Enhanced Knee Osteoarthritis Grading: Transfer Learning with Pre-Trained CNN's For Swift Diagnosis

V. Vijaya Kishore*[1], K. Sahithi[2], K. Siva Jayanth Reddy[3], K. Akash[4], K. Sai Jyothy[5], Sreekanth Yalavarthi[6]

[1]Prof, Dept of ECE, Mohan Babu University, Tirupati, India
*kishiee@rediffmail.com
[2,3,4,5] Sree Vidyanikethan Engineering College, Tirupati, India
[6]HCL Technologies. Buffalo Grove, il 60089

[2]kotasahithi23@gmail.com
[3]jayanthreddy.siva@gmail.com
[4]aakashkuruva18@gmail.com
[5]kalurisaijyothy@gmail.com

Abstract. Knee osteoarthritis (KOA) is a common long-lasting ailment characterized by joint degradation, impacting millions worldwide and posing significant challenges in early detection and management. Radiographic assessment, particularly through the Kellgren-Lawrence (KL) grading scheme, serves as a cornerstone for diagnosis and disease monitoring. However, the subjective nature of visual examination, coupled with the expertise-dependent interpretation, often leads to variations in grading accuracy and delays in intervention. This study introduces an enhanced Computer-Aided Diagnostic (CAD) system framework leveraging Adaptive Pretrained Convolutional Neural Networks (CNNs) for rapid and precise classification of KOA severity based on KL grading By learning on large-scale datasets, transfer learning is utilized to create robust representations, which helps to mitigate the difficulties brought on by the scarcity of medical data. The performance of these transfer learning is enhanced by introducing adaptability to refining through partial fine-tuning of the layers to accommodate the specific nuances of KOA grading. The effectivity of the proposed enhancement is evaluated by using an extensive experimental setup in which eight pretrained CNN models, namely NasNetLarge, InceptionV3, DenseNet169, ResNet152V2, NasNetMobile, ResNet50V2, ResNet101V2 and InceptionResNetV2 are used for KOA using KL grading in clinical scenario. The proposed enhanced approach is applied on Kaggle X-ray data sets repository. The method demonstrates promising results in accurately classifying KOA severity, offering a significant advancement towards early detection and personalized management strategies. The results show that NasNetLarge is the most efficient model, with a validation accuracy of 98.8%, training accuracy of 98.3% and precision of 99.7%. By combining pretrained CNN models and transfer learning with partial

K. R. Madhavi et al. (eds.), *Proceedings of the International Conference on Computational Innovations and Emerging Trends (ICCIET 2024)*, Advances in Computer Science Research 112,
https://doi.org/10.2991/978-94-6463-471-6_2

fine-tuning, the proposed framework facilitates rapid and cost-effective diagnosis, contributing to early diagnosis and help to reduce progression.

Keywords: Knee Osteoarthritis, Kellgren-Lawrence, Artificial Intelligence, Deep learning, Computer aided diagnosis, Rectified Linear Unit (ReLU), Partial fine-tuning.

1 Introduction

Knee osteoarthritis (KOA) stands as a significant health challenge worldwide, affecting millions and imposing substantial burdens on healthcare systems and economies. In India, where it affects 15-20% of individuals above the age of 60, its impact is particularly profound. This chronic degenerative joint disease not only leads to debilitating effects but also strains healthcare resources, emphasizing the urgent need for effective management strategies. Early detection plays a crucial role in addressing knee OA [1-2], offering opportunities for timely intervention and improved treatment outcomes. By identifying the condition in its early stages, healthcare providers can implement measures to slow disease progression, mitigate pain, and preserve joint function. Moreover, early detection has the potential to reduce the need for costly interventions like knee replacement surgery and prevent debilitating complications, thereby alleviating the burden on healthcare systems.

The Kellgren-Lawrence classification system serves as a cornerstone in the diagnosis and management of knee Osteoarthritis. Figure1. illustrates both samples and standards for the KL grading system [3-6]. This widely used system, based on radiographic imaging, enables clinicians to accurately assess disease severity by evaluating parameters such as joint space narrowing, osteophyte formation, and subchondral bone sclerosis. By leveraging this classification system, healthcare providers can tailor treatment strategies to individual patient needs, optimizing therapeutic outcomes and enhancing quality of life. Despite the effectiveness of traditional diagnostic tools like the Kellgren-Lawrence classification system, advancements in technology, particularly in Artificial Intelligence (AI), offer new opportunities for enhancing diagnostic precision. Deep learning algorithms [8-9], such as 3D convolutional neural networks, have demonstrated remarkable capabilities in predicting disease severity from radiographic images with impressive accuracy rates.

This paper provides a comprehensive overview of the challenges posed by knee OA, emphasizing the importance of early detection and effective management strategies. The proposed system explores the role of traditional diagnostic tools like the Kellgren-Lawrence classification system and examines the potential of cutting-edge technologies, such as deep learning algorithms, in enhancing diagnostic precision. Transfer learning with partial fine-tuning can be a powerful technique when applied to image classification tasks such as KOA classification. By integrating these approaches synergistically, healthcare providers can improve patient care, optimize treatment regimens, and ultimately lessen the impact of knee osteoarthritis on individuals and healthcare systems.

Fig. 1. Assigning KL grades to knee joint samples [7].

Knee osteoarthritis (KOA) is a major challenge for healthcare systems worldwide, impacting millions of people globally and posing substantial challenges in diagnosis, management, and treatment. KOA [10-11]is a degenerative joint condition marked by the gradual breakdown of articular cartilage, synovial inflammation, and alterations in subchondral bone, ultimately leading to pain, stiffness, and functional impairment.

Table 1. Description of KL Grading [12].

KL Grade	Classification	Description
0	Normal	No evidence of osteoarthritis is present in the radiographs.
1	Doubtful	Doubtful joint space narrowing and possible osteophytic lipping
2	Mild	Specific osteophytes and potential restriction of the joint space
3	Moderate	Joint space constriction caused by many osteophytes and potential bony deformity
4	Severe	Bone end deformities, joint space constriction, and large osteophytes

While numerous modalities exist for KOA assessment, radiographic evaluation remains a cornerstone in clinical practice, particularly through the utilization of the Kellgren and Lawrence (KL) grading system. Table 1. Shows the detailed description about the KL grading system. Introduced in 1957 by Kellgren and Lawrence, the KL grading system serves as a widely accepted method for categorizing the severity of KOA based on radiographic findings. The method categorizes KOA into five classes (0 to 4) according to the degree of joint space constriction, presence of osteophytes, sclerosis, and overall joint deformity seen on X-ray images. Grade 0 indicates no evidence of osteoarthritis, while grades 1 to 4 denote increasing severity, with grade 4 representing severe degenerative changes and significant joint damage.

2 Literature Review

The Recent literature review highlighted the growing need for automatic grading of knee severity due to the fact that it allows for quicker diagnosis, and it is especially difficult to find radiologists in rural locations due to the shortage. For the purpose of addressing these issues, a number of computer-aided diagnostic (CAD) methods [13-14] have been presented. These methods make use of machine learning (ML) and deep learning (DL) techniques for the purpose of classification, detection, and risk stratification in Knee Osteoarthritis (KOA). The severity of osteoarthritis (OA) can be determined by using these approaches, which try to classify changes in knee joint gaps and osteophyte growth. For predicting radiographic and symptomatic knee osteoarthritis risks, one study presented a scoring system that makes use of artificial neural networks (ANN).

Recently, Convolution Neural Networks (CNNs) and other deep learning-based technologies have been used to detect radiographic knee OA automatically. The knee joint was initially identified in radiographs using ResNet, a Residual Neural Network. Then, to automatically produce a KL-grade prediction, we merged ResNet with CBAM, a Convolutional Block Attention Module [15-16]. Across all classes, the suggested model attained an average accuracy of 74.81. In this study, they suggest using X-ray scans to autonomously divide the knee area and foretell the onset of knee osteoarthritis. Additionally, a comparison study utilizing an ensemble model with a YOLOv5 object detection algorithm for segmenting knee joints is suggested. For the KL grade classification, many classification models, including VGG16, Resnet, and others, are tested. Extensive experiments are carried out to comprehend the necessity of the segmentation stage of the region of interest in the KL grade classification.

The smooth motion of the joints is guaranteed by the cartilage covering the bone. Due to cartilage degeneration, the afflicted bones move together in knee OA, resulting in swelling, discomfort, and eventually loss of motion. This serves as the inspiration for the research, which offers an automated technique to measure the cartilage thickness in the knee's tibia femoral joint [17–18]. The study used a variety of image processing methods on a 2D knee magnetic resonance imaging (MRI). The thickness of the cartilage is measured and contrasted with the reference cartilage thickness provided by research teams. Based on this data, KOA categorization is carried out.

To increase the accuracy of defect recognition, research on picture enhancing techniques is crucial. This paper presents a deep learning-based radiographic image enhancement system that addresses the issues of staff expertise and parameter adjustment in standard enhancement methods. Initially, the intended gathering of data to better radiography images is created based on the needs of the process. Second, an enhanced U-Net network image enhancement model is created to achieve noise reduction and image structure preservation utilizing the deep learning theory. Finally, radiographic pictures of intricate metal components serve as an illustration and verification of the suggested approach [19]. In this work, the dataset was subjected to binary classification (Covid+/Covid-) utilizing the Transfer Learning (TL) architectures of MobileNetV2 and Resnet101V2. The outcomes were also contrasted with those of other TL topologies, including MobileNetV3Large, ResNet50V2, DensNet121, and ResNet152V2. The parameters for f1-score, precision, and recall were utilized to assess the outcomes [20–21]. The MobileNetV2 model produced the best performance values in the dataset that was provided.

Joint osteoarthritis (OA) incidence in many modalities: a semi-supervised graph-based deep learning technique prediction has been reported in a study. The proposed approach makes use of a graph-based regularization methodology that can improve model performance by utilizing unlabeled data and multi-modal data. The results of the study show that the proposed method for knee OA incidence prediction using multi-modal data, including clinical and MRI imaging as well as demographic data, performs better than the state-of-the-art methodologies and the standard deep learning methodology [22–23]. The findings suggest that knee OA incidence prediction accuracy can be improved by the use of semi-supervised graph-based deep learning technique. This is important since early diagnosis and effective treatment of the condition depend on accurate knee OA incidence prediction.

An extensive review of various image segmentation techniques for knee osteoarthritis research is available in one paper. The study focuses on the limitations and performance of deep learning-based and conventional methods for knee radiograph cartilage and bone segmentation. The authors provide information on the problems associated with knee OA segmentation, such as inter-reader variability, noise, and partial volume impact [24]. They also go over the advantages of segmentation techniques based on deep learning, namely increased robustness and accuracy. For researchers working on knee OA segmentation, the study is an excellent resource. It also serves as a solid reference for choosing the best segmentation techniques based on the particular needs of the research. In this paper, ReLU activation units were used for the partial fine tuning. These layers were applied soon after the features extraction as shown in figure 2.

In conclusion, the employment of DL and ML techniques, including transfer learning with partial fine tuning, offers potential for improving knee OA diagnosis and progression monitoring, but further study is needed to overcome issues associated to generalization and data scarcity. Knee osteoarthritis (KOA) stands as a significant health challenge worldwide, affecting millions and imposing substantial burdens on healthcare systems and economies. In India, where it affects 15-20% of individuals above the age of 60, its impact is particularly profound. This chronic degenerative joint disease not only leads to debilitating effects but also strains healthcare resources, emphasizing the urgent need for effective management strategies.

Early detection plays a crucial role in addressing knee OA [1-2], offering opportunities for timely intervention and improved treatment outcomes. By identifying the condition in its early stages, healthcare providers can implement measures to slow disease progression, mitigate pain, and preserve joint function. Moreover, early detection has the potential to reduce the need for costly interventions like knee replacement surgery and prevent debilitating complications, thereby alleviating the burden on healthcare systems. The Kellgren-Lawrence classification system serves as a cornerstone in the diagnosis and management of knee Osteoarthritis. Figure1. illustrates both samples and standards for the KL grading system [3-6]. This widely used system, based on radiographic imaging, enables clinicians to accurately assess disease severity by evaluating parameters such as joint space narrowing, osteophyte formation, and subchondral bone sclerosis. By leveraging this classification system, healthcare providers can tailor treatment strategies to individual patient needs, optimizing therapeutic outcomes and enhancing quality of life.

Despite the effectiveness of traditional diagnostic tools like the Kellgren-Lawrence classification system, advancements in technology, particularly in Artificial Intelligence (AI), offer new opportunities for enhancing diagnostic precision. Deep learning algorithms [8-9], such as 3D convolutional neural networks, have demonstrated remarkable capabilities in predicting disease severity from radiographic images with impressive accuracy rates.

This paper provides a comprehensive overview of the challenges posed by knee OA, emphasizing the importance of early detection and effective management strategies. The proposed system explores the role of traditional diagnostic tools like the Kellgren-Lawrence classification system and examines the potential of cutting-edge technologies, such as deep learning algorithms, in enhancing diagnostic precision. Transfer learning with partial fine-tuning can be a powerful technique when applied to image classification tasks such as KOA classification. By integrating these approaches synergistically, healthcare providers can improve patient care, optimize treatment regimens, and ultimately lessen the impact of knee osteoarthritis on individuals and healthcare systems.

Recent advancements in computer vision and optimization techniques have made image segmentation a critical component of numerous applications including disease diagnosis, autonomous vehicles, and robotics. Early research efforts such as [1-5] explored the application of genetic algorithms (GA) for image segmentation, demonstrating the potential of evolutionary techniques in optimizing segmentation parameters. Subsequently authors of papers [6-10], introduced Particle Swarm Optimization (PSO) as an effective tool for optimizing segmentation algorithms, for improved convergence rates and segmentation quality. Rise of deep learning models, particularly Convolutional Neural Networks (CNNs), reshaped image analysis. Authors of [15-17] utilized CNNs' ability to automatically learn features from data, significantly enhancing segmentation accuracy. Also, challenges persisted in fine-tuning complex networks, prompting exploration into hybrid methods.

Recent literature, such as [18-21], proposed the integration of optimization algorithms with Transformer architectures, originally designed for sequence modeling tasks. Transformer models, known for their attention mechanisms, were adapted to capture complicate spatial dependencies within images, as demonstrated by [22-25].Fusion of these architectures with evolutionary algorithms, like Flower Pollination Optimization (FPO) and its hybrid variants, as discussed in [11-14], led to significant advancements in both accuracy and computational efficiency. However, a research gap remains in exploring the integration of Hybrid Flower Pollination Optimization (HFPO) with Transformer networks for image segmentation tasks. Our proposed work seeks to address this gap by proposing hybrid HFPO and transformer-based approach for image segmentation.

3 Methodology

Further details regarding the proposed computer-aided diagnostic are provided by eight pre-trained Convolution Neural Network models (CNN), taken from NasNetLarge, InceptionV3, DenseNet169, ResNet152V2, NasNetMobile, ResNet50V2, ResNet101V2, and InceptionResNetV2 adapted to the KOA images, with refining the fully connected layers. The final aim is to produce the accurate and precise model to detect the KOA.

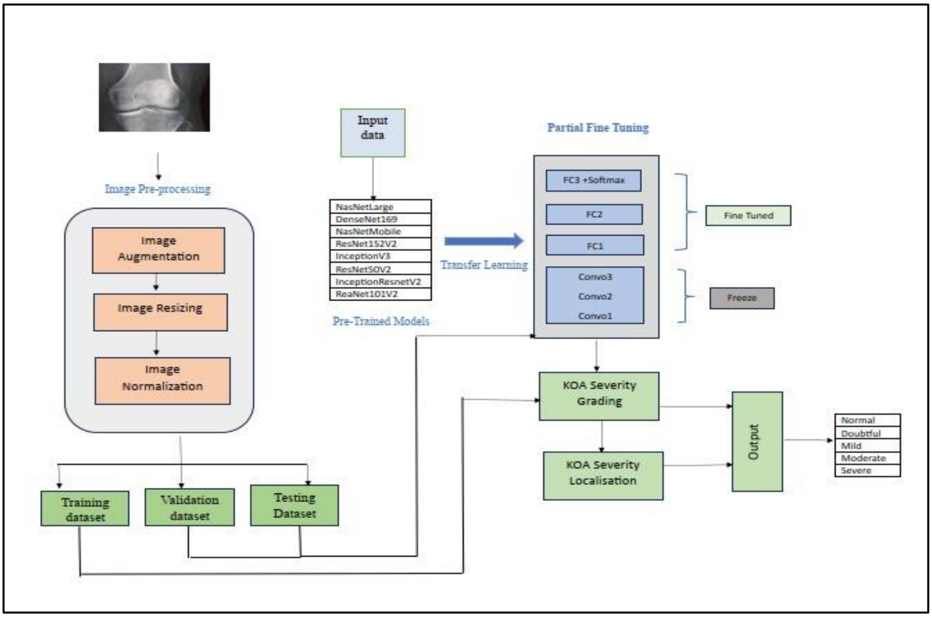

Fig. 2. System Architecture

3.1 Data Set

The Kaggle repository dataset is considered which consists of 8250 images. Out of which, 1650 validation Knee X-ray images are considered, which were divided into 5 classes namely normal of 503 images, doubtful of 488 images, mild of 232 images, moderate of 221 images and severe of 206 images. Careful anonymization was conducted to each medical image in the collection in order to safeguard patient privacy. The dataset also ensure that it complied with international standards and that private data was kept safe.

3.2 Pre-Processing of the Data

In the first step of the preprocessing procedure, the intensities of the pixels are normalized. This is performed by moving their values from the range of 0-255 to the range of 0-1. This is done in order to prevent non-zero gradients during the training phase, which eventually leads to a more rapid learning process. In order to adapt the images to pre-trained networks, the second stage includes scaling them to 224 by 224 pixels. This is crucial since deep learning models on GPUs have memory constraints. Making sure that the images and model parameters are small enough to fit into the GPU RAM (224 x 224) allows for more efficient training and inference. The dataset was separated into three sets: training, validation and testing in the ratio of 70:20:10.

3.3 Data Augmentation

Data Augmentation is used during training to enrich data, reduce overfitting, and improve the model's generalization capability, during training. In this context, the resulting geometrical adjustments boost the quantity of data points while keeping the qualities. Several techniques are applied in this method, including picture rotation, vertical translation, horizontal translation, rescaling, horizontal rotation, and image brightness improvement. Data processing is then started, by separating the database into three sets: training (70%) validation (20%) and testing (10%).

3.4 Adaptive Convolution Neural Network

Activation By refining the responses of the pre-trained models to the investigated database, the extended convolutional neural model is created. In this, we replace the last layer of each of the eight pre-trained CNNs with fully connected layers (FCL). Partial Fine-tuning in each design involves freezing the parameters of maximum layers surrounding the pre-trained network. Freezing most layers helps in retaining the valuable learned features from the pre-trained model and prevents them from being updated during training, which can be particularly useful when the dataset is small or when computational resources are limited.

There are several fine-tuned models in the suggested approach to test whether fine-tuning can be used for KOA prediction and to figure out how to make a fine-tuning CNN that works well. Adding too many fully connected layers can lead to overfitting, especially when the dataset is small. So, add 2 to 4 fully connected layers, and then adjust it based on the performance on a validation set Including 2-4 fully connected layers in transfer learning strikes a balance, offering model adaptability to new tasks without excessive complexity or overfitting. The specific count caters to effective knowledge transfer from pre-trained layers, optimizing performance on the target task. There is a comparison study between the models that were used to find the best one for KOA prediction.

This is accomplished by building a convolutional network tailored to the study data, as well as initializing the optimizer, learning step, convolution size, pooling, and batch size. The SoftMax function is selected as the classification function as shown in figure 3. The Adam optimization method is used to make gradient updating, introduced in reference. The models divide knee severity into five degrees using the Kellgren Lawrence method: normal, doubtful, mild, moderate, and severe.

This study includes all eight pre-trained convolutional neural network designs for image classification, using a technique called partial fine-tuning. This approach involved adding a series of three fully connected layers (FCLs) [35-36] to the all the pretrained models as shown in Figure 3, to enhance its classification capabilities. The FCLs were designed to progressively reduce the dimensionality of the features extracted by the layers present in the eight pre trained models, leading to a more compact and informative representation.
Specifically, we added the following FCLs to all the eight pretrained models:

Dense (1024, activation='relu')
Dense (512, activation='relu')
Dense (256, activation='relu')

These FCLs served to extract higher-level features from the all the pretrained base model, which were then used to classify the input images into their respective classes. The use of multiple FCLs allowed us to capture complex patterns in the data, leading to improved classification performance compared to using a single classifier.

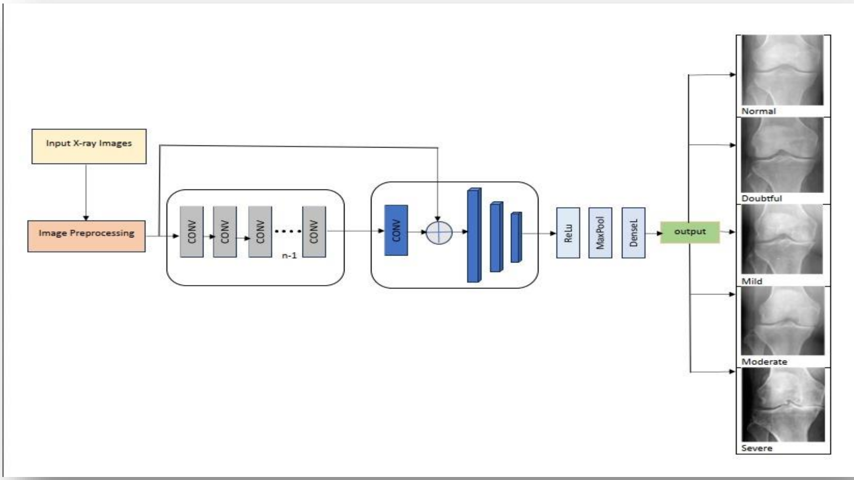

Fig. 3. Structure of partial fine tuning

3.5 Necessity of Transfer Learning

Transfer learning in CNN transfer models is vital for addressing challenges in deep learning, particularly with limited datasets. Leveraging pre-trained models trained on diverse data enhances model knowledge transfer, crucial when data collection is impractical. It optimizes training efficiency by reducing computational demands and time, compared to training from scratch.

Importantly, transfer learning mitigates overfitting on small datasets by leveraging pre-existing generalization. Ultimately, it enables improved performance on new tasks, making it indispensable for efficient and effective CNN model development, especially under data and resource constraints.

3.6 Proposed System

The Pooled Python, the programming language of choice, and Google Colab, with GPU configuration, were used for developing deep learning models for knee osteoarthritis classification. Python's extensive libraries and readability facilitated model development, while Google Colab's cloud-based platform accelerated training. Preprocessing of radiographic images and data augmentation were performed using NumPy, Pandas, and Keras. Transfer learning with adaptive pre-trained Convolutional Neural Networks

(CNNs) improved model performance. Training and evaluation on augmented datasets yielded accurate classification results, showcasing the effectiveness of the approach.

The proposed algorithm consists of the subsequent actions:

1. Collect Knee OA data, importing library files, and building a personalised dataset.
2. Pre-process photos by adjusting and standardizing them to 224 × 224 dimensions.
3. Make sure the Data Loader is ready.
4. Create data generator and augment routines for dataset validation, training, and testing.
5. Create and put together models.
6. Train and test with 8 distinct TL models.
7. Freeze maximum layers which allows leveraging pre-trained knowledge while training only added layers in transfer learning and add fully connected layers for partial tuning of 8 TL techniques.
8. KL grading.
9. Run the model and find the loss and accuracy by looking at the graphs.

4 Evaluation Parameters

Disease Management (DM) strategies rely heavily on accurate diagnosis and prediction to be effective. Evaluating model accuracy is critical for applications such as recognizing unwell patients, predicting future health status and costs, and risk classification. During the training of a neural network, two key metrics are commonly monitored: training loss and validation loss.

Accuracy, defined as the proportion of correctly classified instances to total cases, is an important statistic. It quantifies the method's overall effectiveness based on the available data. Mathematically, accuracy is expressed as the ratio of true positives (TP) and true negatives (TN) to all instances:

$$\text{Accuracy} = \frac{TP+TN}{TN+TP+FP+FN} \tag{1}$$

A model's accuracy can be measured by dividing the total number of positive predictions by the number of predictions that were actually correct. Here is the calculation:

$$\text{Precision} = \frac{TP}{TP+FP} \tag{2}$$

Training loss, also known as the training error or training cost, is a measure of how well the neural network model is performing on the training data during the training process. It quantifies the difference between the predicted output of the model and the actual target output for the training examples.

The validation loss, also known as the validation error, is similar to the training loss but is calculated using a separate dataset called the validation dataset.

The proposed approach makes use of Convolutional Neural Networks (CNNs), a popular Deep Learning (DL) algorithm known for its ability to automatically recognize significant information without human interaction. CNNs, which are inspired by the human visual system, allow computers to experience the environment in the same way that people do, with applications ranging from natural language processing to picture classification and image recognition.

4.1 Fully Connected Layer

High-level information about input images can be extracted using the pooling and convolution layers' outputs. Nevertheless, by more efficiently learning nonlinear combinations of these properties, Fully Connected (FC) layers can offer notable advantages. Convolution and pooling layer data are combined by the FC layer to generate a potential classification score, which makes it easier to classify input images. The output layer, which makes predictions using a softmax activation function, receives the two-dimensional result from the FC layer.

The SoftMax function's mathematical representation is shown below:

$$\sigma(x) = \frac{e^{xj}}{\Sigma_{k=1}^{k} e^{xk}} \tag{3}$$

In the context of multiclass classification, 'k' represents the number of output classes. 'x' signifies the anticipated chance that the test input belongs to class 'j'.

The CNN model calculates the loss function to assess the gap between the predicted and actual values in the data.

5 Results and Discussions

The enhanced Computer-Aided Diagnostic (CAD) system framework leveraging Adaptive Pretrained Convolutional Neural Networks (CNNs) for rapid and precise classification of KOA severity based on KL grading, produced encouraging results. The effectiveness of the proposed enhanced system is evaluated by using an extensive experimental setup in which eight pretrained CNN models, namely NasNetLarge, InceptionV3, DenseNet169, ResNet152V2, NasNetMobile, ResNet50V2, ResNet101V2 and InceptionResNetV2 are used for KOA using KL grading in clinical scenario using partial fine-tuning. Among these models, NasNetLarge achieved the highest validation accuracy (98.79%), with DenseNet169 demonstrating the most significant improvement in reduction of loss. The validation loss for DenseNet169 is 0.0627 and whereas training loss is 0.0565.

The proposed framework exhibited high accuracy in classifying KOA severity, underscoring its potential for early detection and personalized management strategies. The results underscore the effectiveness of transfer learning with partial fine-tuning and pretrained CNN models in enhancing the accuracy and efficiency of KOA severity classification. By tracking both the training loss and the validation loss during training, model's performance can be assessed, and can make informed decisions about when to stop training or adjust hyperparameters to improve generalization. The utilization of deep learning algorithms offers a rapid and cost-effective approach to KOA diagnosis, potentially reducing the need for costly interventions like knee replacement surgery while improving patient outcomes. Overall, the CAD framework demonstrates the feasibility and effectiveness of employing advanced machine leaning techniques for improving medical diagnosis and treatment strategies in orthopedics.

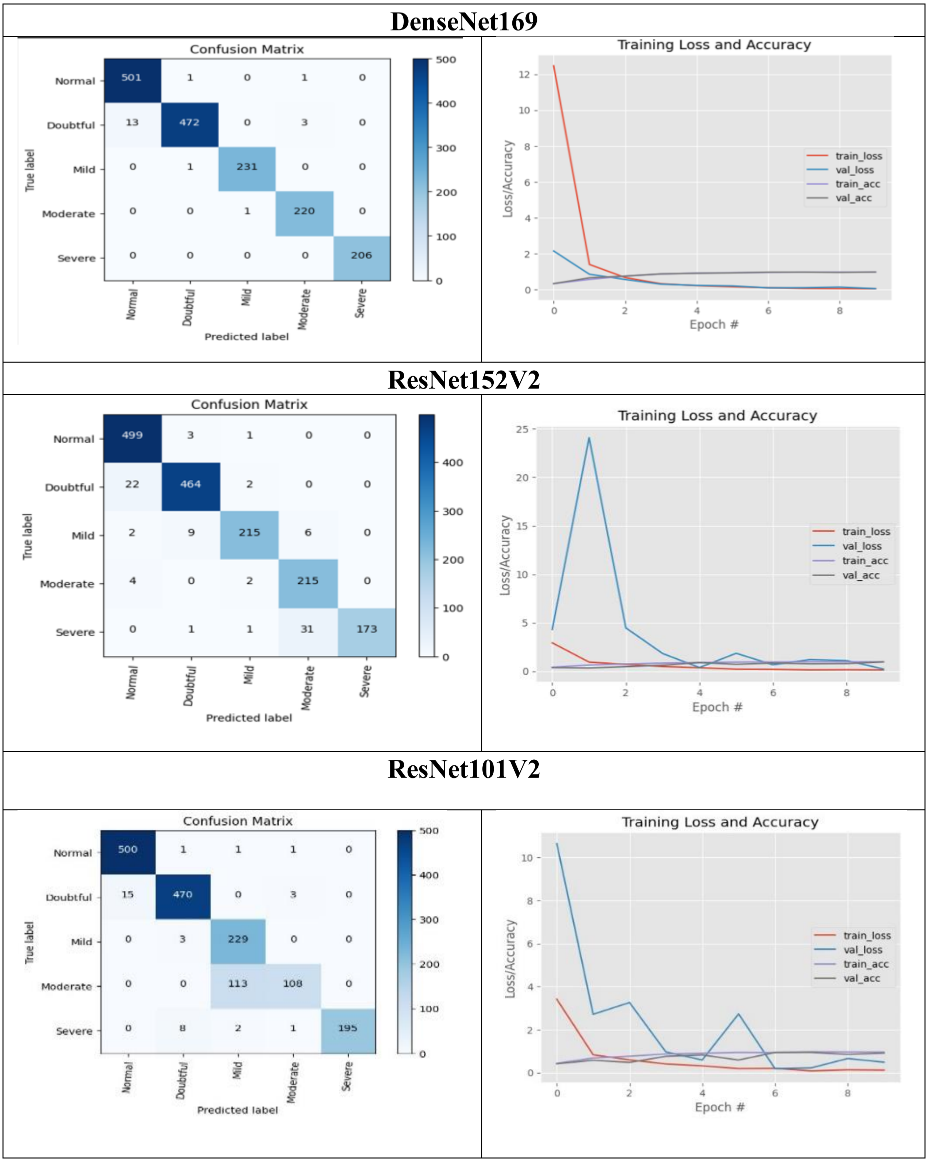

Fig. 4. Confusion matrices, loss and accuracy metrics are displayed in relation to the number of epochs for the models DenseNet169, ResNet152V2 and ResNet101V2

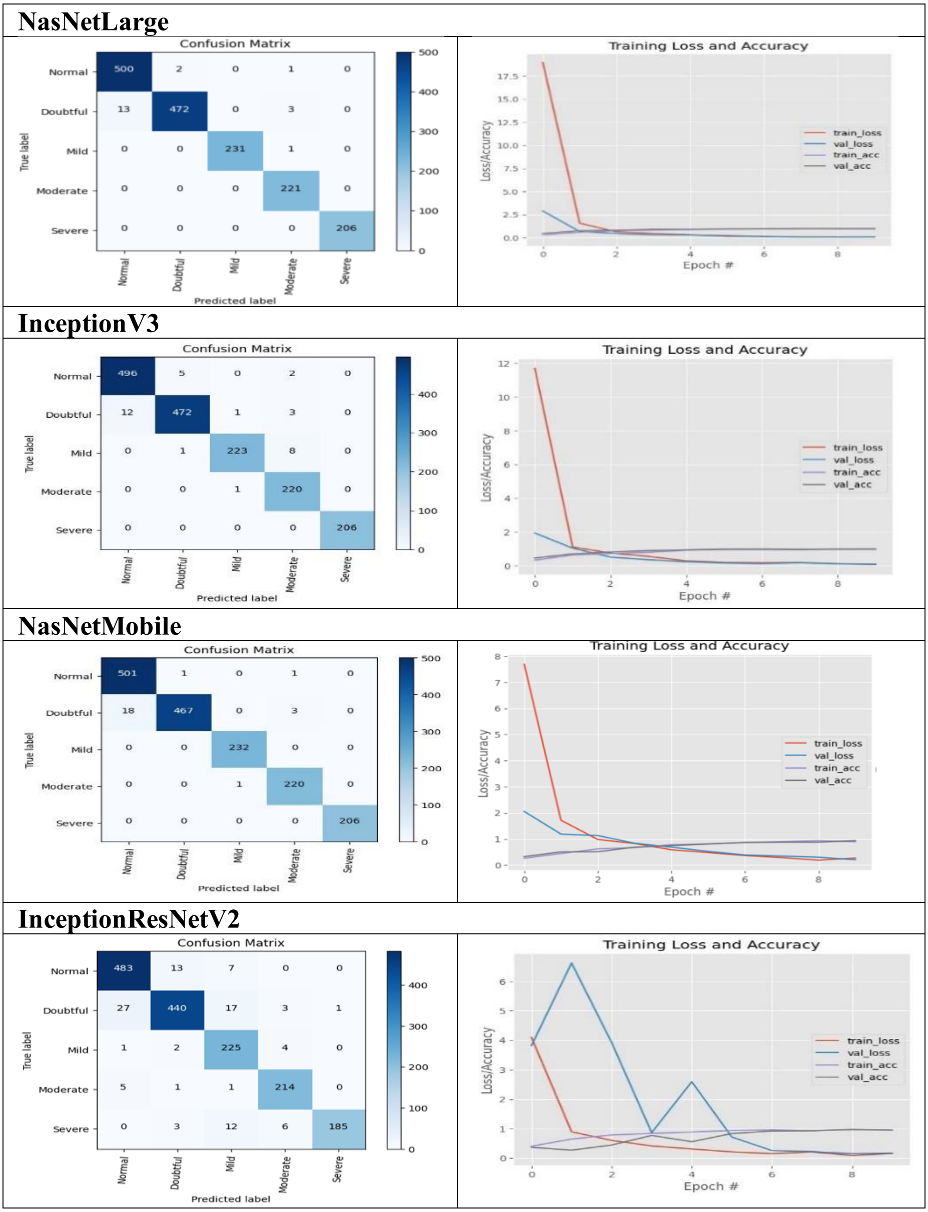

Fig. 5. Confusion matrices, loss and accuracy metrics are displayed in relation to the number of epochs for the models NasNetLarge, InceptionV3 and NasNetMobile and InceptionResNetV2.

ResNet50V2

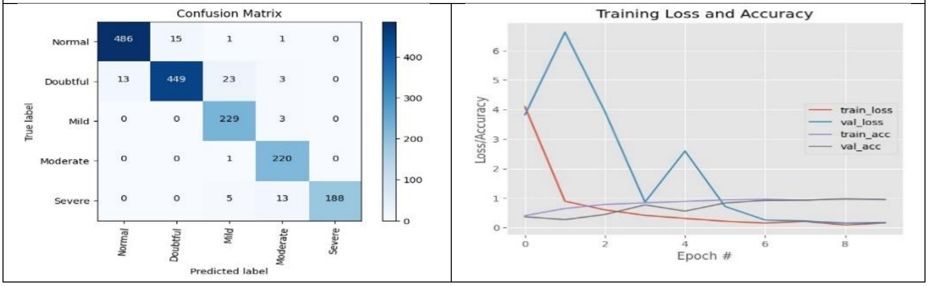

Fig. 6. Confusion matrices, loss and accuracy metrics are displayed in relation to the number of epochs for the model ResNet50V2.

Table.2. Comparison of Val_accuracy, Train_accuracy, Val_Loss, Train_loss and precision of eight pre-trained models.

Model Name	Val_ Accuracy	Train_ Accuracy	Val_ loss	Train_ loss	Precision
NasNetLarge	0.988	0.983	0.1184	0.0938	0.997
InceptionV3	0.98	0.9861	0.074	0.069	0.989
NasNetMobile	0.9855	0.9679	0.0679	0.0936	0.997
ResNet50V2	0.9527	0.9424	0.1654	0.1551	0.938
DenseNet169	0.9869	0.983	0.0627	0.0565	0.996
ResNet152V2	0.9491	0.9588	0.1654	0.1551	0.973
ResNet101V2	0.9103	0.9552	0.4869	0.1183	0.845
InceptionRes-NetV2	0.9376	0.8952	0.2054	0.2718	0.922

6 Conclusion

In conclusion, our proposed work presents an enhanced Computer-Aided Diagnosis (CAD) framework leveraging adaptive pretrained Convolutional Neural Networks (CNNs) with partial fine-tuning for accurate categorization of Knee Osteoarthritis (KOA) severity using the Kellgren-Lawrence (KL) grading method. Through transfer learning and partial fine tuning, our approach offers promising results in enhancing early detection and enabling personalized management strategies. Out of the eight pre-trained models, NasNetLarge showed high accuracy levels when processing both training and testing data, according to the experiment results. Validation accuracy for the proposed NasNetLarge system is 98.8% and on average the training accuracy for recognizing the presence and absence of knee osteoarthritis is 98.3%. The comparative study of the performance of the developed models (NasNetLarge, InceptionV3, DenseNet169, ResNet152V2, NasNetMobile, ResNet50V2, ResNet101V2 and InceptionResNetV2), revealed that by partial fine-tuning, NasNetLarge stands as the most suitable categorization of Knee Osteoarthritis (KOA). By combining pretrained CNN models and transfer learning with partial fine-tuning, the proposed framework facilitates rapid and cost-effective diagnosis, contributing to early diagnosis and help to reduce progression.

7 References

1. Girija Chetty, Jennie Scarvell, Sushmita Mitra. (2013). "Fuzzy texture descriptors for early diagnosis of osteoarthritis". IEEE International conference on FUZZY systems.
2. Bofei Zhang, Jimin Tan, Kyunghyun Cho, Gregory Chang, Cem M. Deniz. (2020). "Attention-based CNN for KL Grade Classification: Data from the Osteoarthritis Initiative". IEEE 17th International Symposium on Biomedical Imaging (ISBI).
3. Sanjeevakumar Kubakaddi, KM Ravikumar, Harini DG. (2013). "Measurement of cartilage thickness for early detection of knee osteoarthritis (KOA)". IEEE Point-of-Care Healthcare Technologies (PHT).
4. Yuvraj Dalia, Adikar Bharath, Veena Mayya, S Sowmya Kamath. (2021). "Deep OA: Clinical Decision Support System for Early Detection and Severity Grading of Knee Osteoarthritis".5th International Conference on Computer, Communication and Signal Processing (ICCCSP). https://10.1109/ICCCSP52374.2021.9465522
5. Supatman, Eko Mulyanto Yuniarno, Mauridhi Hery Purnomo. (2022). "Classification Anterior and Posterior of Knee Osteoarthritis X-Ray Images Grade KL-2 Using Deep Learning with Random Brightness Augmentation". Proceeding of the International Conference on Computer Engineering, Network and Intelligent Multimedia, CENIM 2022.
6. Egor Panfilov, Simo Saarakkala, Miika T. Nieminen, Aleksei Tiulpin. (2022). "Predicting Knee Osteoarthritis Progression from Structural MRI Using Deep Learning". IEEE 19th International Symposium on Biomedical Imaging (ISBI). https://10.1109/ISBI52829.2022.9761458
7. Sozan Mohammed Ahmed, Ramadan j. Mstafa. (2022). "Identifying Severity Grading of Knee Osteoarthritis from X-ray Images Using an Efficient Mixture of Deep Learning and Machine Learning Models". *Diagnostics* 2022. https://doi.org/10.3390/diagnostics12122939
8. Haider Masood, Eisha Hassan, Anum Abdul Salam, Muwahida Liaquat. (2022). "Osteo-Doc: KL-Grading of Osteoarthritis Using Deep-Learning".2nd International Conference on Digital Futures and Transformative Technologies (ICoDT2).https://10.1109/ICoDT255437.2022.9787470
9. Xin Wang Shuang Liu, Changcai Zhou. (2022). "Classification of Knee Osteoarthritis Based on Transfer Learning Model and Magnetic Resonance Images". International Conference on Machine Learning, Control, and Robotics (MLCR).
10. Egor Panfilov, Simo Saarakkala, Miika T. Nieminen, Aleksei Tiulpin. (2022). "Predicting Knee Osteoarthritis Progression from Structural MRI Using Deep Learning". IEEE 19th International Symposium on Biomedical Imaging (ISBI).
11. Hoo-Chang Shin, Holger R. Roth, Mingchen Gao, Le Lu, Ziyue Xu, Isabella Nogues, Jianhua Yao, Daniel Mollura, Ronald M. (2016). "Summers. Deep Convolutional Neural Networks for Computer-Aided Detection: CNN Architectures, Dataset Characteristics and Transfer Learning". IEEE Trans Med Imaging. 2016 May;35(5):1285-98.https://10.1109/TMI.2016.2528162
12. M. Mortada, A. Zeid, Mirvat Abd El-hamid Al-Toukhy, N. Ezzeldin, M. Elgawish.(2016). "Reliability of a Proposed Ultrasonographic Grading Scale for Severity of Primary Knee Osteoarthritis". Clinical Medicine Insights.
13. Ke Han. (2022). "Artificial Neural Network for Processing Fingerprint Image Noise". 23rd ACIS International Summer Virtual Conference on Software Engineering, Artificial

Intelligence, Networking and Parallel/Distributed Computing (SNPD-Summer).https://10.1109/SNPD-Summer57817.2022.00011

14. Milan Sonka. (2011). “Signal processing in medical imaging and image-guided intervention”. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp.5756-5759. https://10.1109/ICASSP.2011.5947668
15. Huyue Cheng, Hongquan Jiang, Zhen Liu, Yonghong Wang, Deyan Yang, Zelin Zhi. (2022). “Radiographic Image Enhancement Method for Complex Components based on Deep Learning Theory”. IEEE 6th Information Technology and Mechatronics Engineering Conference (ITOEC). https://10.1109/ITOEC53115.2022.9734477
16. Ishrat Jahan Swarna, Emrana Kabir Hashi. (2023). “Detection of Colon Cancer Using Inception V3 and Ensembled CNN Model”. International Conference on Electrical, Computer and Communication Engineering (ECCE).
17. Cahyo Adhi Hartanto, Adi Wibowo. (2020). “Development of Mobile Skin Cancer Detection using Faster R-CNN and MobileNet v2 Model”. 7th International Conference on Information Technology, Computer, and Electrical Engineering (ICITACEE).
18. Afia Farjana, Fatema Tabassum Liza, Miraz Al Mamun, Madhab Chandra Das, Md Maruf Hasan. (2023). “SARS Covid AID: Automatic detection of SARS CoV-19 cases from CT scan images with pretrained transfer learning model (VGG19, RESNet50 and DenseNet169) architecture”. International Conference on Smart Applications, Communications and Networking (SmartNets).https://10.1109/SmartNets58706.2023.10216235
19. Ababneh SY, Prescott JW, Gurcan MN. (2011). “Automatic graph-cut based segmentation of bones from knee magnetic resonance images for osteoarthritis research”. Med Image Anal 15:438–448. https://doi.org/10.1016/j.media.2011.01.007
20. Hajar Indah Fitriasari, Mia Rizkinia. (2021). “Improvement of Xception-ResNet50V2 Concatenation for COVID-19 Detection on Chest X-Ray Images”. 3rd East Indonesia Conference on Computer and Information Technology (EIConCIT).
21. Tuba Adar, Elif Kiliç Delice, Orhan. Delice. (2022). “Detection of COVID-19 From A New Dataset Using MobileNetV2 and ResNet101V2 Architectures”. Medical Technologies Congress (TIPTEKNO).https://10.1109/TIPTEKNO56568.2022.9960225
22. Xizhi Wu, Rongzhe Liu, Hanqing Yang, Zizhao Chen. (2020). “An Xception Based Convolutional Neural Network for Scene Image Classification with Transfer Learning”. 2nd International Conference on Information Technology and Computer Application (ITCA).https://10.1109/ITCA52113.2020.00063
23. Ahmet S, Songül A. (2020). “Knee meniscus segmentation and tear detection from MRI: a review current medical”. Imaging 16:2–15. https://doi.org/10.2174/1573405614666181017122109
24. T. Sivakumari, R. Vani. (2013). “Comparative Evaluation of Transfer Learning Models for Knee Osteoarthritis Severity Classification Using KL Grading Scale”. International Conference on Self Sustainable Artificial Intelligence Systems (ICSSAS).https://10.1109/ICSSAS57918.2023.10331895
25. Patrick Jheyd A. Antonio, Jen Aldwayne B. Delmo, Rovenson V. Sevilla, Michael Angelo D. Ligayo, Dolor L. Montesines. Deep (2022). “Transfer Network of Knee Osteoarthritis Progression Rate Classification in MR Imaging for Medical Imaging Support System”. International Conference on Decision Aid Sciences and Applications (DASA).https://10.1109/DASA54658.2022.9765065
26. A. Razmjoo, F. Liu, F. Caliva, A. M. Martinez, S. Majumdar, and V. Pedoia. (2020). “Semi-supervised graph-based deep learning for multi-modal prediction of knee osteoarthritis incidence”. Osteoarthritis and Cartilage 28: S305-S306.https://doi.org/10.1016/j.joca.2020.02.478

27. Almajalid R, Shan J, Zhang M, Stonis G, Zhang M. (2019b). "Knee bone segmentation on three-dimensional MRI". In: IEEE 18th international conference on machine learning and applications (ICMLA), 16–19 Dec. 2019, pp 1725–1730. https://doi.org/10.1109/ICMLA.2019.00280
28. Hyeongyeom Ahn, Byungjin Chung, Changhoon Yim. (2019). "Super-Resolution Convolutional Neural Networks Using Modified and Bilateral ReLU". International Conference on Electronics, Information, and Communication (ICEIC).
29. Antony J, McGuinness K, Moran K, O'Connor N. (2017). "Automatic detection of knee joints and quantification of knee osteoarthritis severity using convolutional neural networks". In: International conference on machine learning and data mining in pattern recognition, Lecture Notes in Computer Science. Springer, Cham.
30. Gan, Hong-Seng; Ramlee, Muhammad Hanif; Wahab, Asnida Abdul; Lee, Yeng-Seng; Shimizu, Akinobu. (2021). From classical to deep learning: review on cartilage and bone segmentation techniques in knee osteoarthritis research**.** Artificial Intelligence Review, 2021, Vol 54, Issue 4, p2445**.**
31. Pengyu Li, Biao Wang, Lei Zhang. (2021). "Virtual fully-connected layer: training a large-scale face recognition dataset with limited computational resources". Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2021, pp. 13315-13324.https://10.1109/CVPR46437.2021.01311
32. VV Kishore, SS Batthala, JV Chamarthi, C Achyutasai. (2023). "Knee osteoarthritis prediction driven by deep learning and the kellgren-lawrence grading". Proceedings on Engineering, pesjournal.net. https://10.24874/PES05.03.011