International Journal of Science and Research (IJSR)
ISSN: 2319-7064
Impact Factor 2025: 7.089

Deep Learning Approaches for Osteoporosis Detection: Advances, Challenges, and Future Directions

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Abstract: ***Osteoporosis is a chronic and progressive skeletal disease that is characterised by a reduction in bone mineral density (BMD) and progressive deterioration of bone microarchitecture, which increases fracture risk. Its largely asymptomatic presentation frequently results in delayed detection, being already in advanced stages of the disease until severe fractures and consequent morbidity appear, so the early and correct diagnosis is fundamental for the implementation of effective interventions and the improvement of patient outcomes. Recent advances in artificial intelligence, particularly in deep learning (DL), have demonstrated significant potential in automating the detection of osteoporosis, estimating BMD, and predicting fracture risk. This review systematically examines fifty research studies involving models based on machine learning (ML) and deep learning (DL), as well as a variety of medical imaging modalities, including X-ray, computed tomography (CT), low-dose computed tomography (LDCT), and magnetic resonance imaging (MRI). Radiography-based convolutional neural network (CNN) models were found to have diagnostic accuracy in the range of 0.74 to 0.93, with ensemble and attention-driven architectures beating the conventional single model frameworks. Models using CT and LDCT images achieved an excellent level of precision (AUROC > 0.90) for BMD predictions and for fracture risk assessment, and the performance of MRI-revealing methods was better for the detection and characterization of vertebral fractures. Multimodal learning approaches incorporating imaging, clinical, and demographic features further improved both the predictive robustness and interpretability. Despite promising advances, there are still considerable research limitations, such as small sample sizes, class imbalance, high computational costs, and a lack of external or cross-population validation. Future investigations should focus on the collection of large and multi-institutional datasets, the development of explainable and privacy-preserving AI models, the improvement of advanced feature-fusion strategies, and the implementation of real-time and clinically integrable decision support systems. Overall, this review highlights the increasing role of deep learning in the diagnosis of osteoporosis and outlines the future direction of deep learning toward clinically reliable, scalable, and interpretable artificial intelligence (AI)-driven solutions.***

Keywords: Osteoporosis detection; Deep learning algorithms; Bone mineral density, X-ray, Computed tomography (CT); Magnetic resonance imaging (MRI); Artificial Intelligence

1. Introduction

Osteoporosis is a chronic bone disease characterised by a progressive decrease in bone mass and deterioration in bone microarchitecture, which increases the fragility of the bones and the rate of fracture, in particular of the hip, lumbar spine, and wrist[1]. The disorder very often goes clinically quiescent in its incipient stages before presenting with a fragility fracture, which is often after the onset, and may have a significant impact on quality of life and contribute to high morbidity and mortality in elderly cohorts [2]. Osteoporosis currently affects over 200 million people worldwide, mostly postmenopausal women and the elderly, and is a major issue for public health, given the challenges of demographic ageing and the associated health care budgets[3, 4]. The disease not only causes skeletal complications but also contributes to long-term disability, loss of mobility, and loss of autonomy, hence the importance of early detection and preventive care [5].

Bone is a dynamic tissue that continuously remodels itself through the balanced action of osteoblasts, the bone-forming cells, and osteoclasts, the bone-resorbing cells. Osteoporosis occurs when this balance is disrupted and a net loss of bone mass and structural integrity of the skeleton takes place. Etiological contributors to osteoporosis include hormonal changes (reduced levels of oestrogen after menopause), nutritional deficiencies, particularly of Calcium and Vitamin D, a sedentary lifestyle, genetic susceptibility, chronic disease states, and the use of medications, such as glucocorticoids [6]. Bone mineral density (BMD) is a key marker of skeletal integrity and is widely used to define osteoporosis.2 A BMD T score 2.5 or more standard deviations below the mean for young adults (T <= -2.5) represents a diagnosis of osteoporosis, while a BMD T score of -1.0 to -2.5 represents the condition osteopenia, which is a transitional phase between osteoporosis [7].

Conventional methods of detecting osteoporosis mainly depend on imaging and laboratory approaches to determine BMD and bone quality. DXA is the gold standard, which is known to provide a quantitative assessment of BMD in the most important skeletal areas (lumbar spine and neck of the femur). Even though DXA offers high diagnostic accuracy, its low accessibility, high cost, and need to use special equipment limit its use in widespread screening, especially in resource-constrained environments. Other imaging methods are also complementary to sonography, like quantitative computed

tomography (QCT), magnetic resonance imaging (MRI), and ultrasound, as they provide more information about bone geometry and trabecular microarchitecture, but at the cost of higher expense, radiation exposure, or reduced accessibility. Radical radiography (X-rays) is the most commonly available, and it is affordable, but it does not have such sensitivity to detect early osteoporosis because the changes in bone density are subtle, and it is not easy to observe them. As a result, there is an increased need to create automated, precise, and inexpensive screening devices with the ability to utilize the available imaging data to identify opportunistic osteoporosis [8].

Machine learning (ML), which is a subfield of artificial intelligence (AI), has shown great promise in using complex biomedical data to improve disease diagnosis and prediction[9]. ML models are trained on marked data and thus can classify or predict results on unknown data [10-12]. Traditional ML methods, including support vector machines (SVM), random forests (RF), and k-nearest neighbors (KNN) have been used in the research to predict fracture risk, categorize BMD levels, and determine high-risk groups of patients in the context of osteoporosis using clinical, biochemical, and imaging data. ML feature selection methods assist in determining the most predictive variables among very large data volumes, enhancing the interpretability of a model and making the computation more complex. but the classical ML approaches tend to do a lot of feature engineering and might not be able to potentially represent the complicated spatial and textural hypotheses that exist in medical images.

Deep learning (DL), a more advanced subset of ML, has revolutionized medical image analysis by automatically extracting hierarchical features from raw data without the need for manual feature engineering [13]. CNNs are excellent at handling radiographs, CT scans, and MRI images in diagnosing osteoporosis, estimating BMD, and determining fracture status. In addition to single CNN networks, there are also ensemble networks and attention-based networks, which also involve multiple feature representations or emphasize the informative part of an image, making them more accurate as a diagnostic. Furthermore, multi-modal deep learning models that integrate imaging with other clinical factors, including age, sex, BMI, and biochemicals, have been shown to perform higher and interpretable, allowing the risk to be stratified on a patient-by-patient basis. The recent advancements in state-of-the-art deep learning frameworks and transformers have further increased the possibilities of exploring the more intricate, high-dimensional datasets, enabling more advanced applications like fracture prediction, opportunistic screening, and automated segmentation of skeletal structures.

The main objective of the review is to syntactically review and analyze recent developments in the field of deep learning and hybrid machine learning models to detect osteoporosis. This will involve assessing the performance of models in diverse imaging modalities (X-ray, CT, MRI), multi-modal integration with clinical data, and strategies of feature extraction. The review also aims to determine the challenges, limitations, and future directions to inform future studies in automated, accurate, and clinically interpretable osteoporosis screening.

2. Radiography-based Deep Learning Models

Radiographs are the most common imaging modality for osteoporosis screening due to accessibility and low cost. Several studies have applied CNN-based models for automatic BMD estimation, fracture prediction, and osteoporosis classification (Table 1). Y Ono et al. [14] used ensembled CNNs on lumbar vertebra X-rays, achieving 0.89 accuracy for fresh vs old fracture detection. Yen et al. [15] predicted lumbar and hip BMD from KUB radiographs, with correlation coefficients of 0.858 (lumbar) and 0.87 (hip). V. Kawade et al. [16] compared YOLOv7, YOLOv8, ResNet-50, and InceptionNet on hip X-rays, achieving the highest accuracy with YOLOv8. Buaruk et al. [17] highlighted the importance of combining clinical features with X-ray images, improving classification accuracy from 0.63 to 0.77 using a two-step binary strategy. Abubakar et al. [18] showed that fine-tuned VGG-16 improved knee X-ray osteoporosis detection from 80% to 88% accuracy. Yoshida et al. [19] showed bidirectional chest X-rays provided higher sensitivity (92.8%) for BMD estimation than single-view CXR. Muzaffar et al. [20] integrated attention mechanisms with LPQ and VGG for fine-texture osteoporosis detection, achieving 74.1% accuracy. Ichahane et al. [21] developed E-DWE CNN combining multiple CNNs with attention and ensemble weighting, reaching 92.8% accuracy. Radiography-based models show promising accuracy (0.74–0.93) for osteoporosis screening and BMD prediction. Ensemble and attention-based networks outperform single CNNs due to better feature extraction and robustness. Combining clinical features with image data (Buaruk et al.) further improves performance. Bidirectional or multi-view X-rays (Yoshida et al.) enhance sensitivity in lumbar BMD estimation. Limitations include small datasets (Kawade et al.) and relatively lower performance for fine-grained osteoporosis classification without clinical data.

Feng et al. [22] designed a U-Net segmentation model of X-rays of the hips (femoral neck, greater trochanter, Ward triangle, and total hip), and then trained DenseNet121 to classify. Without any clinical covariates, the maximum accuracy was 74% with the total hip T-score classification using the image data only. This indicates that image-based segmentation with CNN classification can moderately identify osteoporosis, but possibly is constrained by the size of the datasets or mono-modal use. To train a CNN to classify normal BMD, osteopenia, and osteoporosis, L. Mao et al. (2022) [23] utilized lumbar radiographs. The image-only model had an AUC of 0.909-0.937 for the detection of osteoporosis. The study also emphasized that multiview input (anteroposterior and lateral) outperforms better than the other inputs, which is in line with the finding that more image input enhances predictive accuracy. The dental panoramic radiographs and CNNs (EfficientNet and ResNet variants) were utilized in S. Sukegawa et al. (2022) [24]. The ensemble model of images by itself was highly accurate and AUC, meaning that high-quality dental radiographs alone can offer enough information to detect osteoporosis. A Superfluity deep learning model of knee X-rays was proposed by S. M. Naguib et al. (2024) [25]. The model got 85.42% and 79.39% accuracy on two data sets using pre-trained image data only, which is better than AlexNet and ResNet50. It means that image-specific deep learning models can exceed the

traditional pre-trained networks. P. Varalakshmi et al. (2022) [26] used pre-processing and Inception v3 CNN on the images of DEXA scan to predict images only. The accuracy was 92.05, indicating that image enhancement, augmentation, and CNN depth were very critical to high performance. In [27], R. Dzirzak et al. created a DCNN model on spinal CT images, with a VGG16 ACC of 95%. The transfer learning of image-only models was important and enabled high performance when using pre-trained models and data augmentation on a tiny image dataset.

T. Nakamoto et al. [28] used AlexNet, VGG16, and GoogLeNet to process panoramic dental radiographs. Image-based predictions were found to be accurate 74-79; however, when mixed with clinical data, accuracy improved, which demonstrated that X-ray images do capture considerable but limited osteoporosis-specific signals. R. D. Iman et al. (2023) [29] used CLAHE preprocessing and ResNet50/101 to improve the X-ray contrast. Image-only ResNet101 was found to be 96% accurate, showing that contrast enhancement and preprocessing is essential to X-ray image-based models. Knee X-rays imaged with DenseNet201 were reported to be classified as image-only with 85.11% accuracy [30] , performing better than other CNN versions and supporting the notion that DenseNet is able to identify fine structural details useful in diagnosing osteoporosis. R. Gaudin et al. (2024) [31] applied dental panoramic radiographs and pretrained CNNs. Image-only detection with AUC ranging between 0.8401 and 0.9812 in depending on population, demonstrates the possibility of using the targeted areas of images to make predictions. C.-S. Ho et al. (2025) [32] created DeepDXA-Hand based on hand radiographs. The correlation of image-only BMD was r = 0.745, and the classification accuracy was 80 percent, which implied that hand X-rays could be used to give adequate radiological data to be used in opportunistic screening. The stacked deep learning blocks, as used by A. Siddiqua et al. (2024) [33]In knee X-rays, the realized accuracy of 97-98% in various datasets when using image-only features. The paper notes that improved CNN structures have the potential to utilize the maximum structural information of knee radiographs. D. T. Rao et al., (2022) [34] described a five-level U-Net which utilized imaging and clinical predictors, with an accuracy and AUC of 99.23 and 99.72, respectively, much higher than other traditional CNN architectures like GoogleNet and ResNet. The incorporation of clinical characteristics, including the patient history and laboratory tests, showed that hybrid models could be effective in improving the performance of the models, as multimodal inputs are significant even in using 2D radiographs.

Keerthika et al. [35] were the first to apply this method in comparing various CNN architectures (VGG16, ResNet, DenseNet, AlexNet, GoogLeNet) and demonstrated that effective preprocessing and data augmentation enhance the performance of generalization and classification. The overall implication of these studies is that, with appropriate feature engineering and optimization, radiography-based DL models have the potential to offer rapid and non-invasive high-quality early detection. N. Hong et al., 2025 [36] utilized spine images to train DL models and showed that the prediction of incident fracture with a DL was better than clinical risk factors, with an AUC of 0.926 in fracture and 0.848 in osteoporosis. A. Z. Mohammed et al., 2022 [37] The article trained on DEXA spine scans and, consequently, obtained 98% accuracy in osteoporosis detection. Noise removal, contrast enhancement, and ROI selection were preprocessing operations that were important in feature extraction. This means that even the low-resolution or unclear DEXA images can be exploited to their advantage with the help of DL, which offers a viable alternative to mass screening programs. A. Kumar et al., 2022 [38] Both of the architectures, Osteo-Net and VGG16+FNN, were demonstrated to offer accurate screening of low-quality X-ray images with a relatively low computation cost. Precision was between 82 and 84 per cent on invisible test images. Those models prove that it is possible to apply deep learning in resource-constrained conditions, and it may be used as a supplement to DXA-based diagnosis in a primary-care environment or in developing areas.

Table 1: Radiography-based DL methods

Ref. No.	Approach	Imaging Modality	Sample Size	Key Techniques	Advantages	Limitations
[14]	CNN Ensemble	Lumbar X-ray	500	Ensemble CNN	Ensemble improves robustness and reduces prediction bias	Limited to fracture; lacks osteoporosis-specific biomarkers & clinical fusion
[15]	CNN	KUB X-ray	450	Regression-based	Non-invasive low-cost prediction using plain X-ray	No segmentation; single-view imaging limits structural detail
[16]	YOLOv7/YOLOv8 + ResNet-50 + InceptionNet	Hip X-ray	600	Object detection + deep features	Multiple SOTA models evaluated; strong feature extraction	No clinical features; lacks automated ROI precision
[17]	CNN + Clinical Features	X-ray	350	Two-step classification	Integrates clinical variables, improving interpretability	Small dataset, limited generalization & lower accuracy
[18]	VGG-16 Fine-tuned	Knee X-ray	400	Transfer learning	Transfer learning boosts performance with limited data	Lacks ROI segmentation; single-view imaging
[19]	Multi-view CNN	Chest X-ray	300	Bidirectional input	Multi-view improves structural sensitivity	Small dataset; chest view less anatomically specific
[20]	CNN + Attention	X-ray	280	LPQ + VGG + Attention	Attention enhances feature focus	Very small dataset & low performance
[21]	E-DWE CNN	X-ray	600	Ensemble + Attention	Attention + ensemble improves accuracy & robustness	High computational cost; no external validation

[22]	U-Net + DenseNet121	Hip X-ray	200	Hip segmentation + CNN	ROI segmentation improves reliability	Very small sample & low accuracy
[23]	CNN	Lumbar X-ray	400	Single & Multi-view	View-based comparison strengthens detection	No external testing & limited CNN complexity
[24]	EfficientNet + ResNet Ensemble	Dental X-ray	500	Pretrained CNN ensemble	Non-invasive & easy-to-acquire images	Dental imaging is not the gold standard for osteoporosis
[25]	Superfluity DL	Knee X-ray	250	Custom CNN	Custom design aims at feature enhancement	Very small dataset & no baseline comparison
[26]	Inception v3	DEXA	180	Augmentation + TL	Uses gold-standard omaging modality	Very small dataset & lacks clinical validation
[27]	DCNN (VGG16)	Spinal CT	120	TL + Augmentation	Excellent CT-based structural feature learning	Very small dataset; overfitting risk
[28]	AlexNet, VGG16, GoogLeNet	Dental X-ray	200	Pretrained CNN	Extracts multi-level deep features	Low performance & insufficient data
[29]	CLAHE + ResNet50/101	X-ray	180	Contrast enhancement + TL	Improved visibility through pre-processing	Dataset too small & no segmentation
[30]	DenseNet201	Knee X-ray	300	Fine-tuning	Strong hierarchical feature extraction	Limited sample size; moderate accuracy
[31]	Pretrained CNN Ensemble	Dental X-ray	450	Region-based learning	Ensemble-based ROI-driven analysis	Lacks clinical validation & dental modality limitation
[32]	DeepDXA-Hand	Hand X-ray	400	Regression CNN	Fast, low-cost screening alternative	Anatomically indirect for bone health
[33]	CAD + TL + Feature Enhancement	Knee X-ray	Not Given	Layered Conv-ReLU-MaxPool	Robust architecture with enhanced feature blocks	Dataset size unknown; no multi-center validation
[34]	Efficient U-Net CNN	Knee XR/CT/MRI/US	Not Given	U-Net + Clinical variables	Multimodal + clinical data fusion	Dataset missing; risk of overfitting
[35]	CNN Variants	Knee X-ray	Not Given	Augmentation + CV	Compares multiple architectures for insight	Dataset unspecified; classical CNN limitations
[36]	Pretrained DL	Spine XR + VFA	26,299 XR / 9,276 subjects	TL + fine-tuning	Very large dataset; high reliability	No clinical biomarkers; heavy computation
[37]	DL	Spine DEXA	Not Given	ROI + preprocessing	Uses the strongest imaging modality	Dataset details unclear & opaque
[38]	Osteo-Net	Bone X-ray	Not Given	Deep Residual-style CNN	Lightweight architecture	Unknown dataset & moderate results
[39]	Volumetric DL	Lumbar CT	1,008	3D segmentation & analysis	Fully automated volumetric processing	No classification output; computationally heavy
[40]	Hybrid DL (QDNN + I-DCNN + RNN)	X-ray	Not Given	Multi-stage hybrid optimization	Combines handcrafted + DL + optimization	Pipeline complexity & poor dataset disclosure
[41]	EfficientNet-B5	X-ray (AP + Lat)	1,507 + 104 external	Cross-validation	Excellent generalization with external testing	High computational demand
[42]	VGG16 + FNN	Spine X-ray	Public	VGG16 features + FNN	Good performance using a simple architecture	No multimodal clinical or 3D context

3. CT-based models

CT-based models enable precise bone density assessment and fracture risk prediction (Table 2). Hu et al. [43] predicted subsequent vertebral fractures from CT, achieving 0.839 accuracy. Tong et al. [44] combined deep learning and radiomics on low-dose chest CT, achieving 0.983 AUROC for osteoporosis detection. Cho et al. [45] used CT body composition and MLP for simultaneous prediction of metabolic syndrome, osteoporosis, and sarcopenia; osteoporosis AUROC was 0.90. Fang et al. [46] combined radiomics with DL and transfer learning on chest CT, identifying osteoporosis without additional bone turnover markers. Liu et al. [47] differentiated spinal tuberculosis from acute vertebral compression fractures using sagittal CT/MRI, achieving up to 98.98% accuracy with MVITV2. According to S. Oh et al. (2024) [48], DL-QCT was applied to BMD measurements on regular CT scans (e.g., L1/L2 vertebrae). With the reference method, image-only predictions of 77.7-92.9 were also attained. This demonstrates that opportunistic CT scans may be used as a credible source of screening for osteoporosis even without extra information on the patient. The article by X. Niu et al. (2023) [49] applied a completely automated DL system to low-dose CT (LDCT) targeting the vertebral BMD. Image-only prediction with 3D segmentation (AnatomyNet + DenseNet) resulted in AUC 0.984 on osteoporosis, which demonstrates the predictive accuracy of volumetric CT images compared to 2D X-ray images. The results obtained by H. Park et al. (2024) [50] are also similar to this study: CT datasets across various vendors were used, and the authors applied the DL-BMD models to accurately correlate with the manual BMD values. These CT-based models are robust regardless of the type of scanner and protocol. A completely automated DL pipeline to measure lumbar vertebral segmentation and trabecular attenuation using non-contrast CT scans was proposed by Schmidt et al. (2022) [39] . The model allows opportunistic osteoporosis screening of routine CT scans done because of other indications by automatically excluding cortical bone and quantifying trabecular density. The key benefit is that the

quality of bone is assessed quantitatively and objectively in comparison to qualitative radiographs. Nevertheless, CT-based models have been struggling with issues such as radiation exposure, inability to be available to large population groups, and increased computational demand. CT-based models demonstrate high accuracy and AUROC (>0.90) for osteoporosis detection and fracture prediction. Multi-label and multi-modal approaches allow simultaneous assessment of comorbidities like sarcopenia. LDCT combined with DL is non-invasive and reduces radiation exposure. Radiomics features improve interpretability, but DL alone often achieves comparable performance.

Table 2: CT-based DL methods

Ref. No.	Approach	Imaging Modality	Sample Size	Key Techniques	Advantages	Limitations
[43]	CNN	CT	400	CNN-based deep feature extraction	Learns bone structural patterns directly from CT; useful for early fracture risk detection; improves sensitivity over manual interpretation	Limited generalizability due to small dataset; may misinterpret noisy/low-quality scans; lacks multi-modal feature enrichment
[44]	DL + Radiomics	LDCT	500	Radiomics + CNN	Combines handcrafted and learned features; high accuracy using low-dose CT; effective quantitative biomarker extraction	Requires radiomics expertise and computing overhead; radiomics features may be sensitive to acquisition protocol variations
[45]	MLP	CT Body Composition	450	Multi-layer Perceptron	Low computational complexity; easier integration with clinical variables; suitable for structured feature input	Relies on pre-extracted features, not raw imaging; less effective for spatial feature learning compared to CNN/transformers
[46]	Transfer Learning + Radiomics	Chest CT	350	Pretrained CNN + Radiomics	Requires fewer training samples; radiomics boosts micro-texture analysis; useful when the target bone region not directly imaged	Possible domain mismatch in pre-trained models; high feature dimensionality may lead to overfitting without strong feature selection
[47]	MVITv2 (Transformer)	CT/MRI	250	Multi-view vision transformer	Captures global + contextual relationships; robust under imaging variations; superior performance for similar pathology differentiation	Transformer models require large datasets for general robustness, a high computational cost during training, and inference
[48]	DL-QCT	Routine CT (L1/L2)	350	Automated segmentation + CNN regression	Enables opportunistic osteoporosis screening using routine CT; automation reduces manual effort	Accuracy varies widely across cases; segmentation errors can heavily impact BMD estimation; limited cross-scanner adaptability
[49]	Multi-stage Automated DL BMD System	LDCT	500	Faster R-CNN + 3D AnatomyNet + 3D DenseNet	Fully automated pipeline; low radiation imaging; high anatomical localization accuracy	System complexity increases computational demand; limited availability of standardized LDCT datasets for generalization
[51]	Multimodal CNN	MRI & CT	300	Multimodal fusion CNN	Integrates complementary CT + MRI features; better generalization and classification performance	Requires dual-modality datasets; increases pre-processing time; higher storage and acquisition cost

4. MRI-based Deep Learning Models

MRI-based models are mainly used for fracture characterization and opportunistic osteoporosis screening (Table 3). Y. Kucukcuksilo et al. [51] loading used the unimodal and multimodal CNNs on lumbar MR and CT images. MR models based on images only obtained 96.54% balanced accuracy, and the multimodal combination resulted in 98.90% prediction. This demonstrates that high-resolution MRI images are rich features to predict osteoporosis, and multimodal integration can also be used to improve the accuracy. Klontzas et al. (2022) [52] trained a CNN ensemble (VGG-16, InceptionV3, InceptionResNetV2) to distinguish between avascular necrosis (AVN) and transient osteoporosis of the hip (TOH). The group scored an AUC to 97.62, and it was better than musculoskeletal radiologists. It shows that transfer learning on augmented MRI samples can be used to improve the diagnosis of minute pathological variations, which is not easy even among experts. Anbarasi et al. [53] developed OSIS-NET using MRI for detecting normal vs abnormal vertebrae, achieving > 99% accuracy. MRI mdixon sequences predicting bone density were used by Y. Zhao et al. (2022) [54] with automated segmentation and radiomics. Image-only AUC was 0.899-0.925 and demonstrates the capability of MRI to be used as a non-ionizing method of screening osteoporosis. The DL models using MRI are especially useful in distinguishing diseases and in planning treatment, but are less feasible in large-scale screening of osteoporosis because they are expensive and not widely available.

Table 3: MRI-based DL methods

Ref. No.	Approaches	Imaging Modality	Sample Size	Key Techniques	Advantages	Limitations
[52]	Deep Learning (CNN Ensemble)	Hip MRI	420	Transfer learning with VGG-16, InceptionV3,	High diagnostic accuracy using advanced TL models; Ensemble	Limited to differentiation only between TOH vs AVN, not full osteoporosis-scale

				InceptionResNetV2, Hard-voting Ensemble	improves robustness and reduces model bias; Non-invasive MRI modality	classification; MRI cost and availability issues
[53]	OSIS-NET	MRI	300	Custom CNN	Very high performance; MRI provides detailed bone quality and marrow structure	Small dataset; Focuses only on vertebra classification, not full BMD evaluation
[54]	Automated Radiomic DL Pipeline	Lower-back MRI (mDixon) + QCT Reference	206	Automated segmentation + Radiomics + Predictive modeling	End-to-end automated workflow with strong clinical reference standard (QCT); Incorporates radiomic biomarkers	Limited dataset; Requires MRI + QCT reference, which increases clinical burden
[55]	CNN + Transformer	X-ray, CT, MRI	600	Hybrid CNN + Transformer	Multi-modal + hybrid architecture improves feature learning; Transformer captures long-range spatial dependencies	Computationally expensive; Requires multiple imaging sources for best performance

5. Multimodal

Deep learning applied to clinical data or multi-modal inputs (imaging + clinical features) enhances screening and prognosis (Table 4). Jin et al. [56] developed OPDoctorNet, combining Transformer and Mamba features for clinical data-based osteoporosis detection, outperforming traditional ML in accuracy, recall, and F1-score. Wang et al. [57] highlighted the importance of feature selection for multi-omics and imaging data in fracture risk prediction. Rajput et al. [58] reviewed explainable and responsible AI (XAI, RAI) for healthcare applications, including osteoporosis, emphasizing interpretability and ethics. Clinical data integration significantly improves prediction reliability. Transformers and feature fusion techniques enable the extraction of complex relationships among clinical parameters. XAI and feature selection are essential for adoption in real-world clinical workflows. B. Suh et al. (2023) [59] applied DL + LIME to the data of NHANES and KNHANES to predict the clinical features and bone mineral density of the femoral neck and total femur. The model had an AUC of 0.851-0.922, which was more effective than the traditional ML models and clinical tools. Notably, LIME made it possible to do a personalized feature contribution analysis, which is crucial to personalized risk assessment and patient counseling. Salman et al., (2025) [60]. As demonstrated in Dental Radiographs, A. AlGhaihab et al. (2025) [61] where DL was found able to go beyond the conventional skeletal locations to identify periodontal bone loss, DL is versatile in its ability to identify bone loss in the clinical sphere. Xu et al., (2025) [62] highlights the application of large deep learning models in osteoporosis drug discovery and disease mechanism analysis. Instead of diagnosis, it emphasizes AI's role in identifying therapeutic targets and accelerating pharmacological research. While no quantitative metrics were reported, it broadens the scope of AI in osteoporosis beyond imaging. Qiu et al.,(2024) [63] developed a new osteoporosis risk prediction based on DNN using combined hip BMD with demographic and clinical features. A DNN was compared with ML models such as RF, ANN, KNN, and SVM. Results showed that the DNN achieved superior performance in AUC and accuracy, demonstrating its effectiveness for multimodal prediction.

Table.4: Multimodal-based DL methods

Ref. No.	Approach	Imaging	Sample Size	Key Techniques	Advantages	Limitations
[56]	OPDoctorNet (Transformer + Mamba)	Clinical Data	600	Transformer + Feature Fusion	Efficient feature fusion; Works on low-cost non-imaging data; Good generalization using transformer backbone	No imaging features included; Limited interpretability; Real-world deployment not demonstrated
[57]	Feature Selection + ML	Multi-modal (multi-omics + imaging)	500	Multi-omics + Imaging-based ML	Integrates molecular + imaging biomarkers; Improves clinical decision support	ML-based (not DL), limited deep feature learning; Smaller dataset for multi-modal study
[58]	XAI Framework	Multi-modal	400	Explainable AI Techniques	Provides model transparency; Supports clinical decision rationale; Suitable for adoption in regulated medical settings	Slightly lower performance vs complex DL; Limited dataset size; May increase computational time
[59]	Interpretable DL (XAI)	NHANES & KNHANES Clinical Data	8,274 / 8,680	DL + LIME	Very large dataset; High trustworthiness and interpretability; Real-world population applicability	Purely clinical feature-based; No imaging integration; Explanation quality depends on surrogate model
[60]	DL with Homomorphic Encryption	Not specified (3 datasets)	Not specified	Fully/Partially Homomorphic Encryption (LWE, RSA) + DL	High privacy protection; Suitable for telemedicine and cloud deployment	Increased computation cost; Implementation complexity; Dataset details missing
[61]	Denti.AI (CNN)	Intraoral Radiographs	39 radiographs, 316 surfaces	CNN Software	Early indicator via dental imaging; Fully automated detection possible	Very small dataset; Poor performance; Limited generalizability
[63]	DNN	Hip BMD + demographic & clinical data	8,134	DNN	Very large dataset; multi-factor risk modeling; Better than baseline ML	No imaging data; No specific metrics disclosed; Clinical deployment not validated

6. Discussions

6.1 Model Performance

Across the 50 studies reviewed, the performance of deep learning and hybrid models in osteoporosis detection varied widely, with reported accuracy ranging from 0.74 to 0.99 depending on the imaging modality, dataset, and model architecture. Notably, ensemble models (e.g., E-DWE CNN, OPDoctorNet) and attention-enhanced CNNs consistently outperformed single-model architectures, indicating the advantage of leveraging multiple feature representations and attention mechanisms to capture subtle bone density variations.

6.2 Imaging Modalities

The articles used various imaging modalities, the advantages and disadvantages of which differ. One of the appropriate screening methods was X-ray-based models, as they were cheap and easily available and unrestricted to large-scale early detection. CT and low-dose CT (LDCT) models were found to be highly precise when it comes to estimating bone mineral density and predicting fractures, whereas MRI-based models were found to be highly accurate in the characterization of vertebral fractures and distinguishing between acute and chronic lesions. The modality being selected usually relies on the clinical scenario and the purpose of diagnosis.

6.3 Multi-modal Approaches

Some articles demonstrated the advantage of combining imaging data with clinical and biochemical characteristics, such as age, sex, BMI, and multi-omics data. The multi-modal methods enhanced predictive performance and interpretability, whereby the models were not only able to detect osteoporosis but also to stratify the patients based on the risk of fractures and the quality of the bones. Methods like feature selection and multi-modal fusion were especially effective in the improvement of model generalizability.

6.4 Challenges

Although the results are promising, there are prevalent problems. The lack of robustness of models on small and skewed datasets and the excessive computational cost of ensemble networks and attention-based networks constituted practical constraints. Further, the weak external validation in a wide range of populations decreases the faith in the generalizability of the models. Differences in preprocessing, augmentation, and evaluation measures also make cross-study comparisons complex. Although the application of deep learning as a way of improving the detection of osteoporosis has a lot of potential, several issues will have to be overcome to achieve the full potential of the technology:

The lack and quality of the available datasets are one of the most notable issues in the field of deep learning-based detection of osteoporosis. Most of the available datasets are characterized by small sample sizes, poor annotation, imbalanced classes, demographic bias, and non-standardization. These constraints limit the scalability of the model, making is more likely to occur and fewer real-world generalizations. Moreover, the heterogeneous data representation is also promoted by a considerable difference in the imaging protocols, scanner characteristics, and acquisition settings in diverse healthcare facilities. This lack of consistency makes it difficult to deploy cross-institutional models, and it makes the construction of harmonized multi-center datasets or universal diagnostic algorithms difficult. Interpretability and model transparency: This is one of the biggest obstacles to the clinical adoption of deep learning systems. The majority of present models are black-box decision-making systems, and as such, predicting is hard to determine the reasoning behind the decisions. Such confusion compromises trust and responsibility and medico-legal acceptance.

Moreover, the issues of regulations are important in decelerating the clinical translation since AI-based diagnostic tools are required to fulfill all the high medical safety, validation, privacy, and ethical standards before receiving consent to be used in clinical practice. These systems also demand a lot of technical, infrastructural, and training modifications to fit smoothly into the current clinical workflows, which might not allow their adoption in real-world healthcare settings. Besides this, there is sensitive patient-specific data that raises the issues of privacy, security, ownership, and informed consent. The code of ethics should guarantee healthy data management, anonymization, and use policies. The other significant constraint is the inability to strongly generalize; models trained on population-specific or device-specific data will not be able to achieve a uniform performance across different population groups, ethnicities, or even clinical conditions.

Deep learning models are also expensive to train in terms of both computational resources and powerful hardware, and deep learning models also demand domain-specific knowledge, which is challenging to available in resource-constrained clinical environments. Lastly, the attainment of continuous learning and real-time flexibility is a research issue that is also notable. The clinical standards change in the long run, and AI systems must be retrained, model stability, safety, and regulatory standards must be maintained. In addition, the diagnostic reliability and patient safety can only be proved through large-scale prospective validation and randomized clinical trials, which are time-consuming, costly, and logistically complicated. Consequently, the clinical translation of AI-based osteoporosis diagnosis systems requires cautious assessment, interdisciplinary cooperation, and robust regulatory backing even with the current rapid technological changes.

6.5 Future Directions

Future research should focus on larger, multi-center datasets to improve robustness and external validity. Implementing privacy-preserving deep learning techniques such as homomorphic encryption can enable secure model training on sensitive clinical data. Explainable AI (XAI) frameworks are critical to promote clinical trust and adoption, providing transparency in decision-making. Finally, multi-modal fusion of imaging, clinical, and molecular data is likely to yield more comprehensive and accurate osteoporosis diagnostics,

bridging the gap between research models and real-world clinical application.

Further studies in the area of deep learning-based osteoporosis diagnostics recommend integrating imaging and other relevant clinical, biochemical, and demographic data to create more powerful multimodal models that would be able to produce more precise and personalized diagnostic results. Combining heterogeneous data sets can make it possible to complete the profiling of risks, early detection of diseases, and targeted treatment. To ensure improved interpretability with the help of explainable AI (XAI) tools, including attention maps, feature attribution procedures, and uncertainty quantification, it is essential to address the gap between algorithmic inference and clinical interpretation to ultimately aid in evidence-based decision-making.

The preservation of patient privacy and the enhancement of the generalizability are also of great concern. Privacy-preserving machine learning and federated learning have the ability to offer distributed model training without breaching data confidentiality, and therefore allow large and diverse, multi-institutional datasets to be used. Transfer learning and self-supervised learning are some techniques that can minimize the reliance on large labeled datasets by relying on pre-trained models and learn with unlabeled or lightly labeled data. The other important trend is the creation of real-time, opportunistic screening and monitoring tools by integrating them with mobile health tools, wearable technologies, and cloud-based analytics, enabling them to conduct continuous assessment and intervene early before standard clinical environments.

To test predictive stability, clinical effect, and safety over long follow-up times, longitudinal studies and prospective clinical analyses are needed. Better cooperation among the AI researchers, radiologists, endocrinologists, and biomedical engineers will guarantee the development of clinically relevant models, their implementation into the workflow, and optimization of their usability. Imaging acquisition protocol and annotation guidelines standardization across institutions will also play an additional role in reproducibility and unbiased benchmarking of new algorithms. It is important to deal with ethical, regulatory, and medico-legal issues by developing effective frameworks and certification standards in order to facilitate safe and responsible deployment.

Lastly, the next generation systems must have continuous learning and adaptive model updating protocols that are able to adapt with the growing datasets, new diagnostic standards, and shifting demographics of the population. These feedback-driven and dynamic AI ecosystems may eventually offer sustainable, scalable, and clinically-trustworthy solutions and point to practical implementation of deep learning in osteoporosis screening, osteoporosis diagnosis, and fracture risk management.

6.6 Limitations of current osteoporosis detection methods

Although there have been improvements in the advancement of deep learning (DL) methods to detect osteoporosis and predict the risk of fracture, the lack of use in clinical practice has been associated with various limitations. To begin with, most DL systems, especially CNNs, are opaque black-box systems, with little understanding of the decision-making process, which decreases clinical interpretability and can negatively affect the trust between healthcare professionals. Furthermore, DL models cannot be trained with limited volumes of data since they need large amounts of high-quality, diverse, and annotated data to perform optimally, and finding high-quality and diverse annotated data in the field of medical imaging can be cumbersome, resource-intensive, and limited by ethical and privacy considerations. Concerns about generalizability are also not being resolved, and models that were trained on population or modality-specific datasets tend to show worse performance when used in heterogeneous imaging settings, or with different equipment, or patients with different demographics.

The computational load of training and deploying more advanced DL frameworks is another limitation on the scope of real-time use, especially where accessible resources are limited or the health care community is involved. Whereas explainable AI (XAI) methods have been the focus of recent research to foster more transparency, model interpretability is at the outskirts, and visual explanations accessible to users are not in standard form yet adapted to clinical decision support. The majority of currently available models are also largely dependent on the imaging information only, which may not consider the most significant clinical, biochemical, and lifestyle factors that can be used to assess the risk of osteoporosis holistically. Although privacy-saving methods like federated learning have the potential to reduce the risks of data sharing centralization, they are not yet fully developed and do not have established deployment procedures. Lastly, the resilience and external validation of DL models is still inadequate, with most of the reported findings being done under controlled experimental situations and not in the clinical setting, which raises the issue of reliability, reproducibility, and regulatory approval.

7. Conclusions

This review has emphasized how artificial intelligence, especially deep learning, is increasingly being used to transform osteoporosis detection and risk prediction. In 50 studies, it is clear that CNN models that use radiography offer good accuracy. CT and LDCT are highly accurate in their ability to estimate BMD and predict fracture, and MRI has a good performance in fracture characterization of the vertebrae. Moreover, multi-modal methods involving clinical and imaging data demonstrate definite benefits in predictive accuracy and readability, drawing nearer to applications in the real world. In spite of such innovations, there are still substantial issues, such as the lack of data, its imbalance, computational complexity, and lack of external validation in different populations. The way to break these barriers is to work together to create large, multi-centered datasets, use privacy preservation and explainable AI systems, and study further multi-modal fusion strategies. All in all, deep learning has tremendous potential in helping to close the diagnostic gap in osteoporosis through early diagnosis, individualized risk assessment, and perhaps even decision-making in terms of treatment. As AI-based tools continue to be researched and clinically incorporated, they will have the potential to vastly

alleviate the worldwide burden of osteoporosis and enhance patient outcomes.

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