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Osteoporosis Detection via Deep Learning

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الكشف عن هشاشة العظام باستخدام التعلم العميق

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Abstract
Osteoporosis is a chronic skeletal disorder marked by reduced bone mineral density (BMD) and deterioration of bone microarchitecture, which significantly increases the risk of fractures. Timely and precise diagnosis is essential to initiate early treatment and prevent complications. Osteoporosis can be detected using several diagnostic methods, each varying in accuracy, accessibility, and clinical application. Deep learning can emerge as a tool for detecting osteoporosis by examining imaging data such as X-rays and DEXA scans for subtle indicators. It supports early diagnosis, benefits both patients and specialists, and enhances overall healthcare delivery. In this study, applicability of deep learning-based convolutional neural networks (CNNs)—specifically DenseNet201, ResNet50, and DenseNet121 — investigated for the automatic detection of osteoporosis from knee x-ray radiographic. The used CNN models were trained using transfer learning were adapted for binary classification (normal vs. osteoporotic). To enhance model generalization, standard preprocessing and different aspects of image augmentation techniques were applied. All used models are evaluated using common evaluation metrics and compared. Among the models used, DenseNet201 performed well across all performance metrics, achieving a classification accuracy of 85.11%, outperforming the other models. The study underscores the potential of CNNs to support radiologists in performing efficient osteoporosis screening. The results aid in diagnosing osteoporosis by revealing early signs of bone loss, allowing timely intervention. This supports treatment decisions and helps prevent fractures, ultimately improving patients' quality of life and enabling proactive condition management.

Keywords: BMD, CNNs, Knee, Osteoporosis.

الملخص
هشاشة العظام هي اضطراب هيكلي مزمن يتميز بانخفاض كثافة المعادن في العظام وتدهور التركيبة الدقيقة للعظام، مما يزيد بشكل كبير من خطر الإصابة بالكسور. ان التشخيص الدقيق في الوقت المناسب ضروري لبدء العلاج المبكر ومنع المضاعفات، ويمكن الكشف عن هشاشة العظام باستخدام عدة طرق تشخيصية، تختلف كل منها في الدقة وإمكانية الوصول والتطبيق السريري. كما يمكن أن يظهر التعلم العميق كأداة للكشف عن هشاشة العظام من خلال فحص بيانات الصور مثل صور الأشعة السينية ومسح

ديكسا عن طريق البحث عن مؤشرات دقيقة في الصور وكما يدعم التشخيص المبكر، مما يفيد المرضى ويساعد المتخصصين في عملية الكشف، ويعزز تقديم الرعاية الصحية بشكل عام .
في هذه الدراسة، تم تطبيق الشبكات العصبية التلافيفية القائمة على التعلم العميق للكشف التلقائي عن هشاشة العظام في مجموعة صور الاشعة السينية لمفصل الركبة. تم الاستفادة من تقنية نقل التعلم لتعليم النماذج المستخدم وتم تكييفها للتصنيف الثنائي (طبيعي مقابل هشاشة العظام). ولتعزيز تعميم النموذج، تم تطبيق المعالجة المسبقة للصور المستخدمة اللازمة وكذلك تحويلات مختلفة لتقنيات زيادة الصور. تم تقييم جميع النماذج المستخدمة باستخدام مقاييس التقييم الشائعة ومقارنتها. من بين النماذج المستخدمة، كان أداء نموذج DenseNet201 جيدا في جميع مقاييس الأداء، حيث حقق دقة تصنيف بلغت 85.11٪، متفوقا على النماذج الأخرى. تؤكد الدراسة على إمكانات هذه النماذج لدعم أخصائيي الأشعة في إجراء فحص فعال لهشاشة العظام كما تساعد النتائج في تشخيص هشاشة العظام من خلال الكشف عن العلامات المبكرة لنقص كثافة العظام، مما يسمح بالتدخل في الوقت المناسب. وهذا يدعم قرارات العلاج ويساعد على منع الكسور، مما يؤدي في النهاية إلى تحسين نوعية حياة المرضى وتمكين الاجراءات الاستباقية للحالة المرضية.

الكلمات الدالة: التلافيفية، الركبة، السينية، العظام، هشاشة.

1. Introduction

Osteoporosis is a prevalent public health concern, particularly affecting the elderly and potentially leading to disability. Because the condition typically progresses without noticeable symptoms, it is often only diagnosed after a fracture has occurred. The most frequently observed fractures include vertebral fractures, followed by fractures of the hip and distal forearm [1]. Osteoporosis is a condition marked by reduced bone mass, degradation of bone tissue, and alterations in the bone's microarchitecture. These changes weaken the bones and significantly elevate the risk of fractures [2]. Osteoporosis is commonly referred to as a silent disease, as it typically develops without noticeable symptoms. It is diagnosed when an individual's Bone Mineral Density (BMD) is 2.5 standard deviations or more below the average BMD of healthy young adults [3]. Due to the systemic nature of osteoporosis, the elevated risk of fractures extends to nearly all areas of the skeleton. While hip and vertebral fractures are closely linked to decreases in hip and spine BMD, and are traditionally seen as hallmark indicators of the disease, fractures at other sites (excluding hip and spine) occur more frequently. Collectively, these non-hip, non-vertebral fractures contribute to a significantly higher overall economic burden on the healthcare system [4]. Osteopenia is a condition characterized by lower-than-normal BMD, though not low enough to be classified as osteoporosis. It represents a preclinical stage of osteoporosis. Individuals with either osteoporosis or osteopenia often face difficulties in carrying out daily activities, experience poor sleep quality, and suffer from increased fatigue—all of which negatively impact their quality of life. These challenges become even more significant when fractures occur, placing substantial emotional and financial strain on families. Therefore, early prevention and effective treatment of both osteopenia and osteoporosis are essential to improving patient outcomes and reducing the risk of complications [5]. Osteoporosis typically remains undetected until a fracture occurs, as it often progresses without noticeable symptoms. In fact, about two-thirds of vertebral fractures cause no pain, making early diagnosis even more challenging. Therefore, screening plays a crucial role in identifying the condition early, allowing for timely treatment and prevention of fractures. The DXA scan continues to be the gold standard for measuring BMD and diagnosing osteoporosis [6].

However, DEXA has several limitations, including limited availability, the requirement for strict quality control, reliance on operator skill, and less-than-ideal screening coverage. Alternative methods for assessing BMD, such as quantitative computed tomography, ultrasound, and peripheral DEXA, have not yet been widely adopted in clinical practice [7]. Alternative methods like orthopantomogram radiography show potential for osteoporosis screening, however manual analysis is often time-consuming and inconsistent. AI, especially deep learning using CNNs, offers powerful tools to automate and improve diagnostic accuracy by effectively recognizing patterns in medical images. Deep learning models reduce subjectivity and enhance consistency in detecting osteoporosis from panoramic radiographs, outperforming traditional techniques in sensitivity and specificity. As deep learning plays an increasing role in medical diagnostics, assessing its effectiveness in osteoporosis detection remains essential [8].

Early detection of osteoporosis is crucial, as the condition often remains undiagnosed until serious complications occur. Manual diagnosis can be time-consuming, however recent advances in AI, particularly deep learning, offer promising solutions for automating this process. This study leverages three deep learning models to develop a robust and efficient diagnostic framework capable of detecting early signs of osteoporosis from medical images. By enhancing the accuracy and generalizability of the system, this approach supports timely clinical interventions, potentially reducing the risk of fractures and long-term bone damage. The integration of AI into routine screening can significantly improve preventive healthcare by offering valuable insights into bone density and overall skeletal health. Early diagnosis empowers healthcare providers to recommend appropriate treatments—such as lifestyle changes, medication, or dietary adjustments—ultimately improving patient outcomes and quality of life.

2. Related works

In recent years, deep learning especially CNNs has been increasingly applied to osteoporosis diagnosis, fueled by advances in AI and the growing availability of medical imaging data. Researchers have developed automated systems using X-ray images to accurately detect bone deterioration. This study employs deep learning techniques for binary classification to detect osteoporosis using knee X-ray images. Therefore, the related work section will focus on previous studies that have applied deep learning approaches particularly binary classification models for osteoporosis detection based on knee X-rays.

Mohammed, and George [9] proposed a system for diagnosing osteoporosis using knee X-ray images by applying transfer learning within the same domain. The system is divided into two phases, each involving similar stages such as preprocessing (noise reduction with an average filter, contrast enhancement via histogram equalization, and region of interest extraction using K-means and edge detection) followed by smoothing with a mean filter to aid diagnosis. In phase 1, the model is trained on a large unlabeled X-ray dataset from multiple orthopedic centers to learn general image features. Phase 2 involves fine-tuning this pretrained model using smaller labeled target datasets, which is effective when labeled data is limited or training from scratch is costly. Two different target datasets were utilized to validate the approach.

Siddiqua et al. [10] introduced a computer-aided diagnosis system for detecting knee osteoporosis by utilizing transfer learning in combination with stacked feature enhancement deep learning blocks to address common challenges in the task. The enhanced feature representations are fed into a classification module designed to distinguish between healthy and osteoporotic knee conditions. Their approach was evaluated using three separate datasets, encompassing both binary and multi-class knee X-ray images related to osteoporosis.

Abubakar et al. [11] conducted a study using a dataset of knee radiographs to classify osteoporosis by applying and comparing the training times of three well-established transfer learning models: GoogLeNet, VGG-16, and ResNet50. The study not only focused on training efficiency but also evaluated and compared the diagnostic performance of these models in detecting osteoporosis from knee X-ray images.

O. M., and Kumar [12] proposed an innovative deep learning-based model for the early detection of osteoporosis using knee X-ray images, aiming to meet the urgent need for timely diagnosis. The approach employs a hybrid architecture combining ResNet50 and GRU networks. This model was applied to classify cases as either osteoporotic or normal using a dedicated dataset of knee radiographs.

Sarhan et al. [13] introduced an advanced approach for osteoporosis detection using transfer learning with CNNs on X-ray images. This method not only delivers high diagnostic accuracy but also provides visualized feature maps to support clinical interpretation. The innovation lies in combining multiple pre-trained CNN architectures—such as AlexNet, VGG-16, ResNet-50, VGG-19, Inception, Xception, and a custom-built CNN—with a dataset augmentation strategy aimed at improving learning performance. The study involves both binary and multiclass classification of knee joint X-ray images, categorizing them into normal, osteopenia, and osteoporosis groups.

Sarhan et al. [14] proposed a reliable method for detecting knee osteoporosis using a weighted ensemble approach capable of distinguishing between normal and osteoporotic conditions, even in the presence of slight data variations. To support the design of the ensemble architecture, experiments were conducted using several state-of-the-art CNN-based models with transfer learning. The ensemble model combines the outputs of two transfer learning models through feature concatenation to improve classification accuracy. However, the study notes that the model's performance is highly dependent on the selection of the base classifiers used in the ensemble.

Previous studies have employed deep learning and transfer learning methods for the binary classification of osteoporosis using knee X-ray images, often incorporating data augmentation to enhance accuracy and model interpretability. Collectively, these works highlight the potential of deep learning to support automated osteoporosis diagnosis. However, several challenges persist, such as the scarcity of annotated datasets, inconsistencies in imaging protocols, and the need for models that generalize effectively across diverse patient populations. This body of research emphasizes the promise of deep learning in transforming osteoporosis screening and care, while also pointing to the ongoing need for advancements in model development, validation, and integration into clinical workflows.

3. Methodology

The methodology adopted in this study focuses on exploring and assessing a deep learning-based system for the early detection of osteoporosis through medical imaging, aiming to facilitate timely clinical intervention. The objective is to create a reliable and interpretable diagnostic framework that can be seamlessly integrated into clinical settings to aid in the early identification and prevention of osteoporosis. The proposed approach consists of several key stages, which are visually summarized in Figure 1, providing a clear overview of the overall workflow.

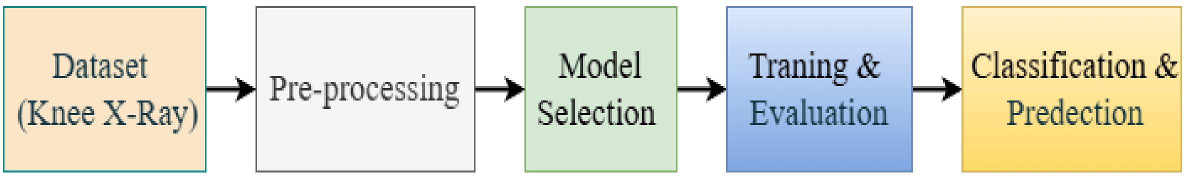

Figure 1: Methodology overview.

3.1. dataset

The dataset used in this study was compiled by merging data from two distinct sources to form a binary classification problem with two classes: Normal and Osteoporosis. The first dataset, publicly available on Kaggle [15], consists of 372 knee X-ray images, including 186 labeled as Normal and 186 as Osteoporosis. The second dataset was obtained from the Mendeley Data [16], which originally includes three categories: Normal (36 images), Osteopenia (154 images), and Osteoporosis (49 images). However, for consistency with the binary classification objective, only the Normal and Osteoporosis images were selected from this source, excluding the Osteopenia class.

After cleaning and merging both datasets, the final dataset comprises 457 images, with 222 labeled as Normal and 235 labeled as Osteoporosis. The dataset collection process from both sources is visually summarized in Figure 2.

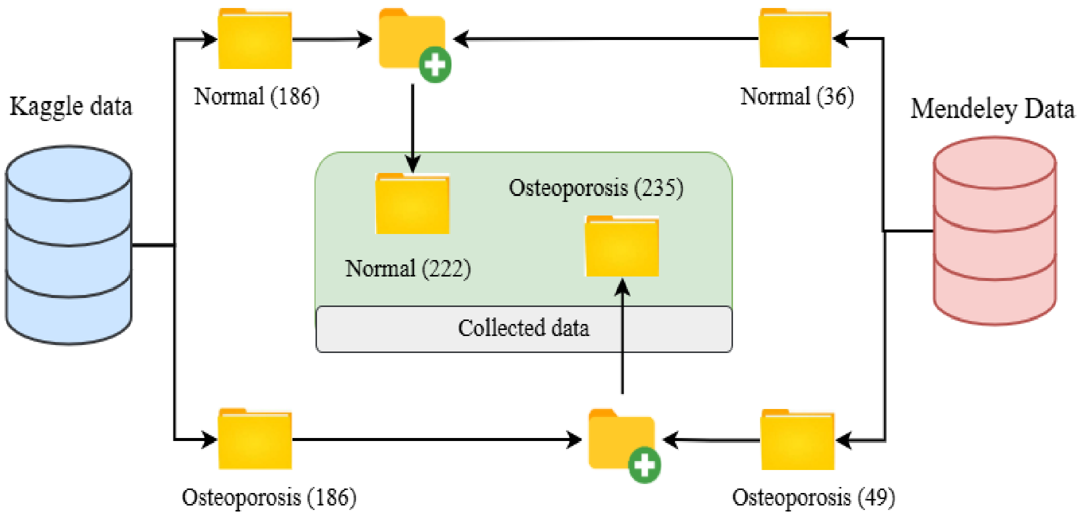

Figure 2: Dataset collection.

In addition, Figure 3 presents a visual sample of images from each class, providing insight into the visual differences the models learn to detect.

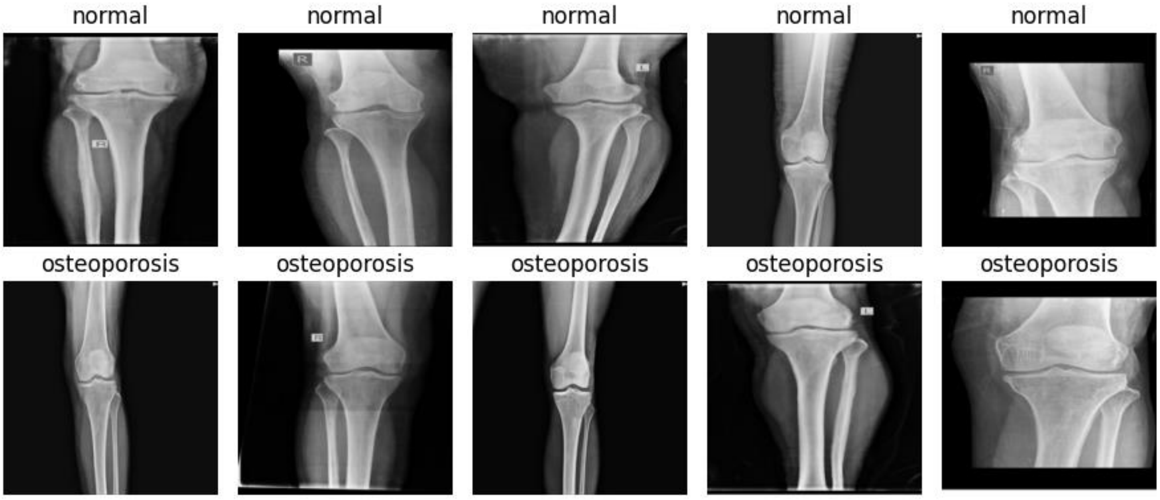

Figure 3: Dataset Image Samples.

3.2. preprocessing

The dataset is split into three subsets: 70% for training, 20% for validation, and 10% for testing. Prior to model training, all images are normalized and resized to 224×224 pixels to ensure uniformity and compatibility with the input requirements of the deep learning model.

To enhance model generalization and minimize the risk of overfitting, data augmentation techniques are applied to both the training and validation sets. These techniques help increase the effective size and diversity of the dataset. The test set remains unaltered to preserve its integrity for unbiased model evaluation. The applied augmentation techniques include horizontal and vertical flipping, which help the model become invariant to orientation. Brightness and contrast were adjusted to simulate varying lighting conditions. Contrast Limited Adaptive Histogram Equalization (CLAHE) was used to improve local contrast in the images, which can aid in highlighting important features. Additionally, rotational transformations were applied, rotating images by fixed angles of 90 and 45 degrees, enabling the model to better recognize patterns regardless of image orientation. Figure 4 illustrates examples of these augmentation methods, while Table 1 provides a summary of the number of images per class and per set, both before and after augmentation. This combined dataset forms the basis for training and evaluating the utilized models.

Table 1: dataset statistics.

Sets	Train	Validation	Test	Total
Original normal	155	44	23	222
Original osteoporosis	164	47	24	235
Augmented normal	930	264	-	1194

Augmented osteoporosis	984	282	-	1266
Total	2233	637	47	2917

Figure 4: Augmentation aspects utilized.

3.3. Implemented models

This study employs three CNN architectures, DenseNet201, ResNet50, and DenseNet121, to develop a deep learning framework for osteoporosis diagnosis using knee X-ray images. All models are fine-tuned through transfer learning, leveraging pre-trained weights to address the limited size of annotated medical data. The models are trained to classify images into two categories: Normal, and Osteoporosis, reflecting the clinical stages of bone density loss. Their use provides a robust and reliable diagnostic system, enhancing clinical relevance and accuracy.

ResNet-50 [17] is a deep CNN widely used for image recognition tasks. It belongs to the ResNet family and is known for its use of residual learning—a technique that allows the model to train deeper networks by using shortcut connections to skip layers. With 50 layers, ResNet-50 strikes a good balance between depth and computational efficiency, making it popular for transfer learning and real-world applications in computer vision.

DenseNet-121 and DenseNet-201 [18] are deep CNNs from the DenseNet family, which stands for Densely Connected Convolutional Networks. In these models, each layer receives input from all previous layers, promoting feature reuse and improving gradient flow. DenseNet-121 has 121 layers, while DenseNet-201 is deeper with 201 layers, offering more complex feature extraction. Both models are known for their efficiency in terms of parameter usage and high performance on image classification tasks.

3.4. Training and evaluation

The training and evaluation process in this study was designed to ensure reliable performance of the utilized models for osteoporosis detection. The models were trained using transfer learning, where the pre-trained weights from the ImageNet

dataset served as a starting point. The final classification layers were modified to accommodate the binary target classes: Normal, and Osteoporosis. The training phase involved fine-tuning these models on the prepared dataset.
In the experimental setup, key hyperparameters included an initial learning rate of 0.001, a batch size of 16, and 50 training epochs. The models were trained using cross-entropy loss and SGD optimizer. To ensure a fair and meaningful comparison of performance, identical parameter settings were applied to all models.
A comprehensive set of evaluation metrics—including accuracy, precision, recall, and F1-score—was employed to evaluate the diagnostic performance of each model and their ability to differentiate between the two bone health categories. Furthermore, confusion matrices were created for all models used to offer a detailed analysis of their classification outcomes.

4. Results and discussions

The results of the performance metrics for DenseNet201, ResNet50, and DenseNet121 are presented in Table 2. The performance trends and metric values for each model are also visually illustrated in Figure 5, providing a clear comparison that supports the numerical data shown in Table 2.

Table 2. performance metrics results

Metrics	Densenet201	Resnet50	Densenet121
Accuracy	0.8511	0.8085	0.7660
Precision	0.8574	0.8139	0.7663
Recall	0.8496	0.8071	0.7663
F1-score	0.8500	0.8071	0.7660

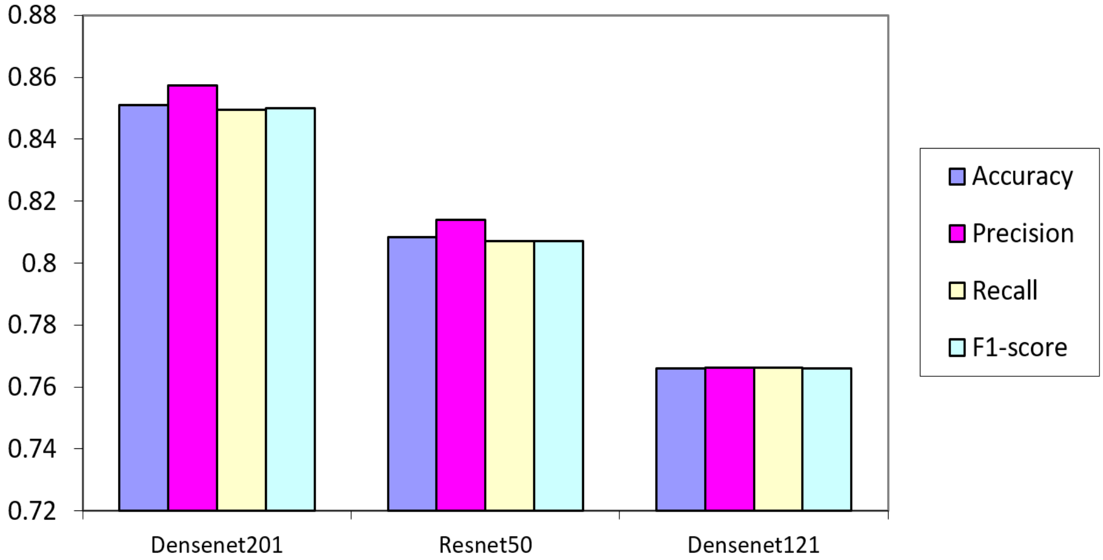

Figure 5: Representation results.

The evaluation metrics indicate that DenseNet201 delivers the strongest performance among the three models. It achieved the highest accuracy (0.8511), confirming its superior ability to correctly classify instances. Its precision (0.8574) and recall (0.8496) values demonstrate effective handling of both false positives and false negatives, while its F1-score (0.8500)—which balances these two metrics—further emphasizes its robustness and consistency.

ResNet50 showed moderate performance, with an accuracy of 0.8085, slightly lower precision (0.8139) and recall (0.8071), and an F1-score of 0.8071. These results suggest that while ResNet50 is reliable, it is somewhat less effective than DenseNet201 in this task.

DenseNet121 recorded the lowest scores across all metrics, with an accuracy of 0.7660, and nearly identical values for precision (0.7663), recall (0.7663), and F1-score (0.7660). This indicates limited capability in accurately distinguishing between the two bone health categories.

Ultimately, DenseNet201 emerges as the most effective model in this comparison, offering the best trade-off between precision and recall, and thus, superior diagnostic performance.

The Figure 6 displays three confusion matrices evaluating the performance of Densenet201, Resnet50, and Densenet121 models in classifying medical images as either normal or indicating osteoporosis. The evaluation was conducted on a test set comprising 47 images, consisting of normal and osteoporosis cases.

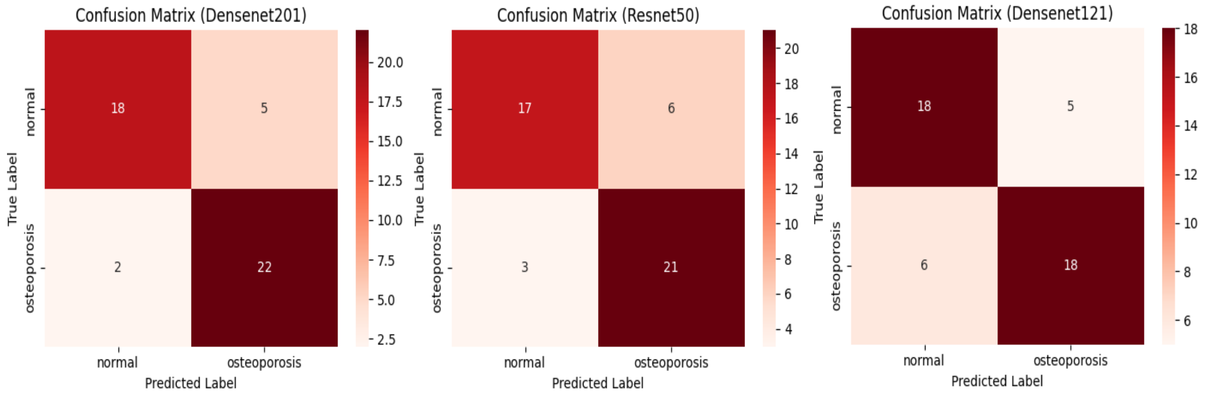

Figure 6: Confusion matrices.

Among the models, DenseNet201 demonstrated the most accurate classification, correctly identifying 18 normal and 22 osteoporosis cases. It made fewer errors, misclassifying only 5 normal cases as osteoporosis and 2 osteoporosis cases as normal.

In comparison, ResNet50 showed slightly lower performance, accurately classifying 17 normal and 21 osteoporosis cases. However, it misclassified 6 normal cases and 3 osteoporosis cases, indicating a higher error rate than DenseNet201.

DenseNet121 exhibited the least favorable performance, correctly predicting 18 normal and 18 osteoporosis cases. It had the highest number of misclassifications, with 5 normal and 6 osteoporosis cases incorrectly labeled.

Overall, DenseNet201 outperformed both ResNet50 and DenseNet121 by achieving the highest number of correct predictions and the fewest misclassifications, making it the most reliable model in this test scenario.

In addition, the prediction results for model’s classification of tested images as either normal or osteoporosis, along with the associated prediction probabilities, offering insight into the confidence of each model's decisions. For the DenseNet201 model, out of a total of 47 test images, 40 cases were correctly predicted, resulting in only 7 misclassifications. The ResNet50 model correctly classified 38 cases, with 9 incorrect predictions, while DenseNet121 achieved 36 correct predictions, misclassifying 11 cases. Sample of prediction results for the higher performance model (DenseNet201) on the test set are illustrated in Figure 7.

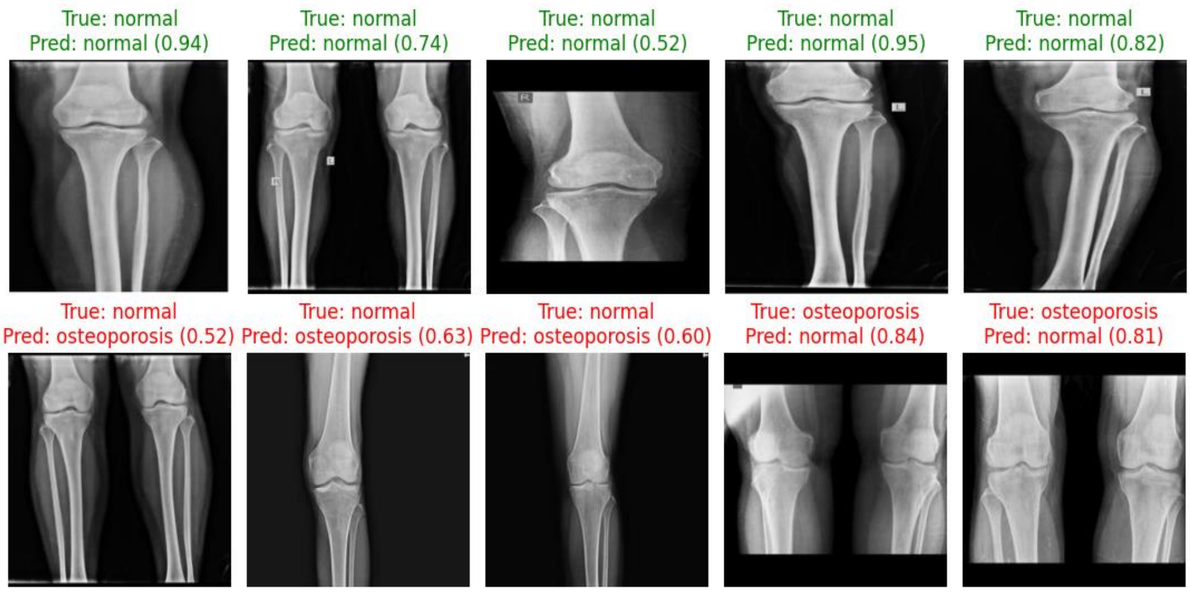

Figure 7: Prediction results for DenseNet201 model.

These results further support the superior performance of DenseNet201, not only in terms of overall accuracy but also in producing fewer incorrect classifications compared to ResNet50 and DenseNet121. The results help visualize these differences by showing individual prediction outcomes and confidence scores across all tested samples.

5. Conclusion

This study introduced a deep learning-based approach for the early diagnosis of osteoporosis using knee X-ray images, evaluating the performance of three pre-trained CNN models: DenseNet201, ResNet50, and DenseNet121. The application of effective data augmentation techniques and pre-trained models contributed significantly to the performance of the framework. Among the tested models, DenseNet201 achieved the highest accuracy in classifying images into two clinically relevant categories—normal and osteoporosis—demonstrating its potential to support timely diagnosis and prevent complications such as fractures and mobility loss. Its superior performance makes it a strong candidate for integration into clinical decision support systems. This study demonstrated the potential of AI-assisted tools to improve osteoporosis diagnosis by enabling earlier and more accurate detection, benefiting both patients and clinicians. Expanding and diversifying the dataset, incorporating clinical information, and utilizing lightweight, deployable models can significantly enhance diagnostic accuracy and contribute to more personalized and preventive approaches in bone health care.

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