Enhancing Orthopaedic Diagnosis through Convolutional Neural Networks for Knee X-ray Analysis

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ABSTRACT
Knee Osteoarthritis is a prevalentillness that requires accurate detection and severity assessment for effective treatment and prognosis. The Kellgren-Lawrence (KL) grading scale, commonly accustomed evaluate abnormalities in X-ray scans, is susceptible to individual variability in grading. Early identification can potentially delay the development of osteoarthritis in knees (KOA). Most of the existing methods prefer ensemble models to improve the accuracy of KOA grade classification, even though it requires more computational cost and space.To address this issue our workobjectives to develop AI driven modelwhich focus on earlier prediction of knee osteoarthritis and bridge the gap between the structural changes in knee joint and symptoms of the patient. This study utilizes an innovative method using YOLO models to train, detect and localize the specific structural changes in knee radiographs, which are indicative of severity grades in association with KL grading system.For automated classification OAI dataset is used and the model's functioning is verified using ten-fold cross-validation. In a five-class OA assessment test, the anticipated technique attains 98.43% mean accuracy, outperforming existing methods. Notably, the study finds that fewer multiclass labels yield better performance, with binary classification reaching an accuracy of 98.2. This research highlights the potential of AI analytics in enhancing treatment and prognosis by accurately predicting reduction in the space between joints (JSN). It advocates for the use of CNNs in KOA detection and severity assessment, using the KL grading system (Grade-0 to Grade-4). The findings advocate for transparent CNN-based analysis techniques, urging medical researchers and developers to adopt AI-assisted tools in clinical settings to enhance KOA diagnoses.

Keywords: Osteoarthritis severity, Convolutional neural networks, Densenet, Fine tuning, Transfer Learning

INTRODUCTION

Knee osteoarthritis as a prevalent and progressive disease identifiable through radiographs. As a result, radiographs are important, particularly in terms of Kellgren and Lawrence grading, a reliable method for determining KOA. Using KL grading method, knee osteoarthritis must be appropriately diagnosed and classified. Healthcare providers can more effectively assess patient severity, create tailored treatment regimens, and put preventive measures into action by using predictive pain progression. Most of the CNN-based methods contain multiple steps like region proposals and classification, as part of YOLO's unified architecture, multiple objects are simultaneously detected and captured in real time with fewer false positives. YOLO's speed, simplicity, and accuracy makes it a better choice for many real-time tasks. Even with few features, the study's application of machine learning and feature selection approaches enabled accurate predictions, which may have advantages for KOA patient treatment. [1] (Tariq et al., 2023) proposed Ensemble ordinal based classification approach with advantages of various pre-trained CNN models, achieves an impressive 98% overall accuracy and shows notable improvements in accuracy for each grading category, surpassing existing automated methods. By integrating object detection, convolution neural networks, and attention mechanisms, the proposed approach aims to optimize this process and improve patient care and research outcomes. While X-rays are commonly used due to their affordability, the existing algorithms for detecting knee disease can still be improved in terms of precision and accuracy. The method was evaluated on radiographs of KOA patients and achieved significant improvements in predicting joint space level narrowing and osteophytes compared to baseline methods. It also demonstrated a substantial improvement in predicting the overall damage in Knee radiographs. Deep learning techniques can assist doctors in this regard, providing them with more precise information. The high accuracy achieved by Yolo models suggests their usefulness in accurately assessing KOA.

LITERATURE SURVEY

Diagnosing osteoarthritis with deep learning and machine learning from X-ray images providing accurate and efficient early-stage detection, which could lead to improved management and treatment of the condition.[2] (Rehman et al,2023) discusses unique CNN Random Forest K-neighbors to diagnose early-stage of KOA, a probabilistic feature engineering technique used by the model to excerpt spatial characteristics from images demonstrated 98%accuracy score in predicting osteoarthritis, suggesting its potential to transform the prediction of this degenerative joint disease.[3] (Wang et al., propose a new approach to learning that categorizes data based on reliability into two groups. To mitigate the impact of uncertain cases and highlight typical examples, they train separate convolutional neural networks (CNNs) for each category using a combined loss function. On a five-class OA assessment test, the suggested strategy outperforms alternative approaches with a mean accuracy of 70.13%.

[4] (Chaturvedi, 2021) The authors propose a two-staged approach to automatically predict joint damage in Rheumatoid Arthritis (RA) patients using radiographs of their hands and feet. The tri-weightage classification model is a hybrid strategy that the authors suggest be used to close the gap in KOA severity grading. This model combines information gathered from the questionnaire, measurements of flexion angle, and structural features extracted from x-ray images, compared with various deep learning models using their own dataset. Among the models tested, RESNET152V2 and INCEPTIONRESNETV2 achieved the highest accuracy of 89.29.[5] By extracting cartilage thickness, researchers aimed to determine the presence of osteoarthritis. To calculate the thickness, the researchers measured the number of pixels between the edges. This method allowed them to assess the abnormality of arthritis based on the cartilage thickness. By comparing the JSW with standard joint space width values, we were able to differentiate between osteoarthritis and normal knees. The Authors [6] (Dr.J.Deny et al,2022) utilized MRI scans and various image processing techniques to extract the boundaries and edges of the cartilage. Anisotropic Diffusion and cany edge detection algorithms were used to measure the number of pixels between the edges to determine the cartilage thickness, which plays a key role in identifying osteoarthritis and highlights the significance of estimating cartilage thickness in diagnosing arthritis.

[7] (Thongsuwan et al., 2021) presents a new concept of deep learning, CNN with XGBoost could learn features automatically, making it a powerful tool for classification tasks. Unlike traditional CNN models that require weight readjustments in a backpropagation cycle, ConvXGB simplifies the process by dropping the quantity of parameters. This makes the model more efficient and reduces the need for weight re-adjustments. The UCL Repository datasets included both images and general datasets. The results showed that ConvXGB performed slightly better than CNN and XGBoost when used separately. TheConvXGB deep learning model combines the advantages of XGBoost and CNN for classification tasks. Features of ConvXGB can automatically learn features and simplify the weight adjustment process makes it a promising approach in the field of classification. [8] (Ntakolia et al., 2020) focuses on calculating Joint space narrowing in the knees of patients with KOA using big data and AI. The pipeline comprises a feature selection approach that is robust and finds the greatest enlightening risk factors for predicting JSN, as well as a clustering process that separates patients into groups based on whether their JSN is progressing or not. To create the final JSN prediction model, the researchers also employed a variety of categorization techniques. The model evaluation revealed a high degree of accuracy, with the left and right legs achieving 78.3% and 77.7% accuracy, respectively, by means of SVM and Logistic Regression.

[9] (Aladhadh&Mahum, 2023) The authors provide a model generates more accurate bounding boxes by utilizing weighted pixel-wise voting technique and representative features. To simplify the model without increasing computational cost, they employ the distillation knowledge concept and information of transfer knowledge across simple and complex networks. The suggestedpixel-wise votingmethodology precisely recognizes knee osteoarthritis (KOA) in knee images and assess the degree of severity. Through the series of tests, the investigators evaluated the performance of their model and found that, with testing accuracy of 99.14% and cross-validation accuracy of 98.97%, it surpassed previous methods.[10] (Gan et al., 2022) The limited flexibility of standard data augmentation methods and the lack of diversity in training medical image analysis has faced difficulties. To address this problem, a team of researchers developed a Generative Adversarial Network (GAN) model called HieGAN, specifically for generating good-quality artificial knee images. The researchers assessed HieGAN's effectiveness and contrasted it with other cutting-edge techniques using measures like Am Score and Mode Score.[11] (Karim et al., 2021)discusses a new method called DeepKneeExplainer, which uses magnetic resonance imaging (MRI)

and radiographs to diagnose knee OA. The method involves preprocessing the images, extracting regions of interest, and training classification algorithms. Experimental results on the MOST cohorts demonstrate classification accuracy up to 91%, surpassing current approaches.[12] (El-Ghany et al., 2023)discusses the limitations of current diagnostic procedures for knee osteoarthritis (KOA) and proposes a deep learning model by applying the DenseNet169 method to address these limitations. The suggested model is considered an exceptional outcome due to its tuning and outperforms existing frameworks. It has the potential to improve KOA diagnosis by reducing costs, expediting diagnosis and offering insightful information about the reasons and severity of the disease.[13] (Yunus et al., 2022) method involves converting 2D radiograph images into 3D ones to extract best features The mined features are merged and inputted to classifiers for KOA grade classification, yielding an accuracy of 90.6% with 10-fold cross-validation. Additionally, the authors propose a model to focus classified images using a neural network (ONNX) and YOLOv2, achieving a mean Average Precision (mAP) of 0.98. [14] (Qadir et al., 2023) proposed method, incorporates ResNet for image segregation and BiLSTM for categorization, and it deals with imbalanced training data through a hybrid architecture, enhancing its resilience. The method achieves 84.09% testing accuracy and 78.57% cross-validation accuracy, outperforming existing methods, and is considered a successful and advanced approach for identifying KOA early and categorizing its severity.

[15] (Yashas et al., 2023) For effective care, it is crucial to have a timely and accurate diagnosis, as manual detection methods are tedious and prone to errors. Computational methods are needed to improve KOA detection. The CNN method reduces the X-ray images to grayscale by applying many convolutional layers to them. Precision is improved by the algorithm with each layer.[16] (Zhuang et al., 2023)proposes the strategy focuses on specific areas of the MRI that are likely to contain cartilage defects, reducing the reliance on irrelevant information. In order to prevent knee OA, the paper emphasizes the significance of early detection and evaluation of cartilage abnormalities in the knee. The use of CNNs shows promise, but additional strategies, such as ROI pooling, are necessary to address the limitations posed by the physiological characteristics of cartilage and the scanning protocols. [17] (Ahmed &Mstafa, 2022) For feature extraction and transfer learning (TL) to optimize CNNs, the researchers developed two frameworks that use convolutional neural networks (CNNs). They also utilized a traditional machine learning (ML) classifier to boost classification efficiency. Five class-based models were used in the first framework, while two, three, and four class-based models' CNNs were optimized for the second framework. The suggested models were assessed and contrasted with the current models using X-ray data. Remarkably, the study discovered that 90.8% accuracy rate was obtained through binary class labels, and fewer multiclass labels resulted in superior performance.

[18](Aladhadh&Mahum, 2023)The authors provide a novel method that automatically extracts characteristics from knee pictures using a pixel-wise voting strategy, based on customized CenterNet. Using a modified CenterNet, the model first predicts a bounding box. The bounding box is then refined based on the vote scores of each pixel inside by using a weighted pixel-wise voting mechanism. In order to streamline the model without raising its computing expense, the authors also make use of the distillation knowledge idea. The suggested model outperforms previous methods with testing accuracy of 99.14% and cross-validation accuracy of 98.97%. The model's foundation is a strong and enhanced architecture that uses a straightforward DenseNet-201 base network for feature extraction. The Mendeley VI benchmark and the OAI dataset are the two benchmarks utilized, performance evaluation of the proposed method [19] (Alexos et al.,2020) develop a forecasting tool that will benefit patients with knee osteoarthritis (KOA) and estimate how their pain will worsen over time. Researchers used machine learning techniques to determine if a patient's pain would lessen, rise, or stabilize based on baseline data collected from KOA patients. These parameters were found to be important risk factors. With just a few characteristics, the study's ability to accurately forecast the course of discomfort up to 84.3%. The suggested approach appears to have promise in detecting the early stages of pain progression, which could enhance efforts to prevent KOA. Subsequent investigations ought to concentrate on verifying these results among more patients and investigating practical application.[20] This research paper explores the use of KL grading method and proposes an automated classification approach using deep neural networks. The KL grading method is commonly used but prone to individual grading errors. They compared the performance of various CNN models and found that the ResNet 20 architecture attained an accuracy of 76%, whereas CNN's accuracy rate was 66%.

[21] The study highlights the significance of image preprocessing in previous unsuccessful attempts to identify knee OA. The findings suggest that sharpening the image can enhance the accuracy of knee KL grading and improve knee joint recognition. [22] The researchers suggest using six pre-trained DNN models for KOA diagnosis since manual KOA diagnosis can be tedious and error-prone. The models that are employed are DenseNet121, ResNet101, MobileNetV2, InceptionResNetV2, and VGG16, VGG19. Two

categorization methods are used by the researchers: binary classification, which ascertains whether KOA is present or not, and three-class classification, which determines the severity of KOA. Three datasets, each including a different number of KOA picture classes, are used in the studies. The findings demonstrate that on the three datasets, the ResNet101 DNN model achieves maximum percentages of 69%, 83%, and 89% for categorization accuracy.[23] In this study, a new approach to knee cartilage defect assessment based on surface convolution and graph representation is proposed. This approach addresses challenges such as information dilution, structure disidentification, and heterogeneous scanning parameters. It displays robustness to the variety of clinical knee MRIs and integrates appearance features and cartilage shapes for assessment at different levels. The method outperforms and provides strong interpretability through 3D visualization of defects and attention maps overlaid on the cartilage surface. Through testing on a clinical knee MRI dataset and comparing it with existing methods, showing promising results in grading knee cartilage defects. Additionally, the paper discusses the potential drawbacks and future research directions for the proposed method.[24] The study investigates whether multi-task models utilizing 3D MRI scans can accurately diagnose osteoarthritis in the knee. OA_MTL and RES_MTL are two 3D multitask models designed to separate knee structures and identify the pervasiveness of knee osteoarthritis. When it came just round the corner to classification tasks, OA_MTL performed better and had a similar segmentation DSC score. The multi-task models were superior with regard to computational complexity and model performance when compared to baseline individual task models and current models of convolutional neural nets. The created multi-task models hold potential for theaccurate and efficient diagnosis of osteoarthritis in the knee utilizing 3D MRI data.

METHODOLOGY

The KL grading classification classifies knee osteoarthritis into five classes: Normal joints are represented by Grade 0, early indications such as mild osteolytic lipping and possible narrowing are denoted by Grade 1, definite osteophytes and doubtful JSN are represented by Grade 2, moderate osteoarthritis is represented by Grade 3, which clearly narrows the joint space and shows moderate formation of osteophytes, and severe osteoarthritis is represented by Grade 4, which includes significant osteophytes, severe sclerosis, and narrowing of the joint space.DenseNet-169 is a deep CNN known for its dense connections, where each layer connects to every other layer through feed-forwarding. It consists of 169 layers, including activation functions, batch normalization, transition layers, and dense blocks. Fine-tune by unfreezing some of the later layers in the base model and continuing to train with a lower learning rate. Finally, preserve the trained model for future use and evaluate the model's efficiency using the test set of data. The network is more efficient at learning complex patterns due to the dense connections, which also serve to encourage feature propagation, enhance feature reuse, and solve the issue of vanishing gradient problem. DenseNet-169 typically requires fewer parameters and computations compared to other architectures like ResNet or VGG, as it avoids redundant feature mapping and leverages the collective knowledge of all preceding layers. This architecture is particularly advantageous in terms of parameter efficiency and performance, especially on tasks with limited data, as it promotes robust learning and better generalization.

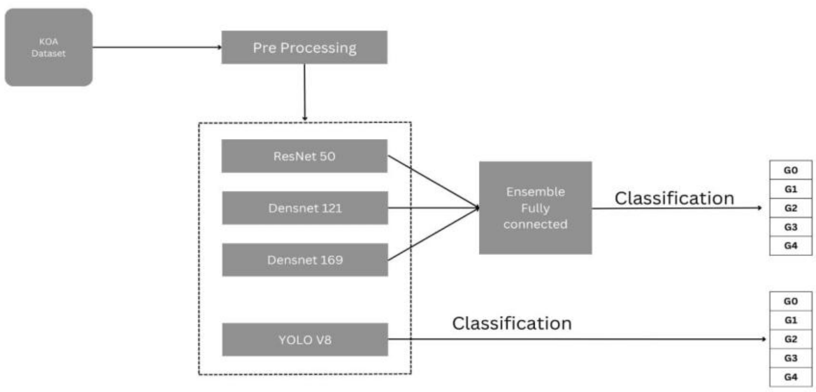

Fig 1. Proposed Framework

The process denoted in Fig: 1 begins by preparing the target dataset, including resizing images and splitting them into training, and validation sets. The pre-trained CNN, excluding its final classification layer, is loaded, and new task-specific layers are added, such as fully connected layers ending in a softmax for classification tasks. The model is compiled with suitable loss functions and optimizers, and initially, only the new layers are trained while keeping the pre-trained layers frozen. This is followed by fine-tuning, where some of the unfrozen layers of the pre-trained prototype is accomplished with a smaller learning rate to adjust to the new task. To fine-tune DenseNet-169 for classifying knee osteoarthritis, start by preparing and preprocessing your dataset, ensuring images are resized to 224x224 pixels and split into proper ratio. Load a pretrained DenseNet, ResNet model without its top layer, then append custom layers for classification. The FCL categorizes the KOA grade and the results of Ensemble model are compared with the YOLO model which provides severity of the KOA with bounding boxes. In YOLO, the CNN serves as the feature extractor, responsible for processing input images and extracting relevant features that are subsequently used for object detection. It is not just a CNN but rather a complete object detection algorithm, it relies heavily on CNNs as the underlying architecture for feature extraction and YOLO (You Only Look Once) can be employed in knee osteoarthritis detection by leveraging its object detection capabilities to identify specific features indicative of the condition within medical images such as X-rays or MRI scans. By utilizing YOLO for knee osteoarthritis detection, healthcare professionals can benefit from automated analysis, accurate identification of osteoarthritic features, and enhanced diagnostic capabilities, ultimately leading to earlier detection, intervention, and management of the condition. YOLO innovates object detection in deep learning, tackling information loss and network efficiency, important components Reversible Functions, and the Information Bottleneck Principle. YOLOv8 achieves higher accuracy and speed with less complexity, offering versatility across different model sizes. YOLO addresses information loss in deep neural networks by acknowledging the Information Bottleneck Principle, which emphasizes how data loses information as it passes through network layers. YOLO employs reversible functions to guarantee that there is no loss of information throughout the process of data transformation, thereby maintaining reliable gradients for model updates. YOLO is designed to improve the productivity and flexibility of the framework, providing a lightweight architecture that supports various computational blocks while maintaining real-time inference capabilities. Enhanced Performance with Less Complexity: YOLO offers multiple model variants to cater to different requirements, from lightweight to performance-intensive applications, ensuring its versatility across various environments and use cases.

Pseudocode

1. Preprocess the knee osteoarthritis dataset
2. Partition the dataset.
3. Load a pre-trained YOLO V8 model for classification
4. Fine tune the model, allowing the modified top layers to learn from the knee osteoarthritis
5. Prevent Overfitting and Further Fine-tuning
6. Evaluate using 10-fold cross validation.

Algorithm: YOLO model for Knee Osteoarthritis Severity Classification

Inputs: - knee osteoarthritis dataset, the number of epochs for fine tuning.

Outputs: - Knee osteoarthritis severity classification- Grade0, Grade1, Grade2, Grade3, Grade4.

1. Preprocess the knee osteoarthritis dataset: preprocessed_image = preprocess_image (image)
2. To detect osteophytes = detect_osteophytes (preprocessed_image)
3. To detect reduced joint_space = detect_joint_space (preprocessed_image)
4. Reduced_joint_space = check_joint_space (joint_space)
5. To detect sclerosis = detect_sclerosis (preprocessed_image)
6. To detect cysts = detect_cysts (preprocessed_image)
7. Function to classify Knee osteoarthritis grade:

IF no_features_detected (osteophytes, joint_space, sclerosis, cysts): grade = 0
ELSE IF minor_osteophytes AND normal_joint_space: grade = 1
ELSE IF certain_osteophytes AND potential_narrowing: grade = 2
ELSE IF modest osteophytes AND definite_narrowing AND sclerosis present (sclerosis): grade = 3
ELSE IF massive_osteophytes AND significant_narrowing AND sclerosis_present AND cysts_evident: grade = 4.

Comparision with State of Art Performance models

Current diagnostic procedures are time-consuming, subject to user variation, and prone to diagnostic errors. The proposed model aims to reduce diagnostic costs, expedite the diagnosing process and slow the course of the illness. The proposed model shows promise in improving the efficiency and accuracy of KOA diagnosis, which would benefit patients through enhancing knowledge of the main causes of KOA.

Table 1. state of art models and their accuracy

S.No	Reference	Model	Accuracy
1	Tariq et al., 2023[1]	Ensemble	98
2	Rehman et al., 2023[2]	CNN Random Forest K-neighbors	99
3	Wang et al., 2022[3]	CNN with hybrid loss function	70.13
4	Masood et al., 2022[5]	Tri-weightage model	89.29
5	Ntakoliaet al., 2020[8]	SVM	78.3
6	Aladhadh&Mahum, 2023 [9]	CenterNet with a pixel-wise voting	98.97
7	Gan et al., 2022[10]	HieGAN	-
8	Karim et al., 2021[11]	DeepKneeExplainer	91
9	Yunus et al., 2022[13]	YOLOv2	98
10	Qadir et al., 2023[14]	(BiLSTM)	84.09
11	Ahmed &Mstafa, 2022[17]	CNN - SVM with transfer learning	90.8%
12	Aladhadh&Mahum, 2023[18]	DenseNet - 201	98.97%.
13	Bellay, M. Z. B.2023 [20]	ResNet 20	76%

RESULTS AND DISCUSSIONS

Knee osteoarthritis classification using deep learning involves employing various models to accurately differentiate between normal and osteoarthritic knee conditions based on imaging data, typically X-rays or MRI scans. Researchers utilize convolutional neural networks (CNNs) such as DenseNet, ResNet, and custom architectures to achieve high classification accuracy. Techniques like Grad-CAM are applied to provide transparency by visualizing the ROI in the images like osteophytes and JSN which persuade the model's severity grading. To accurately pinpoint the afflicted regions inside the knee joint, advanced object detection frameworks like YOLOv8 are integrated, ensuring high precision and recall rates. These developments could improve the precision of diagnoses and help medical practitioners make well-informed decisions for the efficient management of osteoarthritis in the knee. Densenet-169 excels in knee osteoarthritis (OA) classification, which facilitates feature reuse and improves gradient flow, leading to more efficient and robust training compared to other architectures like ResNet, VGG, and Inception. Its parameter efficiency and compact design reduce overfitting risks, making it suitable for medical datasets. Densenet-169's ability to blend elements at different levels results in richer and more discriminative representations, crucial for accurately distinguishing OA severity. Studies have shown that proposed YOLO v8 consistently outperforms other architectures in clinical practice. Fig:2(a) and 2(b) denote KOA grade predictions in Ensemble and proposed model. Fig:3(a) and 3(b) explains about the training, validation loss and ROC curve. Fig:4(a) and 4(b) indicates the differences in confusion matrix models. Yolo models predict the grade with object detection, it helps the practitioners to make a decision precisely. Performance measures, which are shown in Table 1 are conditioned to evaluate the model.

Fig 2. (a) Yolo Prediction

Fig 3. (a)Training Accuracy

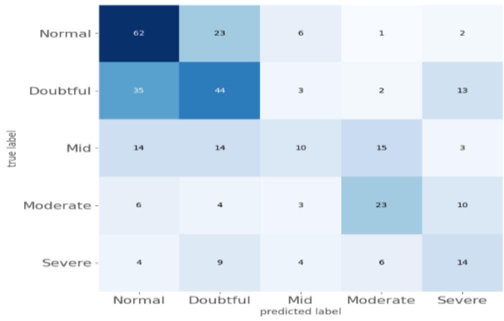

Fig 4(a) Ensemble model CM

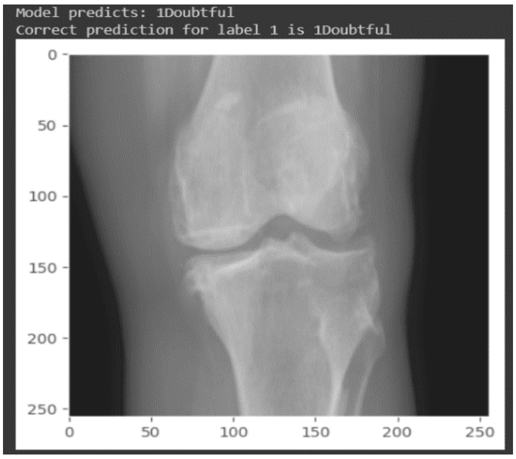

Fig: 2(b) state of art models Prediction

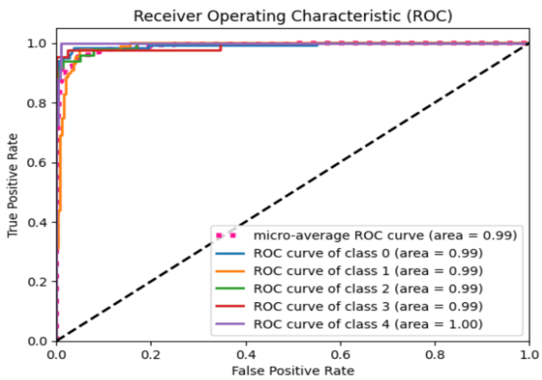

Fig 3. (b) ROC curve

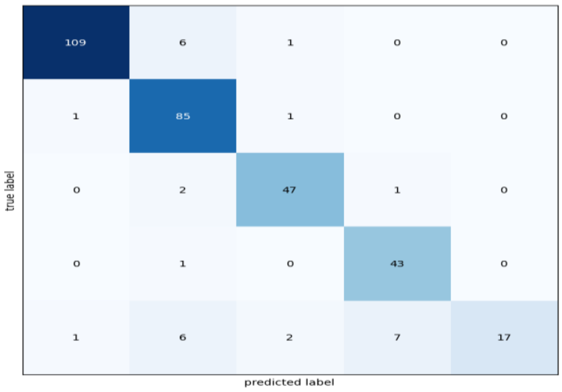

Fig:4(b) YOLO model CM

Table 2. KOA Performance Evaluation

Model	Accuracy	Precision	Recall	F1-Score
ResNet 50	95.63	95.63	94.12	94.31
DenseNet 121	95.46	95.12	95.46	95.22
DenseNet 169	97.47	97.41	97.56	97.34
Ensemble	97.51	97.63	97.89	97.76
Proposed	98.76	98.63	98.46	98.22

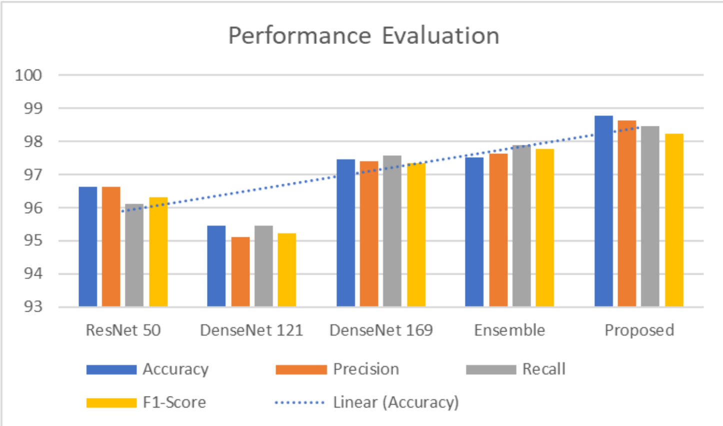

Fig 5. Performance Evaluation

CONCLUSION

This study presents an innovative approach to diagnose KOA, employing advanced transfer learning method, which demonstrates strong performance in detecting osteoarthritis. The approach utilizes a traditional CNN alongside various machine learning methods for comparative analysis. We Fine-tuned DenseNet and ResNet convolutional network to automatically identify knee joints and assess osteoarthritis severity and Ensembled results are compared with yolo v8 model. Additional convolutional layers predict directly from bounding boxes and class probabilities. The proposed method achieves greater accuracy compared to previous methods. However, distinguishing between consecutive KL grades challenges, particularly between grades 0 to 2, where variations are minimal were overcome through object detection. Fig: 5 denotes that the proposed yolo v8 model achieved greater accuracy compared with ensemble model accuracy. Future improvements could involve data augmentation, hyperparameter tuning, and minor architecture tweaks to further enhance performance. Yolo v8 efficient parameter usage and improved gradient flow make it a robust choice for various image classification applications.YOLO's role is more in preprocessing and detection rather than direct classification.For knee OA grading, large, well-annotated datasets are required to effectively train YOLO models to detect subtle features related to disease severity.

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