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Knee Osteoarthritis Detection and Classification Using a Customized CenterNet with DenseNet201

H.Srikanth
Department of CSE (AI&ML)
2111cs020556@mallareddyuniversity.ac.in

D.Srikar
Department of CSE (AI&ML)
2111cs020557@mallareddyuniversity.ac.in

P.Srikar
Department of CSE (AI&ML)
2111cs020558@mallareddyuniversity.ac.in

R.Srilekha
Department of CSE(AI&ML)
2111cs020559@mallareddyuniversity.ac.in

D.Srinath
Department of CSE (AI&ML)
2111cs020560@mallareddyuniversity.ac.in

Prof P.Bhavani Assistant Professor Department of AI & ML

MALLA REDDY UNIVERSITY
HYDERABAD

***Abstract*: -** The Knee osteoarthritis (OA) is a prevalent musculoskeletal disorder that significantly impacts quality of life. Early detection and classification of OA stages are crucial for effective management and treatment. This study proposes a novel approach for the automated detection and classification of knee osteoarthritis using a customized version of the CenterNet object detection model combined with DenseNet201 for feature extraction. The CenterNet model is adapted to detect and localize knee joints, while DenseNet201, a powerful convolutional neural network (CNN), is leveraged for its deep feature extraction and high efficiency in processing medical images. The proposed model is trained and validated on a dataset of knee X-ray images, categorizing them into various OA stages, including normal, mild, moderate, and severe. The integration of DenseNet201 into CenterNet improves the model's ability to capture finegrained details in knee joint structures, enhancing classification accuracy. Experimental results show that the proposed method achieves a high classification performance compared to traditional image-based methods, demonstrating the potential of deep learning techniques in assisting clinicians with early OA detection and monitoring.

Keywords: **Machine learning, detection performance, HCI, classification, deep learning, multi-scale features.**

I. INTRODUCTION

Knee Osteoarthritis (KOA) is a chronic joint disease due to the worsening of articular cartilage in the knee. The symptoms of KOA comprise joint noises due to cracking, swelling, pain, and difficulty in movement. Moreover, the severe symptoms of KOA may cause fall incidents i.e. fracture in the knee bone that ultimately results in disability of leg [1]. Various imaging techniques which have been employed for the analysis of knee disease include MRI, Xray, and CT scans. Furthermore, MRI and CT scans are also considered suitable

Knee Osteoarthritis (KOA) is a chronic joint disease that affects the knee, causing symptoms such as joint noises, swelling, pain, and difficulty in movement. Various imaging techniques, including MRI, X-ray, and CT scans, have been used for the analysis of knee disease, with X-ray being a more feasible and less expensive approach.

The severity of KOA is measured using the Kellgren Lawrence (KL) grading system, which consists of four grades (Grade I, Grade II, Grade III, and Grade IV). Early detection and classification of the disease are important for successful treatment.

The proposed project aims to develop an improved deep learning model, specifically a customized CenterNet with DenseNet201 as the base technique, to overcome the challenges of existing work and achieve better accuracy for all grades of KOA.

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II. LITERATURE REVIEW

The disease detection of the knee involves various methods for the examination of knee joints such as X-rays, MRI, and CT scans. KOA detection techniques can be categorized into three main types such as segmentationbased, feature extraction-based, and classification-based. One of the methods has been discussed in [15], however, it lacks the standard grading system for the assessment of KOA severity. An early KOA detection system has been introduced based on morphological features, mechanical and electrical properties, and molecular context [30]. Furthermore, the system is applicable for MRI images in non-ionized, in-vivo, and non-invasive modalities. In [31], authors used data from the Osteoarthritis Initiative (OAI) to analyze the progression of the disease. Steady State MRI with dual-echo has been used to assess the images, detect the region of comparison, and perform segmentation. Moreover, machine learning algorithms such as Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Networks (ANN) have been employed for comparison and selection of the best approach. Various segmentation-based techniques have been discussed in previous years [32], [33], [34]. Knee bone segmentation has been assessed in [32] and [35], whereas articular cartilage has been segmented only in [35], however, they didn't compare the proposed method quantitatively. Various deep learning-based architectures for bone segmentation and classification have been discussed in [36], [37], [38], [39], [40], and [41]. In [40], SegNet architecture is based on 10 layers without a fully connected layer after the decoder network has been developed for 2D knee images to employ semantic labeling pixel-wise. After this step, the segmented objects have been polished based on the original image. The model had fewer parameters due to the removal of the FC layer. Later, [41] modified the framework to compute numerous tissue segmentation using the conditional Random Forest (RF) for multi-classification. They have achieved 97% accuracy for the femur, 96.2% for the tibia, and 89.8% for the patella. [37] used the concept of segmentation based on the slice and added an extra feature of SSM in U-Net based segmentation framework. The model overcome the challenge of holes in segmentation masks as a result of poor intensity contrast and false-positive voxels that were identified outside the actual range. Although the model attained good accuracy, however, the computational cost was very high. To overcome the challenges, [38] developed a simple CNN-based technique i.e. Holistically Nested Network (HNN) for the ROIsegmentation. HNN removed the decoding path to perform a feed-forward network, therefore reducing the complexity of the model. In [36], authors have discussed various supervised machine learning (SML) methods' implications in the healthcare and biomedical sectors. Deep learning techniques have shown remarkable in results for the medical domain [42], [43]. In [44], a deep learningbased model has been proposed by authors to identify KOA disease considering the minimumjoint space width. The experiments showed that the proposed system significantly considers the knee joint space and classifies disease effectively. Wahid et al. [45], developed a multi-layered convolutional sparse model to categorize the MRI scan as an ACL tear but only for the coronal plane. Although it achieved a good accuracy of 85%, it was not of great use in diagnosis as it assessed only one of the three planes and only one type of injury. An effective object detection model is You Only Look at Once (YOLO) with CNNs can be used to localize the object (an area where the features reveal disease) [46].

III. PROBLEM STATEMENT

The project aims to address the problem of detecting and classifying Knee Osteoarthritis (KOA) using knee images obtained from X-ray scans.The existing methods for knee disease detection using image processing techniques have limitations in terms of accuracy and precision.The objective is to develop an improved deep learning model that can automatically extract features from knee images and accurately detect KOA.The proposed model utilizes an improved CenterNet architecture with a pixel-wise voting scheme and DenseNet201 as the base network for feature extraction.The model aims to provide precise detection of KOA in knee images and determine the severity level according to the KL grading system.

IV. SYSTEM DESIGN

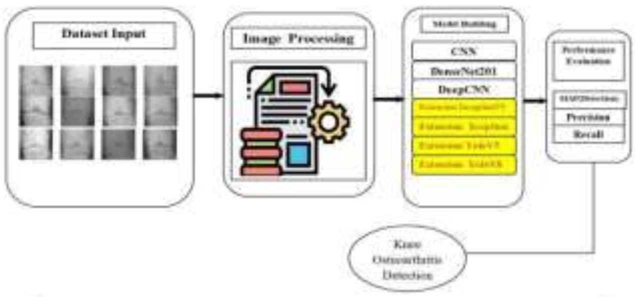

Fig.1. System Architecture

V. METHODOLOGY

Data Collection and Preprocessing

Dataset Acquisition: Medical imaging datasets (e.g., Xrays, CT scans, MRI, etc.) are collected from publicly available repositories or healthcare providers.

Data Annotation: Images are annotated using bounding boxes or segmentation masks depending on the task (e.g., classification, detection).

Image Preprocessing:

Resizing and normalization.

Data augmentation techniques like rotation, flipping, cropping, zoom, and brightness adjustments to enhance model generalization.

Splitting into training, validation, and test sets. Feature Extraction and Model Selection Multiple deep learning architectures are used for performance comparison:

Convolutional Neural Network (CNN): A standard CNN architecture is employed for feature learning and image classification.

DeepCNN: Enhanced depth CNN used specifically for capturing more abstract features in complex medical images. DenseNet201 (used with CenterNet for object detection): Densely connected CNN that enables feature reuse and reduces the vanishing gradient problem. Integrated as a backbone for CenterNet to detect keypoints and bounding boxes effectively. InceptionV3:

Uses factorized convolutions and aggressive regularization to reduce overfitting and computational cost. Xception: Leverages depthwise separable convolutions for better performance with fewer parameters. YOLOv5 and YOLOv8: Used for object detection tasks. YOLOv8 provides better accuracy and speed due to advancements in architecture and anchor-free detection heads. Model Training Transfer Learning: Pretrained weights (ImageNet) are used for faster convergence and improved performance on limited datasets. Training Parameters:Loss functions: Cross-entropy (for classification), IoU loss (for detection). Optimizer: Adam or SGD. Learning rate: Tuned using a scheduler. Epochs: 50–100 (based on convergence). Batch size: 16–64 depending on memory constraints. Evaluation Metrics To assess model performance, the following metrics are used: Classification Tasks: Accuracy, Precision, Recall, F1-Score, ROC-AUC. Object Detection Tasks: Mean Average Precision (mAP), Intersection over Union (IoU), Precision-Recall curves. Computational Metrics: Inference time per image, number of parameters, and FLOPs. Comparison and Analysis All models are compared on a unified dataset split. Performance metrics and confusion matrices are analyzed. Qualitative results are visualized using Grad-CAM or bounding box overlays for interpretability.

Hardware and Tools Environment: Google Colab / Jupyter Notebook / Local Machine with GPU support.

Frameworks: TensorFlow, Keras, PyTorch, Ultralytics for YOLOv5/YOLOv8.Libraries:OpenCV,scikit-learn,NumPy,Pandas, Matplotlib, Seaborn.

VI. RESULTS:

The output of the proposed DenseNet201 and CenterNet integration consists of KOA classification and localization of affected regions. The classification predicts the severity of Knee Osteoarthritis, categorizing it into normal, mild, moderate, or severe cases based on extracted features and detected key points. The system also highlights affected regions by identifying critical anatomical structures such as joint space narrowing, osteophytes, and bone deformities. By marking these areas on the X-ray, the model assists in visualizing disease progression, aiding radiologists in assessment and treatment planning.

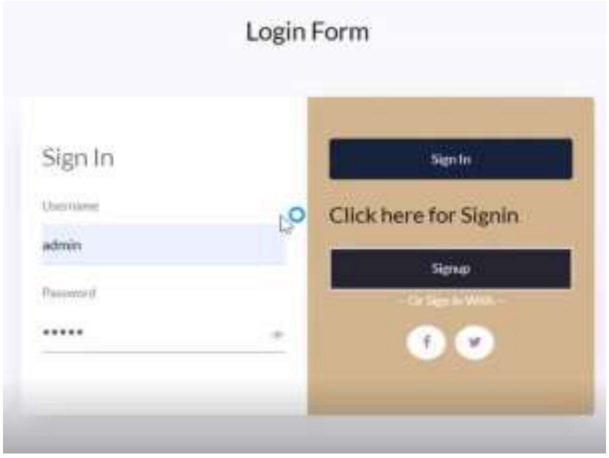

Fig.3. Output screen 1 Login Page

Fig.4. Output screen 2 Home Page

Fig.5. Output screen 3 Image Upload Page

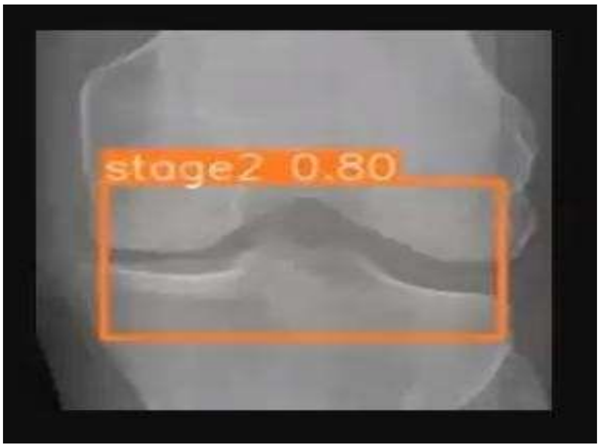

Fig.6 Output screen 4 Detecting the disease

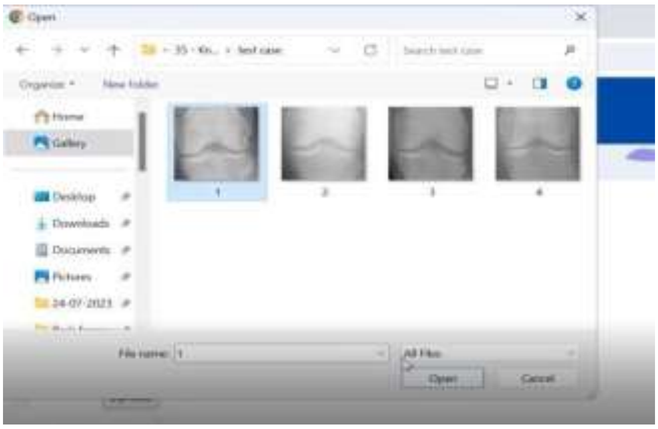

Fig.7. Output screen 5

Fig.8. Output screen 6

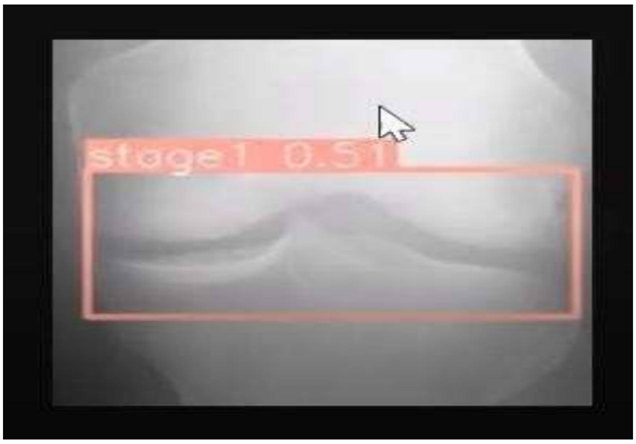

Fig.9. Output screen 7

DenseNet-201 is a robust technique for detecting knee osteoarthritis (KOA) and identifying its severity levels based on KL grading.

The proposed system effectively overcomes the challenge of class imbalance in the dataset and extracts the most

representative features from the identified ROI due to dense connections among all layers. The distillation knowledge concept is employed to make the model simple without increasing its computational cost and transfer knowledge from a complex network to a simple network making it more robust. We utilized two datasets in the proposed study such as:1) Mendeley Dataset used for training and testing, and 2) OAI Dataset used for cross-validation. Various experiments have been performed to assess the performance of the proposed model. The proposed technique outperforms existing techniques with good accuracy over testing and cross-validation.

The proposed model for knee osteoarthritis (KOA) detection uses an improved CenterNet with DenseNet201 as the base network. Dense connections in DenseNet enhance feature extraction, improving the model's performance.

The model's ability to accurately identify the region of interest (ROI) in knee images and extract representative features from it enhances its predictive capabilities.

Advanced classification models like Xception and InceptionV3 which is an extension excels with 99.9% accuracy, demonstrating superior performance and robustness, making it an effective solution for Knee Osteoarthritis Detection .

Extends the project with a Flask-based front end, ensuring a seamless and secure testing environment with integrated authentication for user-friendly testing and validation.

VIII. FUTURE ENHANCEMENT

The knee osteoarthritis detection system has significant potential for future advancements and applications in the medical field. With the continuous evolution of artificial intelligence and deep learning, the model can be further refined to enhance accuracy and efficiency.

Integration with cloud-based platforms can enable remote diagnostics, allowing healthcare professionals to access and analyze patient data from anywhere. Mobile application development can provide a user-friendly interface, making the system more accessible to patients and doctors.

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VII. CONCLUSION

In this study, we proposed a robust deep learning architecture to detect Knee Osteoarthritis (KOA) and identify severity

The incorporation of explainable AI techniques can enhance interpretability, making the system more transparent and reliable for medical professionals. Further, real-time monitoring and predictive analytics can be integrated, enabling early detection and preventive measures for osteoarthritis.

Collaboration with hospitals and research institutions can help in validating the model's performance across various clinical settings. The inclusion of additional medical imaging modalities, such as MRI and CT scans, can provide a more comprehensive analysis of knee joint conditions. Enhancing security measures to ensure data privacy and compliance with medical regulations will also be crucial for real-world deployment.

The system has the potential to revolutionize osteoarthritis detection and diagnosis, reducing the dependency on manual interpretation by radiologists and improving patient outcomes. With ongoing research and development, it can evolve into a fully automated, AI-powered diagnostic tool that supports decision-making in orthopedic care and rehabilitation.

Expanding the dataset to improve model generalization. Integrating multi-modal medical imaging techniques for enhanced diagnosis.

Implementing explainable AI (XAI) to provide insights into the model's decision-making process.

Deploying the system on cloud-based platforms for real-time medical diagnostics and remote accessibility. Enhancing security features to ensure user data privacy and compliance with healthcare regulations.

By continuously improving the model and expanding its capabilities, the system aims to provide an effective and accessible solution for early knee osteoarthritis detection and classification.

IX. REFERENCES

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