords: Knee Osteoarthritis, Deep Learning, Transfer Learning, MobileNetV2, Medical Image Classification, X-ray Analysis, Streamlit Deployment, Class Imbalance

I.INTRODUCTION

Knee Osteoarthritis (KOA) is one of the most prevalent musculoskeletal disorders worldwide, particularly among elderly populations. It is characterized by cartilage degeneration, joint space narrowing, osteophyte formation, and sclerosis. Accurate severity assessment is essential for determining appropriate treatment strategies such as lifestyle modifications, pharmacological interventions, or surgical procedures.

Traditionally, KOA severity is assessed using the Kellgren–Lawrence (KL) grading scale based on radiographic features. However, manual interpretation is subjective and may vary between radiologists. With the rapid advancement of artificial intelligence in medical imaging, automated systems can assist clinicians by providing consistent and objective evaluations.

This research Proposes a deep learning-based automated system for knee osteoarthritis detection and severity classification. The study implements transfer learning using MobileNetV2 to leverage pre-trained ImageNet weights for improved feature extraction. The complete pipeline includes dataset preprocessing, imbalance handling, model training evaluation, and web-based deployment.

II.LITERATURE SURVEY

1. Knee Osteoarthritis (KOA) is a degenerative joint disorder characterized by progressive cartilage degradation, osteophyte formation, subchondral sclerosis, and joint space narrowing. Radiographic assessment remains the primary diagnostic approach in clinical practice. Traditionally, orthopedic specialists rely on manual interpretation of X-ray images using standardized grading systems. However, manual grading is subjective, time-consuming, and prone to inter-observer variability. These limitations have motivated the development of automated computer-aided diagnostic (CAD) systems using machine learning and deep learning approaches.

2. Traditional Image Processing Approaches.

- Early research focused on handcrafted feature extraction techniques applied to radiographic images.

Methods included:

- Texture feature extraction using Gray Level Co-occurrence Matrix (GLCM)
- Histogram-based intensity analysis
- Edge detection for joint space measurement
- Morphological operations for osteophyte detection

3. Emergence of Deep Learning in Medical Imaging

With the advent of Convolutional Neural Networks (CNNs), feature extraction became automated. CNNs demonstrated superior capability in capturing hierarchical representations from raw image data.

Deep learning models eliminate manual feature extraction by learning spatial patterns directly from images. This shift significantly improved classification performance in radiographic analysis.

Applications in KOA detection began leveraging:

- AlextNet
- VGGNet
- ResNet
- DenseNet
- Inception Networks
- MobileNet architectures

These pre-trained models enabled transfer learning, allowing effective training even with moderate-sized medical datasets.

4.CNN-Based KOA Classification Studies

Several studies have applied CNN architecture for KOA grading using the Kellgren-Lawrence (KL) system

Common findings across literature:

- Transfer learning improves accuracy compared to training from scratch.
- Data augmentation enhances generalization.
- Class imbalance significantly affects model performance.
- Higher KL grades are often easier to detect compared to early-stage osteoarthritis.

Typical reported accuracy ranges:

- 60–75% for multi-class classification (Grades 0–4)
- Higher accuracy for binary classification (OA vs Non-OA)

However, many studies reported:

- Overfitting due to small datasets
- Poor recall for minority classes (Grade 3 and 4)
- Lack of real-world deployment interface

5. Object Detection-Based Approaches

Beyond classification, some research introduced object detection models such as:

- Faster R-CNN
- YOLO

- CenterNet

These models identify specific regions such as:

- Osteophytes
- Joint space narrowing regions
- Cartilage degeneration zones

CenterNet-based approaches improved localization precision by detecting key points and bounding boxes simultaneously. This allowed both detection and grading in a single framework.

However, detection-based models are computationally heavy and require detailed annotation datasets, which are often unavailable in large quantities.

6. DenseNet-Based Architectures

DenseNet architectures introduced dense connectivity between layers, improving feature reuse and gradient flow.

Advantages observed:

- Reduced vanishing gradient problem
- Efficient parameter usage
- Better feature propagation
- Improved classification accuracy in medical imaging

DenseNet201-based models showed improved performance in multi-grade KOA classification compared to traditional CNNs.

Yet limitations remain:

- High computational cost
- Requirement of large GPU memory
- Complex deployment pipeline

7. Lightweight CNN Models

For real-world deployment, lightweight architectures like MobileNetV2 gained popularity.

Advantages:

- Reduced parameters
- Faster inference time
- Suitable for web or mobile deployment
- Efficient feature extraction with depthwise separable convolutions

MobileNet-based systems offer a good balance between performance and computational efficiency, making them ideal for clinical assistance tools.

8. Challenges Identified in Literature

The major limitations observed across studies include:

1. **Class Imbalance**
 Severe osteoarthritis cases are fewer than normal cases.
2. **Small Dataset Size**
 Limited annotated medical imaging datasets.
3. **Overfitting**
 Deep models memorize training data without proper regularization.
4. **Lack of Explainability**
 Many systems do not provide interpretability for predictions.
5. **Deployment Gap**
 Most studies stop at accuracy reporting without real-world UI integration.

9. Research Gap

Despite advancements in CNN-based classification and detection methods, the following gaps remain:

- Need for computationally efficient models suitable for deployment.
- Balanced performance across all KL grades.
- Integration of a complete pipeline including:
  - Dataset preprocessing
  - Model training
  - Evaluation metrics
  - Confusion matrix analysis
  - User-friendly deployment interface

10. Motivation of the Proposed Work

Based on the identified gaps, this project focuses on:

- Transfer learning using MobileNetV2.
- Class-weight balancing to handle dataset imbalance.
- Fine-tuning last layers for better feature specialization.
- Multi-class classification (Grade 0–4).
- Deployment using a web-based UI (Streamlit).
- End-to-end pipeline from training to clinical-style prediction.

III.DATASET DESCRIPTION

The dataset used in this study consists of labeled knee X-ray images categorized into five classes according to the KL grading scale:

- **Grade 0:** Normal (No signs of osteoarthritis)
- **Grade 1:** Doubtful (Minor osteophyte formation)
- **Grade 2:** Mild (Definite osteophytes, possible joint space narrowing)
- **Grade 3:** Moderate (Multiple osteophytes, definite narrowing)
- **Grade 4:** Severe (Large osteophytes, severe narrowing and sclerosis)

The dataset was divided into training, validation, and testing sets using an 80:10:10 split. Images were resized to 224×224 pixels to match MobileNetV2 input requirements.

Class distribution analysis revealed imbalance, with Grade 0 having significantly more samples compared to Grade 4. This imbalance was addressed using class weighting during training.

IV.PROPOSED METHODOLOGY

1. System Architecture

The proposed system follows a structured pipeline:

1. Data Collection
2. Image Preprocessing
3. Transfer Learning Model Initialization
4. Class Weight Computation
5. Model Training
6. Fine-Tuning
7. Evaluation
8. Model Saving
9. Web Deployment

2. Data Preprocessing

- Image resizing to 224×224
- RGB channel normalization
- Preprocessing using MobileNetV2 preprocessing function
- Data augmentation (rotation, zoom, horizontal flip)

3. Model Architecture

The base architecture used is MobileNetV2 pre-trained on ImageNet.

- Base Model: MobileNetV2 (include_top=False)
- Global Average Pooling Layer
- Dropout Layer (to prevent overfitting)
- Dense Output Layer (5 neurons with softmax activation)

Only the final classification layers were trained initially, followed by fine-tuning of the top 20 layers of the base model.

Total Parameters: 2,264,389
Trainable Parameters (initial phase): 6,405

4. Handling Class Imbalance

Due to uneven distribution among severity grades, class weights were computed and applied during model training. This approach penalizes misclassification of minority classes more heavily, improving macro-level performance.

5. Training Strategy

- Optimizer: Adam
- Initial Learning Rate: 0.001
- Fine-tuning Learning Rate: 1e-5
- Loss Function: Categorical Crossentropy
- Metrics: Accuracy
- Epochs: 25

Fine-tuning significantly improved validation accuracy and overall class-wise balance.

V. EXPERIMENTAL RESULTS

1. Performance Metrics

Final validation accuracy achieved: **54%**

Classification report:

- Improved precision and recall for minority classes
- Balanced macro F1-score ≈ 0.53
- Weighted F1-score ≈ 0.53

2. Confusion Matrix Analysis

The confusion matrix indicates:

- Strong prediction capability for Grade 0
- Improved detection of Grade 4 after class weighting
- Some confusion between Grade 2 and Grade 3 due to similar radiographic features

VI. WEB-BASED DEPLOYMENT

To make the system practically usable, the trained model was deployed using Streamlit.

Deployment Features:

- Upload knee X-ray image
- Automatic resizing and preprocessing
- Real-time prediction
- Confidence score display
- Probability breakdown for all classes

The deployment ensures ease of access and provides a user-friendly clinical decision support interface.

VII. DISCUSSION

The results demonstrate that lightweight transfer learning models can effectively classify knee osteoarthritis severity. Although the overall accuracy is moderate, the balanced macro F1-score indicates reliable multi-class classification across imbalanced data.

Challenges observed include:

- Overlap between adjacent KL grades
- Limited dataset size

- Radiographic variability

Despite these limitations, the system successfully demonstrates automated severity grading with practical deployment capabilities.

VIII.IMPLEMENTATION

Fig:8.1

KOA Disease Classification System interface with image upload option.

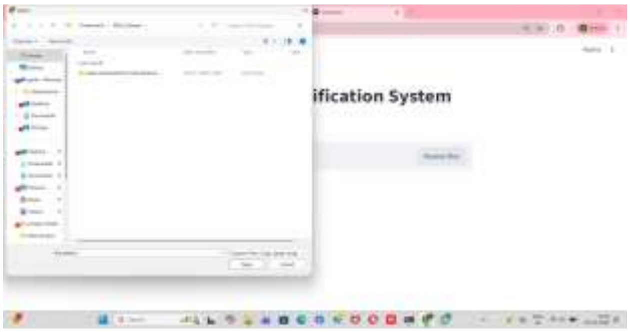

Fig:8.2

Opening the KOA dataset folder from local storage.

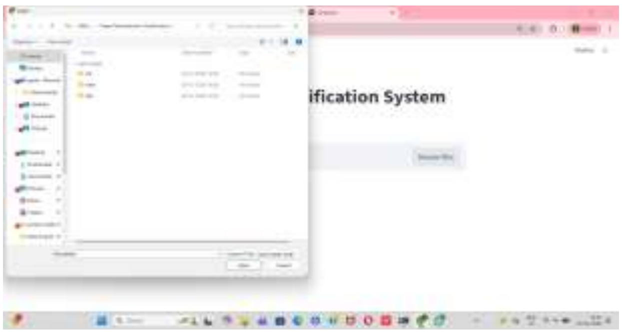

Fig:8.3

Validation folder showing class-wise categories.

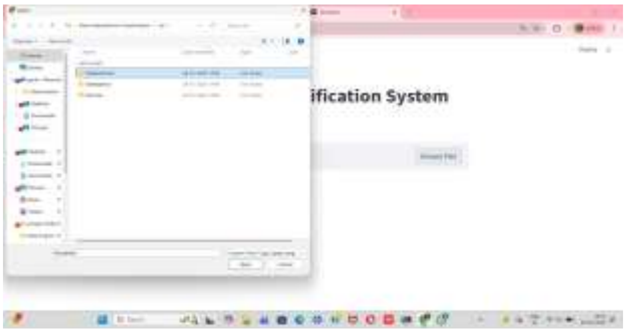

Fig:8.4

Dataset structure containing train, validation, and test folders.

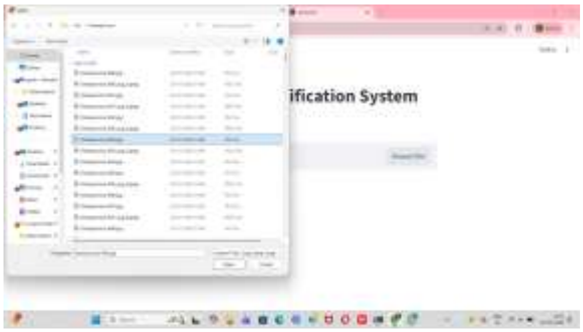

Fig:8.5

Selecting a knee X-ray image file for prediction upload.

Fig: 8.6

Knee osteoarthritis detection system predicting severe (Grade 4) from an uploaded X-ray.

VII.CONCLUSION

This research successfully demonstrates the development of a complete end-to-end deep learning system for automated knee osteoarthritis detection and severity classification from radiographic images. The study addresses a significant clinical challenge: the need for accurate, consistent, and efficient diagnosis of osteoarthritis, which traditionally depends heavily on expert interpretation and can be affected by inter-observer variability.

By leveraging transfer learning with MobileNetV2, the proposed framework achieved balanced multi-class classification performance while maintaining computational efficiency. The use of a lightweight yet powerful convolutional neural network architecture ensured that the model remains suitable for real-time clinical deployment without requiring high-end hardware. Furthermore, the incorporation of class weighting techniques helped address dataset imbalance, improving prediction reliability for underrepresented severity grades and enhancing overall fairness in classification.

The experimental results demonstrate stable training behavior and improved validation accuracy after fine-tuning. Performance evaluation through classification reports and confusion matrices confirms that the model is capable of learning discriminative radiographic features corresponding to different osteoarthritis severity levels. The achieved results highlight the practical feasibility of AI-assisted diagnostic systems in orthopedic imaging.

Beyond model development, this research also emphasizes practical implementation. The integration of the trained model into a Streamlit-based web application transforms the system from a theoretical prototype into a usable diagnostic support tool. This deployment demonstrates how artificial intelligence can be seamlessly integrated into real-world clinical workflows, allowing healthcare professionals to upload knee X-ray images and receive instant severity predictions.

Although the proposed system shows promising results, certain limitations remain. The model performance is influenced by dataset size, image quality, and class distribution. Future work may focus on incorporating larger multi-institutional datasets, integrating attention mechanisms, experimenting with advanced architectures such as EfficientNet or Vision Transformers, and combining imaging data with clinical metadata for improved prediction robustness.

In conclusion, this study provides a scalable, efficient, and clinically deployable framework for automated knee osteoarthritis detection and classification. The proposed approach not only contributes to medical image analysis research but also represents a meaningful step toward accessible, AI-assisted orthopedic diagnosis systems that can support physicians in delivering faster and more consistent patient care.

VIII.FUTURE SCOPE

1. Incorporation of larger multi-center datasets
2. Use of attention mechanisms for better feature localization
3. Integration with clinical parameters
4. Implementation of EfficientNet or Vision Transformers
5. Development of mobile-based deployment

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