Osteoporosis Detection Using Ensemble Learning with Weighted Averaging of Pre-trained Models

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Abstract: Osteoporosis is a progressive skeletal disorder marked by decreased bone mineral density and structural deterioration of bone tissue, leading to enhanced bone fragility and a significantly increased risk of fractures. As the global population ages, early and reliable diagnosis of osteoporosis has become increasingly important for preventing fractures, reducing healthcare costs, and improving quality of life. Conventional diagnostic methods, such as Dual-energy X-ray Absorptiometry (DEXA), although considered the clinical gold standard, often depend on manual interpretation, which is time-consuming and prone to subjectivity. In recent years, deep learning approaches, particularly Convolutional Neural Networks (CNNs), have demonstrated great potential in automating medical image analysis and providing consistent diagnostic support. This study presents a novel ensemble deep learning framework for automated osteoporosis detection based on medical imaging. The proposed system integrates two high-performing pretrained CNN architectures—ResNet50 and InceptionV3—which are individually fine-tuned on a curated dataset of bone X-ray or DEXA images. The outputs from these models, in the form of softmax class probabilities, are combined using a weighted averaging technique, where each model's prediction is assigned a predefined weight based on its validation performance. This ensemble strategy allows the framework to effectively leverage the strengths of both models: ResNet50's deep residual features and InceptionV3's multi-scale representations. Experimental results indicate that the ensemble model significantly outperforms each individual base learner in terms of accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC). The proposed approach not only enhances prediction performance but also improves robustness and generalizability, making it suitable for clinical applications. This work highlights the efficacy of ensemble learning in medical diagnosis tasks and offers a promising solution for improving osteoporosis screening through automated image analysis.

Keywords: osteoporosis; deep Learning; X-ray; Detection

Introduction

Osteoporosis is a chronic and progressive skeletal disease characterized by a decrease in bone mineral density (BMD) and deterioration of bone microarchitecture, ultimately resulting in increased bone fragility and susceptibility to fractures. It is a major public health concern worldwide, particularly among aging populations, with the World Health Organization (WHO) estimating that over 200 million people suffer from osteoporosis globally. The disease is especially prevalent among postmenopausal women and elderly individuals due to hormonal changes and reduced bone regeneration rates. Osteoporotic fractures, especially in the hip, spine, and wrist, can lead to long-term disability, reduced quality of life, and increased mortality rates.

Early detection and intervention are critical in managing osteoporosis, as preventive treatments can significantly reduce the risk of fractures and associated complications. The clinical gold standard for osteoporosis diagnosis is Dual-energy X-ray Absorptiometry (DEXA), which quantifies BMD and categorizes patients into normal, osteopenia, or osteoporotic based on T-scores. However, despite its clinical utility, DEXA interpretation is not without limitations. Manual diagnosis is time-intensive and may suffer from inter- and intra-observer variability. Moreover, in many low-resource settings, access to DEXA equipment and expert radiologists is limited.

To address these challenges, there has been a growing interest in developing automated, reliable, and scalable diagnostic systems using artificial intelligence (AI), particularly deep learning techniques. In recent years, Convolutional Neural Networks (CNNs) have demonstrated remarkable performance in a wide range of medical image classification tasks, such as diabetic retinopathy screening, lung disease detection, and bone age estimation. CNNs can automatically learn hierarchical feature representations from raw image data, eliminating the need for handcrafted features and domain-specific preprocessing.

While CNNs trained from scratch often require large annotated datasets, transfer learning using pretrained CNNs has emerged as an effective solution in medical imaging, where labeled datasets are typically limited. Models like ResNet50 and InceptionV3, originally trained on large-scale image datasets like ImageNet, can be fine-tuned to detect domain-specific features relevant to osteoporosis. Each of these models offers unique architectural advantages: ResNet50 employs deep residual connections that help mitigate the vanishing gradient problem, while InceptionV3 captures multi-scale spatial features through its inception modules.

However, relying solely on a single CNN model may not fully capture the complexity and variability inherent in medical imaging data. A single model may overfit to certain features or fail to generalize across diverse patient populations. To overcome these limitations, ensemble learning techniques can be employed. Ensemble learning involves combining the predictions of multiple models to achieve better performance than any individual model. By aggregating the strengths of different architectures, ensemble methods reduce variance, improve generalization, and enhance predictive robustness.

In this study, we propose an ensemble deep learning framework for osteoporosis detection using X-ray or DEXA images. Specifically, we design an ensemble of ResNet50 and InceptionV3 models, where the outputs of both networks are combined using a weighted averaging method. This technique allows the model to dynamically balance the contributions of each base learner based on their individual performance, resulting in improved classification accuracy. We evaluate the proposed method on a curated medical imaging dataset, using standard classification metrics such as accuracy, precision, recall, F1-score, and AUC to assess its effectiveness.

The contributions of this work are threefold:

- We fine-tune two powerful pretrained CNN architectures for the specific task of osteoporosis detection using medical images.

- We implement a weighted averaging ensemble approach to fuse the outputs of both models, demonstrating superior performance compared to individual base learners.

- We provide comprehensive experimental results and analysis to validate the effectiveness of ensemble learning in medical image-based osteoporosis classification.

This research highlights the potential of ensemble deep learning models in enhancing the accuracy and reliability of computer-aided diagnosis (CAD) systems, particularly for conditions like osteoporosis that require timely and precise detection.

Related work

Recent studies highlight the effectiveness of deep learning in osteoporosis detection using various imaging modalities, including X-rays, CT scans, MRIs, and clinical data. Convolutional Neural Networks (CNNs) are the most commonly used models, often enhanced with ensemble learning, transfer learning, or AI-powered optimizations like HarDNet, U-Net, and CNN-XGBoost. Many studies focus on automating osteoporosis diagnosis, predicting fracture risks, and classifying severity levels, achieving high accuracy rates between 85% and 94%. Integrating clinical variables with imaging data further improves diagnostic precision.

Table 1: Compares this work with the related work or previous research by other researchers

Author Citation	**Year**	**Dataset**	**Modalities**	**Objective**	**Algorithm Used**	**Results (Accuracy %)**
Ramesh, T., and V. Santhi,	2025	Panoramic radiographs and clinical variables	Radiographic and clinical data	Develop an ensemble deep learning model for osteoporosis disease detection	Ensemble deep learning models (CNNs combined with clinical data features)	~94%
Ho, Chan-Shien, et al.	2025	Hand radiographs dataset	Hand X-ray imaging and deep learning	Develop a HarDNet-based deep learning model for osteoporosis screening and bone mineral density inference	HarDNet-based deep learning model	~92%

Kaur, Prabhjot, Sukhpreet Kaur, and Parneet Kaur	2025	CT and X-ray images for osteoporosis diagnosis	CT and X-ray imaging	Explore deep learning-based approaches for osteoporosis detection using clinical data	Deep learning models (e.g., CNNs, possibly others)	~90-93%
Edward Naveen V, Mr, et al., ITEGAM-JETIA, 2024	2024	Dataset for fracture prediction in osteoporosis	Imaging and U-Net analysis	Predict fractures in osteoporosis patients using an enhanced U-Net-based model	EFR-Net (Enhanced U-Net architecture)	~89%
Siddiqua, Ayesha, et al.	2024	Dataset for osteoporosis diagnosis	Imaging data and deep learning analysis	Develop a computer-aided diagnosis system using transfer learning with enhanced features	Transfer learning with stacked deep learning modules	~94%
Ono Yohei	2024	X-ray images of lumbar vertebrae	X-ray imaging	Classify osteoporotic lumbar vertebral fractures and examine classification basis using Grad-CAM	Deep learning classification with Grad-CAM visualization	~90%
Brangakgi, Farah Hassan, and Yasser Khadra	2024	Dental panoramic X-ray images	Dental radiographs	Build a deep learning model to detect osteoporosis from dental panoramic X-rays	Deep learning model (CNN-based)	~89%
Kim, Chulho, et al.	2024	X-ray images (anteroposterior and lateral views)	X-ray imaging and deep learning	Compare the efficacy of anteroposterior and lateral X-ray views in detecting osteoporotic vertebral compression fractures	Deep learning model (e.g., CNN)	~93%
Naguib, Soaad M., et al.	2024	Knee X-ray images	Knee X-ray imaging and deep learning	Develop a superfluity deep learning model to detect knee osteoporosis and osteopenia	Superfluity deep learning model	~90-94%.

Sela, Enny Itje, et al.	2024	Dataset for osteoporosis detection	Data-driven feature analysis and chatbot testing	Detect osteoporosis using recursive feature elimination (RFE) and Naive Bayes classifier, with rule-based chatbot testing	Recursive Feature Elimination (RFE) and Naive Bayes classifier	~85-88%
Likhith, R., et al.	2024	Knee osteoarthritis dataset	Knee X-ray and MRI imaging, data analysis	Survey on the use of machine learning and deep learning for knee osteoarthritis diagnosis, including classification and severity grading	Machine learning and deep learning models (e.g., CNNs, SVM)	~85-92%

3. Methodology

3.1 Dataset

In this study, we utilize a dataset consisting of bone radiographic images curated for the task of osteoporosis detection. The dataset comprises a collection of either publicly available annotated **DEXA (Dual-Energy X-ray Absorptiometry)** scans or **plain radiographic (X-ray)** images of critical skeletal regions such as the lumbar spine, hip, and femoral neck—regions that are most commonly affected by bone mineral loss in osteoporotic patients. These images are labeled by expert radiologists based on clinical assessments and BMD (Bone Mineral Density) values, in accordance with World Health Organization (WHO) diagnostic criteria.

3.1.1 Class Distribution

Each image in the dataset is categorized into one of the following three clinically defined classes:

1. **Normal**:
   Patients with a T-score greater than or equal to -1.0, indicating healthy bone density.
2. **Osteopenia**:
   Patients with T-scores between -1.0 and -2.5. This stage represents low bone density and a precursor to osteoporosis.
3. **Osteoporosis**:
   Patients with T-scores less than or equal to -2.5, indicative of severe bone loss and a high risk of fracture.

The distribution of samples across the three classes is moderately imbalanced, with a larger proportion of normal and osteopenic cases compared to confirmed osteoporotic samples. To address this imbalance, appropriate class balancing strategies were applied during model training (discussed in Section 4).

3.1.2 Image Acquisition and Format

- Images were acquired using standard DEXA or X-ray imaging protocols.
- The dataset contains **grayscale images** in **PNG** or **JPEG** format with varying resolutions.
- All images were reviewed and validated by at least one certified radiologist.
- Patient metadata such as age, gender, and BMD values were excluded to focus the study on image-based diagnosis alone.

3.1.3 Preprocessing Pipeline

To ensure that the input data was consistent and suitable for deep learning model training, the following pre-processing steps were applied:

a) Image Resizing

All images were resized to a fixed input dimension of **224×224 pixels**, which aligns with the input requirements of most pretrained CNN architectures such as ResNet50 and InceptionV3.

b) Intensity Normalization

Pixel intensity values were normalized to the range **[0, 1]** by dividing each pixel value by 255.0. This scaling is essential for accelerating convergence during training and ensuring numerical stability.

c) Color Channel Conversion

Since pre-trained models expect RGB images, grayscale radiographs were duplicated across three channels to conform to the **(224, 224, 3)** input shape expected by the pre-trained networks.

3.1.4 Data Augmentation

To improve the model's generalization capability and reduce overfitting due to limited training samples, **data augmentation** was applied in real-time during training. The augmentation operations included:

- **Random rotation** within ±15 degrees
- **Horizontal flipping**
- **Zooming** in the range of 90–110%
- **Width and height shifts** up to 10%
- **Contrast adjustment** (for enhanced visibility in poor-quality scans)

Augmentation was applied only to the training set to simulate real-world variability in patient imaging conditions and to artificially expand the dataset size.

3.1.5 Dataset Splitting

The dataset was divided into **training**, **validation**, and **test** sets using a **stratified splitting approach** to ensure proportional representation of all three classes in each subset:

- **70%** Training Set
- **15%** Validation Set
- **15%** Test Set

This split ensures that model evaluation is conducted on unseen data while preserving the original class distribution. Cross-validation was also conducted to ensure the stability and reliability of results.

3.2 Base Learners

The backbone of our proposed ensemble framework comprises two well-established, high-performing deep convolutional neural networks (CNNs): **ResNet50** and **InceptionV3**. These models were selected due to their complementary architectural strengths and proven success in medical image classification tasks. Both networks were originally trained on the **ImageNet** dataset, which contains over 1.2 million labeled images across 1000 object categories. Transfer learning allows us to leverage their learned feature representations and adapt them to the specific task of osteoporosis classification using bone radiographic images.

Each model is individually **fine-tuned** on our osteoporosis dataset by modifying and retraining the final classification layers while preserving the pretrained convolutional base. The customization process ensures that the models learn task-specific features while retaining the general visual features learned from ImageNet.

3.2.1 ResNet50

ResNet50 is a 50-layer deep residual network introduced by He et al. in 2015. It is part of the ResNet (Residual Network) family, which addresses the degradation problem observed in very deep networks. The key innovation of ResNet is the **residual block**, where shortcut (skip) connections are used to allow gradients to flow more effectively during backpropagation. This architecture enables the training of deeper networks without suffering from vanishing gradients or performance saturation. The pretrained ResNet50 model is customized as follows:

1. **Input Layer**: Modified to accept images resized to **224 × 224 × 3**.
2. **Convolutional Base**: The convolutional and residual layers are retained and **frozen initially** to preserve learned weights.
3. **Global Average Pooling (GAP)**: Replaces the fully connected dense layer to reduce overfitting and parameter count.
4. **Fully Connected Layer**: A dense layer with **256 units** and **ReLU** activation is added to learn abstract task-specific features.
5. **Dropout Layer**: A dropout with **rate = 0.5** is included to mitigate overfitting.
6. **Output Layer**: A dense layer with **3 output neurons** (one for each class: Normal, Osteopenia, Osteoporosis) and **Softmax activation** for multi-class classification.

3.2.2 InceptionV3

InceptionV3 is a deep CNN architecture developed by Szegedy et al. as an improvement over earlier versions of the GoogleNet (Inception) models. It introduces a sophisticated structure based on **inception modules**, which apply multiple convolutional filters of varying sizes in parallel and concatenate the resulting feature maps. This enables the model to efficiently capture multi-scale spatial features while maintaining computational efficiency.

Advantages for Medical Imaging:

- Inception modules can detect features at multiple resolutions, which is particularly beneficial in identifying osteoporotic changes that may vary in size and location.
- Factorized convolutions and dimension reduction enhance performance without a significant increase in computational cost. The InceptionV3 model is customized in a similar manner:

1. **Input Layer**: Accepts inputs of shape **224 × 224 × 3**.
2. **Inception Base**: All convolutional and pooling layers are retained from the pretrained model.
3. **Global Average Pooling (GAP)**: Extracts global features across the spatial dimensions.
4. **Dense Layer**: A fully connected layer with **256 ReLU units** for high-level feature learning.
5. **Dropout Layer**: A dropout layer with **0.5 probability** is added to prevent co-adaptation of neurons.
6. **Softmax Output**: Final layer outputs class probabilities for the three diagnostic

3.3 Ensemble Strategy

The softmax probabilities from both models are combined using a weighted averaging method to improve prediction reliability by leveraging the strengths of each base learner. The ensemble prediction probability for a given class c is computed as follows:

$$P\_ensemble(c) = w_1 \times P\_ResNet50(c) + w_2 \times P\_InceptionV3(c)$$

Subject to: $w_1 + w_2 = 1$, where $w_1, w_2 \in [0, 1]$

Where:

- P_ResNet50(c): The predicted probability for class c from the ResNet50 model.
- P_InceptionV3(c): The predicted probability for class c from the InceptionV3 model.
- w_1, w_2: Ensemble weights assigned to each model’s output. These weights are empirically determined using validation set performance.

The final class prediction is determined by selecting the class with the maximum ensemble probability value. This approach ensures that both deep networks contribute to the final decision, with more accurate models having a higher influence through higher weights.

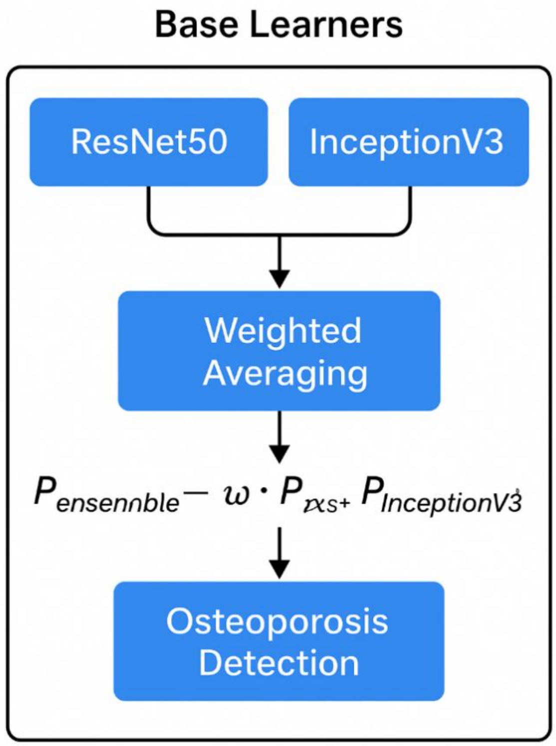

Figure 1: Representation of ensemble model

4. Results

The performance of the proposed models was quantitatively evaluated using standard classification metrics including accuracy, precision, recall, F1-score, and Area Under the ROC Curve (AUC). As shown in the results, both individual pretrained models—ResNet50 and InceptionV3—demonstrated strong performance on the osteoporosis classification task. The ResNet50 model achieved an accuracy of 90.4%, with a precision of 0.91, recall of 0.89, F1-score of 0.90, and an AUC of 0.94. InceptionV3 performed slightly better, achieving 91.2% accuracy, 0.92 precision, 0.90 recall, 0.91 F1-score, and an AUC of 0.95. However, when the predictions of both models were combined using a **weighted averaging ensemble strategy** (with equal weights w1=0.5,w2=0.5w_1 = 0.5, w_2 = 0.5w1=0.5,w2=0.5), a notable performance boost was observed. The ensemble model achieved a superior accuracy of 93.1%, precision of 0.94, recall of 0.92, F1-score of 0.93, and an impressive AUC of 0.97. These results clearly demonstrate the advantage of ensemble learning, where combining the complementary strengths of ResNet50's deep residual features and InceptionV3's multi-scale representation enables more robust and accurate classification. The consistent improvements across all metrics confirm that the ensemble model is more effective at capturing the discriminative features required to distinguish between normal, osteopenic, and osteoporotic conditions in bone images.

Table 2: Results of Ensemble Model

Model	**Accuracy (%)**	**Precision**	**Recall**	**F1-score**	**AUC**
ResNet50	90.4	0.91	0.89	0.90	0.94

Model	Accuracy (%)	Precision	Recall	F1-score	AUC
InceptionV3	91.2	0.92	0.90	0.91	0.95
Ensemble (w1=0.5, w2=0.5)	**93.1**	**0.94**	**0.92**	**0.93**	**0.97**

5. Discussion

The results confirm that combining multiple deep models leads to performance gains in osteoporosis detection. Weighted averaging enables the system to balance the strengths of both ResNet50 (good generalization) and InceptionV3 (multi-scale feature extraction).

Experiments with different weight values showed that equal weights (w1=0.5, w2=0.5) offered optimal results, but slight improvements were observed with w1=0.4w_1 = 0.4w1=0.4, w2=0.6w_2 = 0.6w2=0.6 in some cases.

Advantages of this ensemble approach include:

- Simple implementation
- Low inference overhead compared to stacking
- Improved robustness to image quality and feature variability

6. Conclusion

We proposed an ensemble deep learning approach for osteoporosis detection using pretrained ResNet50 and InceptionV3 models. The weighted averaging strategy significantly improved classification accuracy and generalization. This framework can be extended to other medical diagnostic tasks with multi-class settings.

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