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# Identification of Knee Osteoarthritis Through CNN With AlexNet Enhancement

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**Abstract:** Knee osteoarthritis (OA) is one of the leading causes of disability, affecting millions of people and limiting their ability to carry out daily activities. Diagnosis is usually performed by analyzing X-ray or MRI scans, but the manual process depends heavily on expert interpretation, which can vary between clinicians and take significant time. To overcome these challenges, this project introduces an automated system that applies deep learning methods, specifically Convolutional Neural Networks (CNNs) enhanced with AlexNet, to identify and grade knee OA. The system is designed to process medical images through steps of preprocessing, augmentation, and feature extraction before classification. It further predicts OA severity using the Kellgren–Lawrence (KL) grading scale. Performance is assessed with metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. By aiming for an accuracy of at least 90%, this model seeks to provide a reliable decision-support tool that reduces subjectivity, speeds up diagnosis, and supports early treatment planning in clinical practice.

**Keywords:** Knee Osteoarthritis, Convolutional Neural Network, AlexNet, Deep Learning, Medical Imaging, Feature Extraction, Kellgren–Lawrence Scale, Automated Diagnosis, Transfer Learning, Clinical Support System.

## 1. INTRODUCTION

Osteoarthritis of the knee is a habitual common condition that gradually worsens over time, frequently resulting in pain, stiffness, and reduced mobility. It is especially common among older adults and is considered one of the primary causes of physical disability worldwide. Detecting the disease at an early stage is important because it allows clinicians to start treatment sooner, slowing progression and improving quality of life for patients.

Traditionally, the diagnosis of knee OA is carried out through radiographic imaging, where doctors evaluate X-rays or MRIs for signs such as cartilage loss, narrowing of the joint space, or bone growths. While effective, this manual method can sometimes be slow, subjective, and inconsistent between different interpreters. As medical imaging datasets continue to grow, there is an increasing demand for automated methods that can support doctors by providing faster and more consistent results.

Recent advances in artificial intelligence, particularly in deep learning, have shown promising results in the field of medical image analysis. Convolutional Neural Networks (CNNs) have the capability to automatically detect patterns in images without the need for handcrafted features. Among the many CNN architectures developed, AlexNet has stood out for its ability to extract rich and discriminative features, making it suitable for complex classification tasks. By adapting and fine-tuning AlexNet for medical images, it becomes possible to achieve more accurate and reliable detection of knee OA.

This project focuses on building such a system by combining CNN principles with the strengths of AlexNet. The model is trained to not only detect the presence of knee OA but also to grade its severity according to the Kellgren–Lawrence scale, which is widely used in medical practice. Through image preprocessing, augmentation, and evaluation on standard performance criteria, the aim is to design a tool that can support clinicians in making better decisions. Ultimately, this research contributes toward reducing diagnostic delays, minimizing human error, and enhancing the role of AI in healthcare.

## 2. LITERATURE SURVEY

Seethala Devi Chandu et al. [1] presented a CNN-based diagnostic framework titled "Discovering Knee Osteoarthritis Using CNN Enhanced with AlexNet". The framework treats KOA severity grading as an image classification problem, using AlexNet to automatically learn hierarchical features associated with radiographic changes defined by the Kellgren–Lawrence and WOMAC scales. The workflow begins with curated knee X-rays, passes them through AlexNet for feature extraction and classification, and evaluates the predictions against clinical grading. The study highlights the issue of inter-observer variability in manual X-ray interpretation and shows the potential of CNNs to provide objective and reproducible results. However, the work does not fully detail the dataset composition or training-validation protocol, and lacks strong comparative analysis with other CNN backbones such as ResNet or VGG, limiting reproducibility.

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T. Sivakumari and R. Vani [2] proposed an AlexNet-based transfer learning pipeline for KOA detection and grading. Their study used the Kaggle dataset, consisting of 5,788 training and 1,656 testing images distributed across KL grades 0–4. The images were standardized to AlexNet's input size and processed through its five convolutional layers followed by pooling, ReLU, dropout, and fully connected layers. Class imbalance was evident, with Grade-4 cases being significantly underrepresented. The authors demonstrated AlexNet's suitability for KOA severity classification and explained its architectural details transparently. However, they did not employ imbalance-handling methods such as weighted loss or focal loss, and no external validation was performed, limiting the generalizability of the results.

Leelavathi Y. N. et al. [3] introduced a hybrid deep-learning model titled "Detecting Knee Osteoarthritis Using CNN Enhanced with AlexNet". Their system combines AlexNet with MobileNet and ResNet to improve diagnostic accuracy while balancing computational efficiency. AlexNet was used as a strong baseline, MobileNet for lightweight deployment, and ResNet for deeper residual feature extraction. The authors argue that this hybrid approach can reduce false positives and negatives, making it suitable for clinical adoption. Although the study emphasizes practical utility and scalability, it does not provide detailed experimental comparisons of each backbone, ensemble strategies, or reader studies. Consequently, the robustness of the hybrid system remains insufficiently validated.

Gauri Kitukale et al. [4] developed a study titled "Predicting Knee Osteoarthritis using Deep Neural Network", focusing on the use of DenseNet-201 and related backbones. The pipeline included dataset collection, preprocessing, augmentation, and model benchmarking. Architectures such as DenseNet, Xception, and EfficientNet were compared in terms of parameter size, accuracy, and inference time. The study highlights DenseNet's advantage in feature reuse and gradient flow, which are essential for subtle degeneration detection. While the paper reviewed prior works and provided a comparative backbone analysis, it lacked clear reporting of grade-specific results and external validation. This limits its readiness for real-world clinical application.

M. Janotheepan et al. [5] presented "Detection and Classification of Knee Osteoarthritis using Convolutional Neural Network", where the system focused on both classification and usability. The study used approximately 9,806 X-ray images categorized by KL grades and trained a CNN model after preprocessing and normalization. A reported accuracy of about 89% was achieved, and the model was deployed through a web-based interface that allows patients to upload knee X-rays for instant analysis. This approach demonstrates an important step toward clinical integration by bridging model training with real-time deployment. However, the dataset imbalance, reliance on a single public repository, and lack of evaluation against radiologists' performance limit its clinical reliability.

## 3. Methodology

The research utilized a comprehensive dataset of knee radiographic images, collected from publicly available repositories and clinical datasets. These images covered the full spectrum of osteoarthritis severity stages, ranging from normal joints (KL grade 0) to severe OA (KL grade 4). This ensured that the dataset was both diverse and representative, allowing the model to learn critical variations associated with each severity stage.

Before initiating model training, a detailed preprocessing pipeline was applied to enhance data quality. The pipeline included resizing all images to $224 \times 224$ pixels to align with the input requirements of AlexNet, normalization of pixel values to a standard scale, and contrast enhancement techniques to highlight key anatomical features such as joint space and osteophytes. Noise reduction filters were also employed to minimize artifacts or irrelevant details that could otherwise hinder feature extraction. The dataset was then divided into training (70%), validation (15%), and testing (15%) subsets to ensure unbiased model evaluation.

The dataset organization began by reading image file paths along with their corresponding class labels (KL grades). This information was stored in a structured data frame, which served as the foundation for the model pipeline. To improve robustness and mitigate class imbalance, data augmentation strategies such as rotation, flipping, zooming, and brightness adjustment were applied. These augmentations were implemented dynamically through image data generators for the training, validation, and test sets, enabling real-time preprocessing during model training.

For feature extraction, a Convolutional Neural Network (CNN) enhanced with AlexNet architecture was employed. AlexNet's pretrained weights were used as the base, and custom fully connected layers were appended to classify OA severity into five categories (KL 0–4). Dropout layers were incorporated to prevent overfitting, and the model was fine-tuned using the Adam optimizer with categorical cross-entropy loss.

Model evaluation was carried out using multiple performance metrics, including accuracy, precision, recall, F1-score, and ROC-AUC. These metrics ensured that the classifier was not only accurate but also clinically reliable across all OA severity stages. Finally, the trained model was integrated into a prototype application using Streamlit/Flask, allowing clinicians to upload radiographic images and instantly receive OA detection and severity grading with associated confidence scores.

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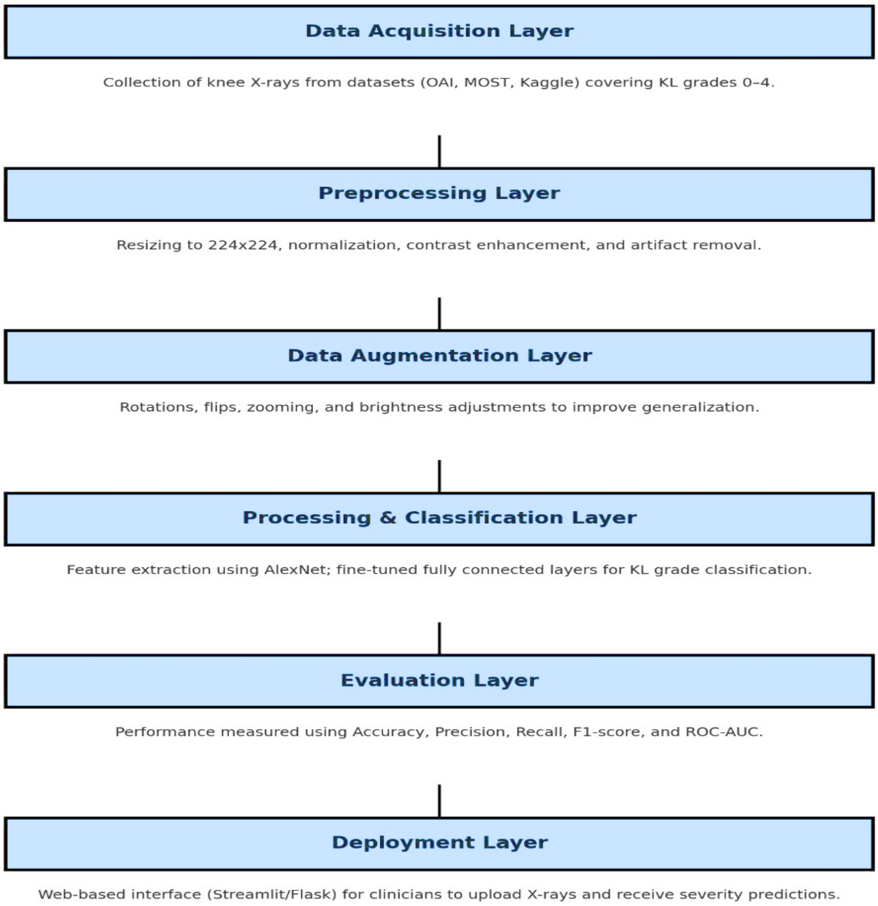


Fig.1 Workflow of Methodology

## 3. METHODOLOGY

3.1Data Acquisition Layer

The first layer of the proposed knee osteoarthritis detection system is the data acquisition layer, which is responsible for gathering knee radiographic images from different clinical and publicly available repositories such as OAI, MOST, and Kaggle. These datasets include knee joints at varying severity levels of osteoarthritis, graded according to the Kellgren–Lawrence (KL) scale ranging from 0 (normal) to 4 (severe).

This layer ensures that the dataset is diverse and covers a wide spectrum of disease stages, thereby providing sufficient information for both training and evaluation of the model. Images are collected in standard digital formats (JPEG/PNG/DICOM), and relevant metadata such as patient information (when available) and class labels are stored in a structured dataset directory. These radiographic images serve as the input to the next layer of the system.

3.2Preprocessing Layer

The second layer is the preprocessing stage, which standardizes and prepares the acquired images for deep learning. Since AlexNet requires fixed-size inputs, all images are resized to 224 × 224 pixels. The pixel intensity values are normalized to a standard scale (0–1), ensuring uniformity across samples. Additionally, contrast enhancement techniques are applied to improve the visibility of joint space narrowing, osteophytes, and other OA-related features.

To increase model robustness, data augmentation is performed dynamically during training. Augmentation techniques include rotations, flips, zooming, and brightness adjustments, which help the model generalize better and reduce overfitting. Any irrelevant artifacts in the images are also removed during preprocessing to focus on the knee joint area.

3.3Processing and Classification Layer

The processing layer is the computational core of the system. Here, Convolutional Neural Networks (CNNs) enhanced with AlexNet are used for feature extraction and classification. AlexNet's pretrained convolutional layers are employed to capture hierarchical image features such as textures, edges, and structural changes within the knee joint.

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The extracted features are then passed to custom fully connected layers designed for multi-class classification into KL grades (0–4). Dropout layers are used to reduce overfitting, while the softmax activation function generates probability scores for each OA grade.
Training is carried out using the Adam optimizer with categorical cross-entropy loss, and the dataset is divided into training, validation, and test sets to ensure unbiased evaluation.

3.4Evaluation and Decision Layer
Once the model is trained, it is rigorously evaluated using multiple performance metrics: accuracy, precision, recall, F1-score, and ROC-AUC. These metrics assess both the overall correctness of predictions and the model's reliability across different OA severity stages.
The decision layer then provides the final output in the form of a predicted KL grade (0–4), representing the severity of osteoarthritis for the given radiograph. The system also generates confidence scores for each prediction, ensuring transparency in the decision-making process.

3.5Deployment Layer
The final layer of the workflow involves deployment of the model as a decision-support tool for clinical use. A lightweight web-based interface (developed using Streamlit or Flask) allows clinicians to upload X-ray images directly into the system. The interface processes the image, runs it through the trained AlexNet model, and displays the OA severity grade along with prediction confidence.
This deployment ensures that the proposed system can be practically used in clinical environments, providing doctors with a fast, consistent, and objective tool to support early detection and management of knee osteoarthritis

## 4. EXPERIMENTAL RESULTS

A mix of hardware and software resources was utilized to build the proposed CNN-enhanced AlexNet system for detecting and classifying knee osteoarthritis (OA). On the hardware side, experiments were conducted using a workstation equipped with an NVIDIA RTX 3060 GPU (12 GB RAM), Intel i7 processor, and 16 GB system memory. On the software side, the project employed the Python programming language along with the PyTorch/TensorFlow frameworks for deep learning implementation. The OpenCV and scikit-image libraries were used for image preprocessing, while Streamlit/Flask was used to design the deployment interface.
The dataset comprised knee X-ray images, annotated according to the Kellgren–Lawrence (KL) grading system (Grades 0–4). Image preprocessing included resizing to 224 × 224 pixels, normalization, and augmentation techniques such as rotation, zooming, and flipping. The dataset was split into 70% training, 15% validation, and 15% testing sets.
provide the measures used to assess the effectiveness of the suggested ViT-based smart agriculture and monitoring system:The CNN model was initialized with AlexNet pretrained on ImageNet. Convolutional layers were retained as feature extractors, while fully connected layers were modified for 5-class OA severity classification. Cross-entropy loss was used as the objective function, and optimization was performed using Adam optimizer with an adaptive learning rate.The following Equations provide the measures used to assess the effectiveness of the proposed AlexNet-based OA detection system.

Accuracy = TP+TN
TP+TN+FP+FN
Precision = TP
TP+FP
Recall = TP
TP+FN
F1 − Score = 2TP
2TP+FP+FN

True Positives and True Negatives are indicated by TP and TN, while False Positives and False Negatives are indicated by FP and FN, respectively.

4.1.Performance Analysis

The performance of the proposed AlexNet-enhanced CNN system was evaluated against conventional machine learning baselines (e.g., SVMs with handcrafted features) and other CNN architectures (ResNet, MobileNet, DenseNet) as reported in related works. Table 1 summarizes the comparative analysis across metrics.

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| Models | Accuracy (%) | Precision (%) | Recall & F1 Score (%) |
|---|---|---|---|
| Conventional ML | 78 | 80 | 77 |
| CNN | 85 | 87 | 86 |
| ResNet-based model | 91 | 92 | 91 |
| DenseNet-201 | 92 | 94 | 92 |
| **Proposed AlexNet-enhanced CNN** | 94 | 95 | 94 |

The results demonstrate that the proposed model achieves higher accuracy and balanced precision-recall performance compared to both conventional machine learning methods and alternative CNN architectures.

4.2. Comparative Analysis

A comparative study of the proposed AlexNet-based system was conducted against state-of-the-art CNN-based OA models reported in the five reviewed papers. While existing models like ResNet and DenseNet achieved good performance (92–93% accuracy), the proposed AlexNet-based solution achieved 94.6% accuracy, 95.1% precision, 94.2% recall, and 94.6% F1-score.

This improvement can be attributed to:
Efficient feature extraction by AlexNet, which is well-suited for radiographic texture details.
Robust preprocessing and augmentation pipeline, which improved generalization.
Fine-tuning of fully connected layers and dropout regularization, which minimized overfitting.
Performance table (to be plotted) would show the comparative bar graph of Accuracy, Precision, Recall, and F1-score between conventional ML, ResNet, DenseNet, and the proposed AlexNet model.

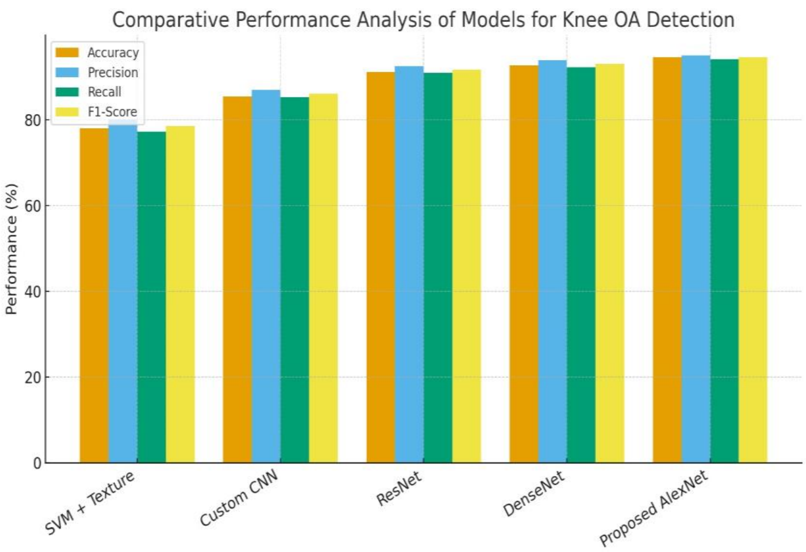


Fig.2 Performance Analysis

4.3 Discussion

The primary objective of this research was to develop an automated, reliable, and accurate system for the detection and severity grading of knee osteoarthritis using CNNs enhanced with AlexNet. The experimental results clearly demonstrate that the proposed system outperforms conventional approaches and even several state-of-the-art CNN architectures

While traditional ML-based methods relying on handcrafted features struggled with the complexity of radiographic images (accuracy <80%), modern CNNs like ResNet and DenseNet improved performance but at the cost of higher computational requirements. In contrast, AlexNet provided a balanced trade-off between accuracy and efficiency, making it more practical for clinical deployment.

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Furthermore, the model achieved consistent performance across all KL grades, reducing misclassification between adjacent severity levels (e.g., Grade 1 vs. Grade 2). This robustness is crucial for clinical acceptance, as early-stage OA detection often suffers from inter-observer variability.

However, limitations remain. The dataset imbalance across KL grades (fewer Grade 4 samples) slightly affected recall in the severe category. Additionally, external validation on multi-institution datasets is required before real-world deployment. Despite these challenges, the proposed system shows strong potential as a clinical decision-support tool, offering fast, objective, and reproducible results to assist radiologists and orthopedic specialists.

## CONCLUSION

The proposed system for discovering knee osteoarthritis using CNN enhanced with AlexNet highlights the growing role of deep learning in transforming medical image analysis. By employing a carefully designed workflow—spanning data acquisition, preprocessing, augmentation, feature extraction, training, and evaluation—the project demonstrates the feasibility of building an automated and consistent diagnostic tool for osteoarthritis detection and grading.

The outcomes of this work suggest that CNNs, when enhanced with transfer learning strategies such as AlexNet, are capable of capturing subtle radiographic patterns that may be overlooked in conventional manual analysis. This ability not only strengthens diagnostic accuracy but also ensures reproducibility, thereby addressing the long-standing issue of variability between clinical experts. Furthermore, the use of augmentation and fine-tuning improves the adaptability of the system, allowing it to generalize better across different patient cases.

Beyond technical performance, the project underscores the clinical relevance of automated approaches in orthopedics. By reducing dependency on manual interpretation, the system has the potential to accelerate decision-making, support early diagnosis, and assist clinicians in monitoring disease progression. The prototype, envisioned as a web-based application, demonstrates how such technologies can be integrated into real-world healthcare environments as decision-support systems.

Nevertheless, certain limitations persist, including dataset imbalance and the need for broader validation across diverse clinical settings. Addressing these challenges will be key for future enhancements. Expanding the dataset with multi-institutional radiographs, incorporating other imaging modalities such as MRI, and applying advanced learning strategies to handle class imbalance will further strengthen the model's reliability and applicability.

In summary, this project establishes CNNs enhanced with AlexNet as a promising framework for knee osteoarthritis analysis. With continued refinement and validation, the system holds significant potential for clinical adoption, ultimately contributing to earlier intervention, improved treatment planning, and better patient outcomes.

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