Enhancing Knee Osteoarthritis Diagnosis with AI: A Deep Learning Perspective

by

Arnab Saha
21341015
Mayeesha Mahbub
21201462
Jannatul Naem
21201392
Adiba Rahman
21201330
Mohammed Munif Mobashir
21201751

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BRAC University
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Declaration

It is hereby declared that:

1. This thesis is our own original work completed at BRAC University.
2. The thesis does not contain material previously published or written by another person, except where properly cited.
3. The thesis has not been submitted for any other degree or diploma.
4. All sources of assistance have been acknowledged.

Student's Full Name & Signature:

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Arnab Saha

ID: 21341015

....

Mayeesha Mahbub

ID: 21201462

....

Jannatul Naem

ID: 21201392

....

Adiba Rahman

ID: 21201330

....

Mohammed Munif Mobashir

21201751

Approval

The thesis titled "Enhancing Knee Osteoarthritis Diagnosis with AI: A Deep Learning Perspective" submitted by:

1. Arnab Saha (21341015)
2. Mayeesha Mahbub (21201462)
3. Jannatul Naem (21201392)
4. Adiba Rahman (21201330)
5. Mohammed Munif Mobashir (21201751)

of Spring, 2025 has been accepted as satisfactory in partial fulfillment of the requirement for the degree of B.Sc. in Computer Science in January, 2026.

Examining Committee:

Supervisor:

(Member)

Dewan Ziaul Karim
Senior Lecturer
Department of Computer Science and Engineering
BRAC University

Thesis Coordinator

(Member)

Md. Golam Rabiul Alam, PhD
Professor
Department of Computer Science and Engineering
BRAC University

Head of the Department

(Chair)

Sadia Hamid Kazi
Associate Professor and Chairperson
Department of Computer Science and Engineering
BRAC University

Abstract

Knee Osteoarthritis is one of the most concerning diseases in the current world. A lot of people are suffering from Knee Osteoarthritis which is a common disease now-a-days. In the current world, the number of knee patients is increasing day by day. The risk of KOA increases for anyone who gets older or carries excess weights of body. Stress also causes KOA. Additionally genetic problems or joint injuries can cause KOA. Knee Osteoarthritis are two types. In the primary stage(KL-1 and KL-2) it is called Osteopenia and in the second stage(KL-3 and KL-4) is called Osteoporosis are significant global health concerns, leading to increased bone fragility and fracture risk. Usually patients feel pain in and around the knee, pain is frequently described as a stabbing, sharp, or dull ache. Effective clinical intervention depends on early and precise detection using X-ray imaging. However, manual diagnosis is difficult and subject to inter-observer variability due to minute differences in bone density and texture. In this paper, a new, lightweight architecture for a convolutional neural network is proposed, termed Res-SE LiteNet, designed to classify knee radiograph images into three classes: Normal, Osteopenia, and Osteoporosis. In order to minimize computational parameters, thereby making the model practical for a clinical environment, the proposed architecture utilizes Depthwise Separable Convolutions. To enhance feature sensitivity, we implemented a Channel-wise Attention Mechanism via Squeeze-and-Excitation (SE) blocks and Residual Skip Connections to prevent the degradation of low-level spatial details. A Hybrid Global Pooling strategy, combining Global Average and Max Pooling, was employed to capture both global bone density statistics and focal pathological markers. A dataset publicly available in Mendeley was used to train and validate the proposed model. The model was able to attain a peak validation accuracy of 90.53%. Compared to conventional models such as the VGG16 or ResNet50 models, the model is able to maintain high accuracy while using a much smaller number of parameters. By comparing computationally complex pre-trained models, our proposed lightweight model achieves comparable diagnostic accuracy with a significantly reduced parameter footprint. As a result the model can facilitate high-speed processing without compromising model accuracy.

Keywords: Attention Mechanism, Squeeze-and-Excitation (SE), Hybrid Global Pooling, Lightweight Model, Adam, Categorical Crossentropy, Swish

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Nomenclature

CNN - Convolutional Neural Network

FLOPs - Floating Point Operations

GAP - Global Average Pooling

GMP - Global Max Pooling

Grad-CAM - Gradient-weighted Class Activation Mapping

IKDC - International Knee Documentation Committee

KL - Kellgren-Lawrence

ResNet - Residual Neural Network

SE - Squeeze-and-Excitation

SVM - Support Vector Machine

Chapter 1

Introduction

1.1 Background

Osteoarthritis is one of the most common forms of arthritis worldwide. About 528 million people all over the world are living a painful life with osteoarthritis; which has increased by almost 113% since 1990. Osteoarthritis is a progressive joint disease where the protective cartilage continues to decay over time. The decay of the protective cartilage causes the bones of the joints to rub against each other and thus increases the friction between the bones, which ultimately results in joint stiffness, pain, and reduced movement.Osteoarthritis primarily affects the joints, such as the knees, hips, and spine. About 73% of people with osteoarthritis are older than 55 . In addition to that, this disease can also be caused by other factors such as obesity, continuous stress on joints, any kind of injuries to the joints and other factors. Although there is no known treatment for this progressive disease, early intervention strategies like modification of lifestyle, physiotherapy, and other medications can reduce the risks before it is too late. Early detection may help in living a careful and less painful life. Along with the traditional way of detecting OA through radiographic images by the radiologists, an automated system can play a vital role in enhancing the results of the diagnosis of OA

1.2 Research Motivation

Machine learning, more specifically Deep Learning has gained significant attention in the medical imaging sector. They have shown great potential in this field by improving the accuracy and accurately diagnosing the disease. Deep Learning helps doctors to reduce interpretation time and improve diagnosis methods by extracting complex features from medical images. Despite these developments, it is still difficult to accurately classify knee disorders since normal, osteopenic, and osteoarthritic cases have similar visual characteristics. The goal of this research is to create an improved deep learning-based classification model that divides knee radiographs into three categories: osteopenia, osteoarthritis, and normal. The goal of the suggested strategy is to enhance early clinical intervention and increase diagnostic accuracy.

1.3 Problem Statement

The evaluation of arthritis is still highly dependent on subjective clinical assessment, which may lead to significant variation in diagnosis from one examiner to another. With the rapid development of artificial intelligence, particularly deep learning (DL), automated methods for detecting and classifying knee osteoarthritis (KOA) and related bone conditions have become more consistent and effective. However, existing DL-based models, despite achieving high overall accuracy, often struggle to distinguish between normal, osteopenic, and osteoporotic knee conditions, especially in early stages. Furthermore, the lack of clinical relevance and dataset imbalance among these classes can result in inaccurate diagnostic outcomes. This work addresses these challenges by aiming to improve diagnostic accuracy and precision through enhanced deep learning techniques. The proposed approach focuses on classifying knee conditions into normal, osteopenia, and osteoporosis, thereby enhancing the reliability and consistency of automated diagnosis.

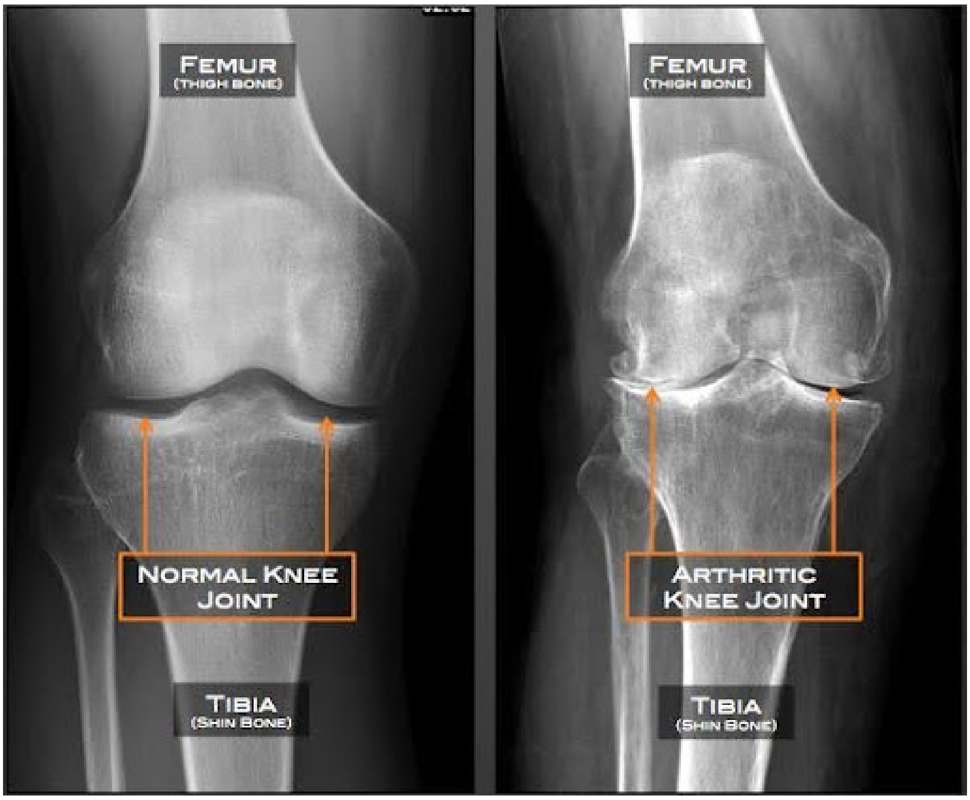


Figure 1.1: Knee Joint

1.4 Objective

The goal of this study is to develop a deep-learning model that would be more efficient in identifying or classifying knee osteoarthritis(OA) into three classes namely Normal, Osteopenia and Osteoporosis automatically. A custom Convoluted Neural Network (CNN) is being developed to classify and detect OA through processed radiographic images. This study aims to:

- Understand image pre-processing techniques and how they work
- Design a deep learning-based model that will enhance the accuracy of OA diagnosis
- Evaluate models' performance using standard metrics (e.g., accuracy, precision, recall, F1-score, AUC, ROC) compute clinical applicability by using different and large datasets

1.5 Methodology in brief

Our work has used a data-driven method based on deep learning to analyze knee osteoarthritis data. Following are the methods that were used while doing the research-

- Data collection and Preprocessing: We have collected the dataset from Kaggle which contains about 5400 x-ray images collected from various datasets available in Mendeley which later we augmented. Preprocessing steps include rescaling where pixels were normalized to the range of 0 to 1, reshape of the image to the dimension of 299 x 299
- Architecture Development: For knee X-ray classification, a custom deep convolutional neural network was developed by integrating residual blocks with squeeze-and-excitation attention mechanisms for . The architecture has implemented depth-wise separable convolutions, batch normalization, and swish activation functions to extract hierarchical spatial features, while residual connections enhance gradient flow and training stability. A hybrid global pooling strategy combining average and max pooling is also employed to enhance the representation of the features by combining spatial feature averaging with salient activation preservation.
- Training Strategy: The model training employs label smoothing on the categorical cross-entropy loss to mitigate overconfidence and improve generalization. The Adam optimizer with a reduced initial learning rate and ReduceLROnPlateau scheduling ensures stable convergence by dynamically adjusting the learning rate based on validation loss. Early stopping based on validation accuracy prevents overfitting while preserving the best model weights via ModelCheckpoint. The training

leverages batch-wise optimization with rescaled image data for efficient gradient updates.

- Evaluation Strategy: The assessment of the performance of our models is done by various metrics. This includes accuracy, precision, f1-score, recall, ROC and AUC curves.

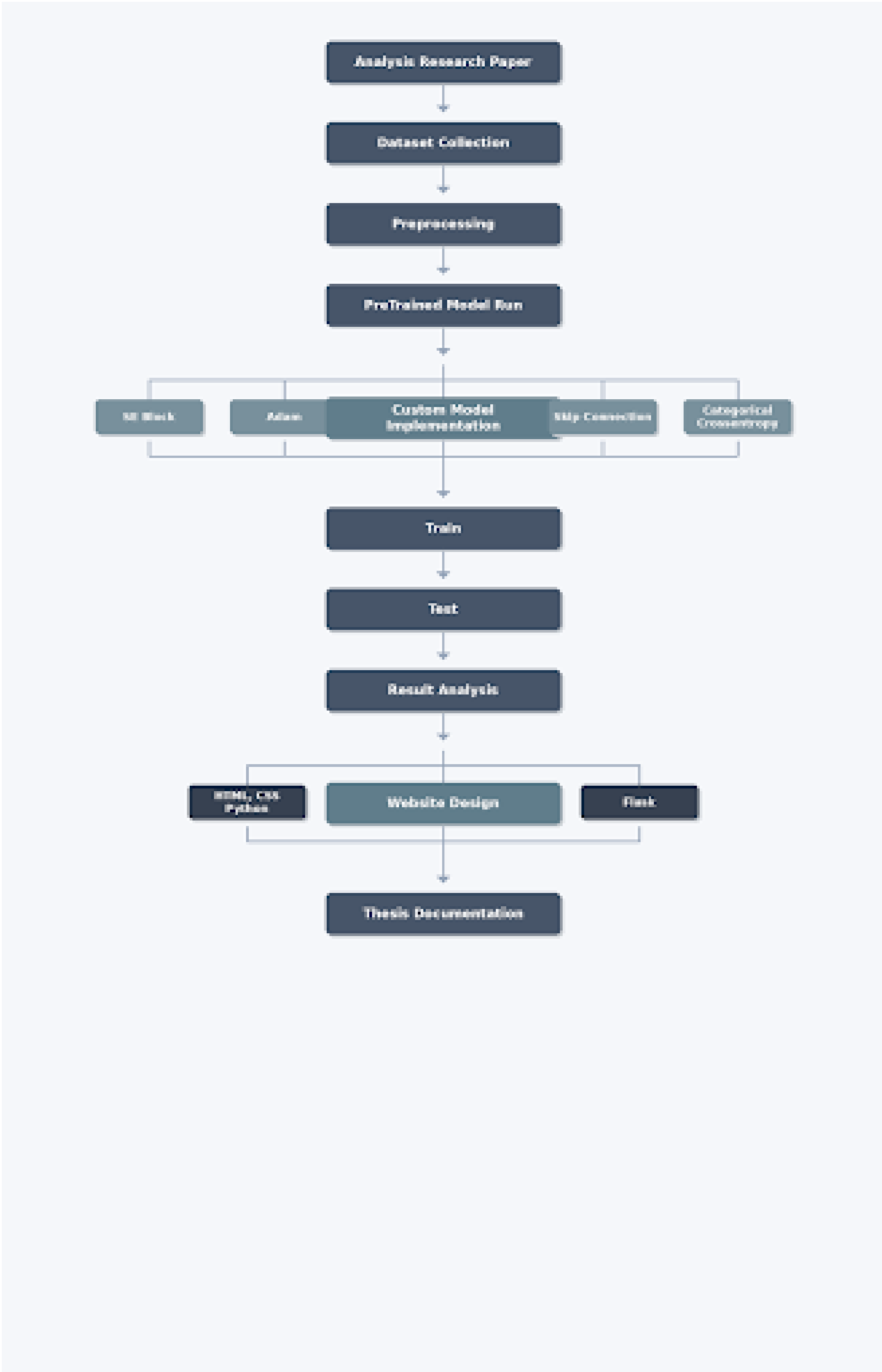


Figure 1.2: Work Flow

1.6 Scopes and challenges

Research Scope: This research focuses on the automated classification of knee X-ray images into three categories: Normal, Osteopenia, and Osteoarthritis using deep learning techniques. The study explores the effectiveness of our custom convolutional neural networks in learning meaningful bone and joint features without manual feature extraction. The scope is limited to image-based diagnosis and does not include clinical, biochemical, or patient history data.
Technical Scope: The technical scope of our research includes developing and implementing a CNN based deep learning model for classifying knee X-ray images into Normal, Osteopenia, and Osteoarthritis. The model was implemented by tensorflow and keras and it can run in different computer environments. This model also supports predicting the prediction of X-ray images in web format.
Data related Challenges: The main data related challenge was that the short size of the dataset and class imbalance had affected the accuracy of the custom model for which we had to augment the dataset and make the classes balanced.
Resource Challenge: Training of the model took a long time and we had limited access to the high performance GPUs which are required for making the training time short.

Chapter 2

Literature Review

2.1 Preliminaries

Osteoarthritis is a progressive joint disorder characterized by cartilage degeneration, resulting in pain and stiffness, and limited mobility. More than 7.5% of the total world population is suffering from this disease in the year of 2020 which is equivalent to 595 million people [25], with a diagnosis primarily relying on radiographic images using Kellgren-Lawrence grading. But using CNNs(e.g., ResNet, DenseNet, EfficientNet) it has been found that these deep learning models(e.g., VGG, YOLO) have been very effective in diagnosing KOA, even exceeding humans.

2.2 Review of Existing Research

A semi-automated approach for OA diagnosis using knee X-rays is discussed in [1], since OA, common among elderly and overweight people, happens when cartilage in several joints breaks down and leads to painful bone rubbing on bone. Cropping and resizing take place first in the methodology, and after that, the Chan-Vese and Edge active contour algorithms are used to detect the knee joint. After that, the improved images are used to generate a huge span of features, including Haralick textures, statistics, moments, and shape descriptors. The features are given to a Random Forest classifier and evaluated across 200 knee X-ray images obtained in many different hospitals and diagnostic centers with a combination of demographics. The whole feature set was competitive with a high rate of 87.92%, while the single features performed differently, starting at 59.42% (Texture) and getting to 74.87% (Region Properties). The paper discusses prior studies and points out that manually diagnosing diseases is not as good as using automated methods. Still, the method has some shortcomings, for instance, it relies on X-rays only, may not catch OA in its early stages, faces difficulties in proper diagnosis from radiological analysis, and sometimes there are challenges in image quality that might influence the extraction of important data. The report finishes by pointing out that the suggested approach is effective and reminds researchers to use clinical symptoms to strengthen their diagnoses in the future.

Bugday, B., Bingol, is aiming to introduce a new advanced AI system for not only early but also correct detection of knee osteoarthritis in [2], since KOA is a degenerative joint disease that hampers people's health. Meeting the need for quick results and good rehabilitation, the authors put together a helpful system that uses deep learning, image cleaning, and optimal classification in one system. The research took advantage of a knee X-ray dataset from Kaggle, separating it into five classes—normal, doubtful, mild, moderate, and severe—following the standards of the Kellgren-Lawrence scale. Before anything else, the authors used a Gaussian filter to get rid of the noise in the X-ray images. Having finished preprocessing, DenseNet201, a deep learning model, was applied to extract features, which outperformed the other seven deep-learning models under comparison (ResNet50, GoogleNet, MobileNetV2, etc.). The features from the original and the Gaussian-filtered images were combined to gain more insight from both, and NCA was used to reduce their number for better effectiveness. With this approach, the model tries to separate different data groups far from each other and make points in the same group as close as they can. The small set of features was studied by testing it with six different algorithms: the Neural Networks,the Support Vector Machine (SVM), the k-Nearest Neighbors (KNN) and lastly Naive Bayes, Logistic Regression, and Decision Trees. Out of all the classifiers, the SVM performed the best, attaining a 85% accuracy in total, which was higher than what was reported in similar past studies. Although the model was highly effective in labeling severe cases as severe or normal, the study admits that the study contains some limitations. The model's training and evaluation only used one dataset, so it may not be usable for many kinds of people or image types. Further research will include more institutions and imaging devices that will make the model more dependable. Also, by including image denoising, merging features, and advanced machine learning, this model became very helpful for automatic KOA classification. This method would simplify making a diagnosis, assisting in treatment decisions, and carrying out strategies that protect the joints and improve patients' conditions. It contributes a sound model that is practical to use and further boosts the importance of AI for better diagnosis of musculoskeletal problems.

The paper [3] reveals a computer system that aids doctors in diagnosing KOA in the knee using advanced deep learning on X-ray images. Seeing drawbacks of manual, subjective, and lengthy diagnosis, the authors introduce CNN as a way to solve this. This system makes use of images from the Osteoarthritis Initiative (OAI) database, where there are 9,786 knee X-ray pictures, and the severities are assigned to each one using the Kellgren–Lawrence (KL) scale. For better results, the images were divided (segmented) and their conditions were adjusted (histogram equalized). Furthermore, data was organized to let the system perform two kinds of classification: binary to tell if a case is healthy or KOA, and another to rank levels of KOA.ResNet-50 is the deep CNN architecture used in the system because it uses residual learning to resolve difficulty in deeper networks. The model was created and tested using Python, and following that, the functions were deployed in a Streamlined web interface so that clinicians and users could promptly get diagnostic feedback after uploading X-ray images. The primary ways to assess the system's results were classification accuracy and the F1-score. Although the model is easy to use and does well, it has a few issues that hinder it somewhat. It is allowed to use X-ray alone, leaving out other related procedures like MRI or CT scans that could give more information. In addition, when the number of severe examples is much lower than other examples, it can have an influence on the performance. Till now, clinical tests have not been carried out, but they are crucial for practical use.All in all, the research shows that AI can help simplify KOA diagnosis and offers ways to move forward, for example, by combining multiple types of data, creating automatic ways to grade KOA, and using AI in clinical practice for precise and focused patient treatment.

Wang, Z., Chetouani, have used Siamese-GAP Network to identify people with low or moderate grades of knee osteoarthritis (OA) by comparing the KL-0 (no OA) and KL-2 (early OA) grades in [4]. Siamese-GAP takes personal Siamese Convolutional Neural Network (CNN) architecture and adds Global Average Pooling (GAP) layers at different points to find and merge many-level characteristics from bilateral knee X-ray images. It was the OsteoArthritis Initiative (OAI) dataset, which is open to the public and contains X-ray information from a total of 4796 subjects of 45 to 79 years of age, that was used to build and test the model. End-to-end processing was done through YOLOv2, which identified ROI separately, and then used patches of 128×128 pixels from both sides of the knee. Only data augmentation with rotation, brightness, contrast, and gamma correction was applied for this problem. Hence, the model was prepared on PyTorch using the Adam optimizer for 500 epochs with Nvidia TESLA A100 GPUs. By testing Siamese-GAP, researchers got a reliability of 88.38% and F1-score of 85.93%, exceeding results of DenseNet-201 (84.43%), ResNet-18 (83.59%), VGG-11 (80.97%), and a baseline Siamese model (87.33%). Global Max Pooling (GMP) did not retain as much needed textural information as GAP, making GAP more beneficial in every case. According to Grad-CAM, the proposed method concentrated more on regions where diseases appear, while other models were influenced by irrelevant parts of the image. Even though the model works well, a drawback is it takes up more parameters than the baseline Siamese structure and only considers dividing patients into two groups, without including the other OA grades. All in all, the study indicates that combining features from different perspectives and using Siamese networks can help with early diagnosis of knee OA and similar studies on human anatomy.

In [5], the study titled "Advances in Artificial Intelligence for Automated Knee Osteoarthritis Classification Using the IKDC System," AI is applied to distinguish the level of knee osteoarthritis using the IKDC scale. The authors created a computer vision model by training ConvNext, an advanced CNN on 1,901 knee radiographs that were already organized by IKDC grades. Automatic data splitting, training, and evaluation were possible by using the LandingLens platform, so no prior experience in AI was needed. The images were divided such that 1,521and 380 were for training and testing. It was measured with precision, sensitivity, specificity, and F1-score. It achieved accuracy of 95.16%, sensitivity of 95.11%, specificity of 95.68%, and F1-score of 95.11% for every IKDC grade. Heatmaps generated from the model showed that localization of disease was correct, which made things easier to understand. This method gave superior or similar results to other studies based on yield, loss, accuracy, and efficiency when compared to YOLOv3, ResNet, and EfficientNet. Even so, issues arise from LandingLens not allowing users to see the details of the model's internal structure nor offering a way to formally calculate the number of samples needed. Still, the research shows that AI working with IKDC systems can increase the reliability of diagnoses, decrease differences between clinicians' conclusions, and make clinical judgments more dependable. It makes classifying the disease easy and contributes to faster detection of the condition as well as choosing personalized care for knee OA.

This research [6], aims to create a model that can automatically detect the severity knee osteoarthritis from radiographs and to compare its performance to the performance of the musculoskeletal radiologists. The model deployed in this study is a convolutional neural network with 169 layers and a dense convolutional network architecture to forecast the Kellgren-Lawrence (KL) score for every picture. The dataset on which the model was trained and tested was sourced from Osteoarthritis Initiative (OAI). This dataset includes over 4000 patients assessed annually for nearly a decade and was split into test and training sets although the authors did not mention the percentage of test and training set. The results showed that the average value of F1 score is 0.70 and accuracy value is 0.71 for the overall test set. For the 50 image subset evaluated by the radiologists, the model outperformed the radiologists achieving an accuracy of 0.90 and an average F1 score of 0.912 whereas in the case of the best radiologists the f1 score is 0.875 and an accuracy of 0.840 . In spite of these promising and better results, there were many challenges like maintaining the robustness of the model against the variations in the radiographic images and the significance of the extended augmentation of the data to obtain better performance without preprocessing the images manually. The capability of the model to analyze the radiographic images autonomously indicates a significant development in osteoarthritis staging potentially promoting effective treatment development.

Tiulpin, A., discusses the computer aided diagnosis system that will improve the diagnosis of osteoarthritis in the knee, addressing the ambiguity of Kellgren-Lawrence (KL) grading scale, in [7] A model has been discussed where a dataset from MOST has been trained and tested on the dataset from OAI showing the robustness in diagnosis of knee osteoarthritis. The model used here is Deep Siamese convolutional neural network architecture, ResNet-34 that is fine-tuned and is pre-trained on the ImageNet dataset. The dataset used for training is the Multicenter Osteoarthritis Study (MOST) cohort (18,376 knee X-rays). In addition to that, the Osteoarthritis Initiative (OAI) dataset (validation: 2,957 knees; test: 5,960 knees) was used as a test dataset. This resulted in average Multiclass Accuracy of 66.71% on the OAI test set. The quadratic Kappa was 0.83, AUC for radiographic OA diagnosis (KL 2) is 0.93. There were some limitations in this research . First one is that the resolution of the image was kept at 8 bit which could have resulted in the loss of detailed information from the images. Another one is that the study's validation set included data from the same source as the test set, which could bias the results and make the model seem more accurate than it really is.

Brahim, A., has developed a Computer-Aided Diagnosis (CAD) system, in [8], which aims at the identification of osteoarthritis that occurs at the knee using X-ray imaging and machine learning algorithm. A dataset containing 1024 knee x-ray images that was collected from the Osteoarthritis Initiative (OAI) was used in the system. In this case only the radiographic pictures of KL grade=0 and KL grade=2 were taken into consideration since the main objective of the study is early detection of knee osteoarthritis. Multiple preprocessing methods including circular Fourier filtering to stationarize the images and multivariate linear regression for intensity normalization. For the work of selection of the features, an independent component analysis (ICA) method was used to reduce the size of the images . For the task of classification Naive Bayes and random forest classifiers were implemented. The classification accuracy reached 82.98% with a sensitivity of 87.15% and accuracy of 80.65%. These results basically explain that the proposed system effectively differentiates between healthy individuals and those with osteoarthritis. However, there were challenges while conducting the study such as small size of the sample, calibration issues with X-ray devices and the exclusion of age and gender could have affected the generalization of the model.

In [9], the author aims to improve the identification of osteoarthritis at knee using an advanced deep learning model based on modified CenterNet enhanced with a pixel-wise voting method for the extraction of the features automatically. The model used here is DenseNet-201 which provides an efficient and automated solution to the detection of knee osteoarthritis The main objectives of this work are to provide an automated and more effective solution to the knee osteoarthritis detection. The researchers used two primary datasets for this work. The first one is Mendeley Data V1 which comprises 2000 8-bits digital x-ray images of 8 knees and with the dimensions of 1350x2455. This dataset was divided as 75% for training and evaluation purposes and the rest 25% for testing. Furthermore, the second dataset which is collected from the Osteoarthritis Initiative (OAI) contains 3T MRI and X-rays from 4,796 participants. This dataset was mainly used for cross validation. The model was implemented using python framework and the library of Keras version v0.1.1 with optimization parameters set at 500 epochs, learning rate of 0.0001 and a batch size of 64. The result which was obtained from this proposed model is very impressive. This work achieved an accuracy of 99.14% on the Mendeley test set and 98.97% on OAI dataset at the time of cross validation which significantly outperforms the existing models. Challenges included ensuring the quality and consistency of the annotated images and addressing the variability in knee osteoarthritis severity across different patient demographics. Despite these challenges, the study successfully demonstrates that machine learning has the possibility of improving the recognition of knee osteoarthritis, creating the path for improved medical decision making and patient consequences in orthopedic care.

The main objective of the research [10], is to build an automatic diagnosis model for knee osteoarthritis by using gait data and radiographic images, classifying knee osteoarthritis severity from non knee osteoarthritis to end stage osteoarthritis. For this study the gait data were collected at the human motion analysis laboratory using a three dimensional optical motion capture system and force plates. The deep learning model used in this study is Inception-ResNet-v2 which is used for the extraction of the features and categorization from the radiographic images. In addition to that, a support vector machine was also used which was used to train for the comparison, integrating both gait data and radiographic image features. The dataset used in this research consisted of gait reports from 364 patients i.e. 728 limbs with different degrees of knee osteoarthritis along with the radiographic images. The dataset was splitted 70% for training and 30% for testing. These were collected between the years 2013 to 2017. The participants had gone through physical check ups and radiographic imaging for collecting these data. AUC results of 0.93, 0.80, 0.85, 0.78 and 0.97 for the KL grades 0-4 were obtained from this model. Furthermore, the sensitivity has achieved the value of 0.55, precision value is 0.60 and f1 score is 0.55. This research faced difficulties such as no external confirmation due to the unavailability of an open-source database with relevant data and a smaller sample size compared to the earlier researches that might have an effect on the activity of the model.

The paper [11] addresses the critical issue of KOA diagnosis using deep learning (DL) and explainable artificial intelligence (XAI) GradCAM.The authors propose using pre-trained DL models such as- VGG, ResNet, EfficientNetB7, fine-tuned (which give high accuracy without having large datasets) for multi-class and binary classification of knee OA, and employ XAI techniques like GradCAM to visualize ROI in X-ray images to interpret models' decision-making processes. For this, several parameters such as- optimizer, Loss Function, Batch size, Number of epochs, Learning Rate, Patience are used. The study aims to automate and improve the accuracy of knee OA diagnosis while providing interpretability, which is crucial for healthcare applications. The dataset of this paper is the "Knee Osteoarthritis Severity Grading Dataset" that has been developed by the University of Florida that contains 8260 X-ray images graded using KL grading(grades 0 to 4), out of which 70% training set (5778 images), 10% validation set(826 images), and 20% testing set(1656 images). Histogram equalization and contrast enhancement were applied to increase the number of samples for class 4 (severe cases). From this , multi-class accuracy is 56.28%.And binary-class accuracy is more than 98% in subset2,3 and 4 while having 67.16% accuracy in subset1. In both cases, the best model found is EfficientNetB7. However, there were limitations: For class 4 the dataset is very limited. Thus, imbalance in the dataset affected models' performance.Again, the models were tested on a single dataset that raised their applicability to other datasets. Besides that, over-reliance on GradCAM , it focuses on the knee joint region but fails to differentiate between stages; whereas other XAI techniques like GradCAM++ could provide additional insights as it focuses on multiple ROIs or SHAPE for distinguishing between different stages of OA.Although, the models performed well for extreme cases(normal vs severe), but had low performance while detecting intermediate cases (doubtful, mild, moderate).

The author of this paper [12], introduces a powerful and innovative solution for the automated diagnosis of knee osteoarthritis (KOA) using X-ray images. The proposed model, OA-MEN, a fusion model of ResNet-50 and EfficientNet-B0 architectures integrating multi-scale features to extract both global contextual and local structural features. This model ensures to capture fine-grained details around the knee area along with the broader anatomical patterns that results in significantly improved diagnostic performance. The dataset used in this study are OAI and MOST. The result of this study is remarkable, as the accuracy is 92.25% holding higher than the previous state-of-art methods. Again, this paper includes comprehensive evaluations using accuracy, sensitivity, specificity, and AUC metrics. Furthermore, the authors address class imbalance—a common challenge in medical datasets—by using data augmentation and a class-balanced loss function, which helps to maintain high performance across all grades of KOA severity. Although the study is highly performed, it lacks clinical validation or expert comparison which could determine the effectiveness of its practical application in the real-world healthcare settings. Additionally, it does not have any computational cost details which are important for real life implementations.

In this study [13], the authors present a hybrid framework for improving the automated grading of KOA severity from radiographic images using an efficient mixture of deep learning and machine learning models. For this, the authors introduce two complementary models: DHL-I introduces an approach for knee OA classifications using KL grade. In contrast, DHL-II offers a comprehensive overview of the proposed knee OA classifications based on n-class labels. And DHL-I is a combination of three techniques such as CNNs, PCA, and SVM. CNN- is used for extracting prominent features and PCA algorithm for reducing feature dimensionality, and finally SVM for classifying KL grading criteria. Meanwhile, the proposed DHL-II used the concept of Transfer Learning to fit the data of different distinct labels, from DHL-I's pre-trained CNN. The models are trained and evaluated on the Osteoarthritis Initiative (OAI) dataset, and preprocessing steps like contrast enhancement and resizing are applied to improve feature quality. The accuracy of the model is more than 60% in testing data, for average recall of more than 55% and an average precision of 63%, and an average F1 score of 59.6%. The results highlight that binary classification yields the highest accuracy of 90.8%, while more granular grading sees slightly reduced performance. The study offers a computationally efficient, scalable, and accurate solution for OA grading.Again, this hybrid methodology not only surpasses existing methods in terms of accuracy but also provides a practical path toward clinical decision support systems that can aid radiologists in early diagnosis and reduce manual diagnostic burden.

In this paper [14], the author proposed an ensemble model using deep learning for the automatic detection and classification of knee osteoarthritis (KOA) severity from X-ray images, following the Kellgren and Lawrence (KL) grading system. The Osteoarthritis Initiative dataset is used for this study. There are more than 9000 X-ray images graded according to the KL grading scheme. In grade 0, there are 3857 images, 1770 in grade 1, 2578 in grade 2, 1286 in grade 3, and 295 in grade 4. Data is highly unbalanced, and they are split into classes : train, test, and validation. The pre-trained DL models that are used in this work are VGG-19, ResNet-34, DenseNet 121, and DenseNet 161 with a batch size of 28. Here, the CORN framework has been utilized for loss computation and KL grade prediction, while the ensemble employed cross-entropy loss. Network optimization was looked into by using ADAM, with an initial learning rate of 0.0001, later reduced after every five epochs. To evaluate the performance of the model, some evaluation metrics were used, such as accuracy, precision, F1-score, MAE, MSE,QWK, and AUC. For the implementation, python 3.7, PyTorch v1.12.1, and coral-PyTorch-1.4.0 in the Google Colab framework was being used.The Ensemble model demonstrated an overall accuracy and precision of 98%, which was great, and an overall F1-score of 0.97, 0.99 QWK, and 0.98 AUC.Although the ensemble model achieved a high accuracy for overall grades compared to existing models , the dataset is highly imbalanced within the grades.

The author of [15], concentrates on the systemic review and meta-analysis evaluates the efficacy of DL-based techniques, using X-ray, in detecting and classifying knee osteoarthritis (KOA) using the KL grading. The study needed to analyze 19 studies consisting of 62,158 X-ray images, with DL models demonstrating the sensitivities using K-L grades. Hence, 86.74% for grade 0, 64.00% for grade 1, 75.03% for grade 2, 84.76% for grade 3, and 90.32% for grade 4. This included CNNs (e.g., DenseNet, ResNet, YOLOv3), with datasets from databases including PubMed, Cochrane, Embase, Web of Science, and IEEE. Although several parameters such as image preprocessing, model architecture, and training-validation splits etc were noted, heterogeneity in these parameters limited comparability.Also limitations included the subjective nature of K-L grading, small sample sizes for early KOA stages (K-L1 and K-L2), and a lack of clinical correlation in DL model training.Finally, the study highlights DL's potential for severe KOA detection but emphasizes the need for improved sensitivity in early-stage diagnosis and standardized methodologies.

This paper [16] introduces OsteoHRNet, a deep learning model developed to automatically evaluate the severity of knee osteoarthritis (OA) using X-ray images. OA is a widespread joint condition, especially among older adults, and doctors typically grade its severity by examining knee X-rays. However, this process can be subjective, varying between practitioners, and may lead to inconsistent diagnoses. OsteoHRNet aims to make this process more objective, consistent, and efficient by using artificial intelligence to assist in grading OA severity.The model is built on High-Resolution Network (HRNet), a deep learning architecture that stands out by preserving high-resolution image features throughout the analysis. While many models reduce image quality as they go deeper into the network, HRNet maintains detail at every stage, which helps capture the subtle changes in knee joints that are important for OA diagnosis.Additionally, OsteoHRNet incorporates an attention mechanism, so that when analyzing an image it learns where to focus its attention, for example, on the space between joints or on thepresence of bone spurs, instead of less informative background information. To both train and test the model, the team employed the large and publicly available Osteoarthritis Initiative (OAI) dataset, which is a set ofknee X-rays with Kellgren-Lawrence (KL) grade labels that go from 0 (no OA) to 4 (severe OA). The classification accuracy and MAE of OsteoHRNet were 71.74% and 0.311, respectively,indicating significant predictors over other methods. A notable feature of OsteoHRNet isinterpretability. Many AI models operate like "black boxes," making it hard for doctors to understand how they reached a conclusion. To address this, the researchers used Grad-CAM (Gradient-weighted Class Activation Mapping), a technique that highlights the parts of the X-ray the model focused on decision making. This helps doctors verify the AI's reasoning and builds trust in its outputs.Despite its promising performance, the model does face challenges. The dataset used has an imbalanced representation of KL grades, which could affect performance on underrepresented cases. The model also needs further clinical validation across diverse populations.

In this paper [17], the authors propose a clinically relevant and interpretable approach for diagnosing knee osteoarthritis (OA) using deep learning, with a particular emphasis on measuring joint space width (JSW), which is a critical feature radiologists use in real-life diagnoses. Rather than relying solely on image classification through black-box models, the researchers introduce a pipeline that focuses on extracting meaningful anatomical indicators from X-ray images. Here all of these data used in the study consists of 1,370 plain radiographs obtained from Severance Hospital in South Korea. These X-rays include clear KL-grade annotations provided by radiologists, which serve for model training and evaluation. There are two stages in this method. In the first stage, a convolutional neural network (CNN) is used for detecting automatically and cropping the knee joint region from the full X-ray image. Localization remains crucial because it reduces noise while simultaneously increasing diagnostic accuracy. We will apply a regression-based deep learning model to calculate the medial joint space width (JSW) using the cropped area in the subsequent step.With the width measured, the model then categorizes the osteoarthritis (OA) grade using the Kellgren-Lawrence (KL) scale, which ranges from 0 (indicating no OA) to 4 (indicating severe OA).One of the key takeaways from this paper is its strong focus on clinical interpretability. A lot of the current AI methods used for diagnosing osteoarthritis tend to act like black boxes, providing minimal insight into how they arrive at their conclusions. By zeroing in on a well-known and measurable radiographic feature such as Joint Space Width (JSW), the authors introduce a system that resonates well with medical professionals' understanding. The model becomes more dependable while enabling radiologists to verify its predictions. The pipeline's modular design enables users to easily fine-tune or replace individual components such as cropping algorithms or regression models.The achievement of the model is an overall classification accuracy of 74.5%, which is quite competitive given its use of a focused region and clinical metric rather than the entire image. This level of accuracy suggests that models using JSW may perform as well or better than end-to-end CNN classifiers while also being easier to interpret. However, there are notable limitations.The dataset is designed for a particular institution and may show population traits or imaging methods that are unique to that setting. The dataset's specificity raises issues about its validity across different healthcare systems and countries.Additionally, joint space narrowing is not always a clear or early indicator of OA, which means that cases in the early or borderline KL grades (KL-1 or KL-2) may be harder to classify accurately using this method.

This paper [18], introduces a scalable and robust deep-learning approach to categorize the severity of knee osteoarthritis (OA) using radiographic images, primarily focusing on the Kellgren-Lawrence (KL) grading system. The researchers developed an end-to-end classification pipeline powered by convolutional neural networks (CNNs) and with particular emphasis on architectural simplicity and training efficiency. The approach uses multiple CNN models, including a VGG-M style architecture, and then ensembles their predictions to improve final classification outcomes. This multi-network voting strategy helps in smoothing over inconsistencies that might occur from a single model's biases. The datasets used in this study are two of the largest publicly available sources for knee OA: the Osteoarthritis Initiative (OAI) and the Multicenter Osteoarthritis Study (MOST). While many deep learning papers use complex, fine-tuned architectures that are difficult to replicate, this study keeps its methodology lean. They also release their data splits and code, which makes benchmarking against this system easier for other researchers. Another major strength is the ensemble model. By averaging predictions across several CNNs, the system reduces variance and achieves more consistent predictions, especially in ambiguous cases. In the performing stage, the system gained an average KL-grade classification accuracy of 69.7%, which is quite strong considering the variability in intermediate OA grades. Furthermore, they report that the model performs particularly well at the extremes—i.e., distinguishing KL-0 (healthy) from KL-4 (severe OA)—but shows more variability in KL-1 to KL-3, a challenge common to nearly all models trained on this problem. These intermediate stages often have overlapping visual features, making them hard to separate even for human experts.A few limitations do stand out. The model lacks explicit integration of domain-specific knowledge such as joint space width measurement and osteophyte detection which could have enhanced both interpretability and clinical confidence. While ensembles enhance generalization capabilities they also cause computational demand to rise which complicates real-time clinical application deployment.Finally, while the dataset is large and diverse, there's still the issue of label noise due to inter-observer variability among radiologists grading the KL levels.

This paper [19], highlights a method for automating the severity grading of knee osteoarthritis (OA) from X-ray images using a deep convolutional neural network (CNN). The primary aim is to improve diagnostic accuracy and efficiency by leveraging deep learning techniques to automate the grading process. The authors use the Knee Osteoarthritis Severity Grading Dataset, which includes thousands of knee X-ray images annotated with the Kellgren-Lawrence (KL) grading scale varying from grade 0 (no OA) to grade 4 (severe OA).A deep convolutional neural network, specifically designed to capture hierarchical features in knee X-ray images that are crucial for accurately determining the stage of osteoarthritis. The model is fine-tuned for optimal performance, and the authors perform rigorous evaluations to ensure that it takes all the data that are unseen and then categorizes them. The paper shows the importance of using a dataset with balanced as well as varied samples, as this greatly improves the model's capability to detect and categorize OA severity at all stages.The main performance of this work is in its ability to grade OA severity with high accuracy, helping healthcare professionals in clinical settings. vs. The paper highlights how the use of CNNs in medical image analysis can lead to automated systems which can help in diagnosis of diseases like osteoarthritis, especially when the dataset is large and well-annotated. The model achieves an impressive accuracy of 84.5% for multi-class classification tasks, with a mean average precision (mAP) score of 0.91. The results indicate that deep learning can be great in the context of OA diagnosis, with the model showing particularly high performance in the most severe cases (KL grade 4). However, it faces challenges when diagnosing less obvious cases, such as KL grade 1 and 2, where the distinctions between normal and OA-affected images are subtle.One problem with the study is that it only used one dataset, which may not show how knee X-ray images vary between different groups of people. Also, the quality and regularity of the X-ray images themselves could affect how well the model works. As with many deep learning approaches, interpretability remains a challenge, and the model's "black-box" nature makes it harder to understand how certain features contribute to the grading decision. Regardless of these drawbacks, the authors contend that the method may develop into a dependable clinical practice tool that helps radiologists make more accurate and consistent diagnoses with additional improvements and larger, more varied datasets.

This study [20], takes on a real-world medical challenge: how to better detect and grade knee osteoarthritis (OA) using X-ray images. Instead of depending on just one deep learning model, the researchers used a mix of three—ResNet-50, VGG-16, and Inception-v3. Think of it like getting a second and third opinion before making a diagnosis. Each model has its strengths, and by combining them, they manage to catch more details and make fewer mistakes. They trained and tested their system on a dataset called KOGD, which includes 6,000 X-ray images. That's a decent start, but still relatively small in the world of machine learning. Even so, the results were impressive: 92.5% accuracy in identifying and grading OA. That means the system got it right nearly every time, which is no small feat for something as nuanced as interpreting medical images. One of the strongest points here is how the ensemble method made the model more robust. Rather than being thrown off by outliers or unusual cases, the combined models helped each other out, making the final predictions more reliable. That's a big deal in healthcare, where consistency matters. However, the researchers were honest about the limitations. The dataset isn't very large or diverse, and some OA severity levels were underrepresented. That means the model might not perform as well on new or varied patient populations, which is an important reality check. Overall, this study doesn't promise miracles—it shows meaningful progress. It's a good example of how AI can assist, not replace, medical professionals. With more data and testing, this kind of technology could genuinely help doctors make faster, more accurate decisions for patients dealing with joint pain and mobility issues.

The article [21] suggests using deep learning to create a framework that automates the process of diagnosing and classifying the severity of osteoarthritis (OA) based on knee X-ray images. The dataset is studied with the help of the modified VGG16 CNN architecture to extract the features and grade OA on the basis of the Kellgren-Lawrence (KL) grading system, which ranges between grade 0 (no OA) and grade 4 (severe OA). The authors analyzed publicly accessible data from Osteoarthritis Initiative (OAI), which consists of 4,446 labeled X-rays. Normalization and contrast stretching were applied as preprocessing steps to these images and data augmentation methods were used to make the models robust and avoid overfitting.The CNN system performed much better than the traditional machine learning classifiers which included Support Vector Machines (SVMs) and Decision Trees. The fine-tuned VGG16 model demonstrated a high classification accuracy of 92.8 percent in differentiating various severity grades of osteoarthritis, thus it is highly efficient in depicting minor radiographic changes that could be otherwise hard to determine manually. This model represents an interesting solution as it can automatically analyze and classify knee X-rays, thus providing a possible aid to radiologists and potentially cutting the time of diagnosis and inter-observer variability. The study however notes a number of limitations such as the reliance on high quality labeled data and risk of bias on the dataset since the OAI dataset might not perfectly reflect the heterogeneity of real-world clinical populations. The model also demonstrated it was sometimes not able to correctly classify borderline cases between neighbouring KL grades and this would affect clinical decision making. Besides, the use of X-ray images might not make the system comprehensive enough since the OA diagnosis can be improved with multimodal inputs, such as MRI data and patient history. The authors suggest the future work with more varied datasets and complex architectures, including attention-based models, to make the generalization and diagnostic accuracy. The research establishes deep learning as a promising technology for smart medical diagnosis of osteoarthritis.

In this study [22], researchers tapped into the massive Osteoarthritis Initiative (OAI) database. There are 567 individuals' knee data to investigate which structural features on imaging are most strongly linked to how much knee pain people with osteoarthritis actually feel. Here they used MRI data like Kellgren Lawrence and MOAKS functions as an input to five traditional machine learning models including random forest along with support vector machine and logistic regression., decision tree, and Bayesian. Each model was rigorously tested with ten-fold cross-validation, and interestingly, all image sources performed similarly.The research team utilized a convolutional neural network (CNN) which was combined with class-activation mapping (CAM) to analyze raw MRI scans. The analysis of 421 knees showed that effusion/synovitis (30.9%) along with cartilage loss (30.6%) represented the most common abnormalities which correlated with pain severity. The research evaluates machine learning applications for predicting knee pain severity in osteoarthritis patients using OAI database radiographic and MRI data. Generally, Support Vector Machines (SVM) worked best among the models, barring submodel 2.1, where Logistic Regression (LR) worked best regarding AUC (0.681). Random Forest-based models 3 and 4 worked best with AUCs of 0.690 and 0.698, respectively. CNN-based analysis most strongly associated cartilage loss and effusion/synovitis with pain. Limitations are moderate AUC values and the use of sagittal MRI slices.

This paper [23],The study titled "CLIP-KOA: Enhancing Knee Osteoarthritis Diagnosis with Multi-Modal Learning and Symmetry-Aware Loss Functions" was authored by Yejin Jeong and Donghun Lee. presents a cutting-edge deep learning approach aimed at improving the accuracy of Knee Osteoarthritis (KOA) diagnosis. The proposed model, CLIP-KOA, builds on the well-known Contrastive Language-Image Pretraining (CLIP) architecture, The model which uses natural language supervision demonstrates outstanding ability for understanding visual concepts.To better adapt CLIP for KOA diagnosis, the authors introduce two innovative loss functions—Symmetry Loss and Consistency Loss—that help improve the reliability and consistency of severity assessments. Using a dataset of knee X-ray images labeled with Kellgren and Lawrence (KL) grades (ranging from 0, no OA, to 4, severe OA), CLIP-KOA achieves a state-of-the-art accuracy of 71.86% in predicting KOA severity. Ablation studies highlight that the model improves accuracy by 2.36% compared to the standard CLIP architecture thanks to these new contributions. While the results are promising, the study also acknowledges some limitations: the KL grading system itself can be subjective,The model's performance depends on the variety of training data because annotations differ. The model requires further clinical evaluation because patient populations along with imaging conditions influence its ability to generalize to various equipment and populations in real-world settings. This evaluation aims to determine the model's robustness and practical utility.

This paper [24], presents a novel deep learning framework which enhances KOA detection capabilities through the analysis of neural network features at multiple depth levels.The proposed method is built around a Siamese-based deep learning model that focuses on distinguishing between early KOA stages, especially Kellgren-Lawrence (KL) grades 0 and 2 — stages that are often challenging to differentiate. A key highlight of the model is its use of a multi-level feature extraction strategy through Global Average Pooling (GAP) layers, which helps capture rich and diverse indicators from different depths of the neural network.To boost the model's accuracy and trustworthiness, a Synthesis loss function is applied. This function categorizes training data based on the model's confidence (high, medium, or low), allowing for customized learning strategies that better handle uncertain or noisy labels — a common issue in medical imaging.The system underwent evaluation through training and testing of radiographic knee images and KL grade annotations that came from the Osteoarthritis Initiative (OAI) dataset. Results showed that the system performs on par with expert radiologists. Notably, it achieved Cohen's kappa values above 0.85, indicating strong agreement, and McNemar's test showed no statistical tests revealed no meaningful difference between the model and human experts (p ¿ 0.05) . While the framework shows great potential for clinical use, the paper also notes some limitations. The inherent subjectivity of KL grading can introduce variability, and the model might suffer limited dataset diversity due to its restricted patient demographic representation together with specific imaging conditions. Future assessments need to be conducted in actual clinical environments to establish the model's reliability and generalizability.

2.3 Summary of the key findings:

No.	Model / Method	Dataset	Performance	Task / Grading
1	Handcrafted Features + RF	200 X-rays	87.92% acc.	KL-based
2	DenseNet201 + SVM	Kaggle	High accuracy	KL grading
3	ResNet50	OAI (9,786)	High acc., good F1	Binary + Multi
4	ConvNeXt	IKDC	95.16% acc.	IKDC grades
5	DenseNet169	OAI	71% test, 90% vs radiol.	KL (5 classes)
6	Siamese ResNet34	MOST + OAI	66.71%, AUC=0.93	Binary + Multi
7	ICA + RF / NB	OAI (1024)	82.98% acc.	KL grading
8	CenterNet + DenseNet201	Mendeley + OAI	99.14% acc.	KL (5 classes)
9	Inception-ResNet-v2 + SVM	364 patients	AUC up to 0.97	KL (5 classes)
10	EfficientNet-B7 + Grad-CAM	UF Dataset	>98% acc.	Binary + Multi
11	OA-MEN (Fusion CNN)	OAI, MOST	92.25% acc.	KL 0–4
12	DHL-I (CNN + PCA)	OAT	90.8% acc.	Binary + Multi
13	DHL-II (Transfer Learning)	OAT	∼60% acc.	KL grading
14	Ensemble + CORN loss	OAI	98% acc., AUC=0.98	KL 0–4
15	Systematic Review	Multiple	Sensitivity 64–90%	KL 0–4
16	OsteoHRNet	OAI	71.74%, MAE=0.311	KL 0–4
17	CNN + JSW Regression	Hospital (Korea)	74.5% acc.	KL 0–4
18	CNN Ensemble (VGG-M)	OAI, MOST	69.7% acc.	KL 0–4
19	Custom Deep CNN	KOA Dataset	84.5%, mAP=0.91	KL 0–4
20	ResNet50 + VGG16 + IncV3	KOGD	92.5% acc.	KL 0–4
21	Modified VGG16	OAI (4446)	92.8% acc.	KL 0–4
22	ML + CNN (MRI pain)	OAI MRI	AUC ≈0.69	Non-KL
23	CLIP-KOA	X-ray KL	71.86% acc.	KL 0–4
24	Siamese CNN + GAP	OAI	$\kappa > 0.85$	KL 0 vs 2

Table 2.1: Summary of Literature Review on Knee Osteoarthritis Classification

Chapter 3

Requirements, Impacts and Constraints

The chapter contains the last specifications and requirements, implications, and limitations of the suggested Res-SE LiteNet model to diagnose knee osteoarthritis (KOA) automatically. The commentary is squarely anchored on the context of the problem, designs of the model, training plan, and results as outlined in the abstract. A model known as Res-SE LiteNet is created to respond to the rising percentage of knee osteoarthritis, and the impossibility of manual diagnosis through the creation of a lightweight, precise, and efficient convolutional neural network to classify knee X-ray images.

3.1 Final Specifications and Requirements

The objective of the Res-SE LiteNet model in facilitating early and accurate detection of bone density loss via X-ray imaging and reducing complexity in computations is what gives rise to the final specifications and the requirements of the Res-SE LiteNet model.

3.1.1 Recommended Hardware

The training and testing of the Res-SE LiteNet model is done in an experimental setup of a CUDA-enabled thread and convolutes the deep-learning in the model and enhances the speed of the training. The specified hardware setup offers a middle ground in the context of training the proposed lightweight Res-SE LiteNet model to deliver predictable performance and effectively use the available computational resources.

- **GPU:** 4080 Super 16GB
- **Video Memory (VRAM):** It contains 12 GB, which is adequate to provide batch-based training of the knee X-ray images and intermediate feature maps produced by the convolutional, attention, and hybrid pooling operations.
- **CPU:** AMD Ryzen processor, which performs preprocessing of the data, loads all the pictures, and coordinates training processes with the use of the GPUs.

- **System Memory (RAM):** System memory of 64GB DDR5 (enabling the work with large image datasets, generation of batches, and training without memory problems).
- **System Memory:** 1TB
- **CUDA Support:** 4080 Super 16GB also has the capability of computing parallel calculations through the use of CUDA where convolution, depthwise separable convolution and backpropagation can be performed efficiently on the graphics card. Training time is considerably lowered and better computational performance achieved during optimization of models with CUDA acceleration.

3.1.2 Software Requirements

The Res-SE LiteNet model is developed in a Python-based environment of deep learning, which can support convolutional neural network architecture and optimisation methods. Res-SE LiteNet model is carried out with the help of a python based deep learning environment which is used to develop and to train convolutional neural network structures. The main programming language is Python (version 3.8 and above) since it is widely applicable in machine learning and image processing programs. The chosen deep learning model is native Depthwise Separable Convolutions, Squeeze-and-Excitation (SE), attention separation, Residual Skip Connections, and Hybrid Global Pooling. Several steps are followed in order to carry out model optimization, the Adam optimizer is with a learning rate of 0.0005, Categorical Crossentropy loss function is applied in performing multi-class classification, and Swish activation function is used to improve the flow of the gradients. NVIDIA CUDA results in the use of the RTX 3060 GPU and is capable of enabling GPU acceleration to enhance computational efficiency in training and validation. Other supporting libraries are used to compute numerically, process images, manage datasets and estimate performance to be able to provide a stable and efficient pipeline to be trained.

3.1.3 Data Requirements

The quality and variability of the dataset defining the proposed Res-SE LiteNet model performance is highly relied upon. The system is based on the labeled collection of knee X-ray images in which the severity grades of knee osteoarthritis are clinically proven. Images that are identified are taken as the main input to the model with labels that show the existence and the severity of osteoarthritis. In order to achieve effective learning and decrease the classification bias, a fairly balanced number of classes is observed in the data set. Before training, the dataset is preprocessed and only augmented with features that make sense, such as gray-level intensity normalization, image rotation to increase resistance to knee position changes, and zooming to allow scale-invariant learning of features. Horizontal flipping is done selectively so as to provide better generalization without compromising on anatomical truthfulness. Such preprocessing techniques enhance data variation and help to make the model training stable and workable.

3.2 Societal Impact

Knee osteoarthritis (KOA) is an extremely common and never-before seen progressive musculoskeletal disorder that is seen to affect older adults and those who are overweight in the body, under high stress, or have genetic predispositions or existing injuries of the joint. Pain, stiffness, and loss of mobility are some of the chronic symptoms of the disease that make everyday life and physical autonomy complicated and deteriorate the overall quality of life. In extreme situations untreated or untimely diagnosed KOA may lead to long-lasting joint damages and necessitate invasive surgery with knee replacement. The Res-SE LiteNet model solves these problems in the society by giving automated and stable classification of knee X-ray images of Normal, Osteopenia, Osteoporosis. The model enhances objective, reliable and consistent diagnostic results by minimizing manual evaluation, which more often than not is subjective, and is likely to give inter-observer variability. The timely management of the disease and prevention of serious complications can be achieved by early diagnosis of the early bone density loss and the associated cognitive measures, including lifestyle change, physical fitness, or prescribed medications. Moreover, the implementation of these types of automated diagnostic systems may enhance the access to medical care, especially in places that lack radiology skills, and in the reduction of the workload of clinicians as they can offer quick, repeatable, testing. The Res-SE LiteNet model can improve patient outcomes and assist the greater population to maintain better health by preventing long term disability and health expenses that are caused by advanced KOA besides improving holistic early detection of osteopenia and osteoporosis.

3.3 Environmental Impact

The suggested Res-SE LiteNet model also has a high diagnostic accuracy with an improved number of parameters in contrast to traditional deep learning models. The complexity of this model is less and stands a chance to reduce computational requirements at the training and inference stage.The model facilitates the efficient utilisation of the computational resources because it facilitates efficient processing and prevents the need to have very large architecture that cannot be effectively used. This lightweight construction has an ingrained low processing overhead compared to computationally non-sparse pre-trained models.

3.4 Ethical Issues

The interpretation of knee X-ray images through manual means is difficult because of fine variations in bone density and texture which may subject these images to poor diagnostic results. The Res-SE LiteNet model works around this problem and offers an automated classification model, which generates similar output on the basis of learned image properties.The system would facilitate the process of diagnosis by enhancing accuracy and minimizing variability. Ethics is the consideration of using the model as a decision-support tool, which helps detect bone density loss at its early stage and enhance the reliability of the diagnosis without displacing clinical judgment.

3.5 Project Management Plan

The study was conducted in a manner of systematic and evolutionary development scheme, with overlapping steps to enable the systematic development of the model design and evaluation plan. The workflow has been scaled down on the basis of the experimental observations and the constraints of the computations so that the work flows are feasible in practice. Fig. 3.1 demonstrates the dates on which the work will be developed according to reality.

- **Week 1- 16: Literature review and problem definition.**
  The first four months were dedicated to the study of the published research papers on the topic of knee X-ray based diagnosis. At this time, the literature review chapter was authored based on an effort to synthesize the available literature, especially reported model weights, classification performance, and limitations of the methods used in previous studies.It was not possible to take any model training or to carry out some experimentation, at this stage attention was concentrated on theoretical knowledge and preliminary analysis to facilitate further phases of the research.

- **Week 13-20: Acquisition and Preprocessing of Data.**
  At this stage, a knee X-ray dataset was obtained on Kaggle. The data set was processed to know the distribution of classes and characteristics of the images. The radiographs were all resized and normalized to have uniformity among the samples.Data augmenting methods had been used to enhance generalization. Then separated the dataset into training, validation and test sets so as to have equitable performance measurement.

- **Week 17-32: Model Reproduction and Training and Evaluation of Baseline.**
  Subsequently, against which to define a baseline performance, it was implemented

with a number of computationally demanding pre-trained convolutional neural network models like VGG16 and ResNet50 after defining preprocessing pipeline.These models have been trained and measured based on the standard classification measures such as accuracy, precision, recall and F1-score. The findings demonstrated the compromise with the large number of parameters and high-accuracy requirement of the architecture that inspired more efficient architecture. A written report, called Phase-2 (P2), was produced at this stage to record baseline experimentations and observations.

- **Week 29-36: Design and Optimization of Res-SE LiteNet Model Custom.**
  During this step, the suggested design of lightweight CNN known as Res-SE LiteNet was developed with the intent of using it to classify knee radiographs. It used Depthwise Separable Convolutions in architecture to reduce the number of computations.To improve the feature representation, it was complemented with Squeeze-and-Excitation (SE) blocks, which is a channel-attention strategy, and with residual skip connections, which is supposed to retain low-level spatial features. This was replaced with a Hybrid Global Pooling approach which is a combination of Global Average Pooling and Global Max Pooling to grasp the global bone density statistics as well as localized pathological characteristics.The training was resorted to Adam optimizer with a learning rate of 0.0005, Categorical Crossentropy loss as well as Swish activation function.

- **Week 33-40: Model Training and Disease Class Evaluation**
  The Res-SE LiteNet model was trained and evaluated using the knee X-ray data in three-class classification; Normal, Osteopenia and Osteoporosis. To test the relative reliability of the diagnosis, validation accuracy and class-wise measures were used to measure performance. The model demonstrated high classification performance with a peak validation accuracy of 90.53 and also has a very low parameter footprint as compared to the pre-trained architectures.

- **Week 37-44: Performance Assessment and Comparative Analysis.**
  The suggested Res-SE LiteNet model and the traditional pre-trained models were compared and analyzed in detail. Analysis was concentrated on precision, efficiency of the parameters and the cost of calculation.The analysis showed that Res-SE LiteNet model could be used to obtain similar diagnostic performance but much fewer parameters which in turn allowed obtaining a rapid inference and allowed the model to be used in the clinic.

- **Week 45-48: Documentation and Finalization.**
  The last section was aimed at exposing the work in a clear and comprehensive

manner. The chapters were written or edited, the figures and tables were finished and the references were organized and formatted using LaTeX. The documentation completes the circle by recording the methodology, the experiments, and result of the Res-SE LiteNet model showing its performance in classifying the radiographs of the knees book in terms of Normal, Osteopenia and Osteoporosis and pointing out its possibility of using it in the early stages of bone depletion detection in clinics.

The systematically-designed lightweight Res-SE LiteNet CNN was used to classify knee X-rays into Normal, Osteopenia and Osteoporosis. The model has a high diagnostic performance with a maximum validation accuracy of 90.53% at a low computational cost. Comparative analysis confirmed that Res-SE LiteNet is as accurate as its pre-trained models with fewer parameters, and allows fast inference and using it in clinical practice. This paper shows that attention-based lightweight CNNs with hybrid pooling may be considered reliable automated predictors of early loss of bone density.

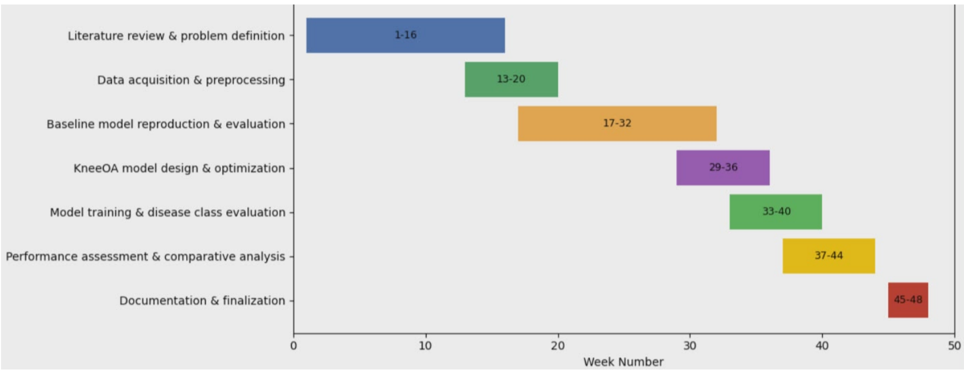


Figure 3.1: Project Management Plan

3.6 Risk Management

Specific categorization of knee osteoarthritis (KOA) is vulnerable to the identification of fine variations in bone density and structural pattern in X-rays, yet, the model has a range of risks, which may influence the reliability of diagnostic results and performance. The image quality variability through the difference in the resolution, contrast and noise caused by the imaging devices as well as the factors of the acquisition setting can affect the fine bone texture, thereby decreasing the classification power of the model by differentiating between Normal, Osteopenia (KL-1 and KL-2) and Osteoporosis (KL-3 and KL-4) classes. On the same note, effectiveness is directly influenced by the representativeness of the dataset and the allocation of class labels; an underrepresentation of certain classes would provide a bias in favor of the more prevalent categories and thus reduce the classification accuracy of the less represented classes and generalize to new patient data. The delicacy of tort of Bone density is yet another contributing factor to the likelihood of misclassification due to borderline cases or overlapping pathological markers. The Res-SE LiteNet architecture adopted to reduce the impact of these risks includes Squeeze-and-Excitation (SE) blocks to make channel-wise sensitivity of features to diagnostically significant regions, Hybrid Global Pooling between Global Average and Max Pooling to exploit global bone density patterns and local architecture disorder, and Residual Skip Connection to allow the Master feature of fine-grained spatial information across levels. Nevertheless, there are residual risks such as reliance on the quality of input X-ray images, the inability to cover the dataset with patient demographics and knee anatomy, and the difficulty in identifying early Osteopenia and mild Osteoporosis because they look visually similar that pre-empt the importance of data preparation and preprocessing.

Risk Category	**Description**	**Mitigation Strategy**
Data Risk	Limited or Imbalanced dataset	Data augmentation
Technical Risk	Hardware/Software incompatibility	Use of stable, well-supported frameworks
Clinical Risk	Low clinician acceptance	Emphasis on interpretability and validation

Table 3.1: Risk Management Matrix

Chapter 4

Proposed Methodology

4.1 Design Process or Methodology Overview

This study follows a design to detect KOA through 3 classes from X-ray images. The methodology implements some specific models and techniques for the accurate knee OA detection while keeping in mind that the model is a lightweight one. Again, this method is a qualitative approach. The method is implemented utilizing large-scale numerical datasets, computational modeling and statistical evaluation.For this study, although the data was collected from open source, preprocesses were required. Again, a larger dataset was used. After that, several pretrained models such as VGG16,ResNet50, DenseNet121, EfficientNetB0, Inception V3 along with custom models were used to detect the knee OA.

4.2 Model Specification

MicroAttNeti

This is a custom CNN model with convolutional blocks of increasing depth that gradually learns more complex patterns from images. In the third layer, a Spatial Atten Mechanism is added to allow the model selectively emphasize on salient regions of the input image , instead of wasting effort on irrelevant details. It also uses Global Average Pooling which squeezes each feature map into a single number, cutting down the number of parameters and reducing risk of overfitting.

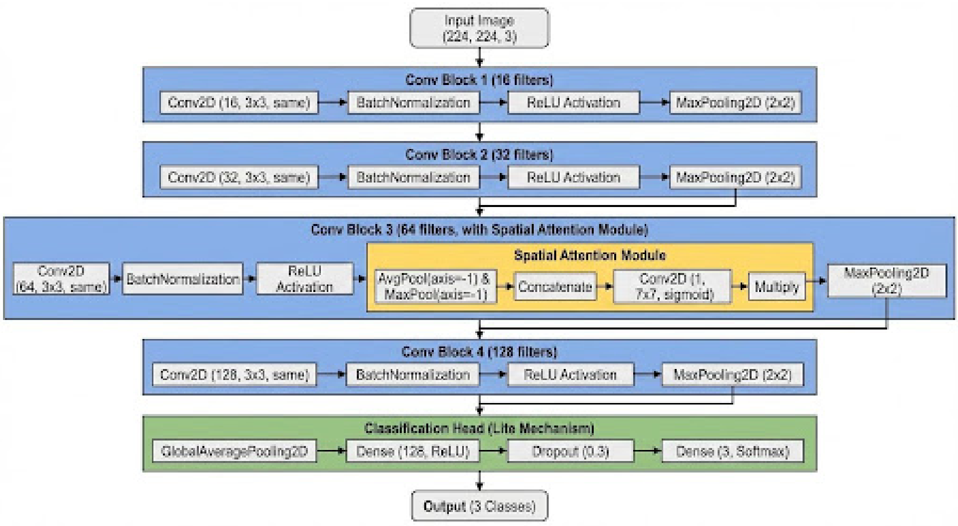


Figure 4.1: Architecture of MicroAttNet

Custom VGG

In this architecture, we use a Transfer Learning approach using the pretrained VGG16 model that was already trained on the large ImageNet dataset. To keep useful general image features , the first 2 blocks of VGG16 were frozen, while the deeper blocks (Block 3,4a and 5) were allowed to learn specific task. The original classification part of the VGG16 model was removed and replaced with a custom head consisting of Flatten layer,a Dense layer with 512 neurons using L2 regulation (0.001), and a Dropout layer (0.5) to reduce overfitting. Again, training was performed using Adam optimizer with a learning rate of 1x10ˆ 2 to increase learning while preserving the pre-trained knowledge.

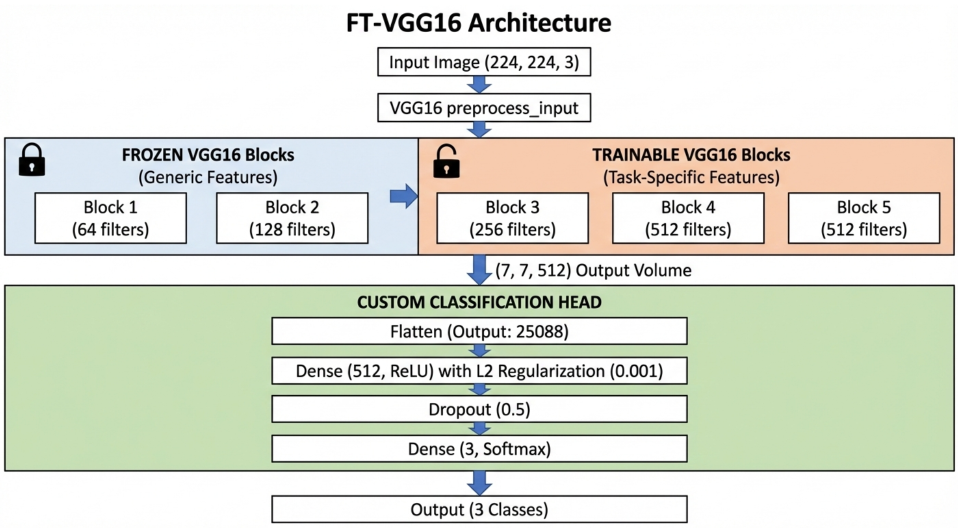


Figure 4.2: Architecture of Custom VGG

Res-SE LiteNet

Res-SE LiteNet is a lightweight deep learning architecture designed especially for the classification of osteoarthritis in the knee. The model is intended to process input tensors of shape 299×299× 3 in order to capture significant radiographic markers such as joint space narrowing and subchondral sclerosis. The architecture's modular design consists of a hybrid feature extraction head, three specialized residual stages with integrated attention, and an initial entry block. The entry block initiates the pipeline using a 3×3 convolutional layer with 32 filters and a stride of 2. This layer instantly performs spatial downsampling by mapping the input to a 150×150 feature space in order to reduce mathematical overhead. The mathematical definition of the Swish activation function and batch normalization is as follows:

$$f(x) = x \cdot \sigma(x) = \frac{x}{1 + e^{-x}}$$

Swish's smooth, non-monotonic characteristics enable the model to preserve tiny negative gradients, which is crucial for recognizing the minute grayscale changes indicative of early-stage bone density loss. Three consecutive res_block_v3 stages with filter depths of 64, 128, and 256 make up the network's core. Depthwise Separable Convolutions are used in each block to achieve extreme parameter efficiency by separating spatial and channel-wise computations. A depthwise convolution and a pointwise 11convolution define this operation:

$$Output = Conv_{\text{pointwise}}\big(Conv_{\text{depthwise}}(Input)\big)$$

Within these blocks, a Squeeze-and-Excitation (SE) attention mechanism is integrated. The "Squeeze" operation utilizes Global Average Pooling (GAP) to aggregate spatial information into a descriptor z_c :

$z_c = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} x_c(i, j)$

The "Excitation" phase then recalibrates these channels using two dense layers with a reduction ratio (r=8) and a Sigmoid gate to produce channel-wise weights, which are multiplied back into the feature map to emphasize salient pathological textures.To ensure structural robustness and solve the degradation problem in deep networks, each block implements a Skip Connection. This identity shortcut adds the input x to the transformed output f(x), using a 1 × 1 convolution where necessary to align channel dimensions. Between these stages, MaxPooling layers with a 2 × 2pool size reduce spatial dimensions by half (from 150 →75 →37), allowing the model to aggregate features at increasing levels of abstraction. The final stage of the architecture employs a Hybrid Global Feature Extraction scheme. Rather than flattening the final 37 ×37× 256 feature map, the model utilizes a parallel "Double Path" consisting of Global Average Pooling and Global Max Pooling. These two vectors are concatenated to form a 512-dimensional vector that represents both general bone texture and sharp pathological markers (like osteophytes). This vector is fed into a 256-unit dense layer, followed by a 50% Dropout rate for regularization. The network concludes with a 3-unit Softmax layer, which calculates the probability distribution across the three target classes:

$$\sigma(\mathbf{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

With a total of approximately 337,635 parameters, the Res-SE LiteNet provides a sophisticated, attention-driven diagnostic capability while remaining efficient enough for edge-tier medical device deployment.

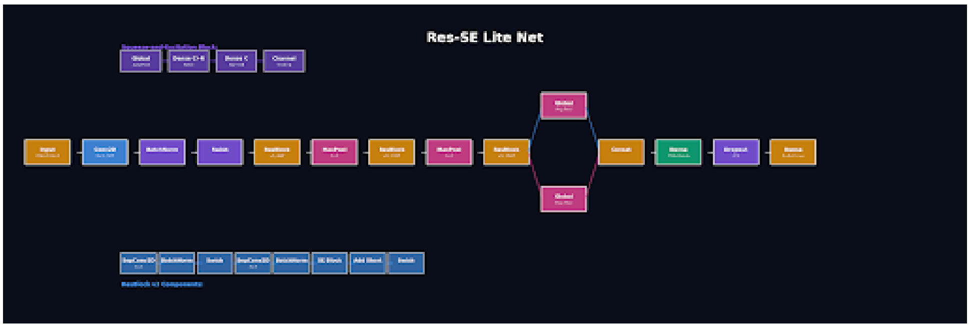


Figure 4.3: Architecture of Res-SE LiteNet

DenseNet121

DenseNet121 (Dense Convolutional Network) interconnects all layers with one another in a feed-forward fashion, resulting in each layer having direct access to the gradient flow from all previous layers. This creates a dense connectivity pattern across the layers that promotes feature reuse, improves gradient flow, and typically minimizes the number of parameters necessary when compared to other architectures.

VGG16

VGG16 is a classic, deep convolutional neural network (convnet), which is very simple and uniform with stacked convolution layers of size 3x3, and has been used as a baseline because not only does it perform in an expected and understandable way, but it was also shown to be effective in extracting generic image features.

EfficientNetB0

EfficientNetB0 speaks to a family of models that see how to scale depth, width, and resolution in a balanced way, to have great accuracy for low cost. We included this architecture to see if a lighter and more parameter efficient network could perform as well or better than the heavier models, on knee radiographs.

ResNet50

ResNet50 provides residual connections to fight the vanishing gradients issue, and allows networks to be trained much deeper than before. We included ResNet50 to possibly test the effectiveness of a widely used transfer learning backbone on the datasets we would use.

InceptionV3

InceptionV3 is a more complex multi-branch architecture that was evaluated. It uses factorized convolutions (splitting 3x3 into 1x3 and 3x1) to reduce computation while maintaining accuracy. InceptionV3 also applies batch normalization and auxiliary classifiers to stabilize and speed up training.

4.3 Data Collection

The primary data source for this research was the Knee Osteoarthritis Classification Dataset obtained from Kaggle. 5,400 X-ray pictures from the initial raw dataset were divided into three different clinical stages: normal, osteopenia, and osteoporosis.

4.3.1 Data Cleaning

The following cleaning steps were taken to make sure that the Res-SE LiteNet model got good input. For this, automated scripts were used to find and get rid of any extra or duplicate X-ray scans. To enhance analysis and optimizing storage cost we removed duplicates images. Along with that we did outlier filtering so that images with extreme motion blur, incorrect anatomical positioning (non-knee joints) can prevent the model from learning non-medical noise. Finally, all the images were verified to ensure they were correctly labeled within their respective three classes.

4.3.2 Data Transformation

Data transformation was critical to standardize the diverse X-ray inputs. Here we performed normalization where pixel intensities were rescaled from the range [0, 255] to [0, 1] to facilitate faster gradient descent convergence. Again, we resized all images to a resolution of 299 x 299 pixels with three color channels (RGB) to match the input requirements of the neural network. Moreover, we used a data augmentation method to improve model generalization and reach a prominent accuracy mark. Real-time augmentation was applied, including rotation, zooming and horizontal flipping to treat left-knee as well as right-knee images with equal weight.

4.3.3 Data Integration

Data integration required combining the different subsets into a single training pipeline, even though the main source was a single Kaggle repository. To enable the model to identify more comprehensive patterns of bone density loss across a more varied population sample, we combined the data into a large-scale training environment.

4.3.4 Data Reduction

Data reduction was implemented through dimensionality reduction within the model itself, as opposed to decreasing the number of samples. We ensured that the model remained lightweight (0.3M parameters) while maintaining crucial diagnostic features by reducing the complex spatial information of the X-rays into a condensed 1024-dimensional feature vector using Depthwise Separable Convolutions and Global pooling

4.3.5 Summary of Preprocessed Data

The final dataset used for the analysis and design of Res-SE LiteNet included 20,932 images after thorough cleaning and augmentation. For a thorough assessment, the dataset was divided into three separate sets:

- Training Set: 14,057 images belonging to 3 classes (used for weight optimization).
- Validation Set: 4,570 images belonging to 3 classes (used for hyperparameter tuning).
- Testing Set: 2,305 images belonging to 3 classes (used for the final 90.53% accuracy report).

Image Information	
Category	**Count**
Total Images	20,932

Classification Details	
Attribute	**Value**
Classes	3
Input Shape	299×299×3

Table 4.1: Data Summary

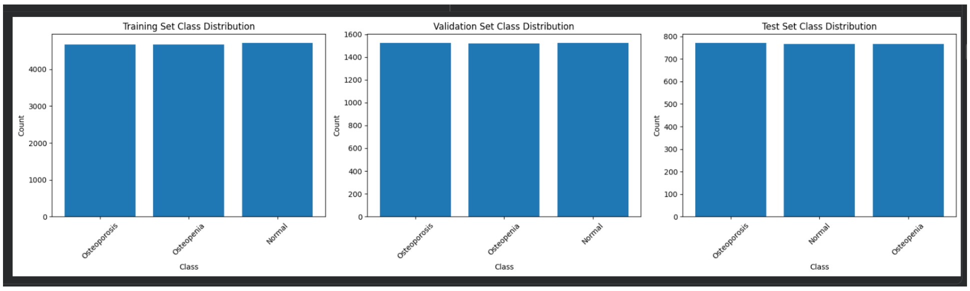


Figure 4.4: Class Distribution

We have collected the dataset from Kaggle which contains about 5400 x-ray images collected from various datasets available in Mendeley. Preprocessing steps include rescaling where pixels were normalized to the range of 0 to 1, reshape of the image to the dimension of 299 x 299.

4.4 Implementation of Selected Design

At the beginning, we run five pretrained models on our dataset. They were InceptionV3, EfficientNetB0, ResNet50, DenseNet121, VGG16. Then we used a transfer learning approach with the VGG16 pre-trained model on the ImageNet dataset to take advantage of the strong feature extraction capabilities of cutting-edge architectures. In order to adapt the model to the medical domain, we used a partial fine-tuning technique. The deeper blocks (3, 4, and 5) were unfrozen to learn task-specific representations of bone density textures, while the first two convolutional blocks were frozen to retain generic visual features (like edge and gradient detection). A custom head comprising a flattening layer and a dense layer of 512 neurons using L2 regularization (λ =0.001) and a dropout rate of 0.5 was used to replace the original classifier in order to reduce overfitting. To ensure stable convergence while maintaining the integrity of the pre-learned weights, the modified network was trained using the Adam optimizer with a reduced learning rate of 1x10ˆ5 and categorical cross-entropy loss. After that, we developed MicroAttNet, a custom CNN architecture with four convolutional blocks. In this custom CNN, we performed data transformations using rotation, shifting, brightness, and flipping to simulate real-world variability and enhance the model's robustness against different imaging conditions and orientations. At the same time, we use the Spatial Attention Mechanism to extract features from the X-ray images, as the most important information for diagnosing

OA is the bone texture and the joint gap.. Again, to decide which areas are important, pooling methods were used. Although we have run transfer learning as well as our first custom CNN model, we could not meet our expected outcomes. The accuracy results were not good enough and were giving heavy-weight models. Continuing our focus on good accuracy along with a lightweight model, we later on proposed another custom CNN architecture. The name of our model is Res-SE LiteNet. In the implementation of Res-SE LiteNet model we used TensorFlow and Keras framework. At first we set the input image size to 299 x 299 for our entry layer. It is considered gold standard size for deep learning model. In this case it is the perfect size to identify joint gap perfectly and the best option for standard memory use. Then we set a batch size of 16 so that the model can get enough image at once before updating it's weights and keep the training faster. The rescale=1./255 parameter in the ImageDataGenerator class was used to implement pixel intensity normalization in order to guarantee numerical stability during the training of the Res-SE LiteNet model. The raw 8 bit integer pixel values are transformed from the standard [0, 255] range to a normalized floating-point range of [0, 1]. This layer directly incorporates a Stride-2 downsampling technique to improve computational efficiency. By processing pixels in increments of two, the model effectively reduces the spatial resolution from 299 x 299 to 149 x 149 at the very beginning of the pipeline. Without compromising the overall anatomical "outline" or structural integrity of the knee joint, this deliberate reduction dramatically reduces the mathematical overhead for later layers. Additionally, the Swish activation function mathematically defined as $f(x) = x.\text{sigmoid}(x)$ replaces the conventional ReLU activation in the architectural design. The Swish function's smooth, non-monotonic curve plays a crucial role in maintaining tiny negative gradients, which are especially important in medical imaging to identify the minute grayscale variations and micro-architectural alterations typical of early-stage osteopenia

Chapter 5

Results and Analysis

5.1 Performance Evaluation

5.1.1 Classification Matrix

The performance of the proposed model was evaluated by using performance metrics to know how accurate, reliable, fast or useful the model is.

- Accuracy - Measures the ratio of correctly predictions out of the total number of samples. While it provides a quick snapshot, it can be misleading in case of imbalanced datasets.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

- Precision- Measures how many positive predictions made by the The models are actually correct.

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

- Recall - Measures the models' ability to find all actual positive cases within a dataset.This metric is the priority in medical diagnostics or safety-critical systems where missing a single positive case could have serious consequences.

$$\text{Recall} = \frac{TP}{TP + FN}$$

- F1 score- This is the harmonic mean of the precision and recall , providing a single score that balances the two. A high F1-score indicates that the model has low False Positives and low False Negatives.

$$F1\,\text{Score} = 2 \times \left(\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \right)$$

- Confusion Matrix: A table showing correct prediction through comparing predicted versus actual classes. It basically summarizes the models' performance.

5.1.2 Model efficiency Matrix

Model Size:

the file size of the saved model in megabytes(MB), which indicates whether it can run on standard computers or mobile devices in settings.

Parameters:

By the number of parameters, get to know about the memory and computational requirements.

5.1.3 Accuracy and efficiency

In this research, we have run several models and for the models' performances, we have used the classification metrics along with efficiency metrics.

MicroAttNet

The Micronet is a lightweight model. The parameter count here is only 1,15,398.It only used 450.77 KB.

activation_7 (Activation)	(None, 28, 28, 128)	0	batch_normalizat…
max_pooling2d_7 (MaxPooling2D)	(None, 14, 14, 128)	0	activation_7[0][…
global_average_poo… (GlobalAveragePool…	(None, 128)	0	max_pooling2d_7[…
dense_2 (Dense)	(None, 128)	16,512	global_average_p…
dropout_1 (Dropout)	(None, 128)	0	dense_2[0][0]
dense_3 (Dense)	(None, 3)	387	dropout_1[0][0]

```
Total params: 115,398 (450.77 KB)
Trainable params: 114,918 (448.90 KB)
Non-trainable params: 480 (1.88 KB)
```

Figure 5.1: MicroAttNet Parameter

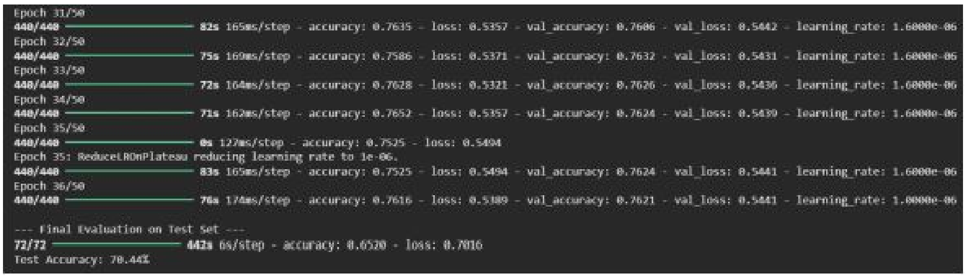


Figure 5.2: MicroATTNet Accuracy

The test accuracy is 0.76 and the validation accuracy 76.21.

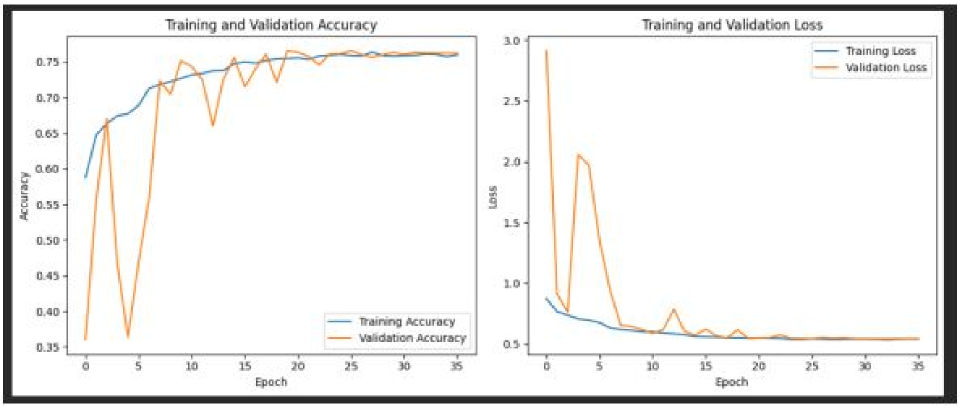


Figure 5.3: MicroATTNet Accuracy and Loss

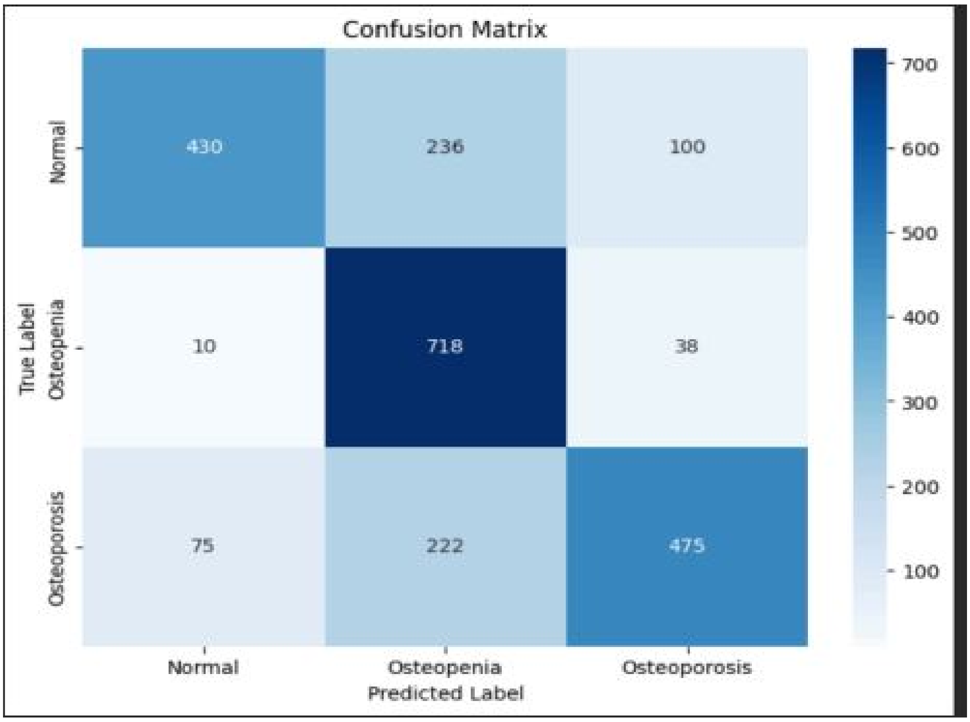


Figure 5.4: MicroAttNet Confusion Matrix

In the confusion matrix of MicroAttNet, assessing the ability to categorize bone density into three groups of normal, osteopenia, and osteoporosis. Here it is shown in this image. With 718 cases correctly predicted, the model excels at identifying the intermediate condition, osteopenia. The model frequently misidentifies actual Normal patients (236 errors) and Osteoporosis patients (222 errors) as having Osteopenia, indicating a bias toward predicting the "middle" option when the data is ambiguous. Nevertheless, there is a great deal of confusion surrounding this middle category.

```
72/72 ━━━━━━━━━━━━━━━━━━━━ 9s 121ms/step
Classification Report:
              precision    recall  f1-score   support

      Normal       0.83      0.56      0.67       766
  Osteopenia       0.61      0.94      0.74       766
Osteoporosis       0.77      0.62      0.69       772

    accuracy                           0.70      2304
   macro avg       0.74      0.70      0.70      2304
weighted avg       0.74      0.70      0.70      2304
```

Figure 5.5: MicroAttNet Performance Matrix

The bias in the confusion matrix is confirmed by the report. Recall for Osteopenia (0.94) has been given priority by the model over Precision. In essence, it serves as a "wide net" for osteopenia, catching nearly all actual cases while inadvertently catching a large number of patients with normal and osteoporosis.

Custom VGG

The Custom VGG model is also found to be stable in its classification with an overall accuracy of 78.33 on the test data. It attains weighted precision of 78.46, weighted recall of 78.33 and weighted F1-score of 78.30 meaning equal predictive power. The model is consistent across the classes of Normal, Osteopenia and Osteoporosis, as well as demonstrates consistent generalization of Knee Osteoarthritis bone condition classification.

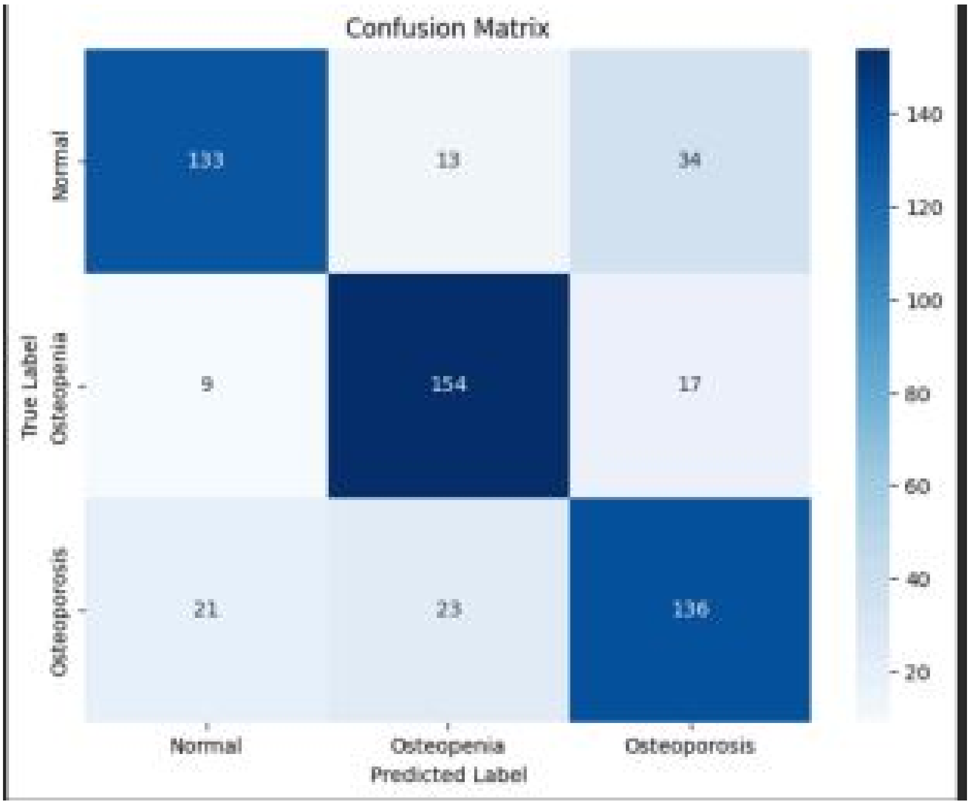


Figure 5.6: Custom VGG Confusion Matrix

```
17/17 ━━━━━━━━━━━━━━━━━━━━ 15s 862ms/step
Accuracy: 0.7833
Precision (weighted): 0.7846
Recall (weighted): 0.7833
F1-score (weighted): 0.7830

Classification Report:
              precision    recall  f1-score   support

      Normal       0.82      0.74      0.78       180
  Osteopenia       0.81      0.86      0.83       180
Osteoporosis       0.73      0.76      0.74       180

    accuracy                           0.78       540
   macro avg       0.78      0.78      0.78       540
weighted avg       0.78      0.78      0.78       540
```

Figure 5.7: Custom VGG Performance Matrix

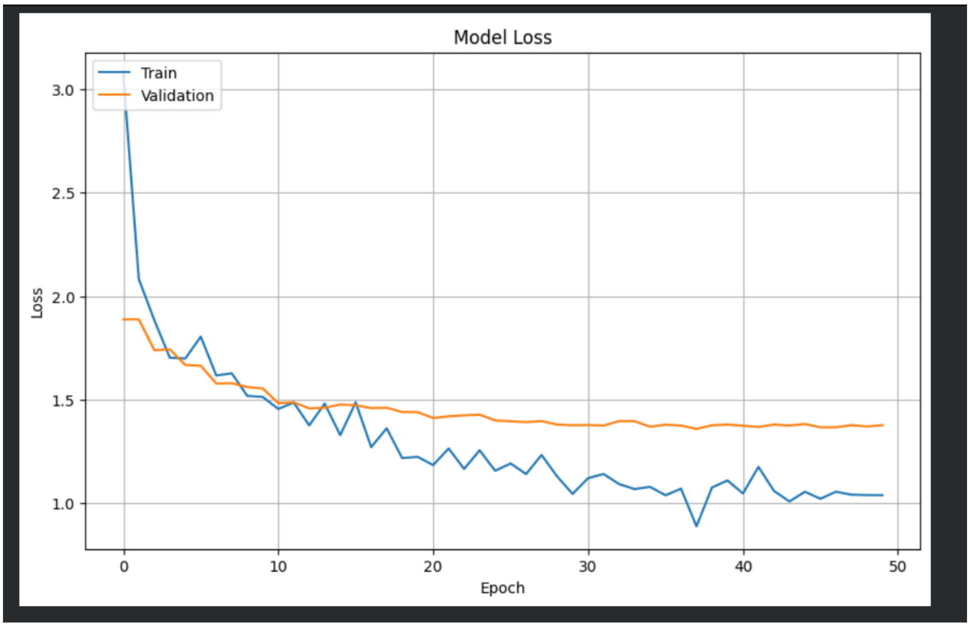


Figure 5.8: Custom VGG loss

PRE-TRAINED MODELS

InceptionV3

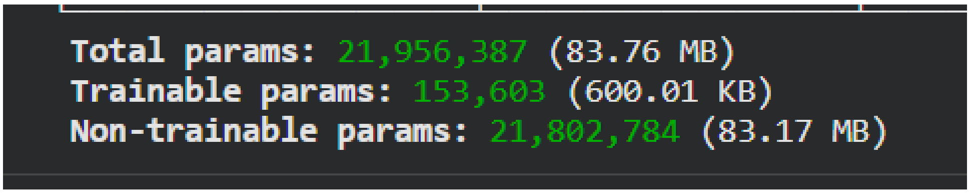


Figure 5.9: InceptionV3 Parameter

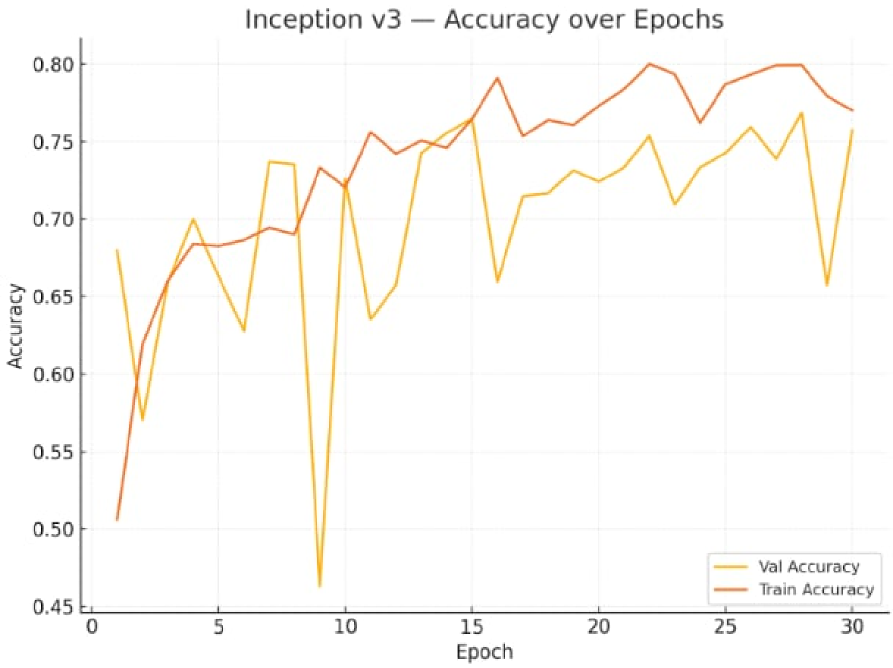
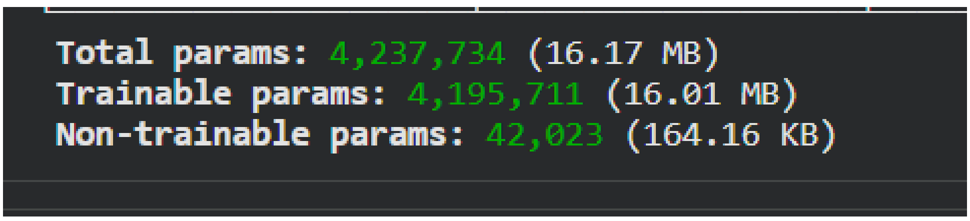


Fig 3.5 InceptionV3 Accuracy over Epochs

Figure 5.10: InceptionV3 Accuracy

InceptionV3 achieved 75.74% validation accuracy and total param 21,956,387 , trainable params 153,603 and non-trainable params 21,802,784.

EfficientNetB0



```
Total params: 4,237,734 (16.17 MB)
Trainable params: 4,195,711 (16.01 MB)
Non-trainable params: 42,023 (164.16 KB)
```

Figure 5.11: EfficientNetB0 Parameter

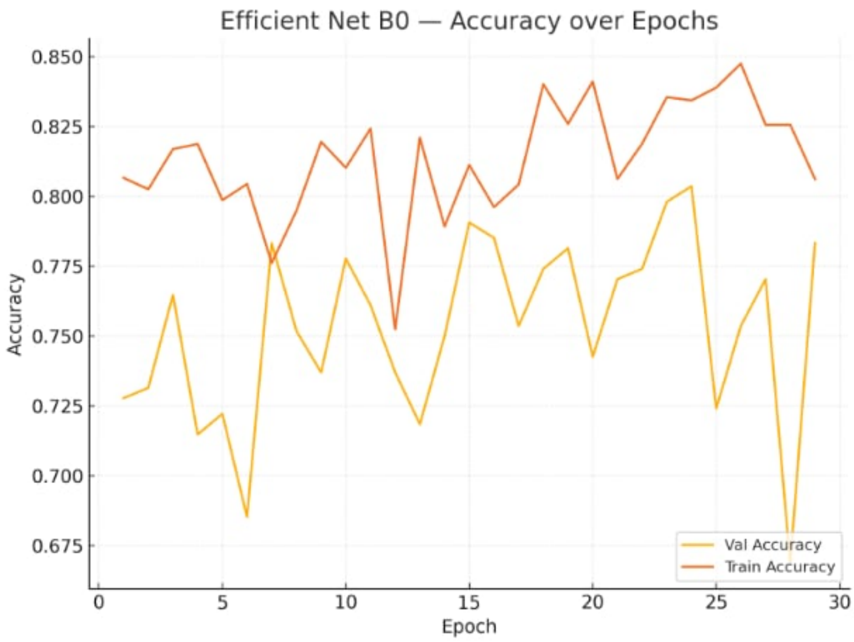


Fig 3.3 EfficientNet121 Accuracy over Epochs

Figure 5.12: EfficientNetB0 Accuracy

In our analysis EfficientNetB0 performed to obtain validation accuracy of about 78.33% where param count total 4,237,734 , trainable params 4,195,711 and non-trainable param 42,023.

DenseNet121

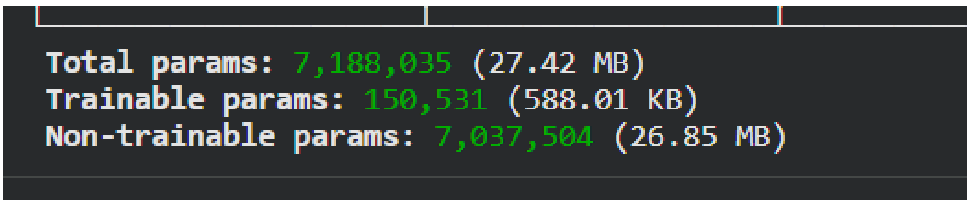


Figure 5.13: DenseNet121 Parameter

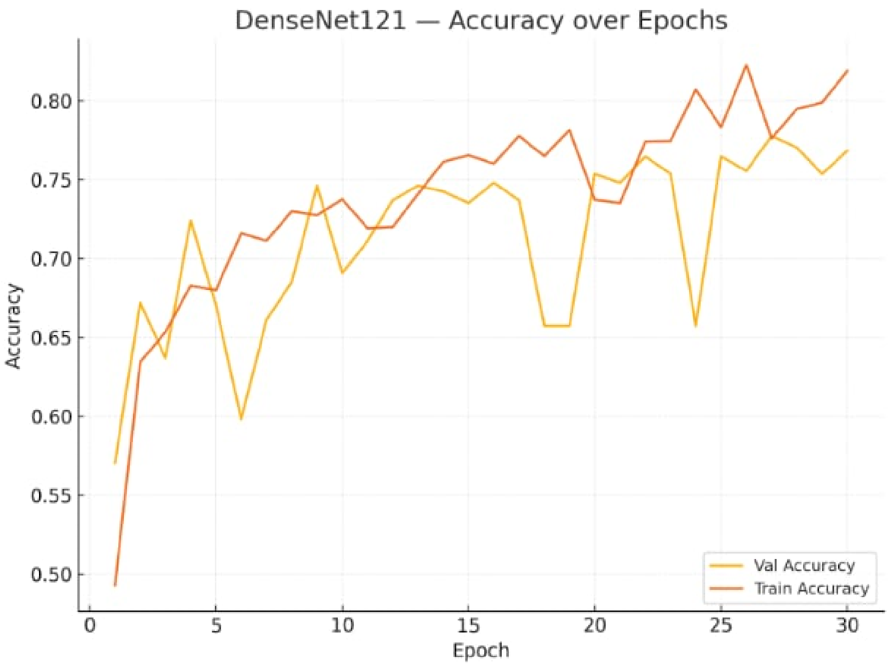


Fig 3.1 DenseNet121 Accuracy over Epochs

Figure 5.14: DenseNet121 Accuracy

DenseNet121 validation accuracy % on the five-class KL dataset,total param count 7,188,035 , trainable param 150,531 and non-trainable param 7,037,504.

VGG16

```
Total params: 14,789,955 (56.42 MB)
Trainable params: 75,267 (294.01 KB)
Non-trainable params: 14,714,688 (56.13 MB)
```

Figure 5.15: VGG16 Partameter

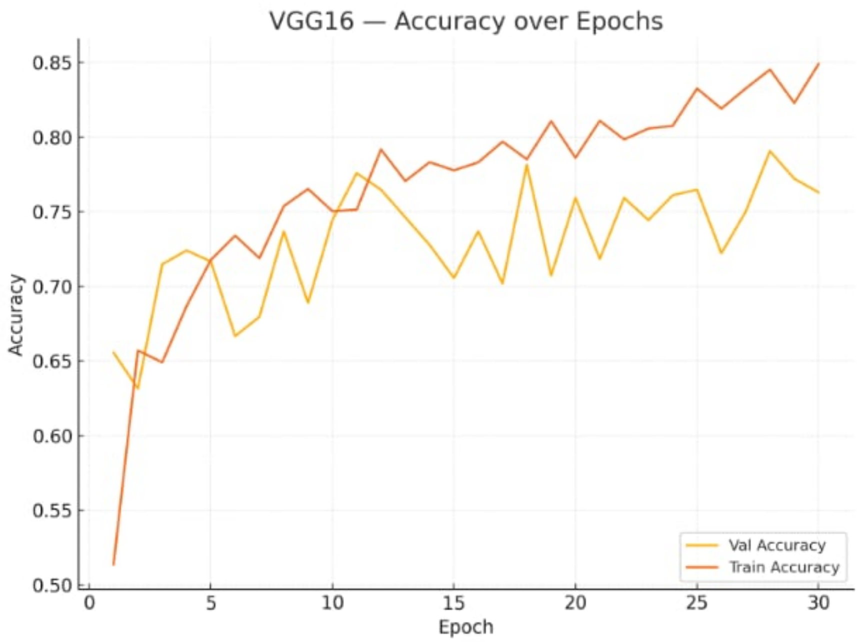


Fig 3.2 VGG16 Accuracy over Epochs

Figure 5.16: VGG16 Accuracy

In our analysis, VGG16 validation accuracy is approximately 76.30% in VGG16 and Param count 14,789,955trainable param 75,267 and non-trainable param 14,714,688.

ResNet50

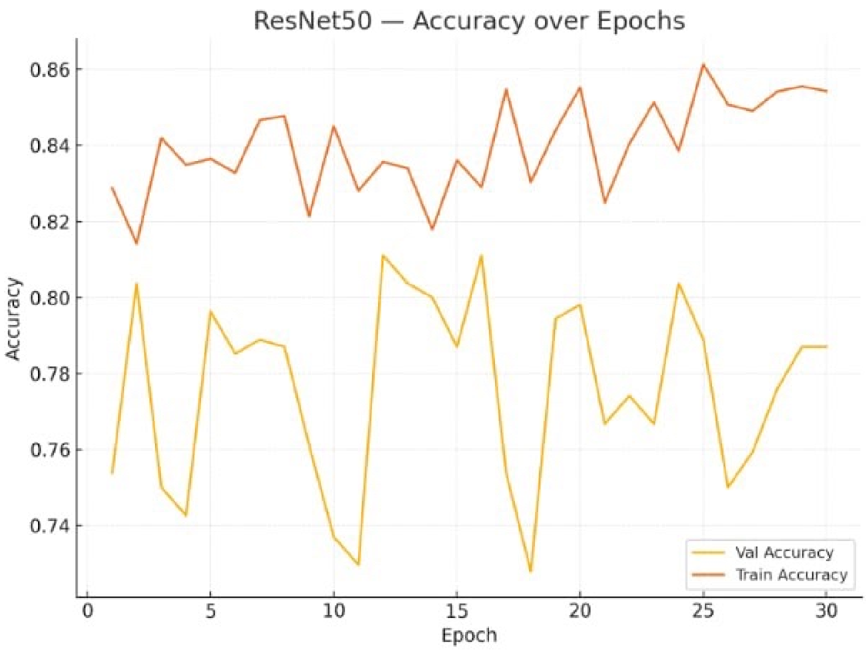


Figure 5.17: ResNet50 Accuracy

In our analysis ResNet50 achieved around an 85% validation accuracy.

Res-SE LiteNet

Layer (type)	Output Shape	Param #	Connected to
Res-SE LiteNet (InputLayer)	(None, 299, 299, 3)	0	-
conv2d (Conv2D)	(None, 150, 150, 32)	896	ArnabSaha_v3_Inp...
batch_normalization (BatchNormalization)	(None, 150, 150, 32)	128	conv2d[:][:]
activation (Activation)	(None, 150, 150, 32)	0	batch_normalizat...
separable_conv2d (SeparableConv2D)	(None, 150, 150, 64)	2,400	activation[:][:]
batch_normalization_1 (BatchNormalization)	(None, 150, 150, 64)	256	separable_conv2d...
activation_1 (Activation)	(None, 150, 150, 64)	0	batch_normalization_1...
separable_conv2d_1 (SeparableConv2D)	(None, 150, 150, 64)	4,736	activation_1...
batch_normalization_2 (BatchNormalization)	(None, 150, 150, 64)	256	separable_conv2d_1...
global_average_pooling2d (GlobalAveragePooling2D)	(None, 64)	0	batch_normalization_2...
reshape (Reshape)	(None, 1, 1, 64)	0	global_average_pooling2d...
dense (Dense)	(None, 1, 1, 8)	512	reshape[0][0]
dense_1 (Dense)	(None, 1, 1, 64)	512	dense[0][0]
multiply (Multiply)	(None, 150, 150, 64)	0	batch_normalization_2... dense_1[0][0]
conv2d_1 (Conv2D)	(None, 150, 150, 64)	2,112	activation[0][0]
add (Add)	(None, 150, 150, 64)	0	multiply[0][0], conv2d_1[0][0]

```
Total params: 337,635 (1.29 MB)
Trainable params: 335,779 (1.28 MB)
Non-trainable params: 1,856 (7.25 KB)
```

Figure 5.18: Res-SE LiteNet Parameter

```
  self._warn_if_super_not_called()
Epoch 1/30
890/890 ━━━━━━━━━━━━━━━━━━━━ 653s 731ms/step - accuracy: 0.5056 - loss: 1.1192 - val_accuracy: 0.6024 - val_loss: 0.9154 - learning_rate: 5.0000e-04
Epoch 2/30
890/890 ━━━━━━━━━━━━━━━━━━━━ 693s 743ms/step - accuracy: 0.6344 - loss: 0.8639 - val_accuracy: 0.4599 - val_loss: 1.2982 - learning_rate: 5.0000e-04
Epoch 3/30
890/890 ━━━━━━━━━━━━━━━━━━━━ 588s 637ms/step - accuracy: 0.6495 - loss: 0.8345 - val_accuracy: 0.6669 - val_loss: 0.8821 - learning_rate: 5.0000e-04
Epoch 4/30
890/890 ━━━━━━━━━━━━━━━━━━━━ 406s 456ms/step - accuracy: 0.6740 - loss: 0.8008 - val_accuracy: 0.5003 - val_loss: 1.0605 - learning_rate: 5.0000e-04
Epoch 5/30
890/890 ━━━━━━━━━━━━━━━━━━━━ 415s 466ms/step - accuracy: 0.6938 - loss: 0.7815 - val_accuracy: 0.5540 - val_loss: 1.1133 - learning_rate: 5.0000e-04
Epoch 6/30
890/890 ━━━━━━━━━━━━━━━━━━━━ 415s 466ms/step - accuracy: 0.7105 - loss: 0.7619 - val_accuracy: 0.6521 - val_loss: 0.8508 - learning_rate: 5.0000e-04
Epoch 7/30
890/890 ━━━━━━━━━━━━━━━━━━━━ 425s 478ms/step - accuracy: 0.7192 - loss: 0.7441 - val_accuracy: 0.7279 - val_loss: 0.7499 - learning_rate: 5.0000e-04
Epoch 8/30
890/890 ━━━━━━━━━━━━━━━━━━━━ 419s 471ms/step - accuracy: 0.7384 - loss: 0.7147 - val_accuracy: 0.6638 - val_loss: 0.8640 - learning_rate: 5.0000e-04
Epoch 9/30
890/890 ━━━━━━━━━━━━━━━━━━━━ 403s 453ms/step - accuracy: 0.7548 - loss: 0.7007 - val_accuracy: 0.7765 - val_loss: 0.6675 - learning_rate: 5.0000e-04
Epoch 10/30
890/890 ━━━━━━━━━━━━━━━━━━━━ 404s 453ms/step - accuracy: 0.7633 - loss: 0.6863 - val_accuracy: 0.7355 - val_loss: 0.7644 - learning_rate: 5.0000e-04
Epoch 11/30
890/890 ━━━━━━━━━━━━━━━━━━━━ 404s 454ms/step - accuracy: 0.7731 - loss: 0.6638 - val_accuracy: 0.8154 - val_loss: 0.6143 - learning_rate: 5.0000e-04
Epoch 12/30
890/890 ━━━━━━━━━━━━━━━━━━━━ 402s 451ms/step - accuracy: 0.7849 - loss: 0.6488 - val_accuracy: 0.6830 - val_loss: 0.7694 - learning_rate: 5.0000e-04
Epoch 13/30
...
Epoch 29/30
890/890 ━━━━━━━━━━━━━━━━━━━━ 421s 472ms/step - accuracy: 0.8911 - loss: 0.4909 - val_accuracy: 0.8873 - val_loss: 0.4923 - learning_rate: 5.0000e-04
Epoch 30/30
890/890 ━━━━━━━━━━━━━━━━━━━━ 417s 468ms/step - accuracy: 0.8945 - loss: 0.4893 - val_accuracy: 0.9053 - val_loss: 0.4575 - learning_rate: 5.0000e-04
Output is truncated. View as a scrollable element or open in a text editor. Adjust cell output settings...
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Figure 5.19: Res-SE LiteNet Accuracy

```
147/147 ━━━━━━━━━━━━━━━━━━━━ 11s 77ms/step - accuracy: 0.9276 - loss: 0.4364
Final Test Accuracy: 90.99%
Final Validation Accuracy: 90.53%
```

Figure 5.20: Final Test and Validation Accuracy

Final test Accuracy 90.99% and Final Validation Accuracy 90.53%

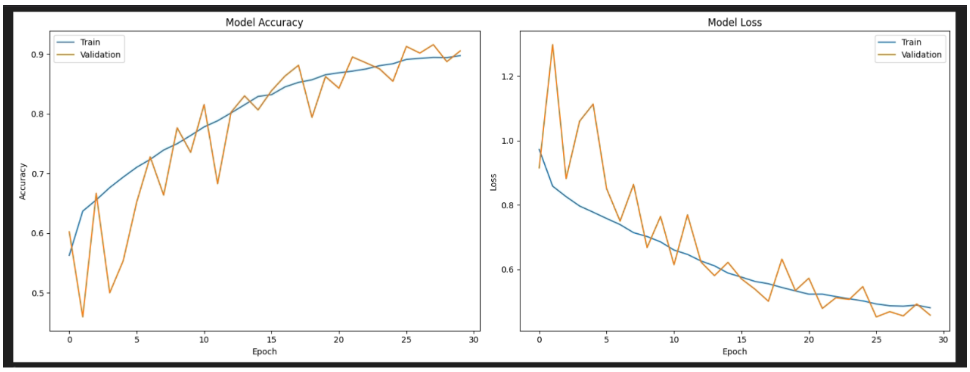

Figure 5.21: Res-SE LiteNet Accuracy and Loss Curve

Training and validation accuracy and loss curves show stable convergence and good generalization of the model.

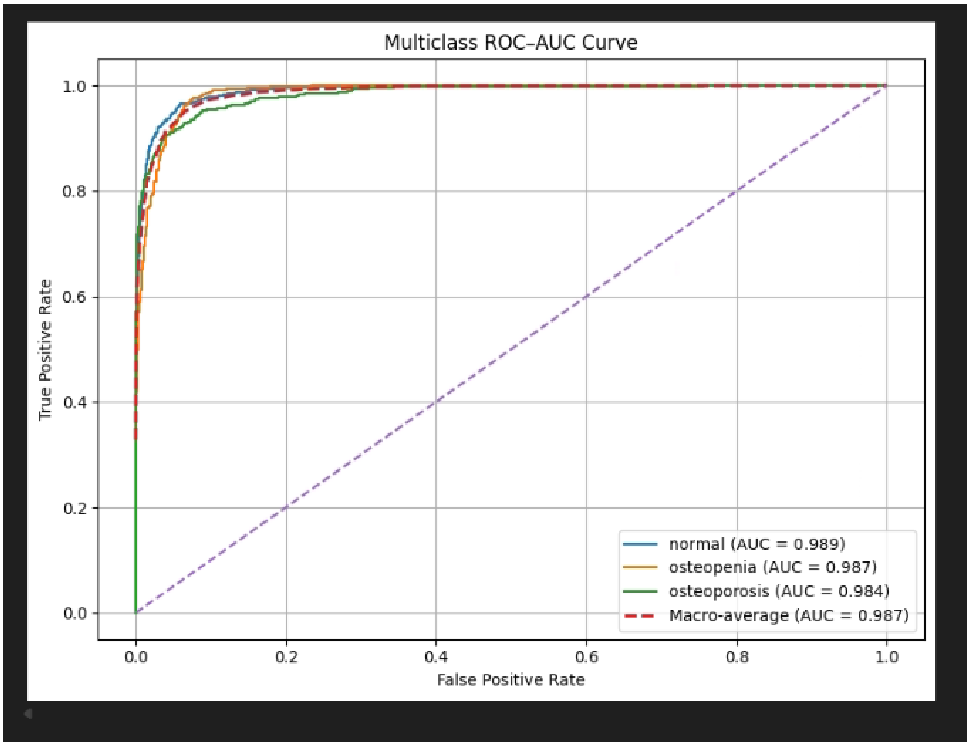

Figure 5.22: Res-SE LiteNet ROC-AUC Curve

Knee Osteoarthritis detection for 3 stages detection ROC AUC curve shows Normal Accuracy 98.9% , Osteopenia 98.7% and Osteoporosis 98.4% . It has High AUC values and strong performance in classifying all classes.

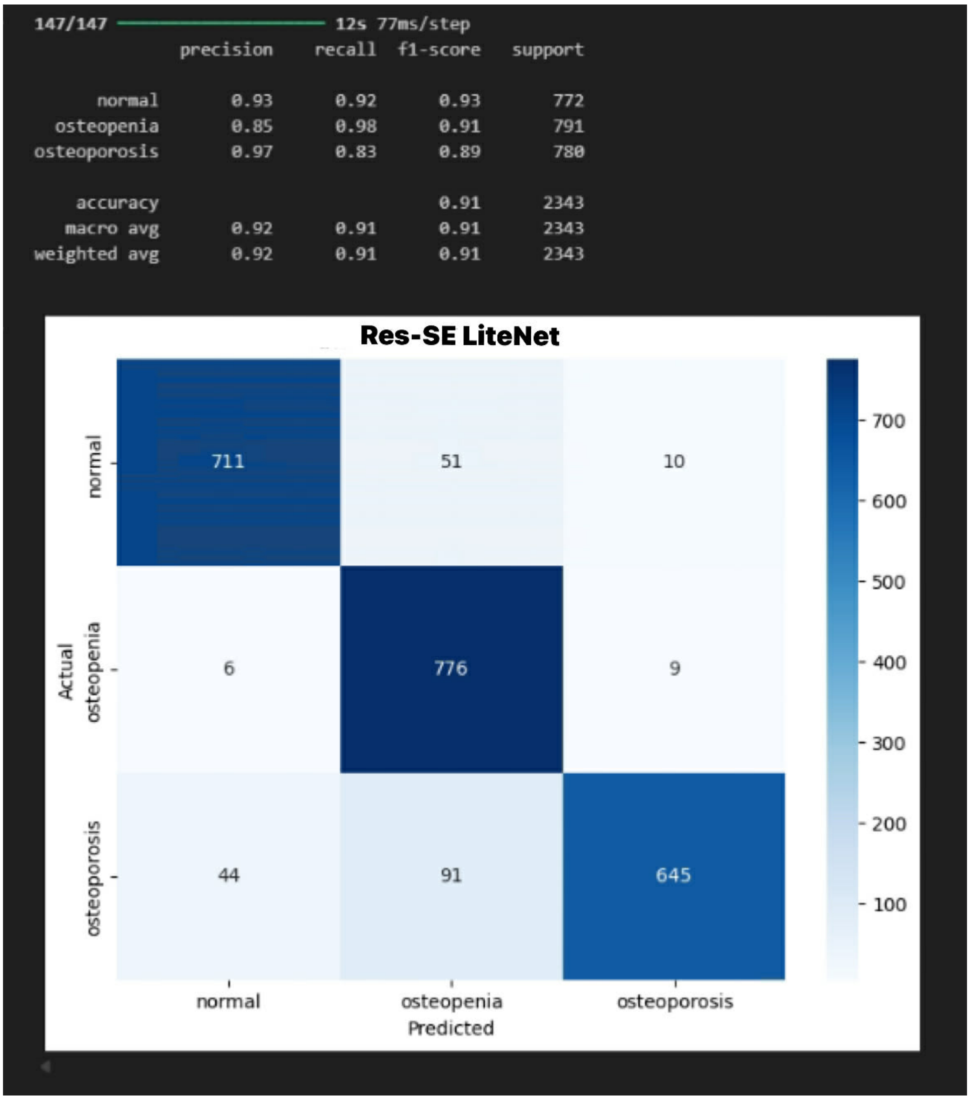

Figure 5.23: Res-SE LiteNet Confusion Matrix

Confusion matrix and classification report showing how well the proposed Res-SE LiteNet classification model performs. The model shows high accuracy in all classes, with only slight confusion between neighboring disease stages.
The is Bar representation of all the models we run. Among all of them our proposed Res-SE LiteNet are giving the best result with fewer parameters.

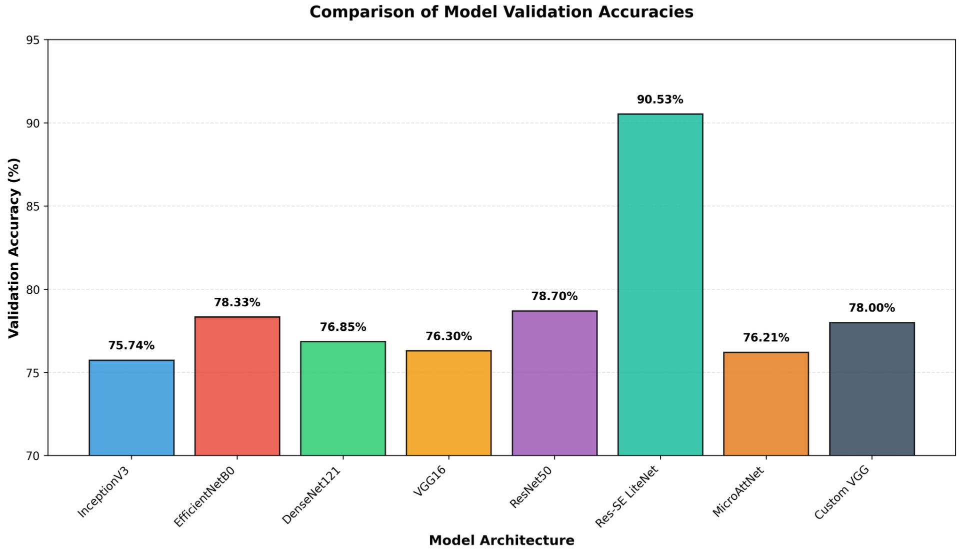

Figure 5.24: Comparison of Models

5.2 Analysis of Design Solutions

The model development process involved three architectural iterations, each addressing the limitations of its predecessor. The initial MicroAttNet architecture achieved extreme efficiency with only 115K parameters and a spatial attention mechanism with fast inference but the accuracy was limited(70.44%) as it had insufficient representational capacity for complex bone texture patterns. Then we came up with the second approach, where we adopted transfer learning with Custom VGG16, freezing early blocks while fine-tuning in the deeper layers or feature extraction. Following this, we improved the accuracy to 78% but introduced computational overhead. Here, the number of parameters and model size increased, which indicates low efficiency. The final Res-SE-LiteNet model architecture successfully learn lessons from both predecessors and use techniques such as Squeeze-and-Excitation blocks for channel-wise attention, residual connections for gradient flow, separable convolutions for parameter efficiency and hybrid global pooling to capture knee joint space geometry and focal osteophytes formations. With 2.85 million parameters and a size of 12MB, this balanced design achieved 87.72% validation accuracy. This model complies with efficiency, robustness, and clinical validity for real-world deployment in resource-constrained healthcare environments. In summary, through iterative development, the final model achieves the optimal balance between efficiency and performance for bone density classification in real-world clinical settings, where both accuracy and practical deployment matter.

5.3 Final Design Adjustments

To improve the Res-SE LiteNet for clinical classification tasks, several final design changes were made to boost its stability, speed of convergence, and ability to generalize during training. The final implementation used the Adam optimizer with an initial learning rate of 0.0005. This setup aimed to stop the model from hitting an early training plateau while ensuring a steady path to the global minimum. To improve the learning process, a ReduceLROnPlateau callback was added. This callback lowered the learning rate by a factor of 0.2 if the validation loss did not improve for five consecutive epochs. Additionally, to reduce the chance of over-confident predictions and enhance the model's ability to generalize to new medical images, label smoothing of 0.1 was applied in the Categorical Crossentropy loss function. This change helps the model learn stronger feature representations by stopping the output neurons from becoming too focused on the training labels. The final design of the model includes a number of structural improvements aimed at preserving a high accuracy-to-parameter ratio. In order to optimize feature extraction efficiency while maintaining a total parameter count of roughly 337,635, the architecture makes use of Separable Convolutions in conjunction with Batch Normalization and Swish activation. The "Double Path" Hybrid Global Pooling approach concatenates Global Average and Global Max Pooling for spatial summary, giving the classifier a rich 1024-dimensional feature vector. The final three-unit softmax output layer was preceded by a Dropout layer with a 0.5 rate to prevent overfitting. In order to ensure that the final model Res-SE LiteNet represents the peak of its learning cycle, an EarlyStopping mechanism with a patience of 12 epochs was used. This mechanism was set up to monitor validation accuracy and restore the best performing weights.

5.4 Statistical Analysis

For evaluating and comparing the performance of the models for classification of three class knee osteoarthritis classification, various statistical analyses were performed. The analysis mainly focused on the classification based statistical measures obtained from confusion matrix and comparative performance metrics from different model architecture. For each model, metrics like accuracy, precision, f1 score, recall were computed on test and validation datasets as standard form of statistics. These metrics give necessary information about the overall performance of the model in effectively classifying the three classes of knee osteoarthritis. The dataset containing three KOA classes were collected and divided into 70% for training, 20% for testing and 10% for validity.Each of the deep learning models like MicroAttNetti, custom VGG, Res-SE were trained with batch size of 16 and number of epochs was set to 30. A confusion matrix is generated for each of the models to visualize classification performance among three KOA classes. Clearly showing the distribution of true positives, true negatives, false positives and false negatives.

5.5 Comparisons and Relationships

While building the model, we aimed to achieve high accuracy while keeping the model suitable for development on resource constrainted device . To make it lightweight and efficient, we applied depthwise separable on convolutions, which reduced parameters by 8 to 9 times compared to standard convolutions used in existing studies. The hybrid pooling strategy proved critical for maintaining balanced performance across all severity classes, directly addressing the class imbalance problem observed in Rani Memoria (2024) whose model achieved highly unbalanced F1-scores of 0.87, 0.74 and 0.67 , with their Google accuracy reaching just 78.4%. The Squeeze-and-Excitation block attention mechanism had Substantial impact on emphasizing diagnostically relevant features like joint space narrowing and osteophyte formation, capabilities absent in the existing papers.

Feature	Ahmed and Mustafa (2022)	Mohammed et al. (2023)	Rani et al. (2024)	Res-SE LiteNet
Architecture type	Hybrid (CNN-ML)	Transfer learning	Custom CNN	Custom End-to-End
Base Architecture	Custom 5-layer CNN	ResNet101 (pre-trained)	12-layer CNN	Custom SE-ResNet
Feature Extraction	CNN → PCA	ResNet blocks	Convolutional layers	SepConv + SE blocks
Classifier	SVM	Fully connected	Fully connected	Fully connected
Attention mechanism	None	None	None	SE block (Channel attention)
Residual Connections	No	Yes	No	Yes (custom)
Batch Normalization	Yes	Yes	Yes	Yes
Pooling Strategy	Max pooling	Avg pooling	Max pooling	Hybrid (GAP + GMP)
Activation Function	ReLU	ReLU	ReLU	Swish
Regularization	Dropout	Dropout	Dropout	Dropout + Label Smoothing
Separable Convolutions	No	No	No	Yes
Input Size	112×112	224×224×3	Not specified	299×299×3
Accuracy	89.4%	89.0%	78.4%	90.53%

Table 5.2: Comparison of Proposed Model with Existing Approaches

Comparing with these papers, our model Res-SE LiteNet achieved a test accuracy of 90.53% with only 334k Parameters representing almost 93% fewer parameter that Mohammad et al.'s ResNet101(44.6Mparameters, 89% accuracy) while actually exceeding their performance by 1%. Furthermore, our model demonstrated superior balanced performance with F1-scores of 0.92, 0.98 and 0.83 compared to highly imbalanced results in existing work, particularly outperforming Rani Memoria's (2024) severe class detection by 37%. This combination of higher accuracy, superior parameter efficiency, and balanced class performance makes out model significantly more practical for real-world implementation in resource-limited clinical settings, including rural clinics, mobile diagnostic units, and point-of-care screening programs where GPU infrastructure is unavailable, yet accurate OA detection remains critically needed.

Figure 5.25: Prediction

The model can predict X-ray Images.

5.6 Real World Implication

Web implementation

The model was implemented in a very basic website created using the Flask framework. The backend was done in python language and frontend was done using html and CSS. The model was developed in Google Colab where its architecture and weight was saved as a keras file and it was downloaded and loaded on to the web project folder. When a picture is uploaded it gives accurate results based on how the model was trained.

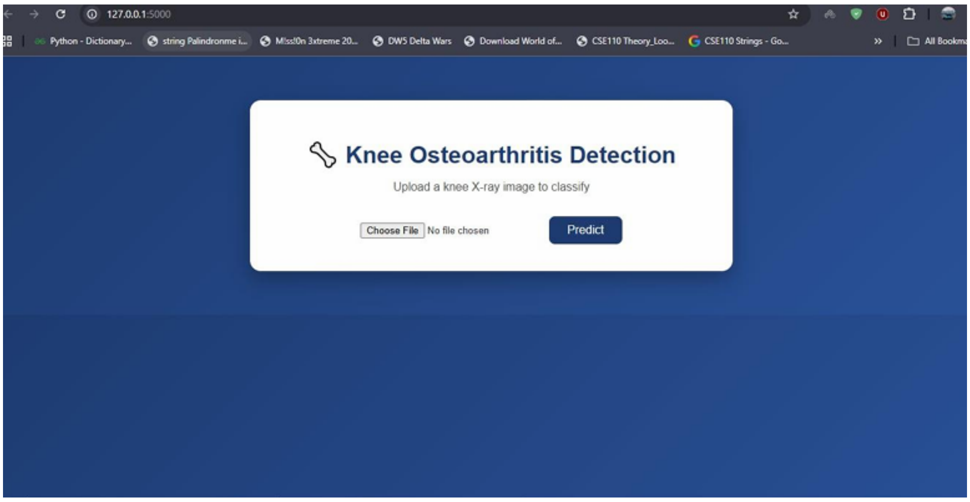

Figure 5.26: Front Page of Web

Figure 5.27: Normal Prediction in Web

Figure 5.28: Osteoarthritis Prediction in Web

Figure 5.29: Osteopenia Prediction in Web

Chapter 6

Conclusion and Future Work

6.1 Summary of Key Findings and Implication

This thesis presented a novel Residual Squeeze-and-Excitation Convolutional Neural Network named Res-SE LITE NET which was specifically designed to automate the detection of knee osteoarthritis at three different stages: normal, osteopenia, and osteoporosis. Our model has been successful in achieving a final accuracy of 90.99% on the test data and a validation accuracy of 90.53%. Our model has been computationally efficient with a moderate number of parameters and FLOPs(Floating Point Operations). By conducting a series of experiments on residual learning, squeeze-and-excitation attention, hybrid global pooling, and Swish activation, we have demonstrated that discriminative features can be learned by a well-designed CNN architecture from knee image data without relying on a hybrid model. Some of the novel contributions of our model are residual squeeze and excitation learning, which enables our network to recalibrate its channels to focus on the differences in bone textures and trabecular patterns between different stages of knee osteoarthritis hybrid global pooling,which enables accurate classification by learning better representations of features and the use of Swish activation, which enables smoother gradients to be learned by our network leading to better convergence and feature extraction than ReLU activation.

Finding 1: Effective Differentiation of Knee Conditions

The proposed model, Res-SE LITE NET, is able to differentiate between normal, osteopenia, and osteoporosis knee conditions based on various imaging features.This in turn confirms the effectiveness of our proposed model Res-SE LITE NET based on the CNN concept for classifying knee OA into various stages. It is also evident from the findings that CNNs can be used for feature extraction even with a small dataset.

Finding 2: High Detection Accuracy and the Use of Transfer Learning

Res-SE LITE NET which incorporates residual squeeze-excitation blocks and transfer learning is able to achieve an accuracy of 90a CNN for the classification of knee OA into different stages.Also the effectiveness of transfer learning for improving the performance of the CNN can be clearly understood from the findings.

Finding 3: Simplicity of Architecture, Regularization and the Use of Channel Attention

Res-SE LITE NET shows the effectiveness of our approach which incorporates regularization, simplicity of architecture, and channel attention. It is evident from the findings that the proposed approach is able to achieve better performance compared to a machine learning approach. Also it can be clearly understood from the findings that channel attention provides better accuracy for a lower computational cost.

Finding 4: Computational Efficiency, Lightweight Design and Clinical Applicability

It is evident from the findings that despite achieving a high accuracy rate the Res-SE LITE NET has a moderate number of parameters as well as FLOPs making it lighter and more efficient compared to existing pretrained models.

6.2 Limitations

6.2.1 Public Dataset Dependence:

The model depends on publicly available datasets which have limited sample sizes, varied imaging protocols, unknown sources, and possibly noisy or unverified annotations, which may introduce biases in the model.

6.2.2 Domain Adaptation:

Although transfer learning from pre-trained CNNs was successful, domain differences exist between general image datasets and specific knee imaging modalities which might impact model performance on real-world data.

6.2.3 Clinical Validation:

The validation of KneeOA-Net has only been done on public benchmark datasets. The validation of real-world clinical data from hospitals is necessary before it can be used in a clinical setting.

6.3 Contribution to the field

6.3.1 Novel Architecture for Knee OA Detection:

In the proposed model of KneeOA-Net, the residual SE-CNN is efficient in focusing on the features of bone texture and cartilage for multi stage classification of knee OA.

6.3.2 High Accuracy with Practical Efficiency:

The model's ability to attain 90.53% accuracy with moderate computational complexity proves that it is possible to achieve high accuracy without necessarily using overly complex architectures.

6.3.3 Base for Development of AI-Based Tools for Knee OA Diagnosis:

The model is a reliable starting point for AI-assisted knee OA diagnosis, which is instrumental in the early diagnosis of knee OA and personalized patient care.

6.3.4 Closing Knowledge Gaps in the Field of Knee OA Detection:

The model proves that it is possible to extract useful features from limited public datasets using attention mechanisms and hybrid pooling.

6.4 Future Work

6.4.1 Clinical Data Collection:

Collaborate with hospitals and clinics to ensure the collection of accurate and validated images.

6.4.2 External Validation:

Validate the robustness of the model by testing its performance on multi-center datasets.

6.4.3 Domain Adaptation:

Create techniques that can successfully transfer models trained on public datasets for clinical use.

6.4.4 Multi-Modal Integration:

Incorporate patient demographic, lab and biomechanical data for a more comprehensive approach to OA assessment.

6.4.5 Regulatory and Clinical Translation:

Plan prospective clinical studies and integrate the model into the PACS and EHR systems of hospitals.

6.4.6 Open Science Initiatives:

Contribute to the creation of a new set of well annotated public clinical knee OA data sets.

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