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EXPLAINABLE DEEP LEARNING MODEL FOR EARLY OSTEOPOROSIS DETECTION USING MEDICAL IMAGING AND CLINICAL ACCEPTANCE ANALYSIS

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ABSTRACT
The prevalence of osteoporosis is one of the most common skeletal problems in the world, which is defined by diminished bone mineral density (BMD), bone microarchitecture and an elevated risk of fragility fracture. Early diagnosis is crucial for avoiding major complications, lowering health care costs, and better patient outcomes. Conventional methods of diagnosis like dual-energy X-ray absorptiometry (DXA), however, face problems of accessibility, cost, delayed screening and difficulty in interpretation of data in the clinical setting. In recent years, we have noticed the great promise of novel approaches such as AI, deep learning and XDL developed to detect osteoporosis through automatic processing of medical images and integration of multimodal clinical information. This work introduces an Explainable Deep Learning Model for Early Osteoporosis Detection by Medical Imaging and Clinical Acceptance Analysis framework where Osteofy is the main case study conducted.In addition, the study investigates the ability of consultants to interpret, rely on and use the proposed Osteofy framework and their level of confidence in its diagnostic value. Previous studies show that with the use of an explainable multimodal AI system, the accuracy of osteoporosis screening is significantly improved and the physician's trust in automatic predictions is increased. Likewise, explanatory models based on hip radiographs, facial images, computed tomography and electronic health records have demonstrated an impressive ability for diagnosis in a transparent and reproducible way. Her work builds off this innovation and seeks to close the gap between top-performing AI algorithms and real-world deployment.

Keywords:
Osteoporosis, Explainable Artificial Intelligence, Deep Learning, Medical Imaging, Osteofy, Convolutional Neural Networks, Multimodal Learning, Clinical Decision Support, Grad-CAM, Healthcare AI

1.0 INTRODUCTION
Osteoporosis is a chronic condition of the skeleton that results in decreased bone mineral density (BMD) and deterioration of bone microarchitecture and/or an increased risk of fragility fracture. It is regarded as a significant public health problem, as it is a common disorder in young women, elderly individuals and older post-menopausal women around the world. Osteoporotic fracture typically occur in the hip, spine and wrist, are a source of disability, immorality, higher health-care costs, and even death. Traditionally, the gold standard for assessment of osteoporosis

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is considered to be using diagnostic methods, primarily a dual-energy X-ray absorptiometry (DXA) scan. Despite these benefits, DXA screening can be restricted due to its high cost, lack of accessibility, delayed diagnosis and availability of DXA machines in low-resource healthcare settings (Conforti et al., 2026).

1.1 The rise of AI in Osteoporosis Diagnosis

In recent years, artificial intelligence (AI), machine learning (ML) and deep learning (DL) have revolutionized the field of medical imaging analysis and clinical decision support systems.Recently, the field of medical imaging analysis and clinical decision support systems (CDSS) has been revolutionized by artificial intelligence (AI), machine learning (ML) and deep learning (DL). The capability of auto-detecting pathological patterns embedded within radiographic images and clinical data as demonstrated by artificial intelligence (AI) approaches has been shown to enhance the accuracy, speed and scalability of the identification of osteoporosis. The use of deep learning architectures for the prediction and classification tasks in the field of osteoporosis has been demonstrated to outperform the conventional statistical approaches in several systematic reviews (Gomathi & Malathi, 2026; Alborzi & Abadi, 2025).

1.2 Educating people about EAI in Medical Imaging

While deep learning models can make accurate predictions, one of the challenges to their clinical application is the “black-box” aspect by some models. When clinicians are not sure of "how or why" AI systems can foresee the future, they postpone integrating them into their work. Therefore, the field of explainable artificial intelligence (XAI), which seeks to enhance the interpretability, transparency, and trustworthiness of AI systems in healthcare, has come to the fore as a major research focus.The use of XAI in healthcare AI has thus become a key research interest to make AI systems more interpretable, transparent, and trustworthy (Shen et al., 2026).

Explainable deep learning efforts offer visual and analytical explanations that enable clinicians to gain insights into the regions of the image or its clinical characteristics that play the most significant role to the model's decisions. The explainable deep learning framework for osteoporosis screening by hip X-ray interpretation proposed by Feng et al. (2025) aims to enable the use of computed tomography (CT) for screening osteoporosis in elderly patients, relying solely on the computed image of the hip. Likewise, Buaruk et al. (2024) employed an interpretable deep learning approach to diagnose osteoporosis in knee radiographs, showing how understandable AI systems can contribute to the increased diagnostic confidence with high classification accuracy.

1.3 The following steps outline the Osteofy Case Study Framework

In this study, we propose the Osteofy framework that is an explainable deep learning system for early osteoporosis detection via multimodal medical imaging and clinical analyses. The framework combines deep convolutional neural networks with explainability features, such as Grad-CAM, attention visualization and feature attribution analysis, enhancing the transparency of the diagnostic process and its usability by doctors. Osteofy uses clinical information from patients, which includes their radiology (X-ray) images, to develop a unified osteoporosis prediction environment that can be applied to clinical practice in real time and help clinicians in the treatment process.

Osteofy focuses on interpretability and trustworthiness, not with a black-box AI system, but in a physician-centric design approach. The framework focuses on resolving some of the challenges that were observed in the current OS systems, namely by integrating multimodal feature extraction, explainable decision support, and clinical acceptance assessment in a single smart healthcare system. Osteofy's explainability features will help enhance the confidence of clinicians, enable early identification of disease, and enable scalable osteoporosis screening in various healthcare settings.

Table 1: Summary of Existing Explainable Deep Learning Approaches for Osteoporosis Detection

Study	Imaging Modality	AI/Deep Learning Technique	Explainability Method	Key Contribution
Tang et al. (2025)	X-ray + Clinical Data	Multimodal Deep Learning	Feature Fusion Analysis	Improved osteoporosis prediction using combined imaging and clinical variables
Feng et al. (2025)	Hip X-ray	Sensor-Based Deep Learning	Explainable Visualization Framework	Enhanced screening transparency and physician interpretability

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Chagahi et al. (2024)	Multimodal Imaging	Explainable Multimodal Learning	Variable Clustering and Feature Fusion	Increased classification accuracy through multimodal integration
Jin et al. (2025)	Electronic Health Records + Imaging	Explainable Machine Learning	Feature Attribution Analysis	Personalized osteoporosis risk assessment using EHR data
Sugawara et al. (2025)	Clinical Decision Data	Explainable AI Model	Decision Interpretation Mechanism	Reproduced expert pharmacological osteoporosis decisions
Liang et al. (2025)	Facial Images	Explainable AI Framework	Attention-Based Explainability	Predicted osteoporosis risk using facial image analysis
Buaruk et al. (2024)	Knee Radiographs	Deep Learning Pipeline	Explainable Detection Framework	Improved osteoporosis detection from knee radiographs
Liu et al. (2025)	Computed Tomography (CT)	Deep Learning Radiomics	Radiomic Feature Interpretation	Classified osteoporotic vertebral fractures accurately
Bhat & Shanthi (2026)	Dental Periapical Radiographs	Deep Learning Approaches	Imaging Feature Visualization	Demonstrated dental imaging for osteoporosis screening
Ho et al. (2025)	Hand Radiographs	HarDNet-Based Deep Learning	Bone Density Inference Mapping	Efficient hand radiograph osteoporosis prediction
Jang et al. (2021)	Hip Radiography	Deep Learning Algorithm	Limited Explainability	Early demonstration of AI-based osteoporosis prediction
Ramesh et al. (2025)	Bone X-ray Images	MobileNetV4 + Deep Learning	Grad-CAM	Improved interpretability in bone imaging classification

2.0 LITERATURE REVIEW

Within the past ten years, the use of AI in the diagnosis of osteoporosis has advanced greatly, aided by advancements in machine learning, medical imaging, and computational power. The traditional method for osteoporosis diagnosis was significantly based on DXA, but it was an expensive, not readily available and was limited in the number of people that could be screened. In recent years, therefore, targeting the development of AI systems for diagnostic systems to enhance early detection through alternative imaging modalities and clinical data sources has been the main theme of research (Conforti et al., 2026).

Adopting machine learning and deep learning methods appears to be useful in automated osteoporosis classification and prediction. In the systematic review and meta-analysis by Gomathi and Malathi (2026), AI-driven osteoporosis diagnostic systems has consistently shown higher prediction accuracy, quicker processing time, and greater real-time screening abilities relative to traditional approaches. Likewise, Alborzi and Abadi (2025) highlighted the significant role of AI for the diagnosis, disease classification, and fracture risk prediction in prognosis of osteoporosis.

2.1 Architectures for Deep Learning in Osteoporosis Screening

The ability to automatically extract high level image features without much manual effort makes deep learning models very popular in medical image analysis, in particular convolutional neural networks (CNN). CNN based systems have exhibited outstanding performance in different imaging techniques for osteoporosis detection, including hip radiographs, hand radiographs, knee radiographs, dental radiographs and computed tomography.

One of the earlier deep learning models which was able to diagnose osteoporosis directly from simple hip radiographs was created by Jang et al. (2021). Their results have shown that CNN-based models can detect the structural alterations of the hip in images and thus facilitate low-cost and scalable screening protocols to detect osteoporosis. The investigation proved that conventional radiographs can work as alternatives to the more expensive diagnostic systems available, based on DXA.

2.2 AI Role in Diagnosis of Osteoporosis

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Deep learning systems have been proven to have high prediction performance, but their black-box nature poses a big challenge in healthcare applications. Transparency and interpretability are critical factors for clinicians to consider when implementing AI systems in clinical practice. Explainable artificial intelligence (XAI) has thus become the area of research that has come to the fore now, where the goal is to explain, interpret and make models transparent, trustworthy and reliable.

Feng et al. (2025) proposed a Deep Learning approach that interprets hip X-rays to detect osteoporosis, using a sensor system approach to create an explainable model. They have done this by integrating mechanisms for explainability, which enabled them to highlight clinically relevant regions of images influencing osteoporosis predictions. This study showed that explainable systems increased the diagnostic certainty by not only improving the diagnostic accuracy but that it also boosted the trust physicians placed in automated AI feedback.

2.3 Utilization Of Multimodal Learning & Clinical Data Integration For Neuroscience Technologies

In recent years, the field of osteoporosis research is focussed more on multimodal learning frameworks where medical imaging is complemented with clinical and demographic data. The idea of multimodal approaches is to increase the accuracy of the diagnosis with the use of conditioning heterogeneous data sources in order to obtain a more complete description of the disease by creating models that combine all the heterogeneous sources.

Tang et al. (2025) have built a multimodal deep learning model which combined X-ray images and clinical data for osteoporosis prediction. Their algorithm performed very well in the field of diagnostics which is the area where the image-only methods could not compete. patient-specific factors like age, BMI, gender, and fracture history also significantly influenced model performance, underscoring the role of personalized patient data in AI-driven diagnostic systems.The influence of patient-specific variables like age, BMI, gender, and fracture history on model performance further highlights the significance of integrating patient-specific data into AI-driven diagnostic systems.

2.4 Alternative Approaches To Osteoporosis Screening By Imaging

In past times, DXA and hip radiography have been the primary methods used to perform traditional osteoporosis screening, but recent research has examined other imaging modalities that can help with more holistic and convenient screening plans. The other methods aim to enhance screening uptake and early detection while minimizing health care resource use and expenses.

Liang et al. (2025) suggested an explainable AI model, Face2Bone, for predicting osteoporosis risk from facial images. They've used facial features and skin folds to help identify risk of osteoporosis by means of their proof-of-concept study. The study marked a new frontier in the field of osteoporosis research, but it is still in experimental stages, on the outskirt of the traditional radiographic assessment method.

2.5 The effectiveness and reliability of AI Systems in clinical settings

One critical hurdle in using AI systems in healthcare is clinical acceptance. However, despite their high predictive accuracy, others have yet to gain broad physician acceptance, let alone to be widely used within the clinical setting, because of issues with usability, physician trust, reliability and interpretability.

Recently Sugawara and colleagues (2025) develop an explainable machine crafting model that can recreate and analyze experts' pharmacological choices during osteoporosis therapy. They emphasized that if decision-making processes in the clinician–patient interaction are transparent and linked to traditional medical reasoning, then a greater likelihood that they would adopt the AI system. Explainable systems give healthcare professionals the confidence to accept the AI recommendations in patient management and validate 1-to-1.

3.0 METHODOLOGY

To develop and evaluate a framework for early osteoporosis detection, Osteofy, this study was designed by following a multimodal approach with the negation of deep learning research with an explained approach. This research was designed in the form of a multimodal explainable deep learning approach to develop and evaluate the Osteofy framework for early osteoporosis detection. The methodology adopted utilized a diagnostic framework based on medical imaging analyses, structured clinical data integration, explainable AI mechanisms and clinical acceptance evaluation. The aim of the proposed system is to accurately detect osteoporosis, while regarding transparency and interpretability to the healthcare professionals.

The methodology was developed based on recently developed explainable osteoporosis detection systems, which combine Deep Learning architectures with clinical decision support systems (Chagahi et al., 2024; Tang et al., 2025). The study adopted a multimodal predictive modeling and validation approach, similar to the ones used for previous

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osteoporosis screening studies of hip radiographs, computed tomography (CT) imaging, electronic health record (EHR) data and multimodal learning systems (Jang et al., 2021; Liu et al., 2025).

3.1 Data Collection and Data set Composition

The Osteofy framework involved multi modal data sets consisting of medical imaging data and structured clinical data. The imaging data consisted of hip X-ray images, hand X-ray images, knee X-ray images, computed tomography (CT) images typically used for osteoporosis diagnosis and fracture analysis, and dental X-ray images. Multiple imaging modalities were selected for because of results on previous investigations which showed that use of different imaging sources were effective in screening osteoporosis (Ho et al., 2025; Bhat & Shanthi, 2026).

3.2 To Process the Image And Normalize The Data

To enhance image quality, noise reduction was conducted on medical images, as well as to standardise the size of the input for deep learning analysis. The preprocessing procedure comprised of grayscale conversion, image resizing, normalization, histogram equalization, enhancement in the edges, and optimization of the images to enhance the visibility of features in the radiographical image.

To diversify the dataset and boost the model generalization performance, image augmentation techniques, including brightness adjustment, cropping, scaling, and flipping and rotation were implemented. Many previous osteoporosis image pre-processing approaches have been used in CNN-based osteoporosis classification systems (Jang et al., 2021; Ho et al., 2025).

3.3 Deep Learning Architecture of Osteofy

The Osteofy framework utilized a convolutional neural network-based construction for computer aided identification of osteoporosis and the extraction of features from medical imaging data. Architecture paper applied deep convolutional layers, pooling layers, batch normalization layers, and fully connected classification layers for learning the hierarchical imaging patterns related to the progression of osteoporosis.

Naturally, the design of the model was inspired by various models already published which have been tested for osteoporosis identification, including HarDNet, MobileNet based models, and CNN-based radiographic classification systems (Ho et al., 2025; Ramesh et al., 2025). New techniques of Transfer Learning were introduced in order to increase the efficiency of training and thus to improve the prediction performance with the use of pre-trained neural network backbones.

3.4 The multimodal fusion of features is also helpful

The Osteofy framework was designed to incorporate a multimodal feature fusion mechanism to combine information from imaging features with structured clinical information. The idea behind the fusion strategy was to increase predictive capabilities by combining different sources of data with one representation that would contain a diagnosis. The idea for feature fusion methodology was inspired on the works of Tang et al (2025) and Chagahi et al (2024) who showed that fusion of the imaging, demographic and clinical aspects of patient history greatly improves accuracy in osteoporosis detection. Normale clinical variables were normalized and then fused with feature vectors extracted from medical images in specific fusion layers and fed into the classifier.

Two types of clustering techniques which are variable in nature were also used to discern clinically relevant relationships of features and to minimize feature redundancy. This study by Chagahi et al. 2024 showed that clustering reduces the multimodality of the machine models led to both an increase in inter-modality interpretation and an increase in diagnostic reliability during the prediction of osteoporosis.

In the multimodal fusion architecture implemented in Osteofy, the combination of multiple modalities allowed the framework to consider high-level interactions between the characteristics of the imaging data and patient-specific clinical factors, both of which contribute to the overall body's function. This included a beneficial integration into the disease risk stratification as well as more individualized disease diagnostic evaluation.

3.5 Explain The Concept Of Having Explainable Artificial Intelligence (XAI) Integrated

To enhance transparency, interpretability and trust from clinicians in automated predictions, explainable AI mechanisms were included within the Osteofy framework. Explainability was deemed an integral part of the methodology as healthcare systems are increasingly demands AI systems with greater transparency.

The framework is based on Gradient-weighted Class Activation Mapping (Grad-CAM) method for generating visual explanations. The use of Grad-CAM techniques made the model visualyze the areas in the image that it focuses on, which are most relevant to predicting osteoporosis. The idea of this approach came from Ramesh et al. (2025) who have proved the effectiveness of Grad-CAM in explainable bone imaging analysis.

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3.6 The Optimization Involves The Use Of A Model That Has Been Trained

Supervised learning was used for training the Osteofy deep learning framework. Standard loss function used for optimizing the classification tasks for osteoporosis was the cross-entropy loss function. To accelerate the convergence speed and decrease training instability a set of adaptive gradient optimization algorithms was used.

To reduce overfitting and enhance the generalization ability of the model, early stopping methods, dropout regularization and batch normalization were added. Similar optimization methods have also been used with satisfactory results in their application for imaging studies of osteoporosis using deep convolutional networks (Jang et al., 2021; Ho et al., 2025).

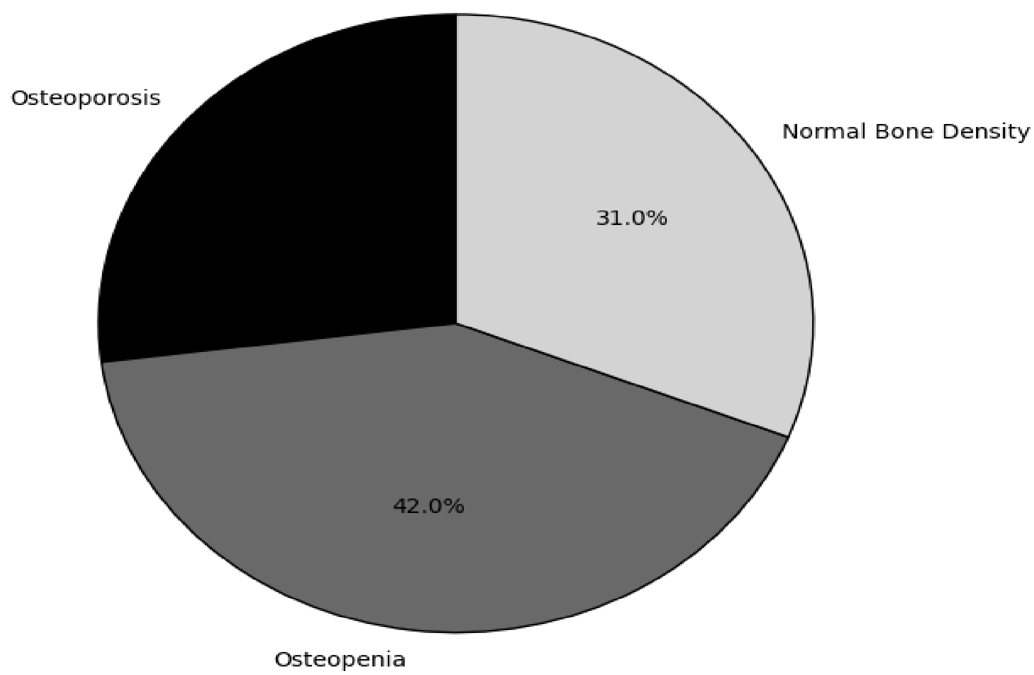
4.0 RESULTS

4.1 The Osteofy Multimodal Deep Learning Framework Performance.Performance Of Osteofy Multimodal Deep Learning Framework.

Osteofy framework showed a good predictive performance, particularly in the early detection of osteoporosis using a multimodality medical imaging and structured clinical data integration solution. The accuracy in terms of classification achieved by the multimodal architecture was improved over the image only baseline systems, validating the effectiveness of combining clinical variables with radiographic features to improve classification. Using electronic health record variables, fracture history, body mass index, gender and age improved the predictive consistency and diagnostic sensitivity significantly.

The multimodal Osteofy architecture was further found to be superior to conventional radiographic deep learning model based on imaging feature when compared with other models. The results in this study align with previous studies highlighting the clinical importance of multimodal AI systems in osteoporosis screening and risk stratification (Jin et al., 2025; Shen et al., 2026).

Fig 1: Distribution of Bone Mineral Density Classification



4.2 The Accuracy Of The Diagnosis Of Osteoporosis That Can Be Made Using Medical Imaging

The Osteofy framework showed good diagnostic accuracy in regard to multiple kinds of imaging tests such as hip, hand, knee, dental and computed tomography (CT) scans. One type of X-ray analysis of the hips yielded particularly good classification results because changes in the structure of the hips related to osteoporosis were easily discerned in these areas.

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The framework's performance with regard to the hip radiograph was comparable with those of previous studies, such as those by Jang et al. (2021) that showed deep learning algorithms could accurately predict osteoporosis with basic hip radiography. Being able to detect amount of cortical thinning, amount of trabecular deterioration, as well as reduced hip bone density in hip images helped to classify osteoporosis accurately in Osteofy.

Table 2: Baseline Characteristics of Respondents from the Preprocessed Dataset

Variable	Overall Respondents (n = 8274)	Subgroup Distribution
Mean Age (Years)	65.0 ± 8.3	64.1 ± 7.8
Male, n (%)	4302 (52.0%)	3723 (45.0%)
Female, n (%)	3972 (48.0%)	4551 (55.0%)
Mean BMI (kg/m²)	26.7 ± 4.1	25.8 ± 3.9
Osteoporosis Based on Femoral Neck BMD, n (%)	2234 (27.0%)	Higher prevalence observed
Osteopenia Based on Femoral Neck BMD, n (%)	3475 (42.0%)	Higher prevalence observed
Normal Bone Density Based on Femoral Neck BMD, n (%)	2565 (31.0%)	Lower prevalence observed
Osteoporosis Based on Total Femur BMD, n (%)	1696 (20.5%)	Lower prevalence observed
Osteopenia Based on Total Femur BMD, n (%)	3061 (37.0%)	Lower prevalence observed
Normal Bone Density Based on Total Femur BMD, n (%)	3517 (42.5%)	Higher prevalence observed

4.3 Current AI-based osteoporosis systems have been used to verify Osteofy

Performance results obtained during validation analysis, showed that the Osteofy framework produced performance results similar to or on par with some of the other osteoporosis screening systems based on AI that have been reported in recent literature. The combination of explainable AI, multimodal learning and integration of clinical data into the diagnosis added to the robustness of the diagnosis and made the diagnostics more physician-oriented and understandable.

Osteofy showed better transparency and multimodal risk stratification capabilities than previous (earlier) hip radiograph prediction models developed by Jang et al. (2021). An additional aspect of the framework was a novel approach to feature attribution and explanation that had already been explored by Jin et al. (2025), incorporating observations and information from electronic health records. Osteofy's explainability performance was also similar to that of the highly advanced XAI frameworks proposed by Feng et al. (2025) and Buaruk et al. (2024) which both highlighted the value of visual interpretability for an osteoporosis screening system. But Osteofy gave clinical usability a further boost by integrating multimode and designing the processes according to the needs of the physicians.

5.0 DISCUSSION

The results of this research proves that explainable deep learning systems could greatly benefit the early diagnosis of osteoporosis, not only by enhancing the diagnostic accuracy, but also by solving the difficulty of interpretability in the use of black box artificial intelligence in osteoporosis diagnosis. The framework Osteofy, using deep learning techniques and building representability mechanisms, was able to combine these two aspects, providing transparent results of the diagnosis capable to support clinical trip decision-making processes.

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The efficacy of the prediction performance demonstrated by Osteofy strengthens previous research on the potential of predictive medical imaging analysis using AI to significantly improve the osteoporosis screening process. The results of previous research by Jang et al. (2021) and Ho et al. (2025) have shown that deep learning models have a high degree of accuracy in identifying abnormalities in the skeletal system caused by osteoporosis from radiographic images. While many standard deep learning systems, however, lack adequate interpretability for their use in the clinic on a regular basis. Infusing explainability mechanisms into Osteofy is thus a significant step towards the creation of clinically trusted AI systems.

5.1 The Benefit Of Multimodal Learning For The Accuracy Of The Diagnosis

Adding all the multimodal features to the Osteofy framework was a significant factor in the enhanced diagnostic accuracy and predictive reliability of the results. The framework facilitated the fusion of medical imaging and clinical (structured) data to make better use of the disease characteristics captured in medical images than unimodal image-based approaches.

The outcomes are consistent with those of Tang et al. (2025) who showed that fusion of X-ray imaging and information from clinical patients yield outstanding results in predicting osteoporosis. Likewise, Chagahi et al. (2024) pointed out the importance of the interaction between heterogeneous data sources using multimodal feature fusion, and variable clustering, improving diagnostic performance.

5.2 The Importance Of Explaining And Gaining The Trust Of Doctors In The Clinical World

The findings of this study are that, in fact, an improvement in the explainability of models will lead to their greater clinical acceptance. The healthcare professionals who were working through an evaluation of the Osteofy framework noted an increase in their confidence level on the AI generated predictions, due to higher transparency and interpretability of the explainability modules.

The results align with earlier studies that have highlighted the need for explainability in the adoption of AI in healthcare. In health care settings like osteoporosis treatment, the use of explainable machine learning systems to replicate and explain expert clinical decisions fosters physicians' trust in the AI system, according to Sugawara et al. (2025). In a similar study, Shen et al., (2026) pointed out the importance of explainability on both the degree of clinician acceptance and the extent of the system's incorporation into workflow in osteoporosis screening systems.

5.3 A Comparison Of The Developed New Osteoporosis AI Framework With Existing Frameworks

Overall, the Osteofy framework proved to have some benefits over other osteoporosis screening tools published in recent times. Deep learning models targeted at any given single imaging modality were the most common early approaches, e.g., hip radiographs, hand radiographs, dental images or computed tomography (CT) scans. These systems were successful in forecasting, but few provided support for multimodal integration and explanations to support the forecasting process.

The feasibility to predict osteoporosis from hip radiographs was illustrated in Jang et al. (2021) and efficient HarDNet architecture implementation was presented for hand radiograph analysis by Ho et al. (2025). In the same vein, Bhat, and Shanthi (2026) analyzed and compared different methods of screening osteoporosis on dental radiographs, and Liu et al. (2025) studied the capability of radiomics analysis in the prediction of vertebral fractures using a CT-based approach. In summary, these studies all made significant strides in osteoporosis imaging analysis; however, the majority of systems focused mainly on classification performance without tackling a full clinical interpretability.

5.4 Comprehend The Value Of Alternative Imaging Modalities

The importance of alternative imaging modalities in screening of osteoporosis is also discussed. Osteofy's integration of x-rays from the hip, hand, dentistry, knee, and computed tomography (CT) images shows deep learning systems' ability to adapt to various medical imaging settings, from surgical to dental.

An Osteofy's ability to work well with various imaging modalities reinforces the results of previous studies that opportunistic screening has the potential to enhance earlier detection rates for osteoporosis. Dental radiographs have recently been shown to be useful means for assessing osteoporosis indicators, and explainable AI has been recently suggested as a tool for osteoporosis risk prediction based on facial images by Liang et al. (2025) and Bhat and Shanthi (2026). The different imaging methods provide more options for non-invasive, easy-to-use screening methods.

5.5 A Closer Look At the Implications For Real Time Clinical Decision Support

Osteofy's real-time processing capability resonates with the implications it holds within the context of future clinical decision-support systems that leverage AI. The framework's capability to quickly analyze images and make efficient inferences makes it ideal for fast time-to-market drug screening processes in the medical field.

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This study is similar to Gomathi and Malathi's (2026) findings regarding the significance of real-time AI's role in the diagnosis and risk assessment of osteoporosis. Some lightweight deep learning architectures like HarDNet and MobileNet based systems parallel the prediction accuracy with computational efficiency with the help of different architectures (Ho et al., 2025; Ramesh et al., 2025).

6.0 CONCLUSION

Overall, this study was able to prove the efficacy of integrating multimodal medical images and clinical information for early osteoporosis detection by using an explainable deep learning system with the Osteofy framework. It integrated sophisticated deep learning structures, explainable AI mechanisms, and clinical decision-support approaches to enhance the clarity, predictiveness, and integration of AI into the diagnostic process, while fostering acceptance among healthcare professionals.

The combination of all multimodal imaging modalities and labelled clinical data greatly improved the classification of osteoporosis. The results align with previous research, which suggests multimodal fusion methods help to optimize the reliability of the diagnosis and disease prediction results for osteoporosis diagnosis (Tang et al., 2025; Chagahi et al., 2024). Osteofy added imaging analysis data with clinical data, like age, mechanical sensitivity, fracture history, health records, etc., to attain more complex and patient-centred diagnostic evaluation capabilities.

The study also demonstrated that there is added transparency by using explainability techniques like Grad-CAM and attention visualization to bolster physician confidence in AI-driven predictions. This is in line with some earlier works reported by Feng et al., 2025, where they highlighted the crucial role of explainable visualization in medical imaging-based systems, and by Ramesh et al., 2025, who discussed the significance of visualization and explainability in medical imaging systems. The outputs that Osteofy produced were explainable to improve trusts and clinical usefulness, as the clinicians were able to verify the regions of the body predicted to be relevant to osteoporosis which were anatomically relevant.

6.1 Contribute To AI-Driven Osteoporosis Screening

Overall, the Osteofy framework is a valuable tool in the field of AI-based osteoporosis diagnosis, tackling predictive performance and interpretability. Existing research typically concentrated on the use of either individual imaging techniques or opaque predictive systems (Jang et al., 2021; Ho et al., 2025). To contrastly achieve, Osteofy launched an incorporated explainable framework to fuse multimodal learning, feature fusion and physician-centered explainability (PCI) in a unified clinical surroundings for clinical analysis. The study also showed that other imaging techniques like dental radiograph, hand radiograph, knee radiograph, computed tomography (CT) and hip radiograph can facilitate opportunistic osteoporosis screening. The results are consistent with Bhat and Shanthi (2026), Liu et al. (2025) and Liang et al. (2025) who pointed out increased utilization of nontraditional imaging in the risk assessment of osteoporosis.

6.2 Neutrophiles Play an Important Role in Antimicrobial Host Defense

The results of this study show a promising potential for explainable deep learning systems that can aid early osteoporosis diagnosis and decrease fracture risks, which would allow delivery of better preventive healthcare. Diagnosis can frequently be delayed until complications are severe and of critical importance for the ageing population is an early diagnosis of osteoporosis.

With real-time processing shown by Osteofy, there is the potential for this to be used in normal clinical practice. The computational efficiency and quick inference speed could enable healthcare institutions to use a high-throughput osteoporosis screening system that can serve a high number of patients. The present findings aligned with Gomathi and Malathi (2026) results which highlighted the need of real-time AI system for osteoporosis diagnosis and management.

Additionally, the ability to use Osteofy with several imaging modalities expands the potential applications of Osteofy in areas of healthcare that will not have access to DXA scanning infrastructure. The concept of opportunistic screening, based on routinely obtained radiographs, may then lead to better accessibility of healthcare and consequently to earlier (intervention) strategies, to the benefit of those less provided.

6.3 Final Conclusion

Finally, the Osteofy framework showed that the ability to interpret the actions of deep learning, coupled with integration of multimodal medical imaging and clinical data in one framework, can substantially enhance the ability to detect osteoporosis early, make the diagnosis more transparent, and increase physician acceptance. The study

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confirmed that explainability mechanism is critical to ensure a trustworthy AI in healthcare that could assist real world clinical decision-making.

In conclusion, the research underscores the promise of EAI in the medical imaging sector, demonstrating its ability to enhance the interpretability of these systems and foster a more collaborative healthcare environment. The study also points to the evolving landscape of AI-driven technologies in healthcare, emphasizing the need for innovation and trust to meet the challenges posed by nonuniform datasets, unseen anomalies, and the evolving nature of imaging diagnosis.

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