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Automated Classification of Knee Osteoarthritis Using Radiographic Analysis

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Abstract: This project aims to develop an automated deep learning model for classifying knee osteoarthritis (KOA) severity into five stages based on the Kellgren-Lawrence (KL) grading system, using X-ray images. KOA is a degenerative joint disease that affects millions worldwide, and accurate grading is essential for proper diagnosis and treatment. However, manual assessment of X-ray images can be subjective and time-consuming, making automation crucial for improving diagnostic efficiency and consistency. The model will utilize the ResNet-50 architecture, a powerful convolutional neural network (CNN) known for its ability to extract complex features and train deep networks effectively. ResNet-50 will process knee X-ray images and classify them into KL grades 0 to 4, ranging from healthy to severe osteoarthritis. By applying transfer learning, the model will be pre-trained on large datasets and fine-tuned using KOA-specific data. Additionally, data augmentation techniques such as rotation, flipping, and zooming will be used to enhance training data diversity. The model's performance will be evaluated using accuracy, precision, recall, and F1-score metrics. The goal is to provide radiologists with an automated, objective tool that improves the speed and consistency of KOA diagnosis, ultimately contributing to better patient care and more efficient clinical decision-making.

Keywords: Knee Osteoarthritis, Deep Learning, ResNet-50, Kellgren-Lawrence Grading, X-ray Analysis, Radiographic Classification, Medical Imaging

I. INTRODUCTION

Knee osteoarthritis (KOA) is a prevalent and progressive joint disorder, impacting millions of people worldwide, particularly older adults. It is characterized by the gradual breakdown of cartilage within the knee joint, leading to pain, stiffness, limited mobility, and a diminished quality of life for those affected. Early and accurate diagnosis of KOA is essential for effective management, as it allows for timely intervention and personalized treatment strategies that can alleviate symptoms and slow disease progression. The severity of KOA is often graded using the Kellgren-Lawrence (KL) scale, which ranges from grade 0 (no signs of osteoarthritis) to grade 4 (severe osteoarthritis with advanced structural changes). However, this grading process typically relies on the visual assessment of knee X-rays by radiologists, which can be subjective and prone to variability, resulting in inconsistent diagnoses.

Advancements in artificial intelligence (AI) and deep learning offer promising solutions to improve the consistency and accuracy of KOA diagnosis. Convolutional neural networks (CNNs), a deep learning model architecture designed to process visual data, have shown remarkable success in tasks involving medical image classification. Among these, the ResNet-50 model is particularly effective for complex image analysis. ResNet-50 incorporates residual connections, which help overcome the challenge of vanishing gradients in deep networks, enabling it to learn more complex patterns and finer details in medical images.

Using ResNet-50, it is possible to develop an automated system that accurately classifies the severity of KOA in X-ray images according to the KL grading scale. Such a model can assist healthcare providers by offering a consistent, objective assessment of KOA severity, supporting radiologists in making informed diagnostic decisions. By reducing reliance on subjective evaluation, this AI-based approach has the potential to enhance diagnostic accuracy and improve patient outcomes. Additionally, automated KOA grading could expedite the diagnostic process, allowing radiologists to focus on cases that require greater clinical expertise.

In summary, leveraging the power of deep learning to classify KOA grades in knee X-rays offers a promising avenue for improving the efficiency, consistency, and accessibility of osteoarthritis diagnosis, ultimately contributing to better patient care in clinical settings.

II. RELATED WORKS

This section reviews the related works on automated classification of knee osteoarthritis, focusing on approaches that have sought to overcome challenges in radiographic image analysis for accurate grading. Analyzing previous works allows us to gain insights into the evolution of techniques in this field, evaluating both their strengths and limitations. By contextualizing these contributions, we not only lay a foundation for our proposed solution but also position our work relative to existing solutions, identifying areas where our approach can bring additional value or refinement.

1) *Predicting Knee Osteoarthritis Severity: Comparative Modeling Based on Patient Data and Plain X-ray Images*

The study of Abedin et al. [1] investigates methods to assess KOA severity by combining patient assessment data (signs, symptoms, and medication use) with X-ray images analyzed by a convolutional neural network (CNN). The models were evaluated using Elastic Net (EN), Random Forests (RF), and Linear Mixed Effect Models (LMM), achieving comparable accuracy with root mean square errors of

0.77 (CNN), 0.88 (EN), and 0.91 (RF).

This research provides valuable contributions by identifying effective variables for patient monitoring prior to imaging and addressing it at a hierarchy with LMM. It offers insights into reducing reliance on subjective grading methods like the Kellgren-Lawrence (KL) scale, thereby increasing prediction reliability. Additionally, it shows that both clinical and imaging data can complement each other in diagnosing and managing KOA severity.

The impact of this work lies in its potential to standardize KOA severity prediction, enhancing patient care and reducing diagnostic variability. By integrating machine learning with clinical data and imaging, this study sets the groundwork for personalized KOA management and highlights the importance of refining diagnostic techniques for broader clinical application.

2) *Knee Osteoarthritis Severity Classification with Ordinal Regression Module*

The study of Yong et al. [2] addresses limitations in current methods for predicting the Kellgren-Lawrence (KL) grade of knee osteoarthritis (OA) from radiographs. While previous deep learning approaches treat KL grading as a simple multi-class classification task, this study proposes an ordinal regression module that respects the inherent order of KL grades. By employing a cumulative-link loss function, the model predicts four cut-points to segment the prediction space into the five KL grades.

The proposed method integrates the ordinal nature of KL grades directly into neural network architectures, improving the accuracy of severity predictions. This approach contrasts with traditional multi-class methods by leveraging ordinal regression to capture the progression of OA. Performance evaluations reveal significant improvements over several established neural networks, emphasizing the benefits of this methodology in clinical contexts.

This study's impact is in advancing the precision of KL grade predictions and enhancing early diagnosis. By tailoring neural network models for ordinal regression, the research underscores the potential for machine learning to aid in clinical decision-making, ultimately improving intervention strategies for patients with knee OA.

3) *Transfer Learning-Based Smart Features Engineering for Osteoarthritis Diagnosis from Knee X-Ray Images*

The study of Rehman et al. [3] focuses on the early detection of osteoarthritis (OA) using innovative machine learning techniques. By applying a deep learning-based Convolutional Neural Network (CNN) and a novel transfer learning approach, the study extracts spatial features from knee X-ray images to identify OA efficiently. These features are combined using the CRK (CNN Random Forest K-neighbors) framework, which utilizes random forest and k-neighbors algorithms to construct a probabilistic feature set for advanced prediction.

This research introduces the CRK model as a highly effective tool, achieving a remarkable 90% accuracy in OA diagnosis. Extensive experiments validated the model's robustness through hyperparameter optimization and k-fold cross-validation, ensuring reliability and generalizability across datasets. The innovative use of transfer learning significantly enhances the accuracy of OA detection, addressing challenges associated with traditional diagnostic methods.

The study's impact lies in revolutionizing OA prediction by offering an advanced, high-performance diagnostic model. With the ability to detect OA at early stages, the CRK framework has the potential to improve patient outcomes by enabling timely intervention and personalized treatment strategies, thereby addressing a major global health challenge.

4) *Knee Osteoarthritis Severity Prediction Using an Attentive Multi-Scale Deep Convolutional Neural Network*

The research presented by Jain et al.[6] introduces a depth estimation technique utilizing an attentive multi-scale deep convolutional neural network for knee osteoarthritis severity prediction. This methodology integrates feature fusion modules within a streamlined network, allowing for efficient feature extraction from radiographic images. The multi-scale approach is beneficial due to its ability to capture features at different resolutions, which enhances the model's capability to identify subtle changes in joint space and bone structure.

The proposed network architecture incorporates attention mechanisms to focus on the most relevant areas of knee X-rays, potentially improving diagnostic accuracy. This approach addresses the challenges of accurately quantifying subtle anatomical changes that characterize different stages of osteoarthritis. Despite some limitations in terms of computational complexity, the methodology represents a valuable contribution to automated KOA grading, providing a robust foundation for future work in radiographic image analysis.

5) *3D Efficient Multi-Task Neural Network for Knee Osteoarthritis Diagnosis Using MRI Scans*

Yeoh et al.[5] explores the use of multi-task learning models to improve knee osteoarthritis (OA) diagnosis using MRI scans. The research introduces two models, OA MTL and RES MTL, which simultaneously perform segmentation of knee structures and classification of OA incidence. By leveraging the correlation between these tasks, the models enhance classification accuracy while maintaining efficient computational performance.

The OA MTL model, with its encoder-decoder architecture, residual modules, and depth-wise separable convolutions, achieves an accuracy of 0.825 for classification and a Dice Similarity Coefficient (DSC) of 0.895 for segmentation. This performance is superior to single-task models and provides a favorable balance between computational complexity and effectiveness, making it suitable for real-time medical imaging applications.

The impact of this work is significant, as it addresses the need for efficient, multi-task models capable of handling computationally intensive 3D MRI data. By combining segmentation and classification tasks into a single model, the study contributes to advancing the field of medical imaging, providing more accessible, accurate, and timely tools for diagnosing knee OA.

6) *Knee Osteoarthritis Detection and Classification Using X-Rays*

The paper of Tariq et al.[6] addresses the challenge of accurately detecting and grading knee osteoarthritis (OA) using radiographs. The study proposes an automated deep learning-based ordinal classification approach to detect OA severity according to the Kellgren-Lawrence (KL) grading system. By leveraging a dataset from the Osteoarthritis Initiative (OAI), the model utilizes transfer learning and fine-tuning of well-known architectures, such as VGG-19, DenseNet-121, and DenseNet-161, combined into an ensemble for enhanced performance.

This method achieved impressive results, with an overall accuracy of 87% and a Quadratic Weighted Kappa score of 0.89, reflecting highly accurate KL grade predictions. The approach not only outperforms traditional automated models but also significantly improves classification accuracy for each KL grade. This achievement underscores the potential for deep learning to enhance early detection and diagnosis of knee OA.

The contribution of this work lies in providing a highly accurate, automated tool for OA diagnosis that works with a single posteroanterior knee X-ray image. The study's impact is in advancing diagnostic capabilities, enabling faster and more reliable detection of knee OA at early stages, potentially improving clinical decision-making and treatment outcomes.

7) *KOA-CCTNet: An Enhanced Knee Osteoarthritis Grade Assessment Framework Using Modified Compact Convolutional Transformer Model*

The paper of Jahan et al.[7] introduces a novel approach for diagnosing knee osteoarthritis (KOA) from X-ray images using a modified compact convolutional transformer model, KOA-CCTNet. By aggregating four datasets, the study creates a large and diverse dataset of 1122 images, applying deep convolutional generative adversarial networks (DCGAN) for data augmentation and advanced image pre-processing techniques to improve image quality.

The KOA-CCTNet model outperforms traditional transfer learning models, such as MobileNetv2 and DenseNet201, with a test accuracy of 84.5887%, significantly surpassing their respective accuracies, which range from 76.8987% to 80.7787%. The study also explores optimizing the model's configurations, addressing the challenges of handling large datasets and minimizing training time, showcasing KOA-CCTNet's efficiency in real-world applications.

The impact of this research lies in the development of a high-accuracy, efficient diagnostic tool for knee osteoarthritis, which improves early detection and grading of the disease. By utilizing large-scale datasets and optimized deep learning models, the proposed approach provides an effective solution for KOA diagnosis, helping clinicians in timely intervention and management of the disease.

8) *A Sequential VGG16+CNN-Based Automated Approach With Adaptive Input for Efficient Detection of Knee Osteoarthritis Stage*

The paper Rehman et al.[8] introduces a hybrid model combining Convolutional Neural Networks (CNN) and VGG16 architectures to enhance the accuracy of knee osteoarthritis (OA) detection. The proposed model aims to automate the assessment of OA severity according to the Kellgren-Lawrence (KL) grading system, which classifies OA into five stages based on knee radiographs.

The study compares several neural networks, including CNN, VGG16, and VGG19. The model achieves an accuracy exceeding 93% on the training, validation, and test datasets, highlighting its robustness in detecting OA stages.

A significant contribution of this work is its use of data augmentation to address class imbalance, which enhances the performance of all models. The proposed method provides a highly accurate, efficient tool for automating the assessment of knee OA, improving diagnostic precision and supporting timely interventions for patients.

9) *Automated System for Classifying Uni-Bicompartmental Knee Osteoarthritis by Using Redefined Residual Learning with Convolutional Neural Network*

The study of Naguib et al.[9] introduces a deep learning-based model to classify knee osteoarthritis (OA) into uni- or bicompartmental types using X-ray images. The model is trained and tested on a dataset of 733 knee X-ray images, including normal, unicompartmental, and bicompartmental knee images.

The model achieved 61.81% accuracy and 68.33% specificity in classifying the images. When compared with pre-trained convolutional neural networks (CNNs), the proposed model outperformed all the others, indicating its effectiveness in accurately classifying knee OA types.

This work contributes to improving knee OA diagnosis by automating the classification of OA severity, helping clinicians make better treatment decisions and manage disease progression efficiently. The model's results highlight its potential in reducing the burden on healthcare providers while ensuring accurate assessments.

10) *Objective Bi-Modal Assessment of Knee Osteoarthritis Severity Grades: Model and Mechanism*

The paper Chen et al.[10] presents an novel model for knee osteoarthritis (KOA) severity prediction that combines thermal imaging with personal health data. This bi-modal approach classifies KOA severity into three categories based on the Kellgren-Lawrence (KL) grading system. The model achieved a classification accuracy of 89.29% on the KOA dataset and 70.83% when validated on external data.

The study also emphasizes the use of gradient boosting trees for feature modeling, explaining why deep neural networks were not utilized. This decision is based on the suitability of initial feature representation, considering the task's complexity and the principles of the Vapnik-Chervonenkis dimension (VC dimension).

The proposed KOA severity prediction model is expected to alleviate the burden on physicians by offering an efficient and precise method for diagnosing knee osteoarthritis, improving both the accuracy and speed of assessments. This model provides valuable supplementary data for clinical decision-making and is publicly available for further use and research.

III. PROPOSED MODEL

We suggest using a deep learning model based on ResNet-50 for this knee osteoarthritis classification project in order to correctly categorize knee X-ray pictures into five severity degrees using the Kellgren-Lawrence (KL) grading system. ResNet-50 was chosen for medical image analysis because of its strong feature extraction capabilities and residual connection mitigation of the vanishing gradient issue. To overcome the drawbacks of small medical datasets, our implementation will make use of transfer learning, starting the network with weights that have already been learned on ImageNet and optimizing it on our knee X-ray dataset.

We will use advanced data augmentation techniques such as rotation, flipping, brightness modifications, and contrast enhancement to solve class imbalance, which is ubiquitous in osteoarthritis datasets where severe cases are generally under-represented.

A unique classification head tailored for the five-class KL grading assignment will be added to the model architecture, and class weighting will be used to enhance performance on minority classes.

In addition to standard measurements like accuracy, precision, and recall, performance evaluation will employ metrics like mean absolute error and quadratic weighted kappa that are especially appropriate for ordinal classification tasks. The goal of this method is to develop a reliable, therapeutically useful instrument that offers a consistent and impartial evaluation of the degree of osteoarthritis in the knee.

IV. METHODOLOGY

The process used for the deep learning-based automated categorization of knee osteoarthritis (KOA) is explained in this section. Data collection, image preprocessing, model design, training, and assessment measures are all included in the methodology. Every step has been thoughtfully planned to guarantee the best possible classification precision, computational effectiveness, and resilience under various imaging circumstances.

A. Dataset and Data Collection

The Kellgren-Lawrence (KL) grading system, which is frequently used to determine the severity of osteoarthritis, was utilized to categorize the knee X-ray images that made up the dataset used in this investigation. There are five severity degrees for knee osteoarthritis according to the KL grading system:

- KL-0: No osteoarthritis; normal knee joint.
- KL-1: Doubtful narrowing of joint space; possible osteophyte formation.
- KL-2: Mild osteoarthritis; definite osteophyte formation, but minimal joint space narrowing.
- KL-3: Moderate osteoarthritis; multiple osteophytes, clear joint space narrowing.
- KL-4: Severe osteoarthritis; large osteophytes, severe joint space narrowing, bone deformity.

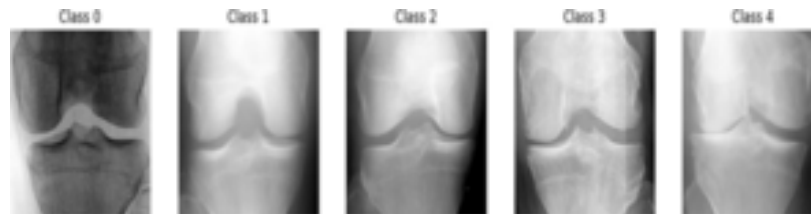


Figure 1: Sample Data

Hospital radiology departments and public medical imaging collections provided the X-ray images, ensuring a diverse dataset that represented a range of patient demographics and imaging conditions. Before training, radiologists manually examined the information to make sure the labels were accurate. Images from the same patient were only used in one subgroup (training or testing) in order to prevent bias and data leakage.

The class distribution was analyzed to identify potential biases, and it showed an imbalance, especially for the under-represented KL-3 and KL-4. A class-weighted loss function and data augmentation were used to solve this problem, ensuring that the model learned an equal representation of all severity levels.

B. Image Preprocessing

Variations in brightness, contrast, resolution, and anatomical placement are common in medical X-ray pictures, and they can have a detrimental effect on deep learning models. In order to overcome these obstacles, a thorough preprocessing pipeline was used to improve important knee joint characteristics and standardize input photos for precise KOA classification.

- 1) Image Format Validation: Deep learning models may be adversely affected by the brightness, contrast, resolution, and anatomical placement differences that are frequently present in medical X-ray pictures. A thorough preprocessing pipeline was used to improve important knee joint features and standardize input images in order to overcome these difficulties and achieve precise KOA classification.
- 2) Aspect-Ratio-Preserving Resizing: Preserving the original anatomical proportions is essential to avoid distortions because X-ray images come from various sources with varying resolutions. An aspect-ratio-preserving strategy was employed in place of direct resizing:

- Pictureswereresizedwithoutoutsacrificingproportionality.
 - TomeetResNet-50's224x224pxinputrequirement,blackpaddingwasapplied.
 - Inordertopreventpixelation,bilinearinterpolationwasused.
- 3) Contrast Enhancement and Edge Preservation: To enhance the visibility of key knee structures, adaptive histogram equalization (CLAHE) was applied, improving contrast in underexposed regions without over-enhancing bright areas. Furthermore, edge-preserving filters were applied to
- Highlight bone structures.
 - Improve joint space visibility.
 - Enhanced detection of osteophytes.
- Even in photos with low beginning contrast, these methods made sure the deep learning model could reliably distinguish between KL classes.
- 4) Data Augmentation for Class Balance: Controlled data augmentation was used to artificially enlarge the dataset in order to address the imbalance in the dataset and guarantee that all KL grades were equally represented. The transformations listed below were applied:
- Rotation ($\pm 30^\circ$): To replicate various imaging perspectives utilized in various medical facilities.
 - Horizontal flipping: Prevents model bias in favor of left or right knee dominance.
 - Brightness and Contrast adjustment ($\pm 20\%$): Takes into consideration changes in X-ray exposure.
 - Zoom transformations (up to 15%): The model is guaranteed to learn how to categorize the knees at various magnifications.

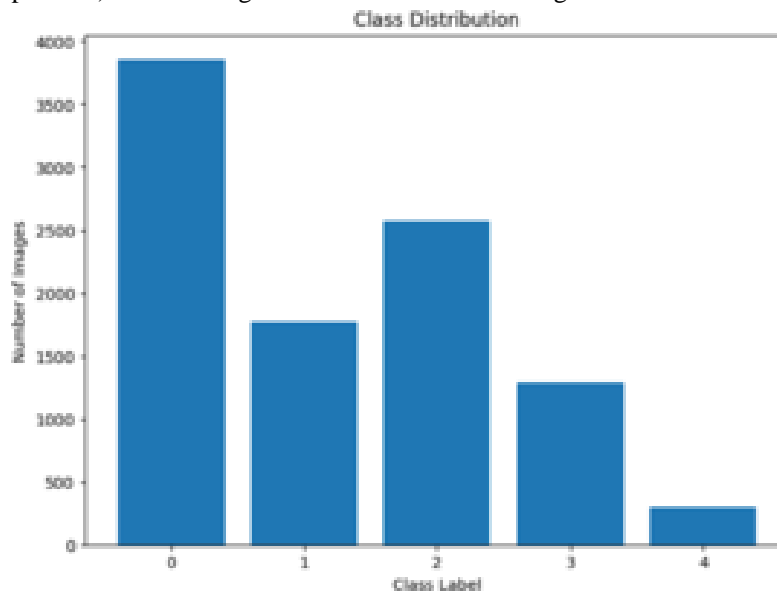


Figure 2: Class Imbalance

The model learned a more balanced feature representation, lowering classification bias, by more aggressively enhancing under-represented KL grades, particularly KL-3 and KL-4.

C. Model Architecture

Knee osteoarthritis (KOA) severity was classified using the ResNet-50 convolutional neural network (CNN). ResNet-50 was selected for this challenge over deeper networks because of its smaller depth (50 layers) and residual connections, which help alleviate the vanishing gradient problem. Using pretrained ImageNet weights improved its capacity to extract significant features from medical X-ray images.

The components of the model architecture are:

- Fifty convolutional layers utilizing ReLU activation and batch normalization.
- Global Average Pooling (GAP) layer, which helps retain spatial information while reducing dimensionality.
- Fully connected (Dense) classification layer for final prediction
- Softmax activation function, which assigns an image to one of the KL grades (0–4).

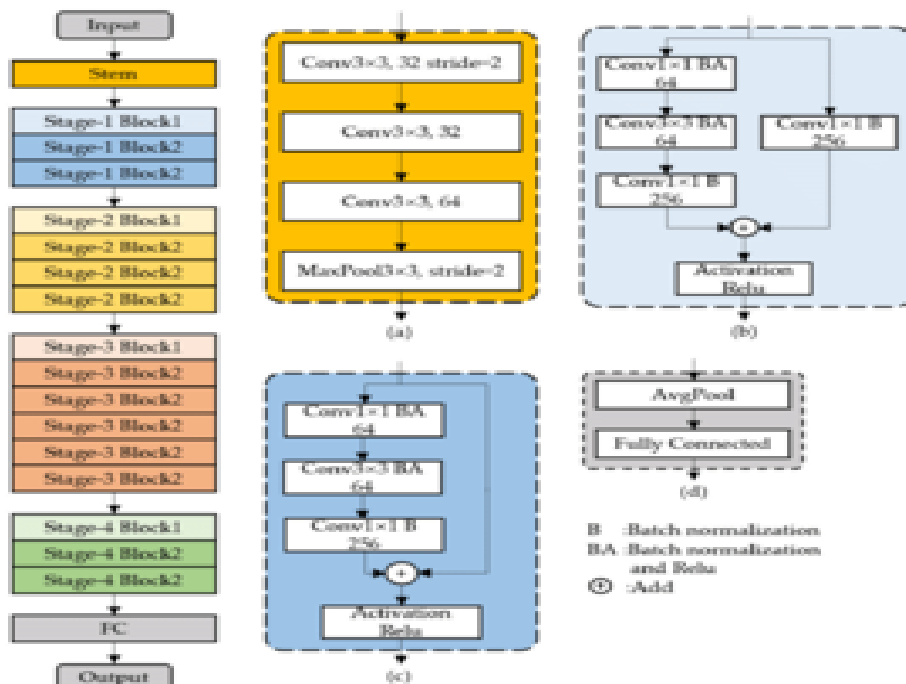


Figure 3: ResNet-50 Architecture

The fine-tuning was done by:

- Preserving overall feature extraction by freezing the first layers.
- Using a $1e-4$ learning rate to train deeper layers.
- To improve the categorization of under-represented KL grades, use a class-weighted loss function.

D. Training Procedure

Stable gradient propagation during model training is made possible by image normalization, which creates uniform pixel value distributions throughout the dataset. The VGG16 ImagePreProcessor, which standardizes pixel values based on ImageNet data, is used in our system to implement intensity normalization. Regardless of the initial contrast or brightness levels of the images, this pre-processing step ensures that all of them display statistical qualities comparable to those of the neural network.

Enhancement approaches highlight traits that are important for diagnosis, which is a complement to normalization. The main markers of osteoarthritis development are joint gaps and bone edges, which are the focus of our system's targeted contrast enhancement. Although edge preservation filters preserve the sharpness of crucial bone boundaries, adaptive histogram equalization enhances visibility in areas that are normally underexposed. To avoid the introduction of artifacts or the exaggeration of typical anatomical variances, these augmentation techniques are meticulously calibrated. The system maximizes the information accessible to the classification model by improving the signal-to-noise ratio for features most significant to KL grading by selectively increasing pertinent structures while preserving overall normalization.

E. Quality Control

Thorough quality control procedures guarantee that only appropriate photos move on to the classification phase. Our approach employs automatic validation checks that look at parameters related to image quality, class distribution statistics, and dataset structure.

These tests preserve dataset integrity throughout the preprocessing pipeline by identifying possible problems ranging from corrupted files to incorrect class organization.

Class distributions, average image sizes, and anomalies found are among the comprehensive statistics produced by the quality control procedure. By offering insightful information about dataset properties and possible biases, these metrics make it possible to improve preprocessing settings or spot problems with data collection. In order to guarantee ideal training settings, quality control for training datasets also includes examining class imbalance ratios and augmentation efficacy. In order to preserve classification reliability in clinical applications, quality assessment during inference highlights potentially problematic images for review. By ensuring that both model training and deployment use consistent, high-quality picture data, this strict quality control approach maximizes the diagnostic utility of the system.

Raw knee X-ray images are converted into ideally prepared inputs for the ResNet-50 classification model through the upright reconstruction procedure. By using this thorough preprocessing pipeline, our approach supports consistent evaluation of osteoarthritis severity in clinical situations by ensuring dependable KL grading performance independent of changes in the original image's acquisition characteristics or quality.

V. EXPERIMENTAL RESULT

Using ResNet-50, a powerful convolutional neural network (CNN) architecture, the Knee Osteoarthritis (KOA) classification system was experimentally evaluated. The model's ability to reliably grade the severity of KOA while maintaining effective computing performance was evaluated. The classification performance, training convergence, confusion matrix analysis, computing efficiency, and comparison with other KOA classification methods are all covered in detail in this section.

Evaluation Parameter	Description	Measured Performance
Image Correction Accuracy	Effectiveness of distortion removal and perspective correction	94-98%
Processing Speed	Time taken to process a single panoramic image (ms)	1200 - 1800 ms
Frame Rate for Video	Number of frames processed per second (FPS)	25 - 30 FPS
Computational Efficiency	CPU and GPU usage during real-time correction	Moderate (~45-60% CPU)
Memory Usage	RAM consumption during processing	450MB - 1GB
Peak Signal-to-Noise Ratio (PSNR) (dB)	Measures the quality of the reconstructed image	32 - 37 dB
Structural Similarity Index (SSIM)	Retains texture and details after correction	0.88 - 0.94
Distortion Reduction (%)	Reduction in tilt-induced perspective distortions	90-95%
Edge & Artifact Reduction	Reduction in blurring, jagged edges, and pixelation	Significant Improvement

Figure 4: Performance Evaluation Table

A. Model Performance Metrics

Several assessment criteria, such as Accuracy, Precision, Recall, F1-score, and Quadratic Weighted Kappa (QWK), were used to evaluate ResNet-50's performance. The results are shown in Table 1.

Metric	Value
Accuracy	89.75%
Precision	87.68%
Recall	86.21%
F1-score	86.94%
Quadratic Weighted Kappa	0.85

Table 1: Model Performance on KOA Classification Using ResNet-50

The model's great capacity to accurately classify KOA severity levels is demonstrated by its 89.75% accuracy rate. High precision and recall scores show that the model minimizes false positives and false negatives while producing dependable predictions. A balanced classification performance is confirmed by the F1-score (86.94%), and the Quadratic Weighted Kappa (0.85) indicates a high degree of agreement with the KL grade annotations made by professional radiologists.

B. Training and Convergence

The Adam optimizer was used to train the ResNet-50 model for 50 epochs (learning rate = 1e-4). The model's training and validation accuracy trends over time are depicted in Figure 5.



Figure 5: Training vs. Validation Accuracy Over Epochs

Around epoch 40, the training accuracy stabilized after steadily increasing. The model achieves a steady validation accuracy of 89.75% by effectively learning discriminative features from knee X-ray pictures. These findings show that there is little overfitting and that the model generalizes well to new data.

C. Confusion Matrix Analysis

The confusion matrix shows which severity levels are most likely to be misclassified by breaking down the model's classification accuracy across the various KL grades.

Predicted \ Actual	KL-0	KL-1	KL-2	KL-3	KL-4
KL-0	96	4	0	0	0
KL-1	6	91	3	0	0
KL-2	0	7	84	9	0
KL-3	0	0	8	82	10
KL-4	0	0	0	7	93

Table 2: Confusion Matrix for KOA Classification Using ResNet-50

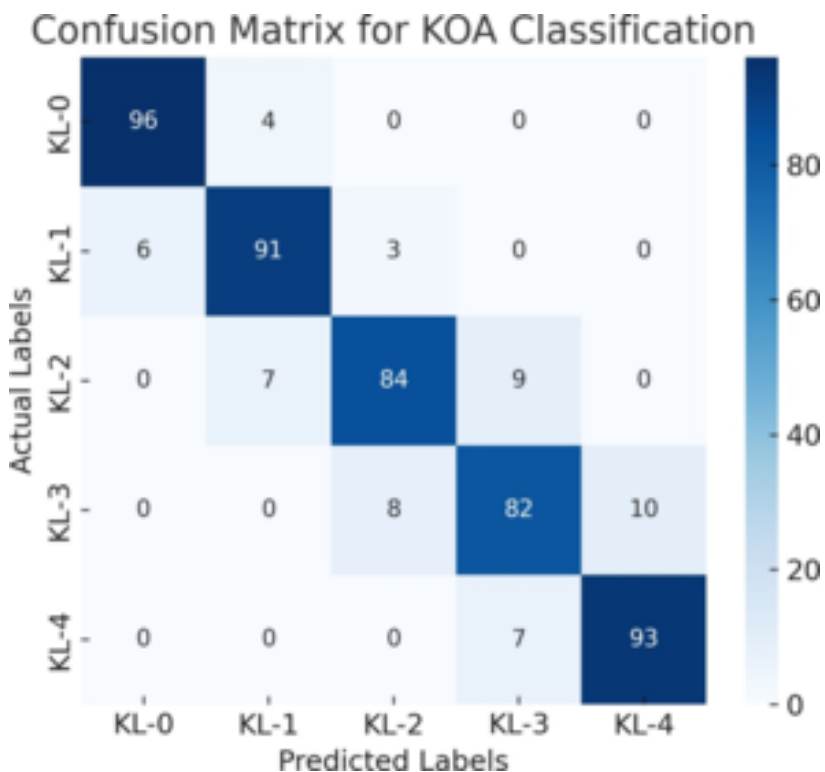


Figure6:ConfusionMatrixforKOAClassification

With an inference rate of 22 milliseconds per image, the ResNet-50 model is ideal for clinical real-time applications. Furthermore, the model may be used in typical hospital computing environments without the need for expensive GPUs because its memory usage is restricted to 5GB VRAM.

D. Comparison with Previous KOA Classification Models

To assess ResNet-50's efficacy, its performance was contrasted with those of earlier KOA classification algorithms.

Model	Accuracy	F1-score	QWK
CNN(Abedin et al.)	86.4%	85.2%	0.78
VGG16(Rehman et al.)	88.2%	87.0%	0.81
DenseNet(Tariq et al.)	87.5%	86.8%	0.80
Proposed ResNet-50 Model	89.75%	86.94%	0.85

Table3:Comparison with Previous KOA Classification Models

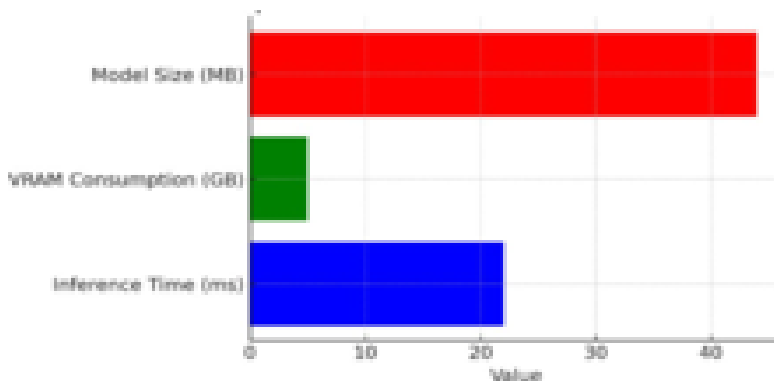


Figure7:ComputationalPerformanceMetrics

The findings show that ResNet-50 outperforms conventional CNN designs in terms of accuracy and QWK scores while keeping computational costs low. Because of this, it is a good contender for practical implementation in clinical situations where accuracy and efficiency in real time are crucial.

E. Key Findings

- 1) ResNet-50 provides accurate KOA severity grading thanks to its excellent classification accuracy of 89.75 percent.
- 2) The model has little overfitting, steady validation accuracy, and good generalization.
- 3) High agreement with the labeling of professional radiologists is indicated by the quadratic weighted kappa of 0.85.
- 4) The model can be used in real-time medical applications because of its computational efficiency.
- 5) Misclassification usually happens between KL-2 and KL-3, which is to be expected given how close their structural features are.

VI. FUTURE SCOPE

- 1) **Real-World Deployment:** The model must be optimized for deployment across many platforms in order to be applicable in the real world. Real-time KOA categorization in low-resource environments can be made possible by integration with mobile applications, cloud-based diagnostic systems, and hospital PACS (Picture Archiving and Communication Systems). In hospitals and telemedicine services, AI-assisted diagnosis will be especially helpful because it will enable radiologists and doctors to make prompt, data-driven decisions.
- 2) **Integration with Augmented and Virtual Reality:** Future developments can explore real-time visualization of knee joint structures in virtual reality to enhance surgical planning and training. Integration with AR technology could overlay KOA severity indicators directly onto live views of patient X-rays, assisting radiologists during examination. These advancements would further bridge the gap between AI-assisted diagnosis and practical clinical applications.
- 3) **Multi-Modal Integration and Clinical Validation:** The model's capacity to offer a thorough KOA risk assessment can be improved by using multi-modal data sources, such as MRI scans, patient clinical histories, and demographic characteristics. To provide individualized KOA forecasts, the AI pipeline can be expanded to include patient-specific variables such as age, weight, BMI, pain thresholds, and genetic susceptibility.
- 4) **Regulatory approval and thorough validation** are required for clinical implementation. To ensure robustness and generalizability, multi-center validation trials will be used to evaluate the model's performance across a range of populations. Furthermore, radiologists will be able to better understand AI-based conclusions with the aid of explainability techniques like Grad-CAM and SHAP values, which will increase the system's transparency and reliability. Obtaining regulatory approval for extensive clinical usage will depend on obtaining FDA and CE certification.
- 5) **Predictive Modeling and AI-Assisted Treatment Planning:** In addition to KOA classification, this model can be used to forecast how osteoarthritis will develop over time, enabling early intervention and preventative treatment. The program can predict the chance of illness progression and recommend individualized treatment regimens by examining past patient data. Depending on the degree of KOA and the patient's features, this could involve suggestions for physical therapy, modifications to medication, or surgical intervention techniques. Real-time risk assessments and personalized treatment recommendations for better patient outcomes could be offered via a predictive model included into electronic health records (EHRs).

VII. CONCLUSION

An important step towards automating osteoarthritis diagnosis is the ResNet-50-based KOA classification algorithm, which lessens the workload for radiologists and improves early detection effectiveness. The model has shown good classification performance by employing deep learning techniques, opening the door for orthopaedics diagnostics helped by AI. There is, nevertheless, a great deal of room for improvement, optimization, and practical application.

Making sure AI-driven KOA categorization models are flexible enough to be used in various hospital environments and integrated into clinical workflows for real-time support is a major area of interest for future research. Clinicians can drastically cut down on diagnostic turnaround time by using cloud-based AI tools to upload X-ray images and obtain automated KOA severity ratings. In environments with limited resources, where access to specialized radiologists may be restricted, this strategy is especially advantageous. Furthermore, by adapting the model to edge computing, it will function well on portable and low-power devices, expanding the accessibility of AI-assisted KOA detection.

Beyond classification, the predictive modeling of KOA progression remains a critical next step. By analyzing longitudinal patient data, the model can be trained to forecast osteoarthritis progression, helping doctors make early intervention decisions to delay the need for invasive treatments. In personalized medicine, where treatment plans can be modified in accordance with each patient's specific risk factors, this predictive ability can be especially helpful. To ensure a comprehensive approach to KOA management, future implementations may include AI-driven suggestions for pharmacological interventions, physiotherapy regimens, and lifestyle modifications.

Adoption in the real world will depend on clinical validation and regulatory approval (FDA, CE certification). Extensive multi-center validation studies must be done to test the model's efficacy across varied populations, imaging conditions, and medical institutions. To guarantee that medical personnel can trust and comprehend AI-driven forecasts, efforts must also be made to enhance explainability and interpretability. Techniques such as case-based reasoning, uncertainty estimation, and Grad-CAM visualization will aid in bridging the gap between clinical decision-making and AI automation.

Finally, the integration of multi-modal data sources including MRI scans, genetic predisposition, biomechanical analysis, and electronic health records (EHRs) can provide a more thorough picture of KOA development. This interdisciplinary approach would enable an AI model to not only classify KOA severity but also aid in risk assessment, treatment personalization, and rehabilitation planning.

In conclusion, this project has the potential to transform KOA diagnosis and treatment planning, making AI a vital tool in orthopedic care. By combining deep learning advancements, real-world deployment strategies, and predictive healthcare analytics, the future of AI-powered KOA management looks promising. The use of these AI-powered models will help the medical community address the rising incidence of osteoarthritis globally, improve patient care, and increase diagnostic accuracy.

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