Automatic Diagnosis of Knee Osteoarthritis Using Deep Learning Approaches

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***Abstract*— Knee osteoarthritis is a common degenerative joint disease that affects millions of people worldwide, especially those aged over 50 years. It is characterized by gradual breakdown of the cartilage in the knee joint, leading to pain, stiffness, and reduced mobility. Knee osteoarthritis can develop because of a variety of factors, including genetics, old injuries, obesity, and repetitive stress on the knee joint. It is a chronic condition that often worsens over time if not treated properly. Various treatment options are available for managing knee osteoarthritis symptoms, including medication, physical therapy, and surgery. Early diagnosis and intervention can help individuals with knee osteoarthritis to manage their symptoms and maintain their quality of life. In this research, a range of deep learning models are utilized to aid clinicians in the diagnosis of knee osteoarthritis, reduce the workload on primary radiologists, and facilitate early detection and treatment. The deep learning model EfficientNetB7 implemented and compared with DenseNet169 and Inception ResNet V2. The EfficientNetB7 model achieved the highest results, with Accuracy 93.90%.**

Keywords*— Deep Learning, knee Osteoarthritis, Classification, EfficientNetB7, DenseNet169, Inception ResNet V2, knee X-ray image

I. Introduction

Knee osteoarthritis (OA) is a common degenerative joint disease, significantly affecting the elderly population and leading to pain, stiffness, and reduced mobility. Early diagnosis is crucial to improve patient outcomes, but traditional methods such as manual X-ray or MRI interpretations are often subjective and inconsistent [1]. The reliance on manual assessments can lead to variability among clinicians, and subtle early signs of OA may be missed, resulting in delayed treatment [2].

Deep learning, particularly convolutional neural networks (CNNs), has emerged as a powerful tool in medical imaging, offering the ability to analyze complex patterns within X-ray images with greater accuracy and consistency than traditional methods [3]. These models can detect intricate features in medical images that may indicate early-stage OA, improving the speed and accuracy of diagnosis [4].

This study focuses on utilizing EfficientNetB7, a scalable and high-performance deep learning model, to automate the detection and severity classification of knee OA from X-ray images. The EfficientNetB7 model, employed as a fully convolutional network (FCN), effectively detects and localizes critical features indicative of OA, such as peripheral opacities and vascular changes, offering high precision in severity grading [5].

By integrating the model into an end-to-end diagnostic pipeline, the system processes X-ray inputs and provides an automated assessment of KOA severity, minimizing the need for manual interpretation by healthcare professionals [6]. The use of EfficientNetB7 significantly enhances both the speed and accuracy of diagnosis, improving clinical workflows and ensuring early intervention for better patient outcomes [7].

II. Literature Review

In the past few years, there has been significant focus on Utilizing deep learning models for the detection of Knee Osteoarthritis has significantly improved diagnosis accuracy.

Akila et al [8]. tackled the problem of variability in manual grading of knee osteoarthritis (KOA) severity using deep learning techniques. They explored models like CNNs, Siamese networks, and Vision Transformer (ViT) to predict KOA severity from X-ray and MRI images. Their study demonstrated that ViT was particularly effective, achieving up to 93% accuracy with fewer computational resources compared to other models.

Zhang et al [9]. proposed a two-step deep learning approach for classifying KOA severity based on the Kellgren-Lawrence (KL) grading system. They combined ResNet with a Convolutional Block Attention Module (CBAM), improving accuracy by focusing on key regions of knee joints, with a classification accuracy of 74.81% and a quadratic Kappa score of 0.88 using the Osteoarthritis Initiative (OAI) dataset.

Alshamrani et al [10]. introduced Osteo-Net, an automated system for detecting knee osteoarthritis using transfer learning with models like VGG-16 and ResNet-50. Their model, trained on a Kaggle dataset, achieved an impressive testing accuracy of 92%, highlighting the potential of transfer learning for early OA detection from X-ray images.

Tiwari et al [11]. evaluated the performance of eight deep learning models in classifying KOA severity. DenseNet201 outperformed others with a classification accuracy of 93%, surpassing even human trainees, demonstrating the capacity of deep learning to assist clinicians in making consistent diagnoses.

Pongsakonpruttikul et al [12]. applied the YOLOv3 tiny algorithm to detect and classify KOA severity. Although the original dataset consisted of five classes, they simplified the classification task by grouping them into three categories: normal, non-severe, and severe OA. With an accuracy of up to 86.7%, their AI-based approach showed significant promise in automating the detection and grading of OA, thus improving diagnostic efficiency.

Ganesh Kumar M. et al [13]. used CNNs with image sharpening techniques for classifying KOA severity. Their model, based on Inception ResNet V2, achieved a testing accuracy of 91.03%, which was a significant improvement over previous methods, showing the benefit of enhanced image preprocessing.

Cueva et al[14].presented a semi-automatic Computer-Aided Diagnosis (CADx) system that combined a Siamese CNN and ResNet-34 to detect KOA lesions. Their model excelled in detecting severe OA, offering a consistent, automated diagnosis system with an accuracy of 61%.

Sheik Abdullah et al[15]. developed a system combining Faster R-CNN and AlexNet to automatically detect joint space width (JSW) and classify KOA severity. Their model achieved remarkable accuracy (98.9%), demonstrating its potential for real-world application in improving the precision of OA diagnosis.

Wahyuningrum et al[16]. proposed a hybrid model using CNN and LSTM for KOA severity classification. Their approach outperformed previous methods, achieving a mean accuracy of 75.28%, and offered a more consistent diagnostic tool for monitoring disease progression.

Ahmed et al[17]. used pre-trained CNN models like VGG16, VGG19, and ResNet50 with transfer learning to classify KOA severity. ResNet50 achieved the highest accuracy at 91.51%, emphasizing the effectiveness of CNNs in automating and improving diagnostic accuracy.

Teo et al[18].explored transfer learning models like InceptionV3 and DenseNet201, combined with machine learning classifiers, for KOA classification. Their approach achieved a multiclass accuracy of 71.33%, demonstrating the value of combining deep learning and machine learning techniques for better diagnostic reliability.

III. Methodology

A. Dataset

The dataset used in this study is publicly available from The Osteoarthritis Initiative (OAI)[19]. It comprises five categories labeled as 0, 1, 2, 3, and 4, representing different levels of knee osteoarthritis severity: 0 for normal images, 1 for doubtful cases, 2 for mild OA, 3 for moderate OA, and 4 for severe OA. The dataset was divided into three subsets for training, testing, and validation purposes. Specifically, the training set included 5,778 images (70%), the test set contained 1,656 images (20%), and the validation set had 826 images (10%). To ensure no data leakage occurred, the training set was further categorized into three classes for multiclass classification [6]. The first class, "Healthy," consisted of images from folders 0, 1, and 2, totaling 4,848 images. The second class, "Moderate," comprised images from folder 3 with 757 images, and the third class, "Severe," included 173 images from folder 4.

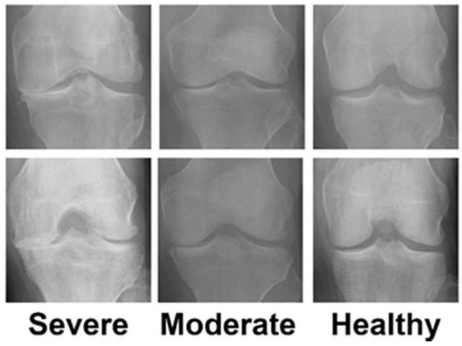

Fig. 1. Sample images from the dataset

B. Proposed Algorithms

To detect and classify Knee Osteoarthritis (KOA), we utilized a deep learning models, EfficientNetB7, DenseNet169 and Inception ResNet V2 and make a comparison between them. For each model, we followed a standardized procedure as shown in Fig. 2:

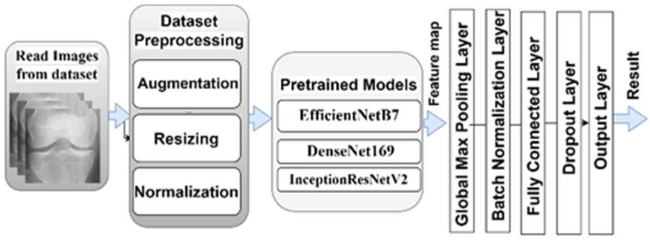

Fig. 2. Proposed model

1) Data preprocessing

Initially, we imported the modules required for deep learning. Then, we read the images and created a data frame containing the image paths and their corresponding class labels. To avoid class imbalance issues, we trimmed the training data frame to contain 500 image samples for each class , Various processing steps were applied to the data, including image enhancement, normalization to scale the pixel values between 0 and 1, and resizing to ensure all images have the required input size of 224*224 for the model. Data augmentation techniques included horizontal flipping, rotation by up to ±20 degrees, shifting images horizontally and vertically by up to 20% of their size, and zooming in and out within a 20% range. Subsequently, we created training, test, and validation generators to split our data into batches during training. To visually inspect our training image samples.

2) Initialization of the Model Parameters

EfficientNet-B7's architecture, rooted in the Mobile Inverted Bottleneck Convolution (MBConv) with squeeze-and-excitation optimization, serves as the foundation for fine-tuning in our knee osteoarthritis (KOA) detection system. During fine-tuning, we excluded the final fully connected layer by setting the include_top parameter to False, which allowed us to customize the output for our specific classification task. The input shape was set to fit high-resolution medical images, and max pooling was applied for down-sampling the spatial dimensions while retaining essential features.

Once the base model was made trainable, we added a batch-normalization layer to the output, ensuring that the activations had a normalized mean of zero and unit variance across the batch dimension. This step mitigates the internal covariate shift, stabilizing and accelerating training by maintaining consistency in the distribution of activations. Following this, we introduced a dense layer with 256 neurons, utilizing a linear transformation of the input, followed by a Rectified Linear Unit (ReLU) activation function to introduce non-linearity.

To prevent overfitting, regularization techniques were applied. Specifically, L2 regularization with a value of 0.016 was employed for the weights, and L1 regularization with a value of 0.006 was used for both the activities and biases. Dropout was set at 40% (a rate of 0.4), meaning each neuron had a 40% chance of being deactivated during training, which forces the model to learn more general, redundant representations and reduces its dependence on particular neurons.

In the output layer, a dense layer with 3 neurons was used, representing the three classes in our KOA dataset. A softmax activation function was applied to convert the raw logits into a probability distribution, with the predicted class being the one with the highest probability. By integrating these fine-tuned layers with EfficientNet-B7's powerful feature extraction capabilities, our model is capable of accurately diagnosing and classifying KOA from input images.

For the training process, we set the learning rate to 0.001 and compiled the model using the Adamax optimizer, chosen for its effective handling of sparse gradients. Categorical cross-entropy was used as the loss function, with accuracy as the evaluation metric. We trained the model with a batch size of 20 for 40 epochs, ensuring sufficient training time for the model to converge.

This approach leverages EfficientNet-B7's scalability and state-of-the-art performance, optimizing it for KOA diagnosis by employing transfer learning. By utilizing a pre-trained model on large-scale datasets like ImageNet, we not only save time and computational resources but also enhance our model's performance through the efficient reuse of learned features. We applied the same steps to DenseNet169 and InceptionResNetV2 models.

IV. Results and discussion

TABLE I. RESULT OF THE PROPOSED MODEL

Model	*Accuracy (%)*	*Recall (%)*	*Precision (%)*	*F1-score (%)*
EfficientNetB7	***93.90***	***93.90***	***94.09***	***93.97***
DenseNet169	***93.18***	***93.18***	***92.79***	***92.78***
Inception_Resnet_v2	***93.54***	***93.54***	***93.71***	***93.61***

Table 1 shows the results of EfficientNetB7, DenseNet169 and Inception ResNet V2 applied to the OAI dataset. The highest values are highlighted in bold, the best Accuracy (93.90) belongs to EfficientNetB7. The EfficientNetB7 requires high computational cost as its structure is very complicated.

TABLE II. TIME FOR MODELS

Model	*Training elapsed time*	*Running time*
EfficientNetB7	1h,8min,21.34 sec	25s 809ms/step
DenseNet169	25min,46.45 sec	8s 255ms/step
Inception_Resnet_v2	29.0 min,12.21 sec	12s 397ms/step

Based on the data provided in the table2, there are notable differences in training speed and running time between the three models—EfficientNetB7, DenseNet169, and InceptionResNetV2.

EfficientNetB7 took the longest time to train, with a total training elapsed time of 1 hour, 8 minutes, and 2.34 seconds, and had a running time of 25 seconds and 809 milliseconds per step. While this model provides state-of-the-art performance, its relatively longer training and running times suggest that it requires more computational resources, likely due to its deeper architecture and the complexity involved in processing larger amounts of data.

In contrast, DenseNet169 had the shortest running time at 8 seconds and 255 milliseconds per step, with a training elapsed time of 25 minutes and 46.45 seconds. This indicates that DenseNet169 is more efficient in terms of speed, making it potentially more suitable for applications requiring faster processing and less computational overhead.

InceptionResNetV2, which took 29 minutes and 12.21 seconds for training, had a running time of 12 seconds and 397 milliseconds per step, placing it between EfficientNetB7 and DenseNet169 in terms of speed. While it is not as fast as DenseNet169, InceptionResNetV2 still provides a balance between efficiency and performance.

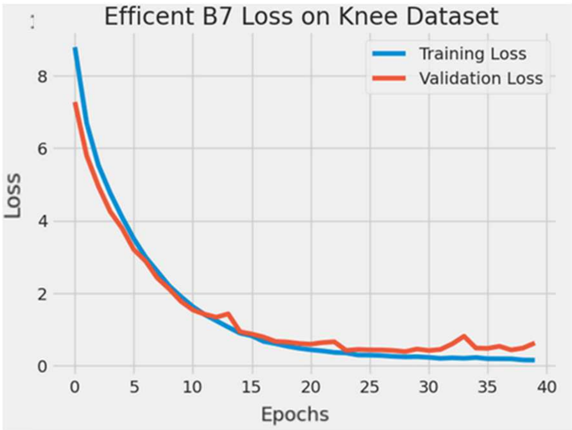

Fig. 3. Efficentnet b7 loss on knee dataset

Fig. 3 illustrates the training and validation loss curves of the Efficient Net B7 model on a knee dataset, providing insights into the model's performance during training. The EfficientNet B7 is a highly efficient neural network architecture, known for achieving state-of-the-art results. The graph shows the y-axis as loss values and the x-axis as epochs, where lower loss values signify better model performance.

Initially, both training and validation losses start high (around 8), which is typical due to random parameter initialization. As training progresses, the loss values decrease significantly, particularly in the early epochs, indicating effective learning. By around epoch 10, the rate of decline slows, suggesting that the model is approaching convergence.

The training loss curve (blue) closely follows the validation loss curve (red), indicating that the model is not overfitting, as there is no significant gap between the curves. Minor fluctuations observed between epochs 20 and 40 are normal and do not indicate instability. By the end of training (around epoch 40), both losses stabilize at low values, reflecting the model's ability to generalize well to new data.

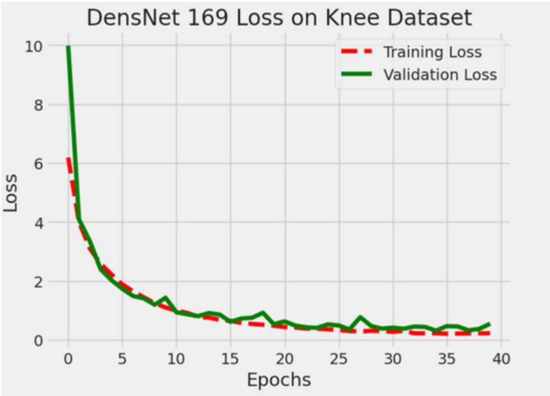

Fig. 4. DensNet169 Loss on Knee Dataset.

Fig. 4 presents the training and validation loss curves for the DenseNet 169 model, which is known for its densely connected convolutional layers that enhance feature reuse and mitigate the vanishing gradient problem. The model's performance is tracked over 40 epochs, with the y-axis representing loss values and the x-axis indicating the number of epochs.

Initially, both training and validation losses are high (around 10), which is typical due to the random initialization of parameters. The loss values decrease rapidly within the first 5 epochs as the model adjusts to the data, and between epochs 5 and 10, the rate of decline slows, signaling the model's convergence towards optimal parameters.

Throughout the training process, the training loss (red dashed line) closely follows the validation loss (green solid line), indicating the model is not overfitting and generalizes well to new data. Minor fluctuations after epoch 10 are expected and do not suggest instability. By epoch 40, both losses stabilize around a low value of approximately 1, confirming the model's effective learning and capacity to generalize to unseen data.

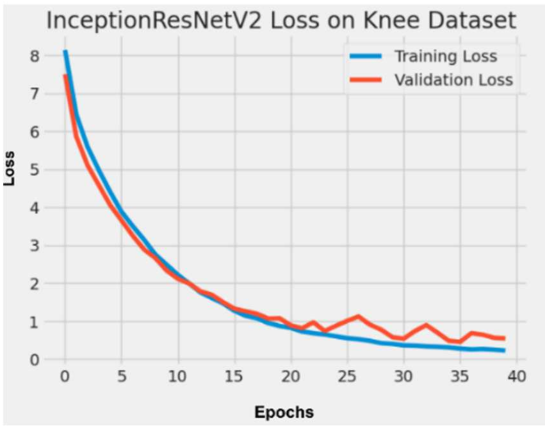

Fig. 5. Inception Resnet_v2 loss on knee dataset

Fig. 5 [13] depicts the loss curves for the InceptionResNetV2 model trained on the knee dataset, showing training and validation losses over 40 epochs. Both curves display a steep decline in the initial epochs, indicating rapid convergence. The training loss begins around 8 and gradually approaches zero by the 40th epoch, reflecting the model's improved performance. The validation loss closely follows the training loss, suggesting good generalization without overfitting. The plateau towards the end indicates the model has reached a point of diminishing returns for further loss reduction.

In comparing the loss curves for InceptionResNetV2, DenseNet 169, and EfficientNet B7 on the same dataset, several key points emerge:

- **InceptionResNetV2:** Both losses start at 8 and decline steadily, stabilizing below 1 by the end. The curves show minimal fluctuations, indicating strong convergence and generalization.
- **DenseNet 169:** Losses start higher, around 10, and decline sharply within the first 5 epochs. Small fluctuations are observed but remain below 1, suggesting robust performance, though some fine-tuning could reduce oscillations.
- **EfficientNet B7:** The model exhibits a smooth, rapid decline in losses from 8 to below 1 by epoch 20, with minimal deviation. This suggests excellent generalization and stability.

All models converge rapidly within the first 10 epochs, with DenseNet 169 showing faster convergence but more fluctuations. In contrast, EfficientNet B7 and InceptionResNetV2 display smoother, more stable curves, indicating stronger generalization capabilities. While none of the models show significant overfitting, DenseNet 169's noisier curve suggests it may benefit from further optimization.

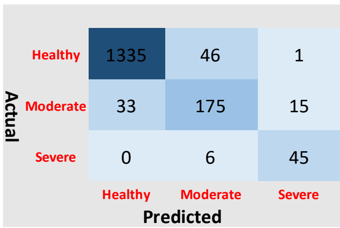

Fig. 6. Efficentnet b7 Confusion matrix

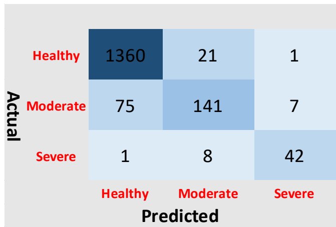

Fig. 7. DensNet169 Confusion matrix

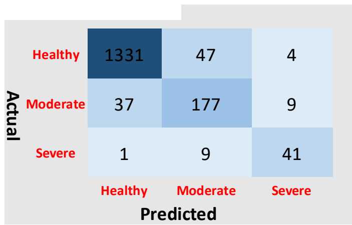

Fig. 8. Inception Resnet_v2 Confusion matrix

Based on the data provided in Fig. 6, 7 and 8 the performance of EfficientNet B7, DenseNet 169, and InceptionResNetV2 models shows different strengths when classifying knee osteoarthritis into healthy, moderate, and severe categories. In terms of identifying healthy cases, DenseNet 169 performs exceptionally well, correctly classifying 1,360 out of 1,382 cases, with minimal errors. It only misclassifies 21 cases as moderate and 1 as severe. EfficientNet B7 also performs well, correctly identifying 1,335 healthy cases, but it misclassifies 46 as moderate and 1 as severe. InceptionResNetV2 falls slightly behind, correctly classifying 1,331 healthy cases, but with a few more misclassifications—47 as moderate and 4 as severe. In this category, DenseNet 169 stands out with the least errors, especially in misclassifying cases as moderate.

When it comes to moderate cases, InceptionResNetV2 proves to be the most reliable model. It correctly classifies 177 out of 223 moderate cases, with fewer errors—37 misclassified as healthy and 9 as severe. EfficientNet B7 performs reasonably well, correctly identifying 175 moderate cases, but it does misclassify 33 as healthy and 15 as severe. DenseNet 169, on the other hand, struggles with moderate cases, correctly classifying only 141 cases while misclassifying 75 as healthy and 7 as severe. In this respect, InceptionResNetV2 demonstrates superior performance, while DenseNet 169 shows significant room for improvement.

For severe cases, EfficientNet B7 demonstrates the best performance, correctly classifying 45 out of 51 cases, with only 6 misclassified as moderate and none as healthy. Both DenseNet 169 and InceptionResNetV2 perform similarly in this category, with DenseNet 169 correctly classifying 42 severe cases and misclassifying 8 as moderate and 1 as healthy. InceptionResNetV2 correctly identifies 41 severe cases, with 9 misclassified as moderate and 1 as healthy. Although the differences between DenseNet 169 and InceptionResNetV2 in this category are minor, EfficientNet B7 shows a clear advantage in accurately identifying severe cases.

EfficientNet B7 provides the most well-rounded performance, excelling in the classification of severe cases and performing well across the other categories. InceptionResNetV2 shows particular strength in classifying moderate cases, while DenseNet 169 excels in identifying healthy cases but struggles more with moderate classifications. Each model has its strengths, with EfficientNet B7 standing out for its balance across the board, and InceptionResNetV2 being particularly strong in moderate classifications.

V. CONCLUSION

This study introduced a diagnostic model for knee osteoarthritis (KOA) using deep learning (DL) techniques aimed at improving diagnostic efficiency, reducing costs, accelerating diagnosis, and slowing disease progression, ultimately enhancing patient experience. The proposed model facilitates the determination of KOA severity through multi-classification, providing clinicians with insights into the underlying factors contributing to the condition, thereby aiding in the understanding of its primary causes.

Experiments conducted using an OAI dataset involved pre-processing steps such as artifact removal, resizing, and normalization. The EfficientNetB7 model was applied to this pre-processed dataset and compared with DenseNet169and Inception ResNet V2. In the multi-classification task, EfficientNetB7 achieved an accuracy of 93.90%, recall of 93.90%, precision of 94.09%, and an F1-score of 93.97%.

The proposed model demonstrated significant potential to enhance KOA diagnosis, offering benefits like high accuracy, faster diagnosis, and delayed disease progression. Additionally, it enables clinicians to understand the primary causes of KOA, facilitating informed decision-making for effective treatment. However, due to its high costs, we suggest an alternative model, Inception ResNet V2, for scenarios with limited budgets, as its accuracy is acceptable for some clinicians who cannot afford the requirements for running the EfficientNetB7 model.

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