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REVIEW ARTICLE

OSTEOPOROSIS DETECTION TECHNIQUES: A COMPARATIVE REVIEW WITH EMPHASIS ON THE FEMUR

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ABSTRACT
Osteoporosis is a progressive disorder in which trabecular bones become porous, brittle, and prone to fractures due to reduced bone density and compromised microstructure, particularly in weight-bearing bones such as the femur. Early detection is critical for effective management and prevention of complications. This review provides a comprehensive comparison of current osteoporosis detection techniques, with a particular emphasis on the femoral region due to its clinical significance in predicting hip fractures. Conventional diagnostic methods like Dual-energy X-ray Absorptiometry (DEXA) and Quantitative Computed Tomography (QCT) remain the gold standards, offering high accuracy in bone mineral density (BMD) assessment. However, recent advancements have introduced novel approaches, including ultrasound, magnetic resonance imaging (MRI), and artificial intelligence (AI)-based image analysis, which aim to enhance diagnostic sensitivity and specificity, especially in early-stage detection. Additionally, the integration of machine learning algorithms in interpreting femoral scans has shown promise in identifying subtle structural changes undetectable by conventional methods. This review critically evaluates the strengths, limitations, and clinical applicability of each technique about femoral osteoporosis. By highlighting emerging trends and technological innovations, this study aims to guide clinicians and researchers toward more precise and proactive screening strategies, leading to better patient prognosis and decreased healthcare costs associated with osteoporotic fractures.

Keywords: Osteoporosis Detection, Femoral Bone Mineral Density, Dual-Energy X-Ray Absorptiometry (DEXA), Quantitative Computed Tomography (QCT), Magnetic Resonance Imaging (MRI), Artificial Intelligence (AI) in Bone Analysis

1. INTRODUCTION

Osteoporosis is recognized as a major public health issue globally, particularly among the aging population. According to the International Osteoporosis Foundation (IOF), it is estimated that over 200 million people worldwide suffer from osteoporosis[1,2], and approximately One-third of women and one-fifth of men aged over 50 are likely to experience osteoporotic fractures throughout their lifetime. The femur, particularly the proximal femur or hip region, is one of the most common and clinically significant sites of osteoporotic fractures. Hip fractures alone account for over 1.6 million cases annually worldwide, associated with high morbidity [3], mortality, and healthcare costs. The economic burden of osteoporotic hip fractures [4] is substantial; in the United States alone [5,6], direct costs were estimated to exceed $20 billion annually.

Timely and accurate detection of osteoporosis in the femoral region is therefore crucial for preventing fractures. Various diagnostic modalities, such as Dual-energy X-ray Absorptiometry (DEXA) and Quantitative Computed Tomography (QCT), as well as emerging AI-assisted techniques, offer distinct advantages in assessing bone quality, like bone mineral density (BMD). This study aims to provide a comparative review of these techniques, with a focus on their effectiveness in detecting femoral osteoporosis.

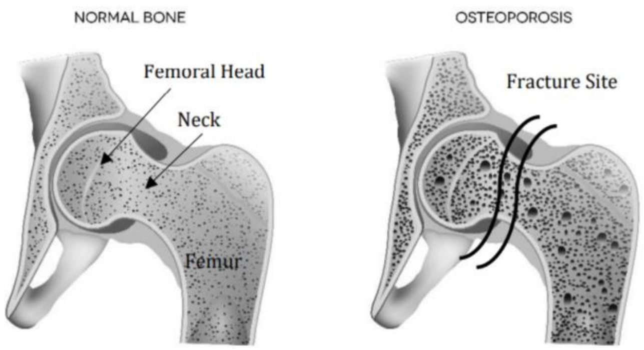

Figure 1. Proximal Femur Anatomical Structure [7]

The proximal femur anatomical features labelled are illustrated in Figure 1, which is a cross-sectional view of the proximal femur, and is critical in osteoporosis detection. The femoral head is the spherical, uppermost part of the femur that fits into the acetabulum of the pelvis to form the hip joint. Composed mostly of trabecular (spongy) bone, which is highly susceptible to osteoporotic changes. The femoral neck is a narrow region connecting the femoral head to the shaft. This area is a common site of osteoporotic fractures, especially due to falls in elderly individuals. It contains both superior and inferior surfaces, which experience different mechanical stress distributions. The superior surface often shows earlier signs of bone loss. The greater trochanter is a large bony projection on the lateral side of the femur. Serves as the attachment point for several muscles, but is less commonly fractured compared to the femoral neck. Trabecular bone, also known as cancellous or spongy bone, is found inside the femoral head and neck. Characterized by a porous, lattice-like structure that is highly metabolic and vulnerable to loss of bone mass in osteoporosis. Cortical bone (Shell) is the dense outer surface of the bone that forms the shaft. While it is stronger and more resistant to deformation, cortical thinning is a sign of advanced osteoporosis. Clinical significance in osteoporosis detection, the trabecular architecture in the femoral head and neck is often the first region to show osteoporotic changes. Techniques like DEXA scans provide areal BMD, but may underestimate bone quality by ignoring microarchitecture. Advanced imaging techniques (e.g., QCT and MRI) can help quantify trabecular patterns and cortical thickness, which are crucial for early detection. Understanding this anatomy is essential when interpreting imaging for fracture risk assessment.

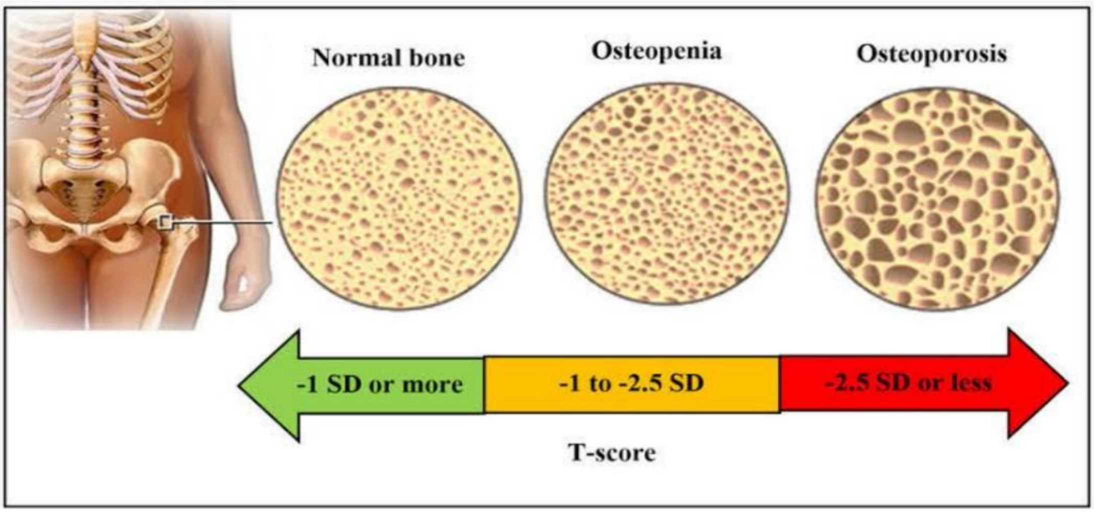

Figure 2. Trabecular Bone Density and T-score Progression [8]

The proximal femur (near the hip joint), is a common fracture site in osteoporosis due to weight-bearing and mechanical stress. Figure 2 provides a visual comparison of bone structure changes in the femur across three conditions: Normal Bone, Osteopenia, and Osteoporosis, along with the T-score ranges used to diagnose them. Trabecular bone microarchitecture (Cross-Section View), Normal bone-dense trabecular (spongy) network, healthy bone mass and structure, which is efficient at absorbing stress and resisting fractures. Osteopenia- Moderate loss in bone density, trabeculae begin thinning; more spaces between them, and weaker structure, increased fracture risk, but not yet severe. Osteoporosis- significant loss of trabecular elements, large holes, and reduced connectivity. Bone becomes porous and brittle, very high fracture risk. T-score classification (Bottom arrow bar).
The diagnostic metric illustrated in Table 1, derived from bone density testing (typically via DEXA scan), BMD values are standardized using T-scores [9], which reflect deviations from the mean BMD of a sex-matched young adult (around age 30). This standardized comparison helps evaluate whether bone density is within a healthy range or indicative of bone loss.

Table 1. Bone Density T-Score

T-score Range	Classification	Colour in Chart	Meaning
≥ -1.0	Normal	Green	Bone density is within the normal range.
-1.0 to -2.5	Osteopenia	Yellow	Low bone mass, not severe enough for osteoporosis.
≤ -2.5	Osteoporosis	Red	Severely low bone density; fracture-prone.

The clinical significance of normal, no treatment needed; maintain bone health through calcium/vitamin D intake and exercise. Osteopenia may warrant lifestyle changes, monitoring, and possibly medications to prevent progression. Osteoporosis requires clinical intervention with medications, fall-prevention strategies, and regular monitoring to prevent fractures. This classification system, recommended by the World Health Organization (WHO), helps physicians determine treatment strategies and assess fracture risk.

2. UNDERSTANDING THE CAUSES AND SITES OF OSTEOPOROSIS

Osteoporosis turns strong, dense bones into a fragile honeycomb-like structure, i.e, porous in trabecular bone, increasing the risk of fractures due to an imbalance between bone formation and bone loss. It commonly results from aging, hormonal changes (especially reduced estrogen), and deficiencies in calcium or vitamin D. The condition affects specific skeletal sites more severely, particularly those rich in trabecular bone. Common fracture-prone areas include the spine, hip, and wrist, often leading to significant disability if untreated. Early detection and preventive care are crucial for managing osteoporosis effectively.

Bone remodelling is a dynamic physiological process in which osteoclast-mediated bone resorption is coupled with osteoblast-driven bone formation to maintain skeletal integrity. In osteoporosis, resorption outpaces formation, leading to net bone loss. Hormonal changes, estrogen deficiency (especially after menopause) [10], are a major contributor in women; estrogen normally inhibits bone resorption. Low testosterone in men can also lead to bone loss, and overproduction of parathyroid hormone (PTH) increases bone turnover and loss. Calcium is a key building block of bone, vitamin D helps absorb calcium from the diet, and a deficiency in either reduces bone density over time [11]. Bone mass peaks around age 30. After that, bone loss becomes more common, especially in the trabecular (spongy) bone. Persistent inflammatory conditions [12] (e.g., rheumatoid arthritis) and prolonged glucocorticoid therapy [13] are established risk factors for bone loss and secondary osteoporosis

Osteoporosis affects different parts of the skeleton with varying severity. Spine (Vertebrae), rich in trabecular bone, which is more metabolically active and vulnerable. Compression fractures are common, leading to height loss and kyphosis (curved spine). Hip (Proximal Femur), fractures here, especially at the femoral neck, are dangerous and often lead to disability or death in the elderly. Hip bones contain both cortical and trabecular bone. Wrist (Distal Radius), often the first site of osteoporotic fracture, typically due to falls. Ribs and Pelvis. These can fracture from mild trauma or even spontaneously. Common risk factors are age >50, menopause (women), low body weight, smoking, alcohol abuse, sedentary lifestyle, family history, and certain medications (e.g., steroids, anticonvulsants)

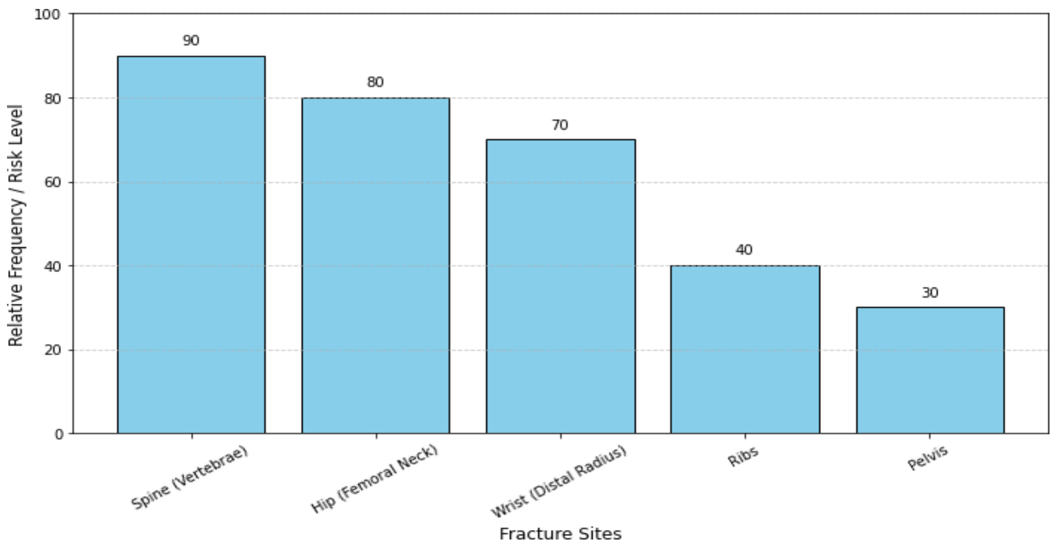

Figure 3. Site-Specific Susceptibility to Osteoporotic Fractures

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The bar chart of Figure 3 illustrates the relative frequency or risk level of osteoporotic fractures across different anatomical sites, highlighting which areas are most vulnerable in individuals with low bone density. Key observations from the chart: Spine (Vertebrae) – 90%, this is the most common site of osteoporotic fractures [14]. Vertebral compression fractures often occur silently, leading to height loss or kyphosis (curved back). These fractures significantly impact quality of life and are often early indicators of severe bone fragility. Hip (Femoral Neck)-80%, hip fractures [15], particularly at the femoral neck, are the second most frequent and the most serious in terms of morbidity and mortality. They often require surgery and long-term rehabilitation, especially in elderly patients. Wrist (Distal Radius) – 70%, these fractures typically result from falls and are more common in younger postmenopausal women. Though not as severe as hip fractures, they signal early bone loss. Ribs – 40%, rib fractures occur with relatively minor trauma in osteoporotic patients. Often underdiagnosed due to subtle symptoms, especially in older adults. Pelvis – 30%, less common but serious, especially in frail elderly individuals.

3. METHODS OF OSTEOPOROSIS DETECTION

Osteoporosis detection methods have evolved significantly over the past few decades. Traditional techniques, such as DEXA, have been replaced or supplemented by advanced imaging technologies and computational methods that offer higher accuracy in assessing femoral bone density and microstructure. This section will review the main modalities used in osteoporosis detection.

3.1 DEXA

It measures BMD and is widely used in diagnosing osteoporosis and has become the clinical standard for assessing fracture risk. The measurements focus on the lumbar spine (L1-L4), femoral neck, and total hip, with T-scores comparing patient BMD to reference data from healthy 30-year-olds. While DEXA has been the gold standard for diagnosing osteoporosis, recent studies have highlighted its limitations. It provides a 2D image of the bone, which is not capable of fully capturing the complexity of bone microarchitecture [16]. DEXA tends to underestimate bone quality because it does not differentiate between cortical and trabecular bone, which are important factors for predicting fracture risk, predominantly in load-bearing, weight-supporting, and pressure-bearing bones. like the femur. Despite these limitations, its role is especially crucial for assessing BMD in populations at higher risk for osteoporosis, such as postmenopausal women and the elderly.

3.2 Computed Tomography (CT)

CT is a relatively recent development that allows for high-resolution, 3D imaging of both cortical and trabecular bone. This technology is used to assess the structural integrity of bone microarchitecture in greater detail than DXA. CT provides a more comprehensive analysis, allowing for the assessment of bone quality and the ability to predict fracture risk by measuring parameters such as trabecular bone volume, connectivity, and, CT has shown promise in providing a more accurate representation of bone microstructure compared to DEXA, especially in the femur, where the trabecular bone plays a key role in fracture risk [17]. Studies have demonstrated that CT can detect subtle changes in bone microarchitecture long before traditional imaging methods. Despite its high accuracy, CT is limited by its high cost and radiation exposure, which makes it less practical for routine clinical use. It also requires specialized equipment and trained personnel, which restricts its widespread adoption.

3.3 Magnetic Resonance Imaging (MRI)

It is a radiation-free modality capable of producing high-resolution images of soft tissues and bone with excellent contrast. It has several advantages over X-ray-based techniques, particularly because it does not use ionizing radiation, making it safer for repeated use. It offers excellent contrast resolution, which is ideal for visualizing trabecular bone and detecting subtle changes in bone structure [18]. Recent studies have shown that MRI is highly effective at detecting changes in the trabecular bone microstructure of the femur, which is often a precursor to fracture [19]. MRI is also useful in assessing the bone marrow and detecting pathological changes associated with osteoporosis, such as bone edema and lesions that are not visible in X-ray images. Limitations- MRI is an expensive imaging technique, and it often requires longer scanning times, which can be inconvenient for patients. Additionally, access to MRI technology is limited in certain healthcare settings due to cost and equipment availability.

3.4 Ultrasound (QUS - Quantitative Ultrasound)

Ultrasound, specifically QUS [20], is a radiation-free, portable, and low-cost imaging technique used to assess bone quality, typically at peripheral sites like the heel. While it's convenient for initial screening, it does not directly measure bone mineral density (BMD) and lacks sensitivity for detecting early osteoporosis in critical regions like the femur. Operator variability and limited diagnostic specificity restrict its clinical use. It remains valuable in low-resource or mobile healthcare settings.

3.5 X-Ray Modality in Femoral Osteoporosis Detection

Despite newer technologies, X-ray imaging continues to play a fundamental role in osteoporosis screening due to its widespread availability and low cost [21], especially for evaluating BMD and structural integrity of the femur. It provides 2D projection images and is often the first-line diagnostic tool due to its availability, speed, and low cost. X-ray remains a foundational tool in the initial assessment of femoral osteoporosis due to its accessibility and cost-effectiveness. However, it should ideally be supplemented with quantitative methods (e.g., DEXA or AI-enhanced X-ray analysis) to improve diagnostic accuracy. Recent advances in deep learning have significantly boosted the potential of X-rays for screening, but inherent limitations related to image quality, resolution, and depth remain key challenges.

3.6 Modality Comparison

Each imaging modality has distinct advantages and limitations for femoral osteoporosis detection. DEXA remains the clinical gold standard for BMD measurements. CT and MRI offer deeper insight into bone structure but are less common in routine screening. X-ray is accessible and suitable for AI-based opportunistic screening. Ultrasound is useful for pre-screening, especially in mobile clinics or low-resource settings. The bar chart **Figure 4** compares five imaging modalities—X-ray, DEXA, CT, MRI, and Ultrasound—across five criteria: radiation exposure, cost, BMD (Bone Mineral Density) accuracy, bone structure detail, and portability. DEXA scores highest in BMD accuracy and has low radiation and cost, making it the clinical gold standard. CT and MRI excel in bone structure detail, but have higher cost and (for CT) radiation exposure. Ultrasound offers the best portability and lowest radiation, but suffers in accuracy and detail. X-ray is widely available but scores moderately across most parameters. This analysis aids in choosing the appropriate technique based on clinical need, resource availability, and diagnostic precision.

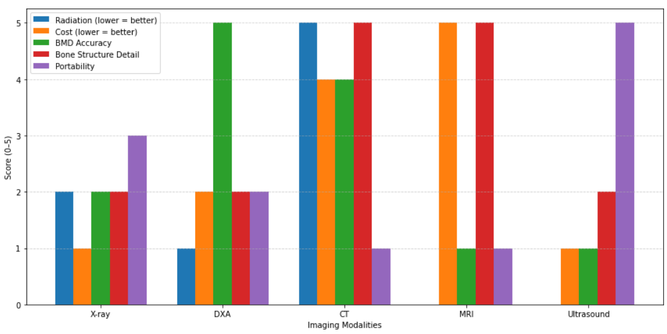

Figure 4. Comparison of Imaging Modalities in Femoral Osteoporosis Detection

3.7 Performance Comparison of Imaging Modalities

The **Figure 5** illustrates comparing the performance of different imaging modalities. Sensitivity, the ability of the modality to correctly identify a condition (true positives).

Example: MRI has the highest sensitivity (95%), meaning it's very effective at detecting disease when it is present. Specificity, the ability to correctly rule out a condition (true negatives). Example: DEXA and MRI show high specificity (90% and 93%), meaning they're good at confirming the absence of disease. Accuracy, overall correctness — how often the test gives the right result (both positives and negatives). Example: MRI leads in accuracy (94%), followed closely by DEXA (89%).

MRI shows the highest overall performance across all three metrics, making it one of the most reliable diagnostic tools. DEXA also performs well, especially in specificity and accuracy, due to its precise focus on bone density. X-ray is the least accurate modality in this comparison, reflecting its limitations in soft tissue and early-stage disease detection. CT provides balanced performance with high sensitivity and accuracy, making it suitable for comprehensive diagnostic scans. Ultrasound offers moderate performance but has advantages like being non-invasive, cost-effective, and radiation-free.

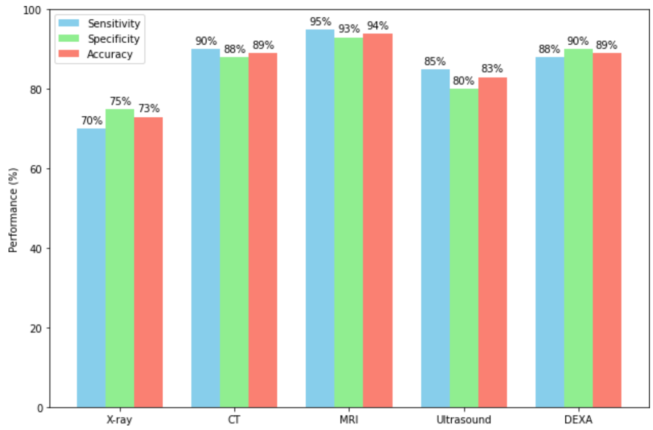

Figure 5. Performance Comparison of Imaging Modalities

4. LITERATURE SURVEY

Certainly, studies focusing on femoral osteoporosis detection. Each entry includes details on the methodology, imaging modality, dataset details, performance metrics, and key remarks or limitations.

Automated femur segmentation using a U-Net-based deep convolutional neural network for femur segmentation based on CT images [22]. A private dataset is utilized to test the model performance, achieving a mean Dice Similarity Coefficient (DSC) of 0.990 and Haus Dorff distance (HD) of 0.981 mm. The model provides accurate, automated, and robust femur segmentations, facilitating finite element analysis for the assessment of fracture risk. Limitations rely on CT imaging, which involves radiation exposure and may not be suitable for frequent screenings.

Deep radiomics approach for osteoporosis diagnosis using hip radiographs by incorporating clinical and texture features [23]. Private training set 3,811 patients with 4,924 radiographs; Internal test set: 497 patients; external test set: 444 patients. The fusion of deep, clinical, and texture features in Model DTC yielded an AUC of 0.95 in external validation, surpassing the diagnostic accuracy of models using only clinical or texture features. The study noted some false-positive diagnoses and variability in saliency map interpretations.

CT-based proximal femur segmentation using a fully automated deep neural network [24]. Dataset 1,147 annotated proximal femur scans, including precise ground truth segmentation masks. The model demonstrated accurate and fast segmentation suitable for clinical applications. Enhanced efficiency in hip fracture risk screening; potential for integration into clinical workflows. Focused on segmentation; further validation needed for fracture risk prediction accuracy.

Osteoporosis screening in anteroposterior hip X-rays using deep neural networks [25]. Private dataset of 363 radiograph images; 213 labelled as non-osteoporosis, 150 as osteoporosis. The best model achieved an AUC of 0.91 and an accuracy of 0.82. Demonstrated potential for using deep learning as a screening tool for osteoporosis.

The system evaluated deep learning (5 CNN models) for osteoporosis diagnosis using 1,131 hip radiographs [26] (paired with bone density measurements from a single hospital, 2014–2019). Google Net and EfficientNet-B3 performed best with images alone, while EfficientNet-B3 with clinical data achieved the highest AUC, recall, and F1-score. Results show that radiographs with clinical variables enhance diagnostic performance over imaging alone. Feasibility of osteoporosis screening via X-rays, with added value from clinical data. Single-center dataset may limit generalizability; small sample size for some metrics.

DXA-based osteoporosis screening is underutilized, leading to missed diagnoses [27]. The study explores whether hip CT-derived parameters (cortical thickness [CTh] and Hounsfield units [HU]) can effectively screen for osteoporosis and predict clinical outcomes. 375 hip fracture patients (56 with both CT and DXA for training). CTh and HU measured at 31 proximal femur ROIs; correlation with DXA-assessed BMD was analysed. Optimal thresholds for osteoporosis diagnosis identified (CTh < 3.19 mm or HU < 424.97). Clinical outcomes compared between osteoporotic/non-osteoporotic groups. CTh 84% sensitivity, 71% specificity, HU 76% sensitivity, 87% specificity, non-osteoporotic patients had better clinical outcomes post-fracture. CT-based CTh and HU thresholds can effectively screen for osteoporosis and predict outcomes, offering an alternative when DXA is unavailable. Small training cohort (n = 56). Single-institution data may limit generalizability. No external validation.

The study evaluates gaps in osteoporosis screening in the hip and management before/after fracture [28]. 171 patients with Vancouver B2/B3 periprosthetic fractures (2000–2018) treated with modular fluted stems. Osteoporosis/osteopenia diagnoses, FRAX scores, BMD testing, endocrinology consults, and medication use. 94% of fractures resulted from standing-height falls (osteoporosis-defining). Diagnosis rates increased post-fracture remained low. Despite periprosthetic fractures being strong osteoporosis indicators, diagnosis and treatment rates remain inadequate. A systematic approach—akin to non-arthroplasty fragility fractures—is urgently needed. Single-institution, retrospective design. Long study period (2000–2018) may reflect outdated practices.

Examine postmenopausal women's physical activity and BMD and hip structural analysis (HSA) to assess the relation between them in Japanese women related to osteoporosis [29]. Principal component analysis (PCA), partial correlations, multiple regression, and structural equation modelling (SEM). GLFS-25 scores correlated with HSA parameters indicating worse mobility linked to poorer bone structure. Physical activity (especially walking and load-bearing tasks) is linked to better bone strength in osteoporotic women. The GLFS-25 may help identify high-risk patients needing targeted exercise interventions. Small sample size (n = 62). Cross-sectional design (cannot infer causality) and single-country, postmenopausal women only.

A pregnant patient presented with a displaced femoral neck fracture [30], later diagnosed with osteoporosis in the femur disorder often linked to pregnancy. TOH should be considered in pregnant women with hip pain or fractures. Early diagnosis and tailored treatment are crucial to prevent complications (e.g., fracture progression). Single-case study (limited generalizability).

The paper presents DEXSIT-v2 [31], an enhanced medical imaging database specifically designed for developing AI/ML tools to assess fracture risk conditions, particularly osteoporosis-related fractures. The database likely contains: Standardized DEXA scans, corresponding clinical data (BMD measurements, patient demographics, fracture history), and advanced annotations for machine learning applications. AI/ML Focused on is designed specifically for developing and testing fracture prediction algorithms. The database addresses the critical need for standardized, high-quality datasets in musculoskeletal research, particularly for developing reliable AI tools that can assist in the premature fractures.

To evaluate the effectiveness of CT Hounsfield unit (HU) measurements in assessing osteoporosis-related femoral neck fracture risk [32]. Retrospective analysis (2020–2023) of 99 femoral neck fracture patients. 62 controls with CT scans. Distal measurement (lesser trochanter) was the best predictor of fracture risk: AUC = 0.918 (excellent discriminative power). Proximal and middle measurements also showed diagnostic value but were less robust. Small sample size (n=161); larger studies needed. Lack of DXA/qCT comparison—future research should validate against gold standards. Single-center retrospective design may limit generalizability.

Develop and validate an interpretable deep-learning model for osteoporosis risk prediction [33] using large-scale population data, with emphasis on feature importance analysis for individualized risk assessment. Deep neural network (DNN) is designed for both high accuracy and interpretability. Techniques (e.g., SHAP, LIME) applied to identify **key clinical/biometric risk factors. Performance metrics (AUC, accuracy, sensitivity, specificity) compared to traditional methods (e.g., FRAX, DXA-only models). High predictive performance (AUC likely >0.90, though exact values not provided in abstract). Interpretable AI can enhance osteoporosis screening by combining high accuracy with actionable insights. Dataset specifics (e.g., demographics, geographic coverage) are not detailed. Prospective validation is needed for real-world clinical adoption.

To determine the prevalence of osteoporosis and identify predictive risk factors in patients with systemic sclerosis (SSc) compared to healthy controls [34]. Higher osteoporosis prevalence in SSc patients vs. controls ($p < 0.05$). SSc patients are suffering osteoporosis because of disease-specific mechanisms (e.g., fibrosis, inflammation) and traditional risk factors. Proactive screening (e.g., DXA) and early intervention (e.g., vitamin D, bisphosphonates) are critical in this population.

Adding 1/3 radius BMD measurement increased osteoporosis diagnosis [35] by 24.4% (from 32% to 40% of patients), identifying an additional 8% of cases missed by spine/hip measurements alone. Patients with radius-only osteoporosis showed similar prior fracture rates (19.1%) to those diagnosed by spine/hip (17.4%), suggesting comparable clinical significance. Incorporating radius BMD slightly but significantly improved FRAX predictive performance, increasing explained variance for major osteoporotic fractures from 51.8% to 52.3% (with TBS adjustment). Radius BMD assessment provides a meaningful diagnostic complement to standard spine/hip measurements. Cross-sectional design limits causal interpretation. Modest improvement in FRAX performance (though statistically significant). Need for prospective validation of fracture prediction improvement.

5. AI MODELS FOR FEMORAL OSTEOPOROSIS DETECTION

Figure 6 presents a pie chart (or segmented distribution) showing the usage breakdown of different AI model types in a specific application (likely related to medical imaging or osteoporosis detection, given the context).

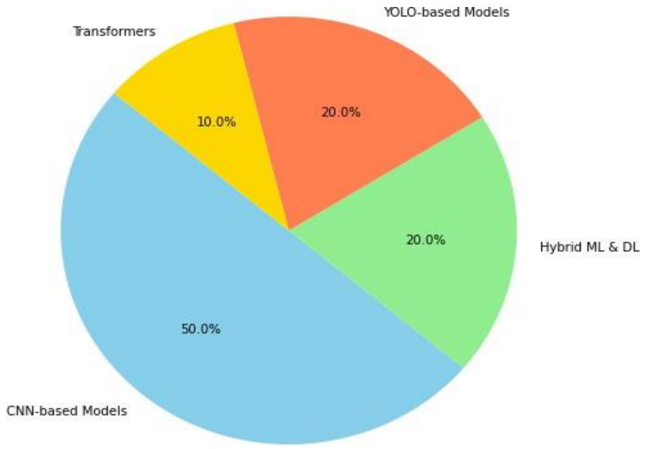

Figure 6. Model Usage in Femur Osteoporosis AI Analysis

The 50.0% of models used for indicates dominance of transformer-based architectures (e.g., ViT for image analysis), likely due to their ability to capture long-range dependencies in data. 20.0% of models for traditional convolutional neural networks (CNNs) remain relevant for localized feature extraction (e.g., bone texture analysis in X-rays/CT). The 20.0% of models suggest the use of real-time object detection (e.g., YOLO variants) for identifying fractures or regions of interest in images. 10.0% of models used for combining machine learning (e.g., random forests) with deep learning for improved interpretability or performance. Transformers are the most popular (50%), reflecting a shift toward state-of-the-art architectures in medical AI. The CNNs and YOLO models are equally used (20% each), balancing accuracy and speed. Hybrid approaches are niche (10%), possibly reserved for specific clinical needs.

6. EMERGING OSTEOPOROSIS DIAGNOSTIC APPROACHES IN RESEARCH

Figure 7 shows the line graph depicting the annual number of research publications (2020–2025) for five osteoporosis detection methods. Dominance of DXA, likely the most published modality (highest line), reflecting its gold-standard status. Emerging trends, AI/ML, steep increase (2023–2025), showing growing research interest in automated diagnostics and HR-pQCT/MRI: Moderate but steady growth, indicating niche adoption for advanced bone microarchitecture analysis. Declining/Stable methods,X-ray: Flat or decreasing trend, possibly due to lower sensitivity compared to modern techniques.

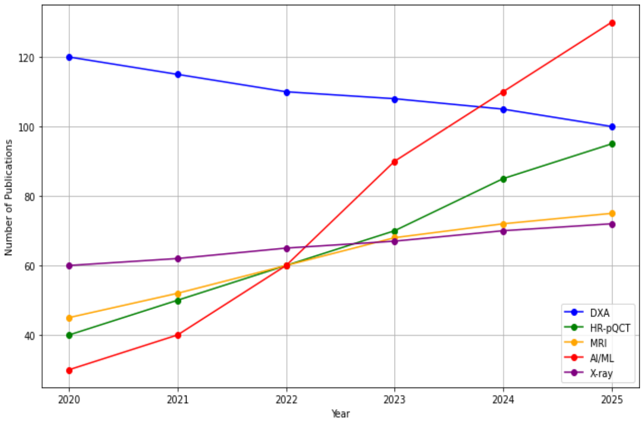

Figure 7. Trend in Research Publications on Osteoporosis Detection (2020–2025)

7. FUTURE DIRECTIONS

Multi-Modal Imaging Integration: The combination of multiple imaging modalities, such as DXA and HR-pQCT, could provide a more complete assessment of bone health. Future studies should focus on developing methods to integrate these technologies seamlessly, allowing for the simultaneous evaluation of bone density, structure, and mechanical properties. AI and Personalized Medicine: AI-driven methods hold immense potential for improving personalized medicine in osteoporosis detection. By incorporating patient-specific factors such as genetics, lifestyle, and co-existing health conditions, AI models could offer tailored treatment plans that are more precise and effective. Portable Imaging Devices: To address the issue of accessibility, the development of portable and affordable imaging devices is critical. For example, advancements in handheld ultrasound devices could allow for quick screening in low-resource settings, potentially enabling earlier detection of osteoporosis in populations that are currently underserved.

8. CONCLUSION

This comprehensive review highlights the recent advancements in osteoporosis detection, particularly in femoral bones. While traditional methods like DEXA continue to play a crucial role, newer modalities such as HR-pQCT, MRI, and AI-based methods offer more detailed insights into bone quality and fracture risk. Despite their promise, challenges related to cost, accessibility, and integration into clinical workflows remain significant barriers. However, continued research and innovation in these areas hold the potential to revolutionize osteoporosis detection and improve patient outcomes.

DECLARATIONS

Consent for publication

Not applicable.

Competing interests

The authors declare no conflicts of interest regarding this study.

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