International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: IV Month of publication: April 2025

DOI: https://doi.org/10.22214/ijraset.2025.69796

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IV Apr 2025- Available at www.ijraset.com

Automated Osteoporosis Detection and Severity Prediction using CNN with VGG19 on Knee Radiographs

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Abstract: Automated Osteoporosis Detection And Severity Prediction Using CNN With VGG19 On Knee Radiographs develops a deep learning model to automatically classify osteoporosis severity using knee X-ray images. A Convolutional Neural Network (CNN), combined with a pre-trained VGG19 model, extracts critical features for accurate classification. The model is fine-tuned with multiple a convolutional and max-pooling layers, followed by dense layers for improved learning. Techniques such as data augmentation, learning rate scheduling, and early stopping are applied to enhance model performance. The classification process is optimized using the Adam optimizer and evaluated with standard metrics. The results demonstrate promising accuracy in distinguishing between various osteoporosis classes, providing reliable and consistent assessments to support radiologists in clinical settings.
Keywords: Convolution Neural Networks, Feature extraction, Knee X-ray images, Osteoporosis

I. INTRODUCTION

Automated Detection of Osteoporosis and Severity Prediction with CNN and VGG19 on Knee Radiographs focuses on developing an advanced deep learning model to automatically classify the severity of osteoporosis using knee X-ray images. The core architecture integrates a Convolutional Neural Network (CNN) combined with a pre-trained VGG19 model to efficiently extract critical features from the X-ray images. The model is fine-tuned using multiple convolutional and max-pooling layers, followed by dense layers that further refine the learning process to ensure accurate classification.

To enhance the model's performance, various techniques such as data augmentation, learning rate scheduling, and early stopping are applied. These techniques help improve generalization, prevent overfitting, and optimize the classification process. The input data consists of knee X-ray images categorized into three classes — Healthy, Osteopenia, and Osteoporosis. The dataset is pre processed by resizing, zooming, and flipping images to introduce variability, making the model robust across different types of input images.

The classification model is trained using the Adam optimizer and evaluated using standard metrics, including accuracy, precision, recall, and F1-score. The results show that the model achieves high accuracy in distinguishing between different osteoporosis severity levels, ensuring reliable and consistent assessments. By automating the classification process, this model significantly reduces the workload for radiologists and improves the speed and consistency of osteoporosis diagnosis in clinical settings.

II. LITERATURE REVIEW

I.M. Wani and S. Arora[1] have applied transfer learning using convolutional neural networks (CNNs) to detect osteoporosis from knee X-ray images. They fine-tuned pre-trained models to adapt to medical imaging tasks, achieving significant accuracy in classifying osteoporotic conditions. Their work showcases how leveraging existing models can reduce computational costs while delivering solid results.. He et al.,[2] have exploreed the growing role of deep learning in the radiologic diagnosis of osteoporosis. The authors summarized various neural network models, imaging modalities, and evaluation metrics. They also pointed out current limitations and suggested directions for future research in medical AI applications. Jaman Shawon et al.,[3] have developed an osteoporosis prediction system using two powerful CNN architectures—VGG16 and ResNet50. Their approach focused on classifying X-ray images into normal and osteoporotic categories. The models were evaluated for accuracy and showed promising results, highlighting the effectiveness of deep learning in skeletal health analysis.

Hua Xie et al.,[4] have proposed a few-shot learning framework for diagnosing osteopenia and osteoporosis from knee X-rays. The approach is designed to work with limited training data, addressing one of the key challenges in medical imaging. Results showed the model could generalize well, even in low-data scenarios, making it suitable for real-world clinical use.

Mengyuan Shen[5] has developed a deep learning-based system specifically tailored to detect osteoporosis via knee X-ray analysis. The work focused on optimizing neural network parameters to improve diagnostic performance. Presented at an AI conference, this study demonstrated the utility of machine learning in supporting early osteoporosis detection. S. M. Naguib et al.[6] have introduced a novel "superfluity" deep learning model for diagnosing both osteoporosis and osteopenia using knee X-ray images. The model leveraged complex feature extraction techniques to improve classification performance. Their experimental results showed high precision, suggesting real potential for clinical deployment.

A. M. Sarhan et al.,[7] have created a deep learning system for knee osteoporosis detection, incorporating preprocessing techniques to enhance image quality and learning efficiency. They tested the model on real X-ray datasets and reported strong diagnostic accuracy. The study reinforces the reliability of AI-based tools in medical imaging diagnostics. T. Y. Yen et al.,[8] have reviewed and meta-analyzed evaluating the diagnostic accuracy of deep learning models for predicting osteoporosis from plain X-rays. By combining data from multiple studies, they quantified the overall performance and effectiveness of AI in this domain. Their findings support the clinical viability of deep learning for osteoporosis screening. Siddiqua et al.,[9] have proposed a transfer learning-based system with enhanced feature extraction using stacked deep learning modules. The model aimed to improve the reliability and accuracy of computer-aided osteoporosis diagnosis. Their layered approach showed superior performance compared to traditional CNN setups, emphasizing the power of deep architectures.

III. METHODOLOGY

The VGG19 model is a deep learning architecture designed for image recognition, consisting of 19 layers, including 16 convolutional layers followed by fully connected layers. It was originally developed by the Visual Geometry Group (VGG) at Oxford and has been widely used for feature extraction due to its ability to capture intricate patterns in images. In your project, VGG19 serves as a pre-trained feature extractor for classifying the severity of osteoporosis using knee X-ray images. Instead of building a model from scratch, the pre-trained VGG19 model extracts critical image features, such as bone density variations and structural differences, which are essential for accurate classification. The model is fine-tuned by adding additional convolutional, max-pooling, and dense layers, enabling it to specialize in osteoporosis classification. Furthermore, techniques like data augmentation, learning rate scheduling, and early stopping are incorporated to enhance performance and prevent overfitting. The Adam optimizer is used to refine the learning process, ensuring efficient convergence. Ultimately, the integration of VGG19 significantly improves classification accuracy, providing reliable assessments to assist radiologists in clinical decision-making.

VGG19 is a deep convolutional neural network (CNN) with 19 layers, including 16 convolutional layers and 3 fully connected layers. It uses small 3x3 filters and is pre-trained on ImageNet, making it highly effective for feature extraction. VGG19 is commonly fine-tuned for tasks like classifying osteoporosis severity from knee X-rays.

IV. RESULTS AND DISCUSSIONS

This table compares VGG-19 and ResNet50 in classifying knee X-ray images into Healthy Knee, Osteopenia, and Osteoporosis. VGG-19 consistently outperforms ResNet50, achieving higher accuracy (91.1% vs. 89.1%) and better F1-scores across all categories. It excels in precision and recall, particularly in osteoporosis detection (F1-score: 0.91 vs. 0.88). Overall, VGG-19 proves to be the more effective model for diagnosing knee osteoporosis-related conditions.

Table 1: Comparison of Performance Metrics

Disease	Model	Accuracy	Recall	Precision	F1 Score
Osteoporosis-Healthy	VGG 19	91.1	93	95	94
	RESNET50	89.1	92	94	93
Osteoporosis-osteopenia	VGG 19	91.1	84	86	85
	RESNET50	89.1	86	80	83
Osteoporosis	VGG 19	91.1	92	90	91
	RESNET50	89.1	88	89	88

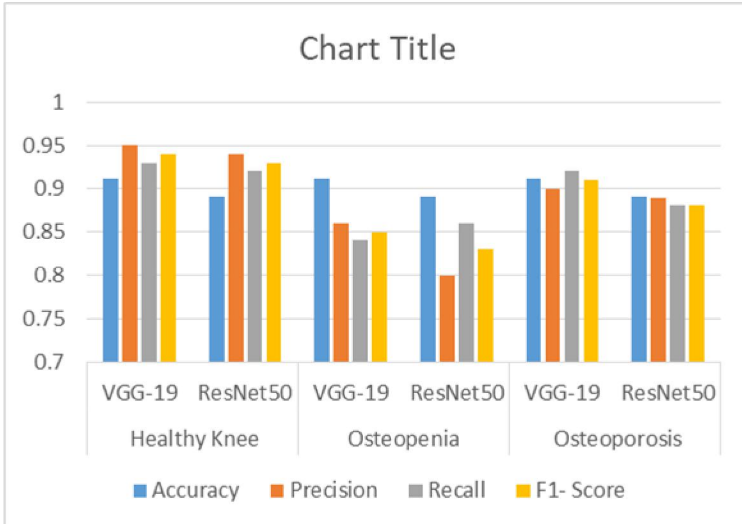

Figure.1 Bar plot of performance metrics

A. Accuracy

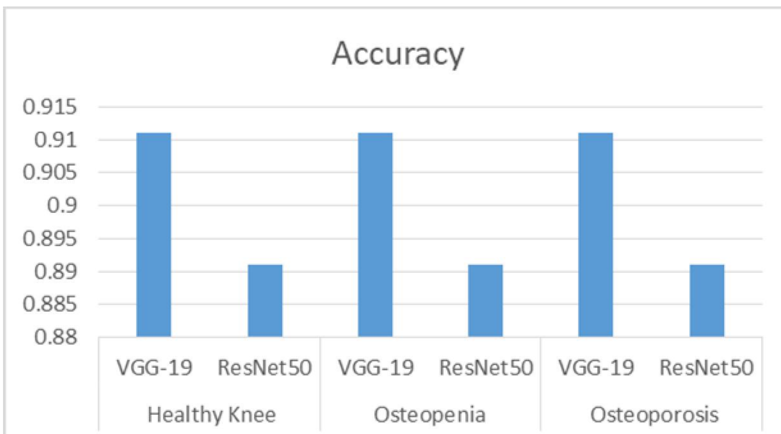

Figure.2 Accuracy of the Knee Osteoarthritis Severity

It varies depending on factors such as dataset size, model architecture and fine-tuning techniques. However, with proper optimization and tuning these models often achieve high levels of accuracy, frequently surpassing traditional machine learning approaches.

B. Graphs

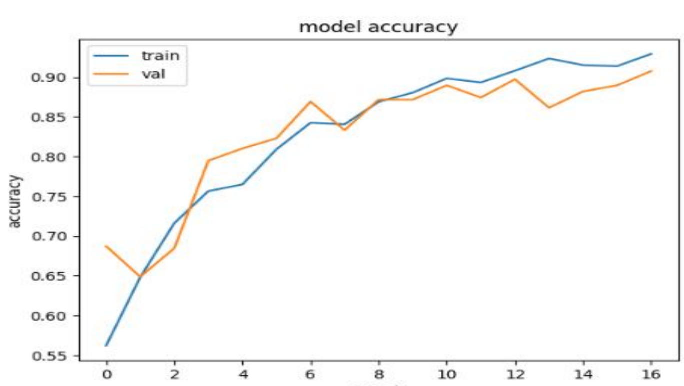

Figure.3 Model Accuracy

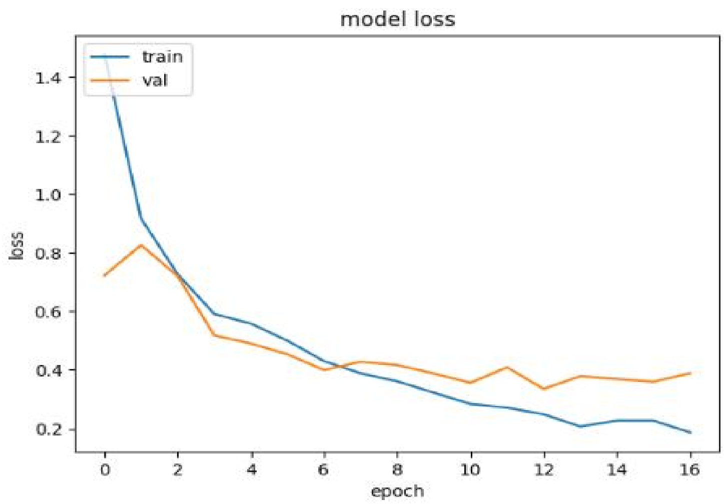

Figure.4 Model Loss

This graph shows the training and validation accuracy over 16 epochs, with both steadily increasing. Early fluctuations in validation accuracy stabilize, closely following training accuracy. The model achieves over 90% accuracy in later epochs, indicating effective learning and minimal overfitting.

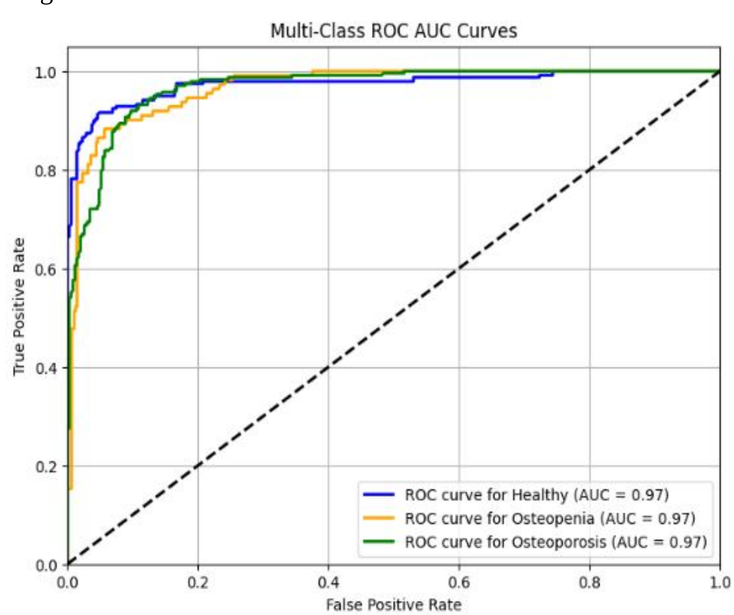

Figure.5 Multiclass ROC Curve

This plot of an ROC curve represents the performance of a VGG-19 model classifying between three classes: Healthy, Osteopenia, and Osteoporosis. Each colored curve represents the model's ability to discriminate one class from the others, i.e., the ability of the classifier to discriminate between the positive class and others at different thresholds. The Area Under Curve (AUC) for each of the three classes—blue, orange, and green—comes out to be 0.97, which reflects a very good classification performance. The highest AUC (1.0) reflects a perfect model and an AUC of 0.5 reflects a lack of discriminative power, so an AUC of 0.97 implies the VGG-19 model performs very well in classifying each of the conditions. The closer the curves to the top-left corner, the better the model at reducing false positives while maximizing true positives, as is visible here.

C. Formulas

Accuracy = (TP+TN) / (FP+FN+TP+TN)

Precision = TP / (FP+TP)

Recall = TP / (FN+TP)

F1-Score = 2×(Precision*Recall) / (Precision + Recall)

D. Confusion Matrices

A confusion matrix in CNN classification is a handy tool that shows how well the model is predicting by comparing actual vs. predicted labels. It highlights correct predictions and errors like false positives or missed classifications. For multi-class tasks, it reveals which classes the model tends to confuse. This helps spot patterns in misclassification and guides model improvements. Think of it as a quick performance report for your CNN.

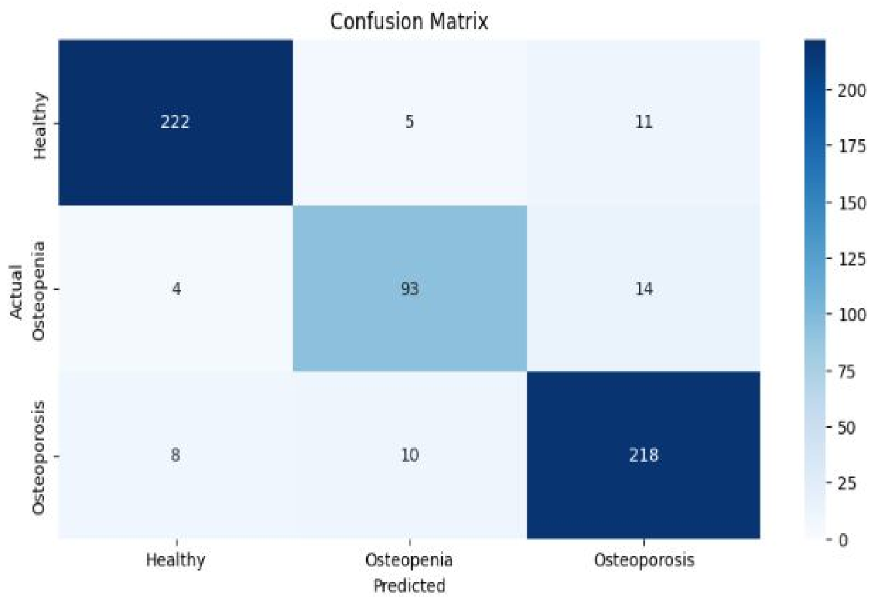

Figure.5 Confusion Matrices of Knee Osteoporosis

V. CONCLUSIONS

Osteoporosis is a serious condition that affects millions worldwide, and early detection can make a significant difference in patient outcomes. In this project, we successfully developed an automated system for osteoporosis detection and severity classification using deep learning techniques, specifically a CNN model integrated with VGG19. By leveraging knee X-ray images, our approach provides a reliable, efficient, and consistent method for diagnosing osteoporosis stages healthy, osteopenia, and osteoporosis.````

Our results demonstrate that deep learning can assist radiologists in making faster and more accurate diagnoses, reducing subjectivity and improving healthcare efficiency.

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