NICOLAUS COPERNICUS UNIVERSITY IN TORUŃ

Journal of Education, Health and Sport. eISSN 2391-8306.

Journal Home Page
https://apcz.umk.pl/JEHS/index

KULIG, Lidia, MALEC, Julia Anna, WIERCIOCH, Eliza, WINIARSKA, Zuzanna, WOŹNIAK, Weronika Maria, ZAPALSKA, Magdalena, STEĆ, Sara, WIELEBA, Marcin, WŁODARCZYK, Franciszek and KRUPSKA, Barbara Izabela. Applications of Artificial Intelligence in Opportunistic Screening and Diagnostic Imaging of Osteoporotic Fractures: A Systematic Review. Journal of Education, Health and Sport. 2026;89:70382. eISSN 2391-8306. https://doi.org/10.12775/JEHS.2026.89.70382

The journal has had 40 points in Minister of Science and Higher Education of Poland parametric evaluation. Annex to the announcement of the Minister of Education and Science of 05.01.2024 No. 32318. Has a Journal's Unique Identifier: 201159. Scientific disciplines assigned: Physical culture sciences (Field of medical and health sciences); Health Sciences (Field of medical and health sciences).
Punkty Ministerialne 40 punktów. Załącznik do komunikatu Ministra Nauki i Szkolnictwa Wyższego z dnia 05.01.2024 Lp. 32318. Posiada Unikatowy Identyfikator Czasopisma: 201159. Przypisane dyscypliny naukowe: Nauki o kulturze fizycznej (Dziedzina nauk medycznych i nauk o zdrowiu); Nauki o zdrowiu (Dziedzina nauk medycznych i nauk o zdrowiu). **© The Authors 2026;**
This article is published with open access at Licensee Open Journal Systems of Nicolaus Copernicus University in Torun, Poland
Open Access. This article is distributed under the terms of the Creative Commons Attribution Noncommercial License which permits any noncommercial use, distribution, and reproduction in any medium, provided the original author (s) and source are credited. This is an open access article licensed under the terms of the Creative Commons Attribution Non commercial license Share alike.
(http://creativecommons.org/licenses/by-nc-sa/4.0/) which permits unrestricted, non commercial use, distribution and reproduction in any medium, provided the work is properly cited.
The authors declare that there is no conflict of interests regarding the publication of this paper.
Received: 29.03.2026. Revised: 06.04.2026. Accepted: 06.04.2026. Published: 10.04.2026.

Applications of Artificial Intelligence in Opportunistic Screening and Diagnostic Imaging of Osteoporotic Fractures: A Systematic Review

Lidia Kulig,

ORCID https://orcid.org/0009-0008-0709-574X

E-mail lidia.kulig01@gmail.com

Medical University of Warsaw, Poland

Julia Anna Malec,

ORCID https://orcid.org/0009-0002-2564-2889

E-mail jmalec17@wp.pl

Medical University of Warsaw, Poland

Eliza Wiercioch,

ORCID https://orcid.org/0009-0004-0044-301X

E-mail eliza.wiercioch2001@gmail.com

Medical University of Lublin, Poland

Zuzanna Winiarska,

ORCID https://orcid.org/0009-0002-3177-4271

E-mail zuzawiniarska22@gmail.com

Medical University of Lublin, Poland

Weronika Maria Woźniak,

ORCID https://orcid.org/0009-0007-4906-7125

E-mail weronika7801@gmail.com

Medical University of Lublin, Poland

Magdalena Zapalska,

ORCID https://orcid.org/0009-0007-5777-2959

E-mail magda.zapalska1@gmail.com

Medical University of Lublin, Poland

Sara Steć

ORCID https://orcid.org/0009-0007-2661-5328

E-mail sara.stec1@gmail.com

Medical University of Warsaw, Poland

Marcin Wieleba,

ORCID https://orcid.org/0009-0006-9815-4340

E-mail marcin.wieleba09@gmail.com

Medical University of Lublin, Poland

Franciszek Włodarczyk,

ORCID https://orcid.org/0009-0005-0754-4558

E-mail fwlodarczyk576@gmail.com

Medical University of Lublin, Poland

Barbara Izabela Krupska,

ORCID https://orcid.org/0009-0002-5755-9377

E-mail bkrupska07@wp.pl

Medical University of Lublin, Poland

Corresponding Author

Lidia Kulig, E-mail lidia.kulig01@gmail.com

Abstract

Background: Osteoporosis remains a "silent epidemic," with 80% of high-risk patients untreated. This systematic review assesses the clinical utility of Artificial Intelligence (AI) in opportunistic screening. It examines how routine CT and MRI scans identify vertebral fractures and low bone mineral density (BMD) without an extra dose of radiation.

Methods: Using PRISMA guidelines, we systematically searched major databases and identified 30 studies focused on Deep Learning and Convolutional Neural Networks (CNNs) in clinical procedures.

Results: AI models achieved Area Under the Curve (AUC) between 0.81 and 0.99. About 50% of studies used routine chest and abdominal CT scans, in which AI-driven 3D volumetric analysis outperformed traditional 2D DXA densitometry (AUC 0.82 vs. 0.72). The algorithms reduced diagnostic errors from aortic calcifications and degenerative changes and enabled the prediction of 5- to 10-year fracture risk.

Conclusions: Opportunistic screening in connection with AI-Based programs closes the diagnostic gap in bone and skeletal system screening and diagnostics. Integrating automated vertebral checks into daily imaging workflows supports early diagnosis. This proactive approach improves long-term patient health and reduces the financial burden on the healthcare system.

Keywords: Osteoporosis, Artificial Intelligence, Opportunistic Screening, Computed Tomography, Vertebral Fractures.

Introduction

1.1 Epidemiology and characteristics

According to the WHO definition, osteoporosis is "a systemic skeletal disease characterized by low bone mass and microarchitectural deterioration of bone tissue, causing enhanced bone fragility and a consequent increase in fracture risk." [1]

Osteoporosis is a public health challenge impacting over 200 million people, causing about 1.66 million hip fractures annually. One in three women and one in five men over age 50 will have an osteoporotic fracture during their lifetime.

Secondary osteoporosis is still a major concern, affecting up to 30% of postmenopausal women, over b50% of premenopausal women, and between 50% and 80% of men [2]. However, secondary causes are often overlooked in patients with low bone density. It is critical to exclude these factors in patients with fragility fractures when traditional clinical risk factors are absent, or in younger populations, such as premenopausal women and men under the age of 50.

On a global scale, an osteoporotic fracture occurs every three seconds. Despite this frequency, approximately 80% of individuals with a fragility fracture are neither identified as having osteoporosis nor treated for it [3].

Osteoporosis is known for its asymptomatic nature; it is often referred to as a "silent disease" because it progresses without causing pain. Consequently, the first clinical symptom is frequently a serious low-energy fracture of the vertebra or hip. Such injuries often lead to a significant loss of independence, creating a serious personal burden for patients and an enormous financial obligation for public healthcare budgets.

1.2 Diagnostic Imaging and Its Limitations

Low bone mineral density—less mineral than normal in bones—can be diagnosed using several factors discussed later. The gold standard for fracture risk screening is a dual-energy X-ray absorptiometry (DEXA, also known as DXA) scan, which measures bone density and may use a fracture risk tool (FRAX). A DXA scan measures the lumbar spine and hip or femoral neck. DXA assesses bone mineral density (BMD) in grams per square centimeter (g/cm^2) and converts it to a T-score, which compares the patient's BMD to a healthy reference population. Despite an aging population, many patients still lack access to this screening due to long wait times, limited referrals, or a lack of equipment in smaller cities.

Also, the accuracy of DXA can be compromised by degenerative bone changes (such as bone spurs, called osteophytes) and vascular calcifications (including atherosclerotic plaques—calcium deposits—within blood vessels, such as the aorta), which can overlap with the bone image. This often leads to falsely elevated bone mineral density (BMD), resulting in false-positive results.

Standard X-Ray imaging can detect a complete fracture. In contrast, Computed Tomography (CT) scans present a more detailed picture of the bone. However, CT is rarely used solely for bone evaluation due to its significantly higher radiation dose than DXA. This creates a diagnostic gap that opportunistic screening addresses by using existing CT data without additional radiation exposure.

1.3 Artificial Intelligence in Medical Imaging

The rapid technological development has led to the appearance of Computer-Aided Diagnosis (CAD) systems, which operate as the foundation for modern artificial intelligence in radiology. Traditionally, skeletal evaluation required radiologists to measure bones manually. The process is not only time-consuming but also prone to human error.

However, current Deep Learning (DL, a subset of artificial intelligence methods for teaching computers to learn from data), especially Convolutional Neural Networks (CNNs, algorithms for processing images), is enabling the modernization of this field. These models can segment vertebrae (separate each spinal bone in an image) and, in parallel, calculate bone density with high precision in fractions of a second. A main benefit of AI-based diagnostics is its objectivity and consistency, which exceed those of human practitioners. AI algorithms are not affected by fatigue, excessive workloads, or personal biases, providing the same level of care regardless of clinical conditions.

1.4. The Opportunistic Screening approach

Opportunistic screening is a combination of techniques for identifying subjects at high risk of osteoporotic fracture using routine clinical CT scans prescribed for diagnoses unrelated to osteoporosis. The two main components are automated identification of vertebral fractures and measurement of bone mineral density (BMD) in CT scans, in which a phantom for calibration of CT to BMD values is not used. [4]

Every day, a vast number of patients undergo CT scans of the chest or abdomen to diagnose a wide variety of conditions. In the meantime, AI allows for the evaluation of these images for signs of osteoporosis "in the background." The utilization of existing radiological data, combined with the speed and automation of Artificial Intelligence, defines the essence of opportunistic screening—transforming routine diagnostic procedures into an active tool for bone health assessment without additional radiation exposure.

1.5 Aim of the Study and Research Question

This systematic review evaluates the diagnostic efficacy of AI-based opportunistic screening for osteoporotic fractures and assesses bone mineral density across a range of routine imaging techniques.

The primary research question of this study is: "What is the diagnostic performance of AI-based opportunistic screening in the identification of vertebral fractures and low bone mineral density in routine medical imaging compared to standard clinical assessments?"

Materials and Methods

2.1 Materials and Methods

This systematic review was prepared according to the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. This study protocol has not been registered in external databases. However, all stages of the analysis were carefully planned, including the selection criteria and data extraction methods, which were established prior to the study and strictly followed to ensure transparency and the objectivity of the results.

2.2 Literature Search Strategy

A systematic search on Artificial Intelligence and osteoporosis management was performed in PubMed and Scopus. The primary search period was from January 2020 to March 2026. The specific combination of Medical Subject Headings (MeSH) terms and text keywords, connected by Boolean Operators (OR, AND), was used to create a search string.

The keywords included

> "Artificial Intelligence" OR "Deep Learning" OR "Machine Learning."
>
> AND "Osteoporosis" OR "Vertebral Fracture" OR "Bone Mineral Density."
>
> AND "Opportunistic Screening" OR "Incidental" OR "Routine CT".

The primary search was limited to both Polish and English languages and original research.

2.3 Inclusion and Exclusion Criteria

The study selection was based on a predefined set of inclusion criteria, as summarized in Table 1.

In order to provide a structured and objective literature selection process, the research question was defined using the PICO criteria (Population, Intervention, Comparison, Outcome) as follows:

P (Population): Adults undergoing routine radiographic diagnostics (CT, X-ray, MRI) or patients at risk of osteoporosis.

I (Intervention): Use of Artificial Intelligence algorithms, including Deep Learning, Convolutional Neural Networks (CNN), and Radiomics for medical imaging analysis.

C (Comparison): Standard radiological assessment (manual reading) or "gold standard" DXA densitometry.

O (Outcome) Diagnostic effectiveness. The principal indicator for evaluating and comparing the diagnostic performance of AI models was the Area Under the Curve (AUC/AUROC). Additionally, where available, other parameters such as sensitivity, specificity, and cost-effectiveness (ICER) were analyzed to provide a comprehensive evaluation.

Table 1: Inclusion and Exclusion Criteria

Criterium	Inclusion	Exclusion
Study design	original research, clinical trial, cohort study, validation study.	Reviews, case reports, position statements, commentary, letters to the editor, meta-analysis
Population	adults (> 18 yo), patients with risk of osteoporosis, geriatric patients, patients undergoing routine radiographic diagnostic	pediatric population (< 18 yo.), studies on animals, cadavers, or ex vivo models
AI Intervention – Technology	Artificial Intelligence Algorithms for imaging diagnostics (Deep Learning, Convolutional Neural Networks(CNN), Radiomics, Machine Learning)	Statistical methods that exclude machine learning, traditional radiological scale without automation
Settings	Opportunistic screening, routine diagnostic path, emergency medicine department, and specialized clinics	NONE
Imaging methods	X-ray (digital radiography), CT (Computed Tomography), MRI (Magnetic Resonance Imaging).Opportunistic imaging (routine CT/X-ray/MRI)	USG (ultrasound), Scintigraphy, PET-CT (except as the comparative method).
Subject of the analysis	Detection of osteoporotic fractures, assessment of bone density (BMD), and differentiation of fractures (differential diagnosis).	High-energy fractures (traffic accidents) and primary bone tumors (as the sole purpose of the study).
Language and time of publication	Publication in the Polish and English languages, from January 2021 to March 2026	Articles published in other languages or earlier than the frame time.

2.4 Study selection

The article selection process in this study followed the PRISMA 2020 guidelines. The initial database search identified 389 records. After duplicates were removed and the initial screening of titles and abstracts was completed, the primary screening identified 164 records for further analysis. As a result, 84 reports were not retrieved due to a lack of access to the full text (e.g., conference abstracts or restricted access). A total of 80 reports were assessed for eligibility due to the condition of inclusion/exclusion criteria presented in TABLE 1. Fifty records were excluded. Consequently, the final analysis included 30 primary studies. The workflow of the process is detailed in Figure 1 (PRISMA Flow diagram). During the data extraction phase, the Area Under the Curve (AUC/AUROC) was identified as the primary metric for evaluating and comparing the diagnostic performance of the AI models across the included studies.

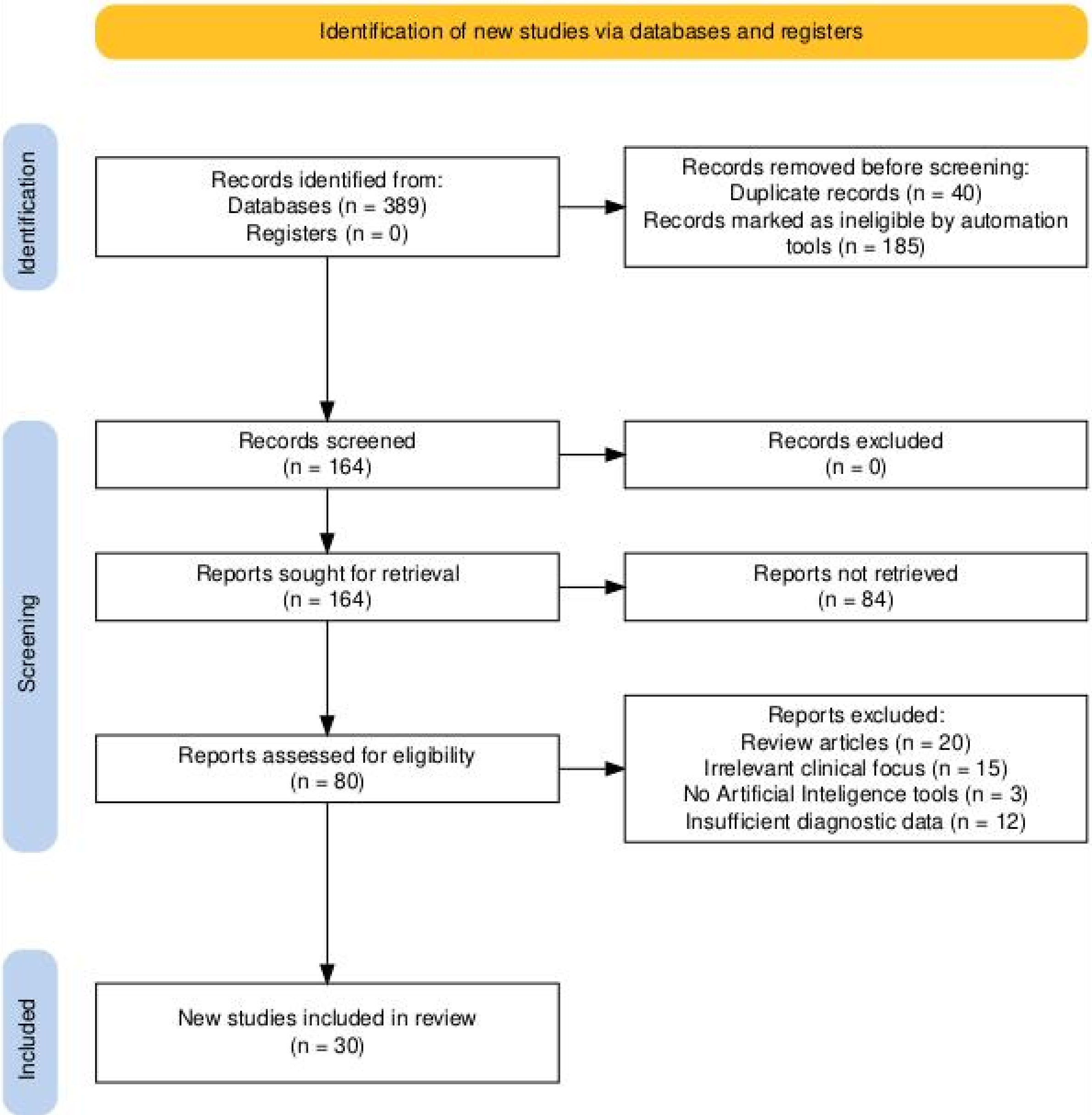

Figure 1. PRISMA 2020 flowchart showing the literature selection process

Review articles were also initially identified and excluded from the main comparative examination, but were used as supplementary literature to provide a theoretical background.

RESULTS

Table 2. Results

No.	Author & Year	Title	Method (Imaging)	AI Model	Study Group (N)	Results AUC AUROC	Other Parameters	Key Conclusion
1	Shen et al. (2023)	*Using Artificial Intelligence to Diagnose Osteoporosis*	Plain Radiographs (X-RAY)	the-AI_DVF	12,670 images	AUC = 0.92	Sens: 88.3%; Spec: 84.7%	High performance in automatically identifying fractures on various clinical datasets. [5]
2	Hung et al. (2022)	*Deep-Learning-Based Detection of Vertebral Fracture and Osteoporosis Using Lateral Spine X-Ray Radiography*	Lateral Spine X-Ray	CNN (VGG-16)	5,671 patients	AUC = 0.94	Accuracy: 88.5%	Developed the V-FRACTURE system for automated opportunistic screening.[6]
3	Guermazi et al. (2022)	*Improving Radiographic Fracture Recognition Performance and Efficiency Using Artificial Intelligence*	X-RAY (various)	Rayvolve	480 patentu	AUC = 0.97	Sens: 75.2% vs 64.8% (rads)	AI assists experts in identifying fractures while reducing interpretation time.[7]
No.	Author & Year	Tytuł	Method (Imaging)	AI Model	Study Group (N)	Results AUC AUROC	Other Parameters	Key Conclusion
4	Del et al. (2022)	*Computer-Aided Diagnosis of Vertebral Compression Fractures Using Convolutional Neural Networks and Radiomics*	MRI (T1, STIR)	Hybrid (CNN + Radiomics)	129 patients	AUC = 0.95	Accuracy: 87.2%	The hybrid model effectively distinguishes between acute and chronic fractures.[8]
5	Zhang et al. (2024)	*Exploring deep learning radiomics for classifying osteoporotic vertebral fractures in X-ray images*	X-RAY (Thoracolumbar)	DLR (ResNet-50 + Radiomics)	441 patients	AUC = 0.91	Sens: 0.88; Spec: 0.87	The hybrid model outperforms standalone DL or radiomics.[9]
6	Hsieh et al. (2021)	*Automated bone mineral density prediction and fracture risk assessment using plain radiographs.*	Pelvic/Spine X-RAY	Ensemble (ResNet-50)	23,303 patients	AUC = 0.82	Accuracy: 91.1% (AAC)	Can predict BMD and risk from pelvic radiographs.[10]
No.	Author & Year	Tytuł	Method (Imaging)	AI Model	Study Group (N)	Results AUC AUROC	Other Parameters	Key Conclusion
7	Boonrod et al. (2024)	*Deep learning for osteoporosis screening using an anteroposterior hip radiograph image*	Hip X-RAY (AP)	ResNet-50	1,900 patients	AUC = 0.81	Sens: 91.0%; Spec: 53.0%	High sensitivity in screening osteoporosis from standard hip images. [11]
8	Cross et al. (2024)	*Subject-Level Spinal Osteoporotic Fracture Prediction Combining Deep Learning Vertebral Outputs and Limited Demographic Data*	Pelvic/Spine X-RAY	Deep Learning + GAM	10,334 patients	AUC = 0.91	Sens: 97.0%; Spec: 85.0%	Integrates AI with clinical data to predict future fractures. [12]
9	Kong et al. (2022)	*Development of a Spine X-Ray-Based Fracture Prediction Model Using a Deep Learning Algorithm*	Lumbar Spine X-RAY	DeepServ (CNN)	1,595 patients	AUC = 0.73	C-index = 0.73	An AI model predicts future fracture risk based on baseline images. [13]
No.	Author & Year	Title	Method (Imaging)	AI Model	Study Group (N)	Results AUC AUROC	Other Parameters	Key Conclusion
10	Biamonte et al. (2022)	*Artificial intelligence-based radiomics on computed tomography of the lumbar spine in subjects with fragility vertebral fracture*	Lumbar CT	Radiomics (Random Forest)	240 patients	AUC = 0.81	Sens: 0.73; Spec: 0.88	Radiomics identifies high-risk patients on routine CT scans.[14]
11	Nadeem et al. (2024)	*Chest CT-based Automated Vertebral Fracture Assessment using Artificial Intelligence and Morphologic Features*	Chest CT	DL + Morphologic al Features	3,231 patients	AUC = 0.99	Sens: 94.6%; Spec: 99.5%	First fully automated system for pulmonary and skeletal screening.[15]
No.	Author & Year	Title	Method (Imaging)	AI Model	Study Group (N)	Results AUC AUROC	Other Parameters	Key Conclusion
12	Riedel et al. (2023)	*Diagnostic accuracy of deep learning vs. human raters for detecting osteoporotic vertebral compression fractures in routine CT scans*	Routine CT	Hybrid DL (ensemble)	251 patients	AUC = 0.93	Sens: 88% (AI) vs 72% (rads)	AI identifies more fractures than radiologists in routine CT. [16]
13	Duan et al. (2024)	*Differential diagnosis of benign and malignant vertebral compression fractures: Comparison and correlation of radiomics and deep learning frameworks.*	Spine CT	Hybrid (Radiomics + DL + Clinical)	414 patients	AUC = 0.94	Sens: 88.1%; Spec: 95.3%	Integrates AI with clinical data to differentiate cancer from osteoporosis.[17]
No.	Author & Year	Title	Method (Imaging)	AI Model	Study Group (N)	Results AUC AUROC	Other Parameters	Key Conclusion
14	Dong et al. (2022)	*Deep Learning Classification of Spinal Osteoporotic Compression Fractures on Radiographs using an Adaptation of the Genant Semiquantitative Criteria*	Lumbar Spine X-RAY	ResNet-50	7,609 images	AUC = 0.81	Accuracy: 93.8%	Model based on Genant scale maximized for diagnostic sensitivity.[18]
15	Löffler et al. (2021)	*Automatic opportunistic osteoporosis screening in routine CT: improved prediction of patients with prevalent vertebral fractures compared to DXA*	Routine CT vs DXA	CNN (Framework BoneVense)	162 patients nts	AUC = 0.82	AI (CT) > DXA (AUC 0.72)	Automated CT analysis is better at predicting fractures than DXA.[19]
No.	Author & Year	Title	Method (Imaging)	AI Model	Study Group (N)	Results AUC AUROC	Other Parameters	Key Conclusion
16	Huang et al. (2024)	*Application of a deep learning model based on unenhanced chest CT for opportunistic screening of osteoporosis: a multicenter retrospective cohort study*	Chest CT	CNN (Seg + Class)	1,130 patients	AUC = 0.93	Sens: ~84%; Spec: ~88%	Accurate screening for osteoporosis and fractures on chest CT.[6]
17	Liu et al. (2024)	*Deep Learning Radiomics Model Based on Computed Tomography Image for Predicting the Classification of Osteoporotic Vertebral Fractures.*	Spine CT	DLR (ResNet + Radiomics)	991 patients	AUC = 0.93	Sens: 88.5%; Spec: 91.2%	The hybrid model (DLR) provides high accuracy in clinical classification.[20]
No.	Author & Year	Title	Method (Imaging)	AI Model	Study Group (N)	Results AUC AUROC	Other Parameters	Key Conclusion
18	Spångeus et al. (2025)	*Breaking the silence: AI's contribution to detecting vertebral fractures in opportunistic CT scans in older people—a validation study*	Routine Chest/Abdomen CT	IB Lab FLAMINGO (CNN)	246 patients	AUC = 0.93	Sens: 88%; Spec: 99%	Validated commercial system reduces the "diagnostic gap" significantly.[21]
19	Park et al. (2025)	*Opportunistic screening of low bone mass using knowledge distillation-based deep learning in chest X-rays with external validation.*	Chest X-RAY	OsPenScree n (ResNet-18)	76,000 patients	AUC = 0.81	Sens: 72.0%; Spec: 71.0%	Enables identification of low bone mass on standard chest X-rays.[22]

No.	Author & Year	Title	Method (Imaging)	AI Model	Study Group (N)	Results AUC AUROC	Other Parameters	Key Conclusion
20	Wang et al. (2024)	*Deep learning-driven diagnosis of multi-type vertebral diseases based on computed tomography images*	Spine CT	U-Net + ResNet-50	2,557 patients	AUC = 0.98	Sens: 94.6% (Fracture)	Comprehensive model for identifying various vertebral pathologies.[23]
21	Imani et al. (2025)	*Deep Learning Technique for Automatic Segmentation of Proximal Hip Musculoskeletal Tissues From CT Scan Images: A MrOS Study*	Hip CT	U-Net	1,791 patients	AUC = 0.91	High correlation with BMD	Enables simultaneous automated tissue segmentation with high precision.[24]
No.	Author & Year	Title	Method (Imaging)	AI Model	Study Group (N)	Results AUC AUROC	Other Parameters	Key Conclusion
22	Pignolo et al. (2025)	*Opportunistic assessment of osteoporosis using hip and pelvic X-rays with OsteoSight™: validation of an AI-based tool in a US population*	Hip/Pelvis X-RAY	OsteoSight (DL)	1,481 patients	AUC = 0.88	Sens: 87%; Spec: 76%; ICC: 0.99	The tool delivers results equivalent to DXA based on standard radiographs.[25]
23	Yoda et al. (2022)	*Automated Differentiation Between Osteoporotic Vertebral Fracture and Malignant Vertebral Fracture on MRI Using a Deep Convolutional Neural Network*	MRI (T1, STIR)	CNN (ResNet)	451 patients	AUC = 0.96	Accuracy: 90.1%	Automatically differentiates osteoporotic from malignant fractures on MRI. [26]
No.	Author & Year	Title	Method (Imaging)	AI Model	Study Group (N)	Results AUC AUROC	Other Parameters	Key Conclusion
24	Zhang et al. (2023)	*Automated detection and classification of acute vertebral body fractures using a convolutional neural network on computed tomography*	Routine CT	Cascade CNN	565 patients	AUC = 0.93	Accuracy: 90.1%	High sensitivity in detecting and classifying fractures according to Genant.[27}
25	Du et al. (2023)	*Application of intelligent X-ray image analysis in risk assessment of osteoporotic fracture of the femoral neck in the elderly*	Hip X-RAY	Deep Learning	250 patients	AUC = 0.93	Sens: 88%; Spec: 82.5%	Precisely identifies risk in elderly patients with femoral neck fractures. [28]
No.	Author & Year	Title	Method (Imaging)	AI Model	Study Group (N)	Results AUC AUROC	Other Parameters	Key Conclusion
26	Chen et al. (2024)	*Deep learning meets chest X-rays: a promising approach for predicting future compression fracture risk*	Chest X-RAY	AI-VFA	166,000 patients	AUC = 0.78	Better than T-score at predicting fractures	Standard chest X-rays can be used to predict future osteoporotic fractures.[29]
27	Breit et al. (2023)	*CNN-based evaluation of bone density improves diagnostic performance to detect osteopenia and osteoporosis in patients with non-contrast chest CT examinations.*	Chest CT	CNN	252 patients	AUC = 0.91	Sens: 83%; Spec: 90%	AI on chest CT outperforms standard radiologist reports in identifying low BMD.[30]
No.	Author & Year	Title	Method (Imaging)	AI Model	Study Group (N)	Results AUC AUROC	Other Parameters	Key Conclusion
28	Behanova et al. (2026)	*AI-supported opportunistic detection of vertebral fractures on routine CT scans: Diagnostic performance and clinical relevance*	Thoracic/Abdominal CT	IB Lab FLAMINGO (DL)	418 patients (7,847 vertebrae)	AUC = 0.94	Sens: 88.5%; Spec: 99.3%	AI identifies fractures in patients previously described as "normal" by radiologists. [31]
29	Schousboe et al. (2024)	*Simultaneous automated ascertainment of prevalent vertebral fracture and abdominal aortic calcification in clinical practice: role in fracture risk assessment*	VFA (DXA lateral spine)	Automated VFA + AAC (CNN)	11,013 patients	AUC = 0.94	Hip fracture risk $\uparrow$ 1.62x	Simultaneous detection of fractures and aortic calcification improves risk assessment. [32]
No.	Author & Year	Title	Method (Imaging)	AI Model	Study Group (N)	Results AUC AUROC	Other Parameters	Key Conclusion
30	Curl et al. (2024)	*Cost-effectiveness of AI-based opportunistic compression fracture screening of existing radiographs*	Existing X-RAY (Chest/Abdomen)	Cost-effectiveness analysis (Markov)	Population 65+ (Simulation)	N/A	ICER: $42,411 USD/QALY	AI screening of existing radiographs is cost-effective for healthcare systems. [33]

3.1. Study Characteristics

Following a literature review, 30 original research papers published between 2021 and 2025 were qualified for detailed analysis. Research material is heterogeneous across imaging modalities and sample sizes.

The majority of the identified studies used Computed tomography (CT) (n=15; 50%), highlighting an emerging trend towards opportunistic screening. Conventional radiographs were used in part of the analyzed studies (n=12; 40%). The remaining ones included Magnetic Resonance Imaging (MRI=2) and automated densitometry analysis, especially vertebral fracture assessment (VFA,n=1)

The analyzed population shows differences among studies. Both clinical cohorts, containing several hundred patients [14,26], and large-scale multicenter studies using Big Data sets that contain over 160,000 images [29]. Notably, a subset of studies relied on established international databases, such as the VerSe datasets or the MrOS (Osteoporotic Fractures in Men) cohort, thereby enhancing the credibility of the findings.

3.2. Diagnostic Effectiveness of the deep learning models

The collective analysis of diagnostic parameters across the collected studies indicates that models based on artificial intelligence, especially *Convolutional Neural Networks* (CNNs), demonstrate diagnostic effectiveness that not only matches but also exceeds, in many respects, standard radiologist examinations. [16]. The diagnostic performance of the artificial intelligence models was assessed based on the area under the ROC curve (AUROC; hereinafter AUC for methodological consistency), which ranged from 0.81 to 0.99, indicating high performance. These results show that artificial intelligence models demonstrate a significant ability to distinguish between healthy and diseased tissue.

A key finding of the research was the advantage of Deep Learning technology for detecting vertebral fractures in routine CT scans. In studies conducted by Riedel and by Wang, the AI models reached a sensitivity of 88-97%, while the human raters, including students, residents, and specialists, had a sensitivity range of 72%.[16,23] Furthermore, this difference is particularly evident in Grade I fractures on the Genant scale, which are often overlooked in daily clinical practice because subtle morphological changes in the bone are easily missed. By utilizing pixel-level analysis and patterns invisible to the human eye, AI-based tools have reduced the number of such diagnostic oversights.

In technological terms, the most commonly used AI architectures in the analyzed studies were the ResNet-50 network, valued for its stability in medical image classification [10,11,18], and the U-Net network, typically used for fully automated and precise anatomical structure segmentation. However, publications between 2024 and 2025 clearly indicate the hybrid approach combining deep learning tools and *Deep Learning Radiomics* (DLR). This methodology grants the ability to extract thousands of image parameters, paving the way for enhanced precision in differential diagnosis of fracture characteristics, such as distinguishing between osteoporotic and cancerous fractures [17,20]

It is also worth noting that the high performance of these models extends beyond fracture detection to include differential diagnosis. Studies by Yoda and by Duan demonstrated that deep learning algorithms achieve an AUC of 0.94–0.96 in the highly challenging task of distinguishing benign osteoporotic fractures from malignant lesions.[17,26] This distinction is crucial for selecting appropriate therapeutic pathways and determining patient prognosis, underscoring the clinical utility of AI-integrated diagnostics in modern orthopedics and radiology.

3.3. Opportunistic screening in chest and abdomen imaging

Central to this discussion in the analyzed studies is the untapped diagnostic potential of routine imaging screening, known as opportunistic screening. Synthesis of the collected studies confirms the prevelance of this approach, as many as 18 out of 30 articles (60%)directly focused on using chest and abdominal imaging (both CT and X-ray) for bone fracture detection This growing representation is evident in a significant number of studies dedicated to both CT analyzed imaging[30,19,6, 21, 31, 15] and chest conventional radiography (X-RAY)[22, 29]. In this case, the application of textural AI-algorithm analysis provides an automated, precise skeletal examination during procedures intended for pulmonary, cardiac, or internal organ diseases.

Studies based on specifically burdened populations, such as those with chronic obstructive pulmonary disease (COPD), revealed that AI-Integrated models are able to link together the pulmonary examination with vertebral simultaneous segmentation assessment and morphological analysis [15]. Notably, in regular diagnostics, the attention of the radiologist is focused on the primary purpose of the test, which leads to the omission of bone changes treated as additional, side results. The AI systems - IB Lab FLAMINGO reveal substantial capability to identify „silent fractures" which do not produce significant clinical symptoms, however, are crucial for further incident risk assessment. In a study by Behanova, the algorithm detected fractures that the radiologist initially assessed as normal.[31]

It is worth noting that automated opportunistic analysis outperforms traditional diagnostic methods in many aspects. As presented by Löffler, automated bone density assessment based on routine CT scans (AUC 0.82) proved to be a more effective tool for predicting future fractures than DXA densitometry, considered as the "gold standard" (AUC 0.72)[19]. This is due to the fact that artificial intelligence analyzes the three-dimensional (3D) structure of trabecular bone, eliminating artifacts that often distort DXA results in elderly patients, such as degenerative changes or abdominal aortic calcifications. The application of AI in this field (e.g., the OsPenScreen model for chest X-rays – Park[22]) represents a promising approach for early detection of low bone mass in the general population. This approach provides the identification of high-risk patients without generating additional costs for the healthcare system or exposing patients to unnecessary ionizing radiation.

3.4. Emerging Trends: Differential Diagnosis, Special Populations, and Cost-Effectiveness

Current trends in the development of artificial intelligence in radiology focus not only on detecting bone fractures but also on providing advanced tools to resolve complex clinical cases and predict risk in new patient groups. The main challenge remains distinguishing between osteoporotic fractures and neoplastic processes.

AI models based on deep neuronal networks (CNNs) used in MRI imaging reached, in this case, high efficiency with AUC 0.96-0.97 [26]. By combining Artificial Intelligence with radiomics, it is possible to detect subtle features of bone structure that are invisible to the human eye, enabling the rapid implementation of appropriate treatment [17,20].

There is a clear trend toward focusing on population groups that undergo screening less frequently, such as men. The use of the U-NET network to automate tissue analysis in the hip region enables the simultaneous assessment of bone and muscle mass, providing a more comprehensive picture of the patient's condition [24]. Modern AI systems also possess forward-looking capabilities; rather than merely assessing the current state of the spine, they analyze additional factors, such as abdominal aortic calcifications, to predict the risk of future fractures over a multi-year perspective [13,32].

Last but not least, the economic effectiveness of AI supports its implementation in clinical practice. Studies demonstrate that utilizing Artificial Intelligence to analyze existing X-ray images is a highly cost-effective solution for healthcare systems. The Incremental Cost-Effectiveness Ratio (ICER) for such interventions is approximately $42,411 per Quality-Adjusted Life Year (QALY), which is significantly below the thresholds commonly accepted in medical economics [33].In addition, AI tools not only save patients' lives through early diagnosis but also generate financial savings by avoiding the costs associated with the treatment of complications from fractures that were not detected earlier.

In summary, artificial intelligence is considered an integral part of modern osteoporosis diagnosis and prevention due to its unique combination of precision in disease detection, the ability to predict future cases, and proven cost-effectiveness.

Discussion

4.1 Diagnostic Efficacy of AI

The results of this systematic review indicate that artificial intelligence (AI) models, particularly those based on deep learning and convolutional neural networks (CNNs), demonstrate significant diagnostic accuracy in detecting osteoporotic fractures. The analyzed studies consistently reported Area Under the Curve (AUC) values ranging from 0.81 to 0.99, which signifies a high degree of reliability in clinical settings. As evidenced by the results of Riedel and Guermazi, AI algorithms often outperform human readers, including experienced radiologists, by significantly reducing the rate of false negatives.[7,16] This is particularly crucial for identifying Grade 1 fractures according to the Genant scale, which are frequently overlooked in manual assessments due to subtle morphological changes. In this way, artificial intelligence acts as an extra set of eyes, improving diagnostic accuracy.

All of the studies presented in this review point to artificial intelligence as a method for detecting anomalies.

It contains a range of AI architectures. The focus was primarily on convolutional neural networks (CNNs), such as ResNet and VGG, designed for classification. In contrast, the U-Net network was used for precise anatomical assessment. A trend toward hybrid models integrating deep learning with radiomics and classical machine learning algorithms, such as Random Forest and Support Vector Machine (SVM), to enhance diagnostic accuracy.

Despite the remarkable diversity of the analyzed AI architectures, ranging from specialized U-Net segmentations to complex hybrid radiomic systems, the collective evidence points to a consistent and accelerating upward trend. This variety of methodologies denotes a broader transition in clinical practice, where automated opportunistic screening is rapidly evolving from an innovative research concept into an indispensable standard of modern radiological diagnostics.

Ultimately, AI tools serve as objective systems that operate independently of human limitations. It is well known that diagnostic errors in radiology can occur due to human factors, such as fatigue, high workloads, and environmental distractions. Unlike humans, artificial intelligence algorithms evaluate every image consistently—with the same precision—which makes AI an ideal tool for standardizing diagnostics, ensuring reproducible results, and reducing the risk of missing "silent" fractures in routine clinical practice.

4.2. The Potential of Opportunistic Screening in Routine Imaging

1 The scale of this phenomenon is significant, as more than half of the analyzed studies focused on routine imaging of the abdomen and chest [15,31]. Millions of CT scans are performed annually for non-bone-related indications, such as oncology, cardiology, pulmonology, or referrals from primary care doctors. As noted in the reviewed literature, the vast amount of densitometric data contained in these images is traditionally underutilized by radiologists focused on the primary clinical question. Consequently, many bone-related changes are overlooked because they are not the main focus of the examination. As a result, by integrating AI models, these 'wasted' data points can be recovered and utilized for simultaneous diagnosis. This effectively transforms a single-purpose scan into a comprehensive screening tool, ensuring that no critical information about the patient's skeletal health is lost

The integration of AI into routine imaging changes the patient's clinical pathway. It allows for the detection of incidental findings. Nadeem and Behanova demonstrated that a patient undergoing a chest CT for respiratory symptoms can be screened for vertebral fractures and bone mineral density (BMD) at the same time. [15,31]This approach tackles the "silent epidemic" of osteoporosis. Vertebral fractures often go unnoticed and undiagnosed until a major fracture occurs. Identifying high-risk individuals with automated systems enables early pharmacological intervention before secondary injuries, like hip fractures, happen.

It is worth noting that using AI models for opportunistic screening provides several practical advantages. From a logistical standpoint, it simplifies the diagnostic process by removing the need for new medical referrals, additional appointments, and long waiting times. This approach effectively saves the patient time and optimizes the use of hospital staff and equipment.

Furthermore, patient safety is a key priority in medical imaging. Since AI analyzes existing scans, it enables bone assessment without additional radiation dose. This creates a win-win situation: doctors receive more diagnostic data, while patients avoid unnecessary radiation exposure.

4.3 AI vs. The "Gold Standard": Challenges and Limitations of DXA Densitometry

In current clinical practice, Dual-energy X-ray Absorptiometry (DXA) remains the 'gold standard' for osteoporosis monitoring and diagnosis. While it has served for years, DXA is a two-dimensional (2D) imaging technique that presents significant limitations, particularly in elderly populations. Degenerative bone changes, such as osteophytes and vascular calcifications, like atherosclerotic plaques in the aorta, can overlap with the bone image. This often leads to a falsely elevated Bone Mineral Density (BMD) reading. Consequently, a high-risk patient may receive a 'normal' result despite having fragile bones, leading to an underestimation of fracture risk.

In contrast, AI-integrated models enable a three-dimensional (3D) assessment of bone structure, permitting detailed analysis of microarchitecture invisible to the human eye. Research by Muehlematter et al. (2021) highlights that machine learning models can identify subtle structural changes that 2D densitometry fails to detect. Furthermore, it was noted that AI systems successfully mitigate measurement errors caused by aortic calcification, which frequently leads to overestimation of BMD on DXA[32]. This high accuracy was demonstrated by Löffler, who showed that AI-based opportunistic screening significantly outperformed traditional DXA in fracture prediction, yielding an AUC of 0.82 compared to 0.72 for the gold standard.[19]

It is important to note that AI-based opportunistic screening is not intended to replace DXA as the current gold standard. Instead, it operates as a powerful complementary tool that can identify high-risk patients who might otherwise be overlooked due to the innate limitations of 2D densitometry. By integrating AI into routine clinical workflows, we can create a multi-layered diagnostic approach that significantly improves early detection and patient outcomes.

4.4 Future Directions: MRI Analysis, Oncological Differentiation, and Risk Prediction

Many common types of malignant tumors frequently metastasize to the skeletal system. In clinical diagnosis, one of the most challenging tasks for radiologists is distinguishing between malignant and benign lesions. This differentiation is crucial for patient survival and for determining the appropriate treatment strategy. AI tools provide significant support; deep learning models can help differentiate between osteoporotic vertebral fractures and malignant infiltrates on MRI scans, thereby reducing the need for invasive procedures such as bone marrow biopsies.[17,26]

It is worth noting that while MRI analysis is technically more demanding for AI than CT-based methods, due to signal variability, it offers a more comprehensive assessment of bone marrow and soft tissue. It provides a more holistic view of skeletal health. Furthermore, there is a clear trend toward AI models evolving from purely diagnostic tools to predictive ones.

Research by Kong points out that AI can now estimate the 5- to 10-year risk of future osteoporotic fractures from baseline imaging data.[13]. Earlier detection is synonymous with earlier intervention for the patient.

4.5 Cost-Effectiveness, Study Limitations, and the Role of the Radiologist

Ultimately, the economic impact of introducing AI into healthcare systems is a critical factor. While the initial implementation requires significant financial outlays, the long-term perspective suggests substantial savings. These savings result from improved time management, optimized staffing, and early disease detection, leading to less demanding, less expensive treatments.

For instance, the costs associated with hip fracture surgery, hospitalization, and subsequent rehabilitation are immense. By identifying high-risk patients 'opportunistically' during other routine scans, AI enables cost-effective pharmacological prevention. According to Curl, AI-driven screening is highly cost-effective, as the investment in software is quickly offset by savings from reduced costs associated with acute fractures and long-term disability.[33]

Despite the range of AI's advantages, it is not a perfect solution, with several barriers. Most current studies are retrospective. To present the best possible outcomes of AI-related applications, they need to be conducted as prospective or real-world trials. Furthermore, the equipment used across different hospitals differs – different brands or software. All of this makes it difficult to generalize AI algorithms, as they usually require site-specific adjustments.

Last but not least, AI should be taken as a synergistic human-AI interaction rather than as a replacement for radiologists; these tools serve as support systems. They can increase diagnostic capacity and, in turn, guarantee that high-risk patients are not overlooked in high-volume clinical settings.

Conclusions

1. High Diagnostic Accuracy: Artificial Intelligence models, particularly those based on Deep Learning and Convolutional Neural Networks (CNNs), demonstrate exceptional efficacy in detecting osteoporotic fractures, achieving AUC values of 0.81-0.99.
2. Efficacy of Opportunistic Screening: Automated screening using routine chest and abdominal CT scans can effectively detect undiagnosed osteoporosis. They allow for the reuse of existing radiological data without exposing the patient to additional radiation.

3. Identification of a diagnostic gap: Artificial intelligence serves as an additional verification step, replacing the need for re-reading, which helps reduce the rate of false-negative results and detection of subtle fractures (Grade 1 according to the Genant scale), frequently overlooked by primary radiological assessments.
4. Advantage Over DXA: AI-integrated 3D volumetric analysis from CT scans provides a more reliable assessment of bone fragility than traditional 2D DXA densitometry, especially in elderly populations where degenerative changes and aortic calcifications often distort standard BMD readings.
5. Beyond Detection to Prediction: Modern AI algorithms are evolving from purely diagnostic tools into predictive systems capable of estimating long-term (5-to-10-year) fracture risks, supporting personalized preventive interventions.
6. Clinical and Economic Synergy: Implementing AI as a decision-support tool is highly cost-effective. Facilitating early diagnosis and pharmacological treatment reduces the substantial medical and social costs associated with acute osteoporotic complications and long-term disability.

Disclosure

Conceptualization, L.K., J.A.M., and E.W.; methodology, L.K. and J.A.M.; software, E.W.; validation, L.K., J.A.M., and E.W.; formal analysis, L.K., J.A.M., and E.W.; investigation, Z.W., W.M.W., M.Z., S.S., F.W., M.W., and B.I.K.; resources, L.K. and J.A.M.; data curation, E.W., Z.W., W.M.W., M.Z., and S.S.; writing—original draft preparation, L.K., J.A.M., and E.W.; writing—review and editing, Z.W., W.M.W., M.Z., S.S., F.W., M.W., and B.I.K.; visualization, F.W., M.W., and B.I.K.; supervision, L.K.; project administration, J.A.M. and E.W.; funding acquisition, L.K. All authors have read and agreed to the published version of the manuscript.

All authors have read and agreed to the published version of the manuscript.

Funding statement: This research received no external funding.

Conflict of interest statement: The authors declare no conflict of interest

References

1. World Health Organization. „Guidelines for preclinical evaluation and clinical trials in osteoporosis". *WHO Technical Report Series*, Geneva, 1998, s. 1–74. IRIS WHO, https://iris.who.int/handle/10665/42078.

2. Ebeling, Peter R., et al. „Secondary Osteoporosis”. *Endocrine Reviews*, t. 43, nr 2, marca 2022, s. 240–313. *DOI.org (Crossref)*, https://doi.org/10.1210/endrev/bnab028.
3. Smith, Ashlyn. „An update on osteoporosis management and fracture prevention strategies”. *Journal of the American Academy of Physician Associates (JAAPA)*, t. 36, nr 11, listopada 2023, s. 1–7. DOI.org (Crossref), https://doi.org/10.1097/01.JAA.0000991388.62104.9a.
4. Engelke, Klaus, et al. „Opportunistic Screening Techniques for Analysis of CT Scans”. *Current Osteoporosis Reports*, t. 21, nr 1, lutego 2023, s. 65–76. *DOI.org (Crossref)*, https://doi.org/10.1007/s11914-022-00764-5.
5. Shen, Li, et al. „Using Artificial Intelligence to Diagnose Osteoporotic Vertebral Fractures on Plain Radiographs”. *Journal of Bone and Mineral Research*, t. 38, nr 9, września 2023, s. 1278–87. *DOI.org (Crossref)*, https://doi.org/10.1002/jbmr.4879.
6. Huang, Chengbin, et al. „Application of Deep Learning Model Based on Unenhanced Chest CT for Opportunistic Screening of Osteoporosis: A Multicenter Retrospective Cohort Study”. *Insights into Imaging*, t. 16, nr 1, stycznia 2025, s. 10. *DOI.org (Crossref)*, https://doi.org/10.1186/s13244-024-01817-2.
7. Guermazi, Ali, et al. „Improving Radiographic Fracture Recognition Performance and Efficiency Using Artificial Intelligence”. *Radiology*, t. 302, nr 3, marca 2022, s. 627–36. *DOI.org (Crossref)*, https://doi.org/10.1148/radiol.210937.
8. Del Lama, Rafael Silva, et al. „Computer-Aided Diagnosis of Vertebral Compression Fractures Using Convolutional Neural Networks and Radiomics”. *Journal of Digital Imaging*, t. 35, nr 3, czerwca 2022, s. 446–58. *DOI.org (Crossref)*, https://doi.org/10.1007/s10278-022-00586-y.
9. Zhang, Jun, et al. „Exploring deep learning radiomics for classifying osteoporotic vertebral fractures in X-ray images”. *Frontiers in Endocrinology*, t. 15, marca 2024, s. 1370838. *DOI.org (Crossref)*, https://doi.org/10.3389/fendo.2024.1370838.
10. Hsieh, Chen-I., et al. „Automated Bone Mineral Density Prediction and Fracture Risk Assessment Using Plain Radiographs via Deep Learning”. *Nature Communications*, t. 12, nr 1, września 2021, s. 5472. *DOI.org (Crossref)*, https://doi.org/10.1038/s41467-021-25779-x.
11. Boonrod, Artit, et al. „Deep Learning for Osteoporosis Screening Using an Anteroposterior Hip Radiograph Image”. *European Journal of Orthopaedic Surgery & Traumatology*, t. 34, nr 6, czerwca 2024, s. 3045–51. *DOI.org (Crossref)*, https://doi.org/10.1007/s00590-024-04032-3.

12. Cross, Nathan M., et al. „Subject-Level Spinal Osteoporotic Fracture Prediction Combining Deep Learning Vertebral Outputs and Limited Demographic Data". *Archives of Osteoporosis*, t. 19, nr 1, września 2024, s. 87. *DOI.org (Crossref)*, https://doi.org/10.1007/s11657-024-01433-z.
13. Kong, Sung Hye, et al. „Development of a Spine X-Ray-Based Fracture Prediction Model Using a Deep Learning Algorithm". *Endocrinology and Metabolism*, t. 37, nr 4, sierpnia 2022, s. 674–83. *DOI.org (Crossref)*, https://doi.org/10.3803/EnM.2022.1461.
14. Biamonte, E., et al. „Artificial Intelligence-Based Radiomics on Computed Tomography of Lumbar Spine in Subjects with Fragility Vertebral Fractures". *Journal of Endocrinological Investigation*, t. 45, nr 10, czerwca 2022, s. 2007–17. *DOI.org (Crossref)*, https://doi.org/10.1007/s40618-022-01837-z.
15. Nadeem, Syed Ahmed, et al. „Chest CT-based Automated Vertebral Fracture Assessment Using Artificial Intelligence and Morphologic Features". *Medical Physics*, t. 51, nr 6, czerwca 2024, s. 4201–18. *DOI.org (Crossref)*, https://doi.org/10.1002/mp.17072.
16. Riedel, Evamaria O., et al. „Diagnostic Accuracy of Deep Learning vs. Human Raters for Detecting Osteoporotic Vertebral Compression Fractures in Routine CT Scans". *European Radiology*, lutego 2026. *DOI.org (Crossref)*, https://doi.org/10.1007/s00330-026-12393-y.
17. Duan, Shuo, et al. „Differential Diagnosis of Benign and Malignant Vertebral Compression Fractures: Comparison and Correlation of Radiomics and Deep Learning Frameworks Based on Spinal CT and Clinical Characteristics". *European Journal of Radiology*, t. 165, sierpnia 2023, s. 110899. *DOI.org (Crossref)*, https://doi.org/10.1016/j.ejrad.2023.110899.
18. Dong, Qifei, et al. „Deep Learning Classification of Spinal Osteoporotic Compression Fractures on Radiographs Using an Adaptation of the Genant Semiquantitative Criteria". *Academic Radiology*, t. 29, nr 12, grudnia 2022, s. 1819–32. *DOI.org (Crossref)*, https://doi.org/10.1016/j.acra.2022.02.020.
19. Löffler, Maximilian T., et al. „Automatic Opportunistic Osteoporosis Screening in Routine CT: Improved Prediction of Patients with Prevalent Vertebral Fractures Compared to DXA". *European Radiology*, t. 31, nr 8, sierpnia 2021, s. 6069–77. *DOI.org (Crossref)*, https://doi.org/10.1007/s00330-020-07655-2.
20. Liu, Jiayi, et al. „Deep Learning Radiomics Model Based on Computed Tomography Image for Predicting the Classification of Osteoporotic Vertebral Fractures: Algorithm

Development and Validation". *JMIR Medical Informatics*, t. 13, sierpnia 2025, s. e75665–e75665. *DOI.org (Crossref)*, https://doi.org/10.2196/75665.

21. Spångeus, Anna, et al. „Breaking the Silence: AI's Contribution to Detecting Vertebral Fractures in Opportunistic CT Scans in the Elderly—a Validation Study". *Archives of Osteoporosis*, t. 20, nr 1, marca 2025, s. 42. *DOI.org (Crossref)*, https://doi.org/10.1007/s11657-025-01524-5.
22. Park, Junhyeok, et al. „Opportunistic Screening of Low Bone Mass Using Knowledge Distillation-Based Deep Learning in Chest X-Rays with External Validations". *Archives of Osteoporosis*, t. 20, nr 1, października 2025, s. 131. *DOI.org (Crossref)*, https://doi.org/10.1007/s11657-025-01609-1.
23. Wang, Yongjie, et al. „Deep Learning-Driven Diagnosis of Multi-Type Vertebra Diseases Based on Computed Tomography Images". *Quantitative Imaging in Medicine and Surgery*, t. 14, nr 1, stycznia 2024, s. 80013–813. *qims.amegroups.org*, https://doi.org/10.21037/qims-23-685
24. Imani, Mahdi, et al. „Deep Learning Technique for Automatic Segmentation of Proximal Hip Musculoskeletal Tissues From CT Scan Images: A MrOS Study". *Journal of Cachexia, Sarcopenia and Muscle*, t. 16, nr 2, kwietnia 2025, s. e13728. *DOI.org (Crossref)*, https://doi.org/10.1002/jcsm.13728.
25. Pignolo, Robert J., et al. „Opportunistic Assessment of Osteoporosis Using Hip and Pelvic X-Rays with OsteoSightTM: Validation of an AI-Based Tool in a US Population". *Osteoporosis International*, t. 36, nr 6, czerwca 2025, s. 1053–60. *DOI.org (Crossref)*, https://doi.org/10.1007/s00198-025-07487-0.
26. Yoda, Takafumi, et al. „Automated Differentiation Between Osteoporotic Vertebral Fracture and Malignant Vertebral Fracture on MRI Using a Deep Convolutional Neural Network". *Spine*, t. 47, nr 8, kwietnia 2022, s. E347–52. *DOI.org (Crossref)*, https://doi.org/10.1097/BRS.0000000000004307.
27. Zhang, Jianlun, et al. „Automated detection and classification of acute vertebral body fractures using a convolutional neural network on computed tomography". *Frontiers in Endocrinology*, t. 14, marca 2023, s. 1132725. *DOI.org (Crossref)*, https://doi.org/10.3389/fendo.2023.1132725.
28. Du, Juan, et al. „Application of intelligent X-ray image analysis in risk assessment of osteoporotic fracture of femoral neck in the elderly". *Mathematical Biosciences and Engineering*, t. 20, nr 1, października 2022 (publ. 2023), s. 879–893. DOI.org (Crossref), https://doi.org/10.3934/mbe.2023040

29. Chen, Kai-Chieh, et al. „Deep Learning Meets Chest X-Rays: A Promising Approach for Predicting Future Compression Fracture Risk". *Therapeutic Advances in Musculoskeletal Disease*, t. 17, lipca 2025, s. 1759720X251357157. *DOI.org (Crossref)*, https://doi.org/10.1177/1759720X251357157.
30. Breit, Hanns-Christian, et al. „CNN-Based Evaluation of Bone Density Improves Diagnostic Performance to Detect Osteopenia and Osteoporosis in Patients with Non-Contrast Chest CT Examinations". *European Journal of Radiology*, t. 161, kwietnia 2023, s. 110728. *DOI.org (Crossref)*, https://doi.org/10.1016/j.ejrad.2023.110728
31. Behanova, Martina, et al. „AI-Supported Opportunistic Detection of Vertebral Fractures on Routine CT Scans: Diagnostic Performance and Clinical Relevance". *Bone*, t. 203, lutego 2026, s. 117735. *DOI.org (Crossref)*, https://doi.org/10.1016/j.bone.2025.117735.
32. Schousboe, John T., et al. „Simultaneous Automated Ascertainment of Prevalent Vertebral Fracture and Abdominal Aortic Calcification in Clinical Practice: Role in Fracture Risk Assessment". *Journal of Bone and Mineral Research*, t. 39, nr 7, sierpnia 2024, s. 898–905. *DOI.org (Crossref)*, https://doi.org/10.1093/jbmr/zjae066.
33. Curl, Patti K., et al. „Cost-Effectiveness of Artificial Intelligence–Based Opportunistic Compression Fracture Screening of Existing Radiographs". *Journal of the American College of Radiology*, t. 21, nr 9, września 2024, s. 1489–96. *DOI.org (Crossref)*,