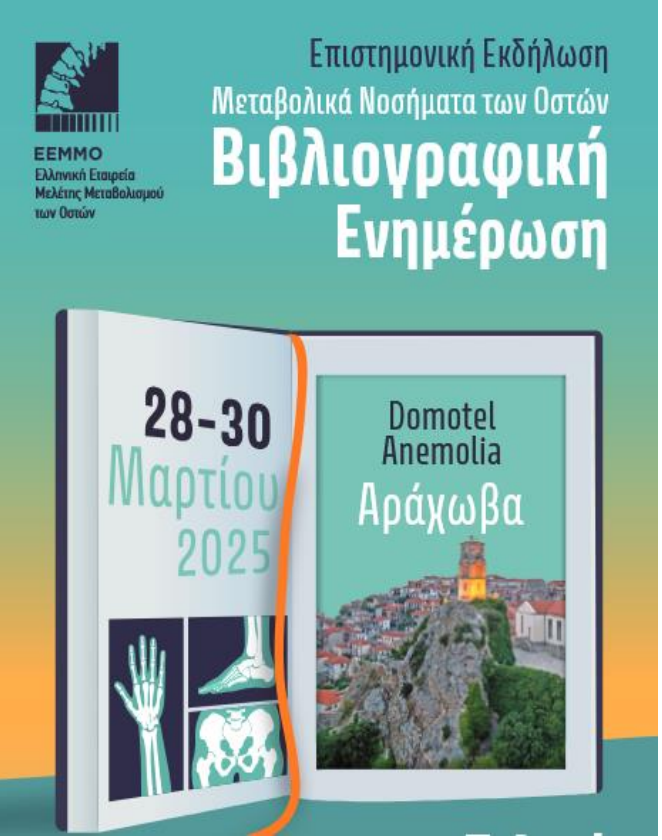

Τεχνητή νοημοσύνη Εφαρμογές στα μεταβολικά νοσήματα των οστών

Πέλλιος Σταύρος MD, Phd

Αναπλ. Διευθυντής Α΄ Ορθοπαιδικής Κλινικής 424 Γ.Σ.Ν.Ε

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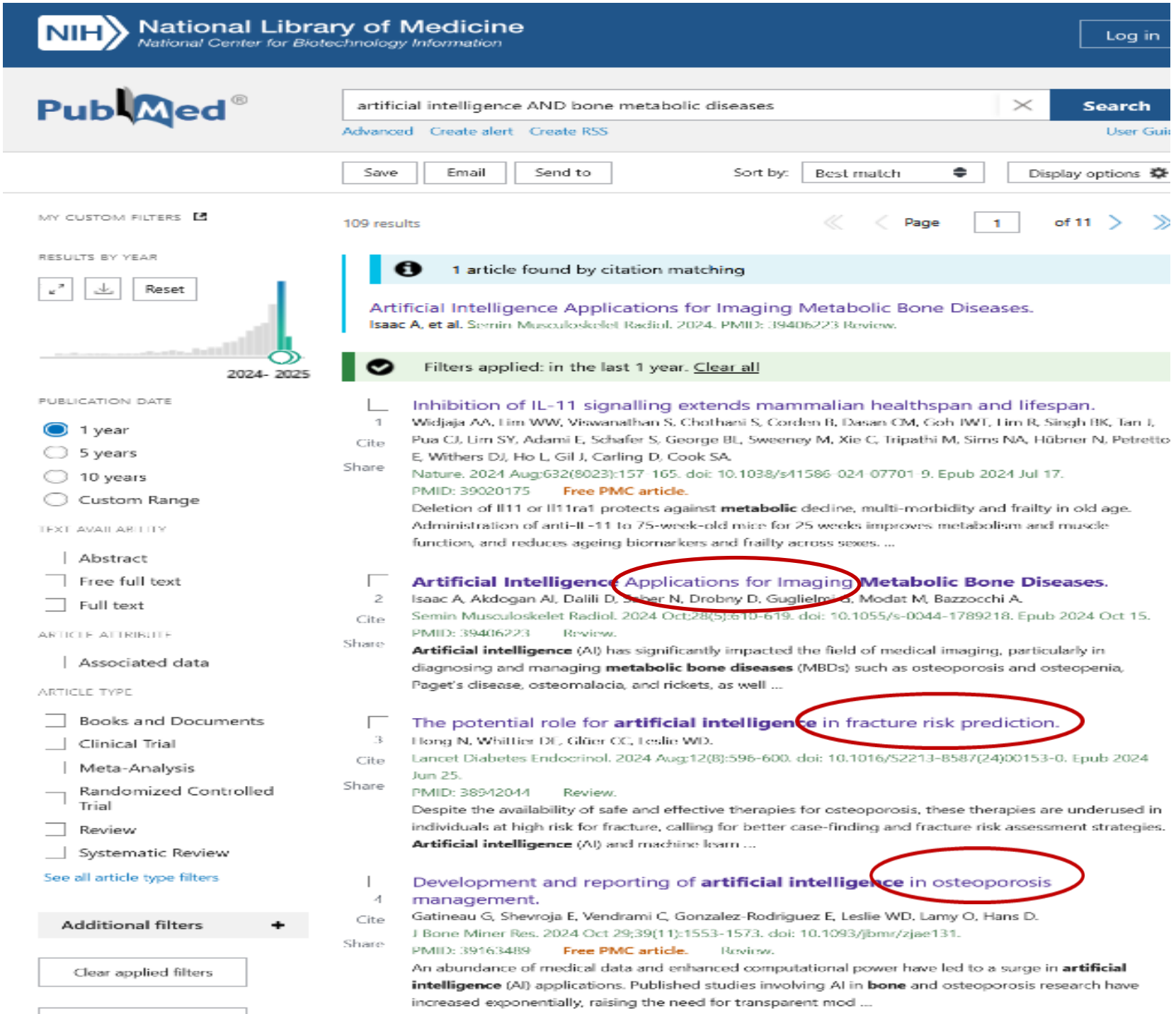
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Artificial Intelligence Applications for Imaging Metabolic Bone Diseases.
Isaac A, et al. Semin Musculoskelet Radiol. 2024. PMID: 39406223 Review.
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Inhibition of IL-11 signalling extends mammalian healthspan and lifespan.
Widjaja AA, Lim WW, Viswanathan S, Chothani S, Corden B, Dasan CM, Goh JWT, Lim R, Singh BK, Tan J, Pua CJ, Lim SY, Adami E, Schafer S, George BL, Sweeney M, Xie C, Tripathi M, Sims NA, Hübner N, Petretto E, Withers DJ, Ho L, Gil J, Carling D, Cook SA.
Nature. 2024 Aug;632(8023):157-165. doi: 10.1038/s41586-024-07701-9. Epub 2024 Jul 17.
PMID: 39020175 Free PMC article.
Deletion of Il11 or Il11ra1 protects against metabolic decline, multi-morbidity and frailty in old age. Administration of anti-IL-11 to 75-week-old mice for 25 weeks improves metabolism and muscle function, and reduces ageing biomarkers and frailty across sexes. ...
2
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Artificial Intelligence Applications for Imaging Metabolic Bone Diseases.
Isaac A, Akdogan AI, Dalili D, Sabet N, Drobny D, Guglielmi G, Modat M, Bazzocchi A.
Semin Musculoskelet Radiol. 2024 Oct;28(5):610-619. doi: 10.1055/s-0044-1789218. Epub 2024 Oct 15.
PMID: 39406223 Review.
Artificial intelligence (AI) has significantly impacted the field of medical imaging, particularly in diagnosing and managing metabolic bone diseases (MBDs) such as osteoporosis and osteopenia, Paget's disease, osteomalacia, and rickets, as well ...
3
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The potential role for artificial intelligence in fracture risk prediction.
Hong N, Whittier DE, Glüer CC, Leslie WD.
Lancet Diabetes Endocrinol. 2024 Aug;12(8):596-600. doi: 10.1016/S2213-8587(24)00153-0. Epub 2024 Jun 25.
PMID: 38942044 Review.
Despite the availability of safe and effective therapies for osteoporosis, these therapies are underused in individuals at high risk for fracture, calling for better case-finding and fracture risk assessment strategies. Artificial intelligence (AI) and machine learn ...
4
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Development and reporting of artificial intelligence in osteoporosis management.
Gatineau G, Shevroja E, Vendrami C, Gonzalez-Rodriguez E, Leslie WD, Lamy O, Hans D.
J Bone Miner Res. 2024 Oct 29;39(11):1553-1573. doi: 10.1093/jbmr/zjae131.
PMID: 39163489 Free PMC article. Review.
An abundance of medical data and enhanced computational power have led to a surge in artificial intelligence (AI) applications. Published studies involving AI in bone and osteoporosis research have increased exponentially, raising the need for transparent mod ...

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fragility fracture AND artificial intelligence (AI)

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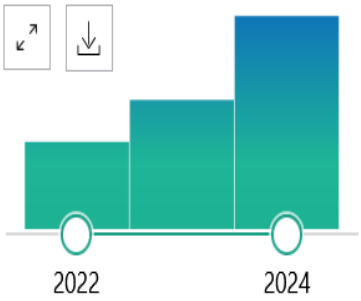

TEXT AVAILABILITY

- Abstract
- Free full text

1 Digital health interventions for osteoporosis and post-**fragility fracture** care.

Cite Share

Gupta A, Maslen C, Vindlacheruvu M, Abel RL, Bhattacharya P, Bromiley PA, Clark EM, Compston JE, Crabtree N, Gregory JS, Kariki EP, Harvey NC, McCloskey E, Ward KA, Poole KES.

Ther Adv Musculoskelet Dis. 2022 Mar 28;14:1759720X221083523. doi: 10.1177/1759720X221083523. eCollection 2022.

PMID: 35368375 **Free PMC article.** Review.

The growing burden from osteoporosis and **fragility fractures** highlights a need to improve osteoporosis management across healthcare systems. ...The term 'Digital Health' covers a variety of different tools including clinical decision support systems, electronic medi ...

2 Editorial: Quantitative **bone** imaging methods.

Salmon P, Alavi F, Ghasem-Zadeh A.

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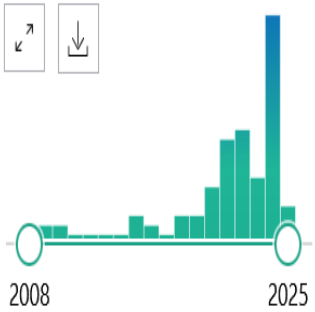

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- 10 years
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TEXT AVAILABILITY

1 **Artificial intelligence**, osteoporosis and **fragility fractures**.

Ferizi U, Honig S, Chang G.

Cite

Curr Opin Rheumatol. 2019 Jul;31(4):368-375. doi: 10.1097/BOR.0000000000000607.

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PMID: 31045948 Free PMC article. Review.

PURPOSE OF REVIEW: **Artificial intelligence** tools have found new applications in medical diagnosis. These tools have the potential to capture underlying trends and patterns, otherwise impossible with previous modeling capabilities. Machine learning and deep learning ...

2 Risk assessment tools for osteoporosis and **fractures** in 2022.

Carey JJ, Chih-Hsing Wu P, Bergin D.

Cite

Best Pract Res Clin Rheumatol. 2022 Sep;36(3):101775. doi: 10.1016/j.berh.2022.101775. Epub 2022 Aug 29.

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PMID: 36050210 Review.

Several hundred million people have osteoporosis, with many more at risk. The clinical feature is a **fragility fracture** (FF), which results in major reductions in the quality and quantity of life, coupled with a huge financial burden. ...Modern technology, enhanced i ...

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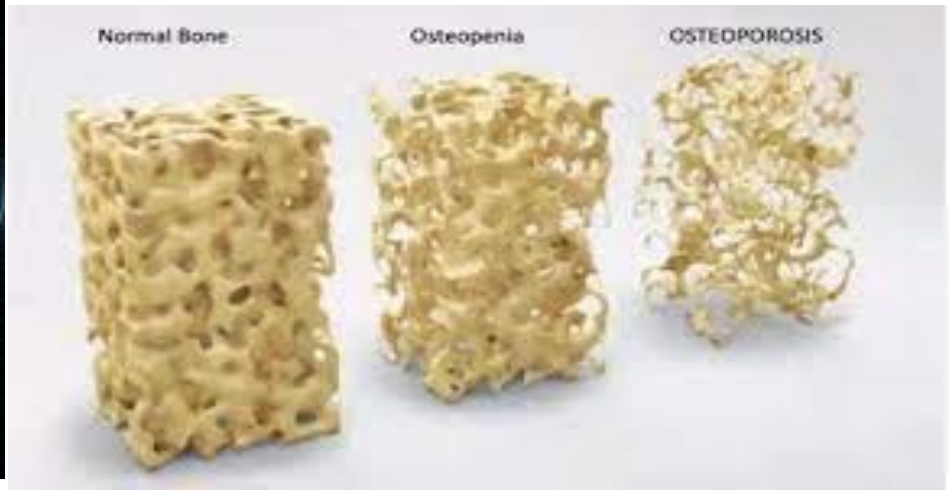
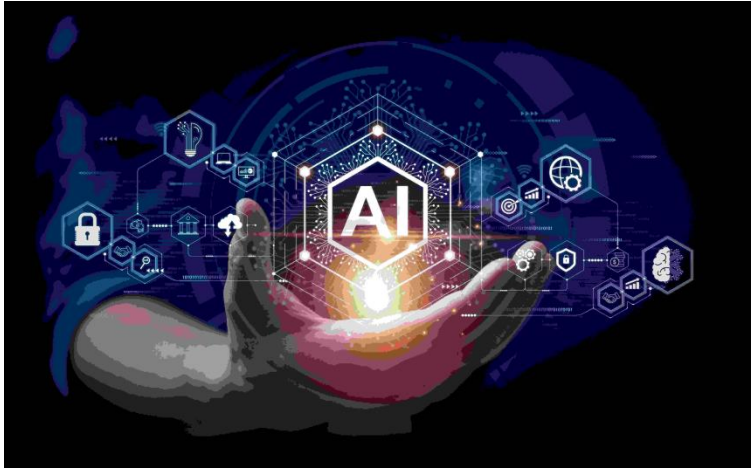


- ✓ ***Osteoporosis*** is a skeletal disorder in which reductions in bone strength predispose to an increased risk for fractures

- ✓ Currently, the diagnosis is officially made based exclusively on bone mineral density T-scores that are ≤-2.5 at the spine or hip

FRAX ® Εργαλείο αξιολόγησης του κινδύνου κατάγματος

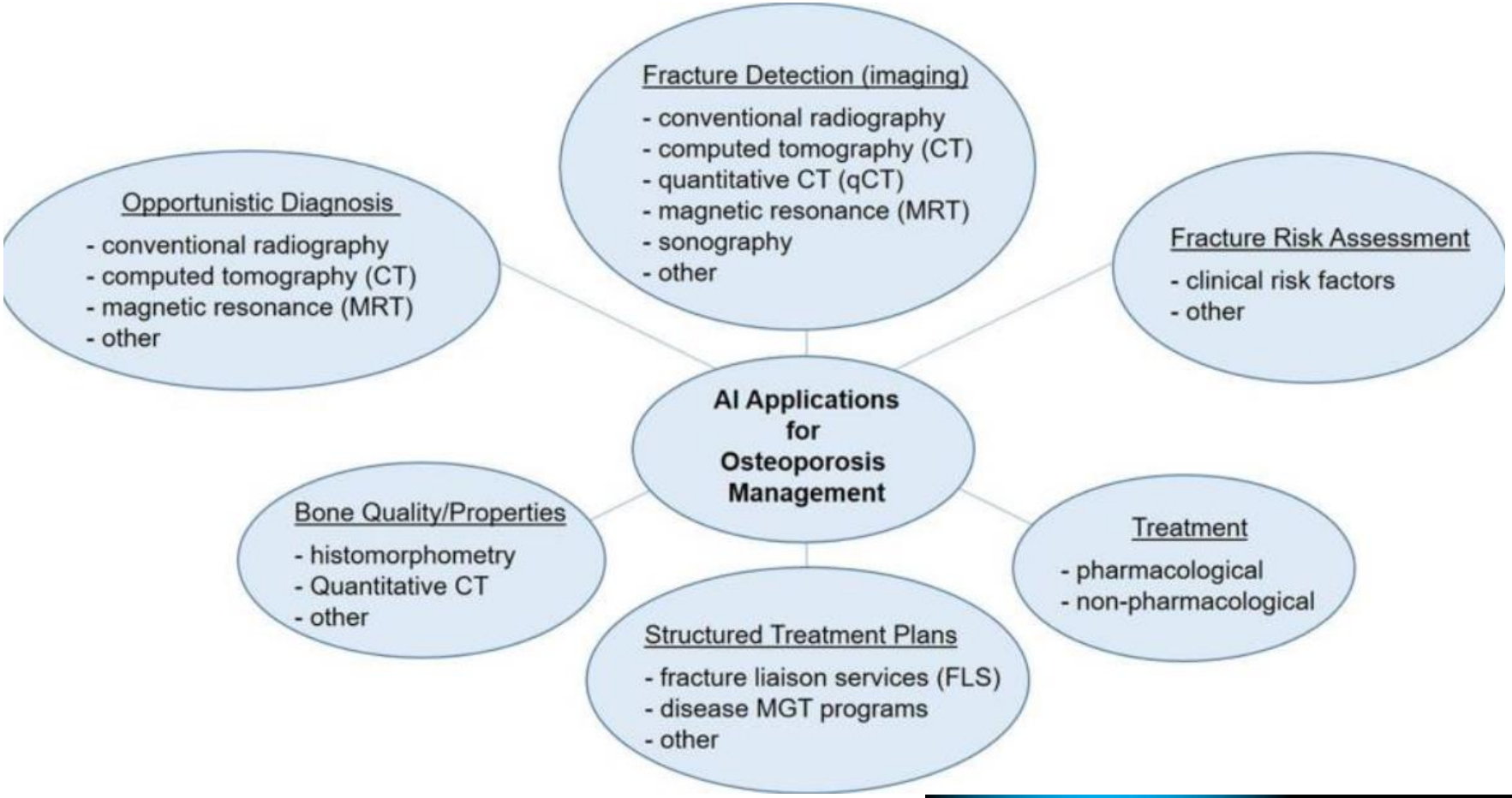


- ✓ *One of the major challenges in the management of osteoporosis lies in the fact that although the operational diagnosis is based on bone mineral density (BMD) as measured by dual x-ray absorptiometry, the majority of fractures occur at non osteoporotic BMD values*

- ✓ Osteoporosis often remains undiagnosed regardless of the low severity of the underlying trauma

- ➢ *There is only weak consensus among the major guidelines worldwide, when to treat, whom to treat, and which drug to use*

Increasing efforts have been undertaken in the past few years by artificial intelligence (AI) developers to support and improve the management of osteoporosis disease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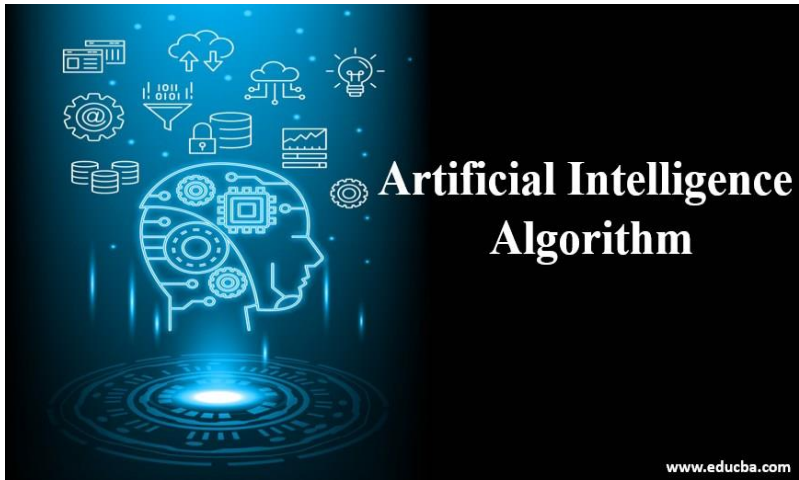
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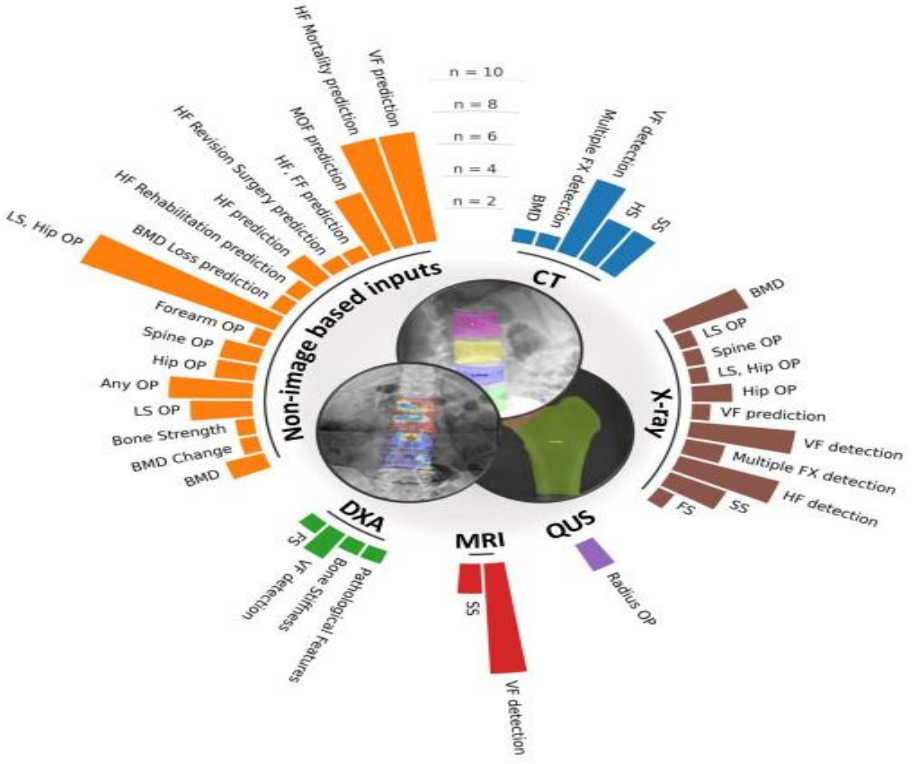
Journal of Bone and Mineral Research, 2024, **39**, 1553–1573
https://doi.org/10.1093/jbmr/zjae131
Advance access publication: August 20, 2024
Research Article

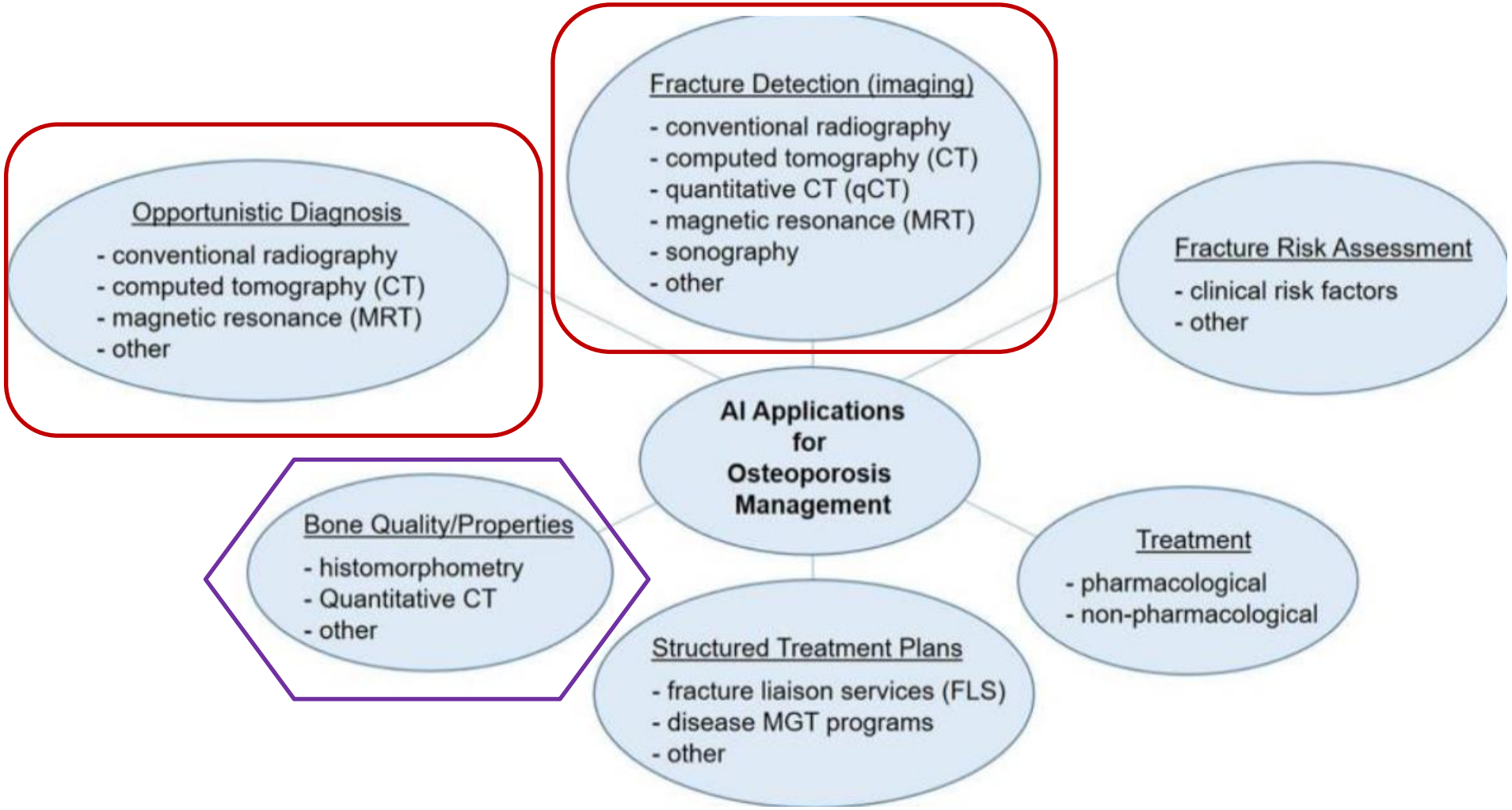
Development and reporting of artificial intelligence in osteoporosis management

Guillaume Gatineau[1,*], Enisa Shevroja[1], Colin Vendrami[1], Elena Gonzalez-Rodriguez[1], William D. Leslie[2], Olivier Lamy[3], Didier Hans[1]

[1]Interdisciplinary Center of Bone Diseases, Rheumatology Unit, Bone and Joint Department, Lausanne University Hospital and University of Lausanne, Av. Pierre-Decker 4, 1011 Lausanne, Switzerland
[2]Department of Medicine, University of Manitoba, Winnipeg, MB R3T 2N2, Canada
[3]Internal Medicine Unit, Internal Medicine Department, Lausanne University Hospital and University of Lausanne, 1005 Lausanne, Switzerland
*Corresponding author: Guillaume Gatineau, Bone and Joint Department, Interdisciplinary Center of Bone Diseases, Avenue Pierre Decker, 1011 Lausanne, Switzerland (guillaume.gatineau@chuv.ch).

Graphical Abstract

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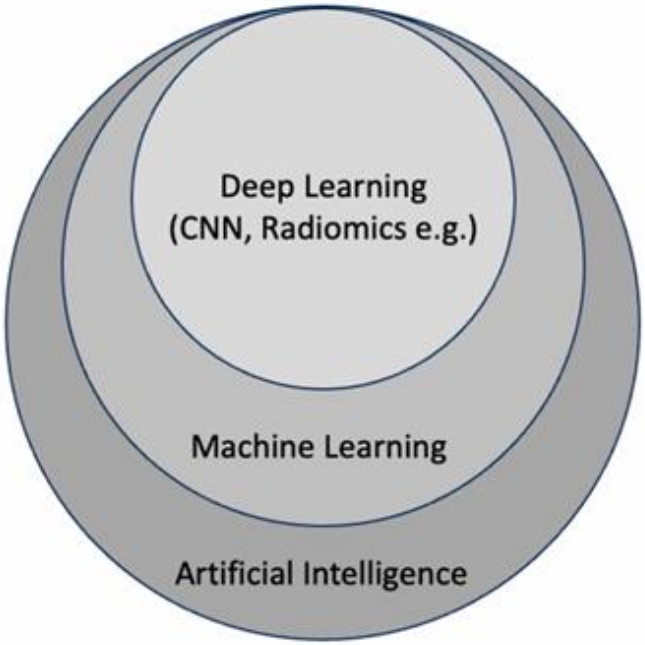


With the recent advent of artificial intelligence (AI) technology, machine learning and deep learning models have applications in osteoporosis detection and classification

- ✓ *Machine learning (ML) is a branch of artificial intelligence (AI) that involves training models to make predictions on the basis of existing datasets.*

- ✓ *Deep learning (DL), a subset of ML mimics the structure of neural networks in the brain*

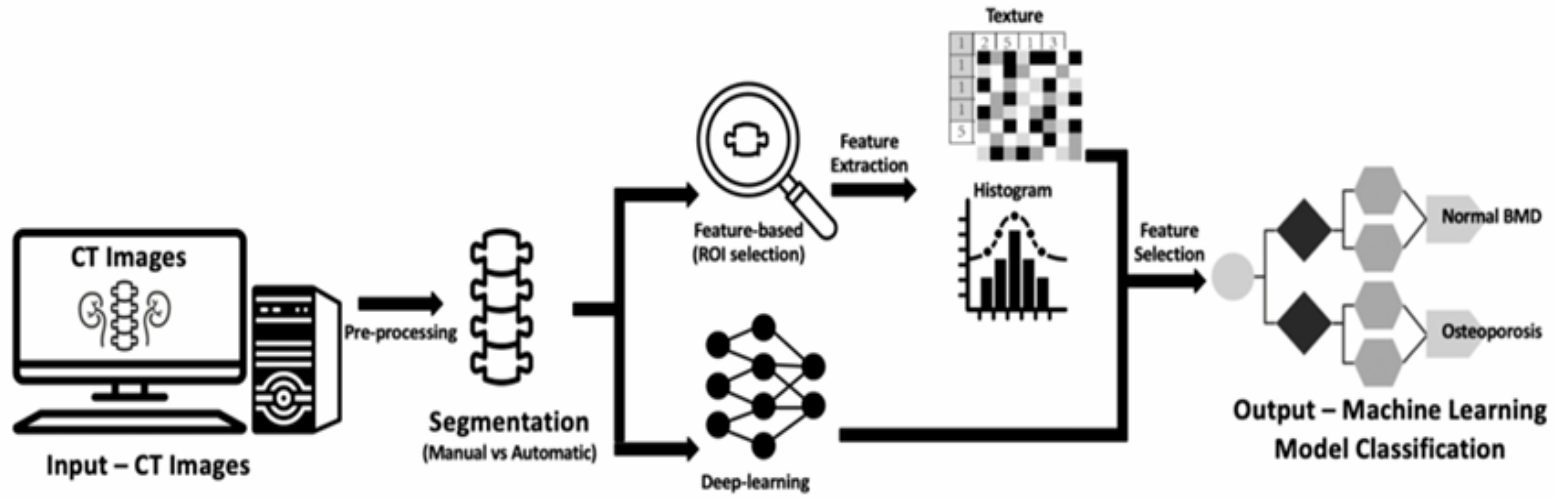
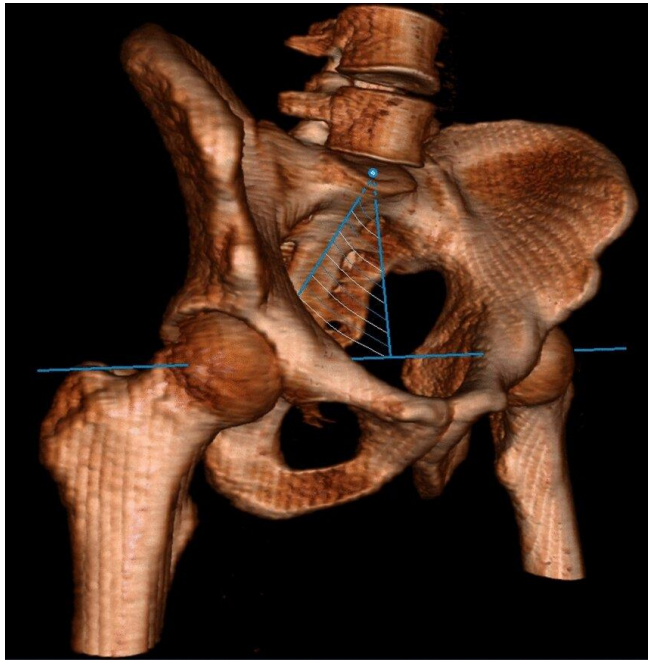
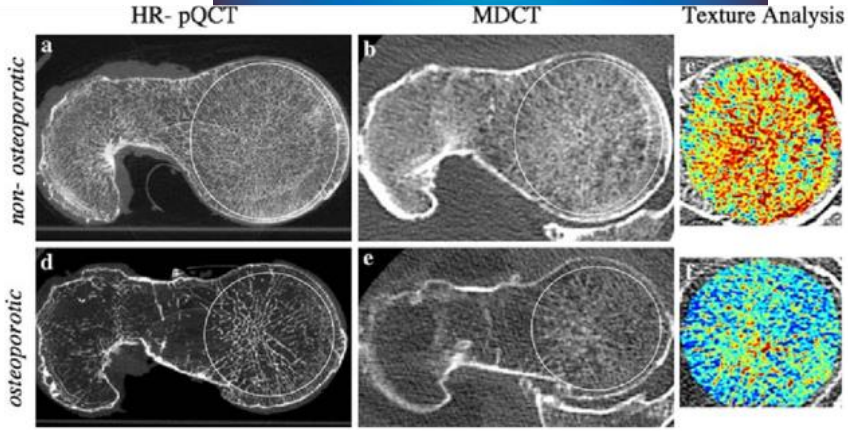
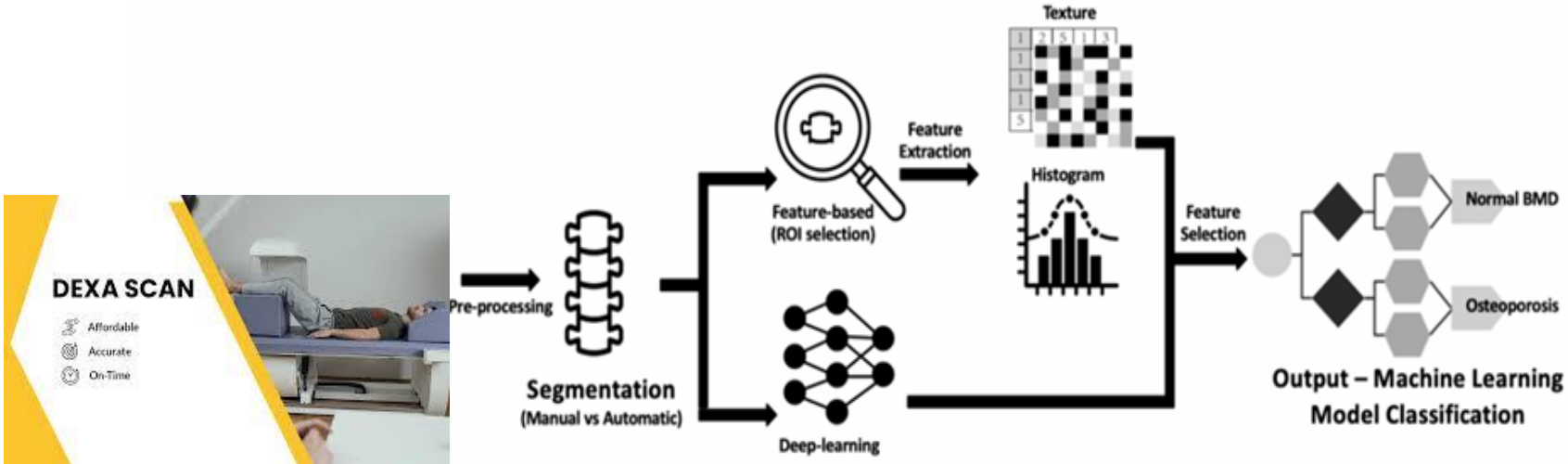


Diagram showing the general framework and main steps of radiomics, namely data selection (input), segmentation, feature extraction in the regions of interest (ROIs), exploratory analysis, and modeling.







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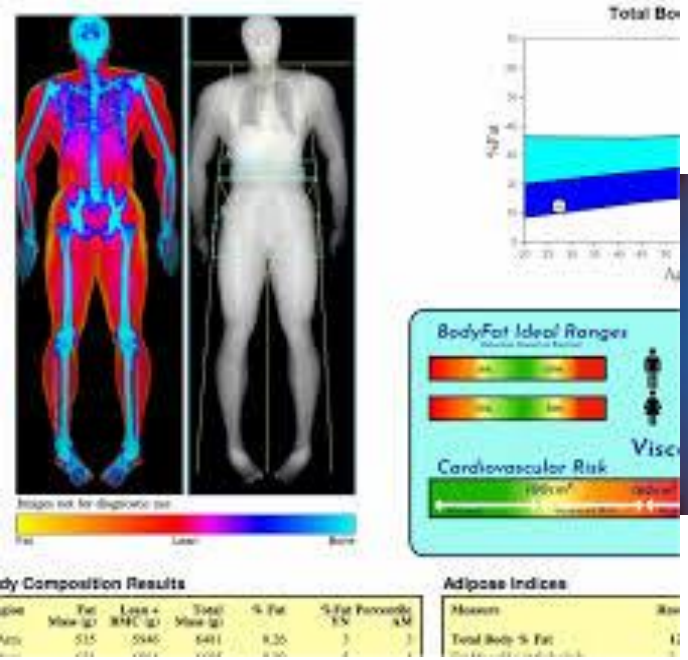
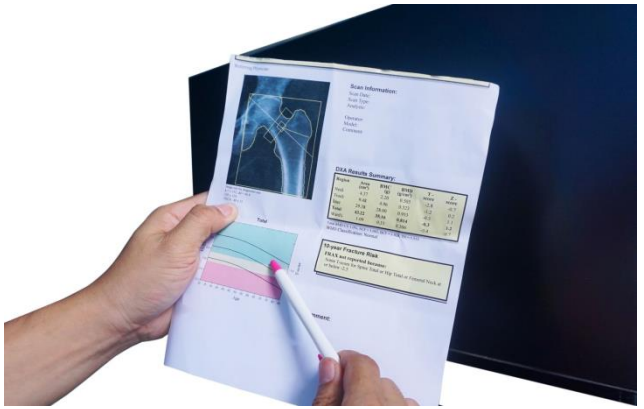


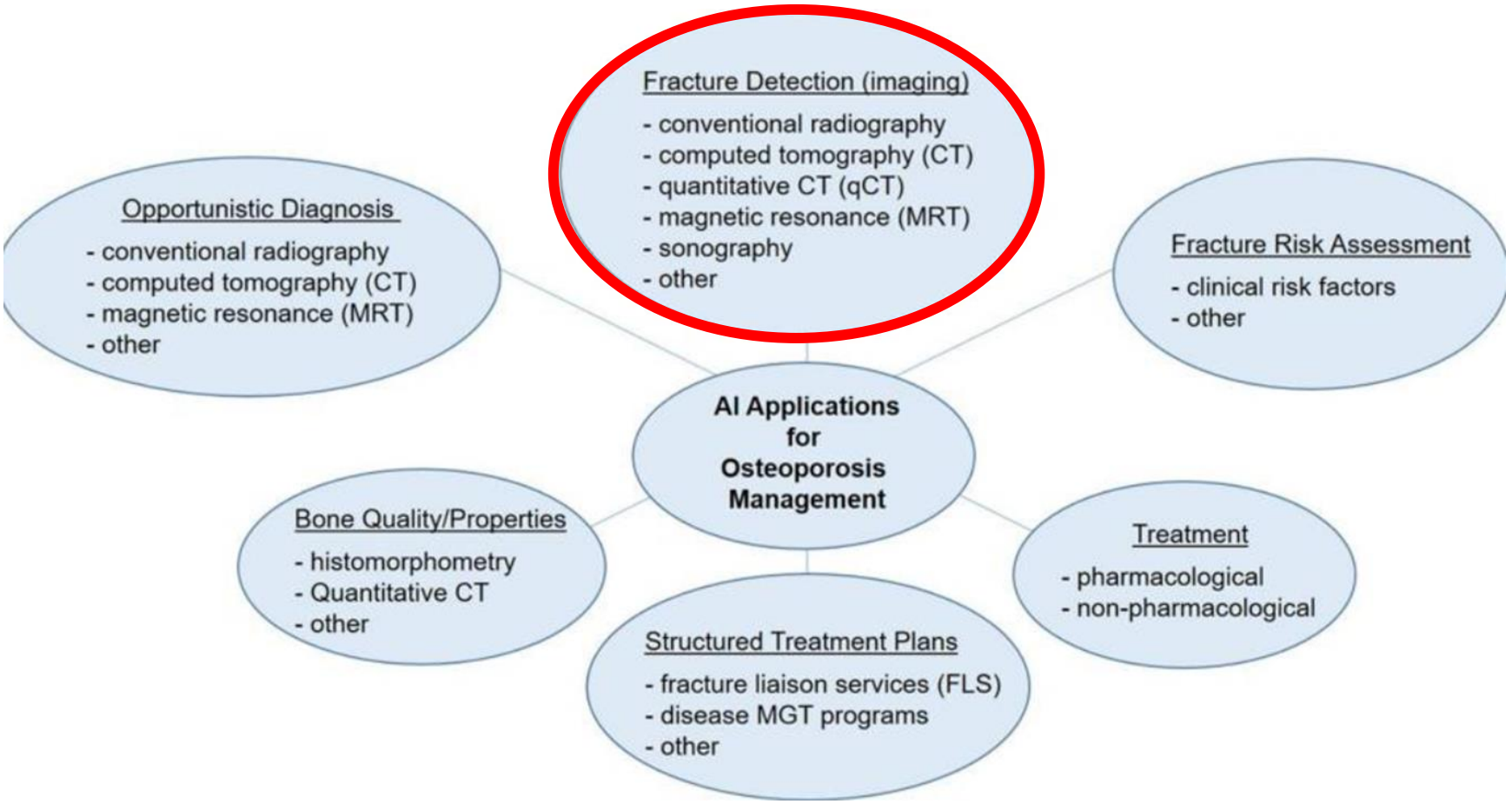


Meta-Analysis > BMC Musculoskelet Disord. 2024 Dec 4;25(1):991.
doi: 10.1186/s12891-024-08120-7.

Diagnostic accuracy of deep learning in prediction of osteoporosis: a systematic review and meta-analysis

Firouz Amani [1], Masoud Amanzadeh [2], Mahnaz Hamedan [3], Paniz Amani [4]

- ✓ Literature search was performed in electronic databases including PubMed, Elsevier, and Google Scholar to identify relevant articles until December 2023
- ✓ Out of the 181 articles initially identified, 10 studies were included in the analysis
- ✓ The pooled sensitivity and specificity were 0.86 (95% CI, 0.82-0.89) and 0.89 (95% CI, 0.85-0.91), respectively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RSNA Journals

Radiology. 2022 Mar 29;304(1):50–62. doi: 10.1148/radiol.211785

Artificial Intelligence in Fracture Detection: A Systematic Review and Meta-Analysis

Rachel Y L Kuo [1,✉], Conrad Harrison [1], Terry-Ann Curran [1], Benjamin Jones [1], Alexander Freethy [1], David Cussons [1], Max Stewart [1], Gary S Collins [1], Dominic Furniss [1]

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PMCID: PMC9270679 PMID: 35348381

- To perform a systematic review and meta-analysis comparing the diagnostic performance in fracture detection between AI and clinicians in peer-reviewed publications

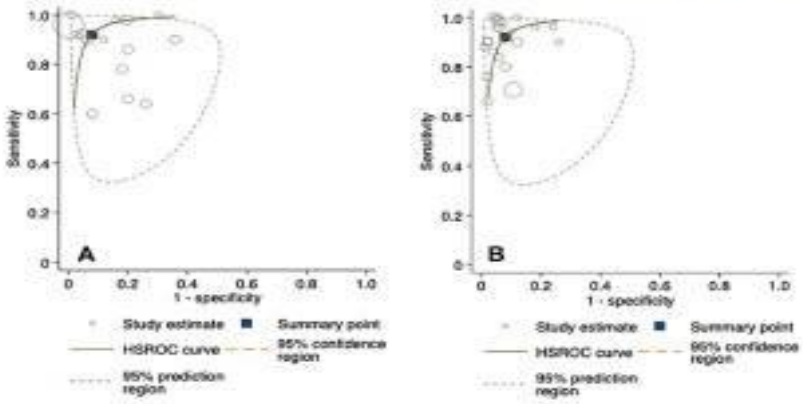
- A search of multiple electronic databases between January 2018 and June 2021 was performed that included any primary research studies that developed and/or validated AI for the purposes of fracture detection at any imaging modality and excluded studies that evaluated image segmentation algorithms.

❖ 42 studies

✓ 37 studies identified fractures on radiographs
✓ 5 studies identified fractures on CT images

❖ 55 061 images

Artificial Intelligence in Fracture Detection: A Systematic Review and Meta-Analysis

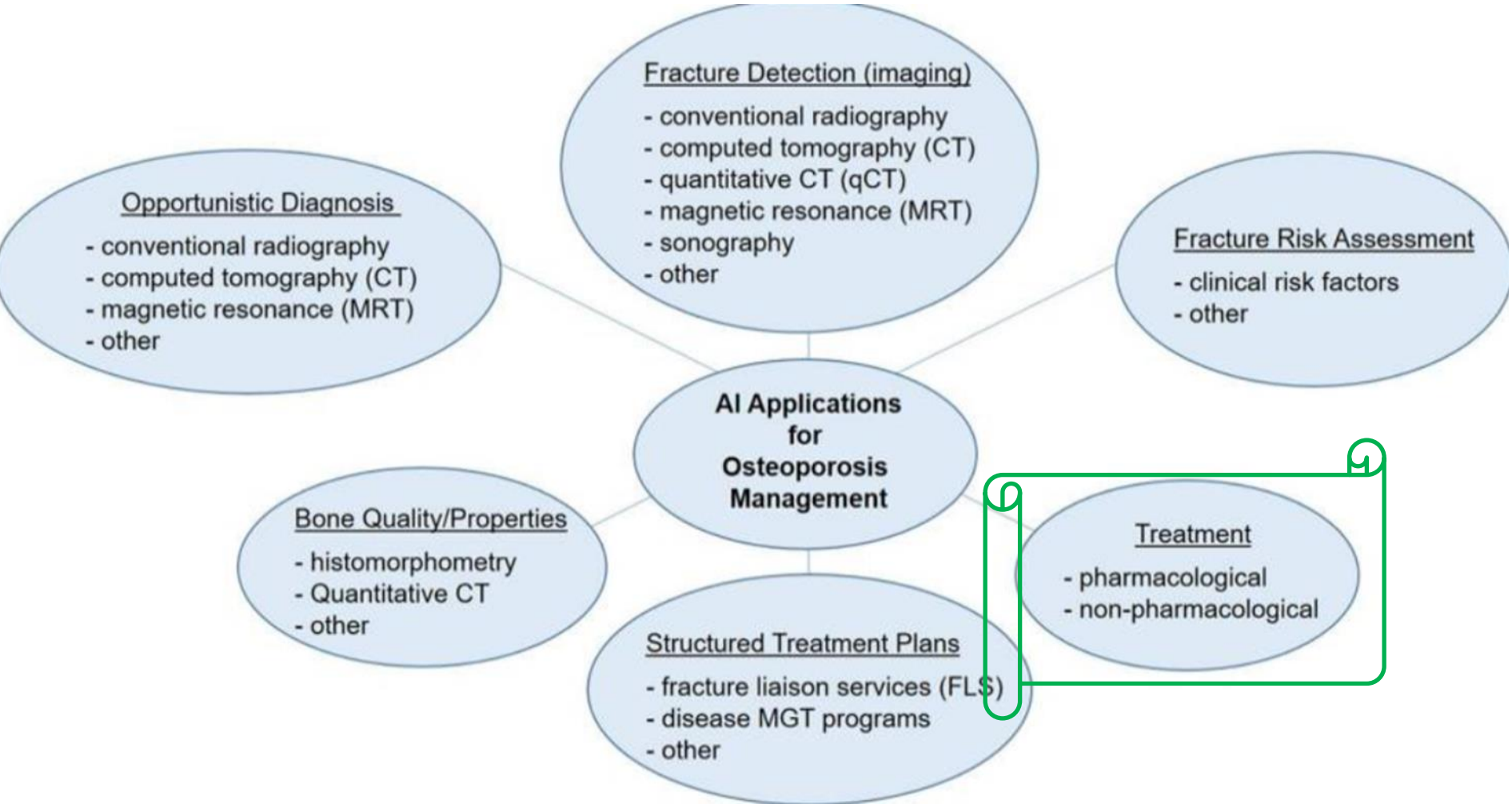


Hierarchical summary receiver operating characteristic (HSROC) curves for **(A)** fracture detection algorithms and **(B)** clinicians with external validation test sets.

- In a meta-analysis of 42 studies (37 with radiography and five with CT), the pooled diagnostic performance using AI to detect fractures had a sensitivity of 92% and 91% and specificity of 91% and 91% on internal and external validation, respectively.
- Clinician performance was comparable to AI in fracture detection (sensitivity 91%, 92%; specificity 94%, 94%).
- Only 13 studies externally validated results, and only one study evaluated AI performance in a prospective clinical trial.

Kuo RYL et al. Published Online: March 29, 2022
https://doi.org/10.1148/radiol.211785

Radiology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SCIENTIFIC REPORTS
nature research

Sci Rep. 2021 Jul 5;11:13811. doi: 10.1038/s41598-021-93152-5

Bone mineral density response prediction following osteoporosis treatment using machine learning to aid personalized therapy

Thiraphat Tanphiriyakun [1,3], Sattaya Rojanasthien [1], Piyapong Khumrin [2,3]

Bibliography for a Research Paper

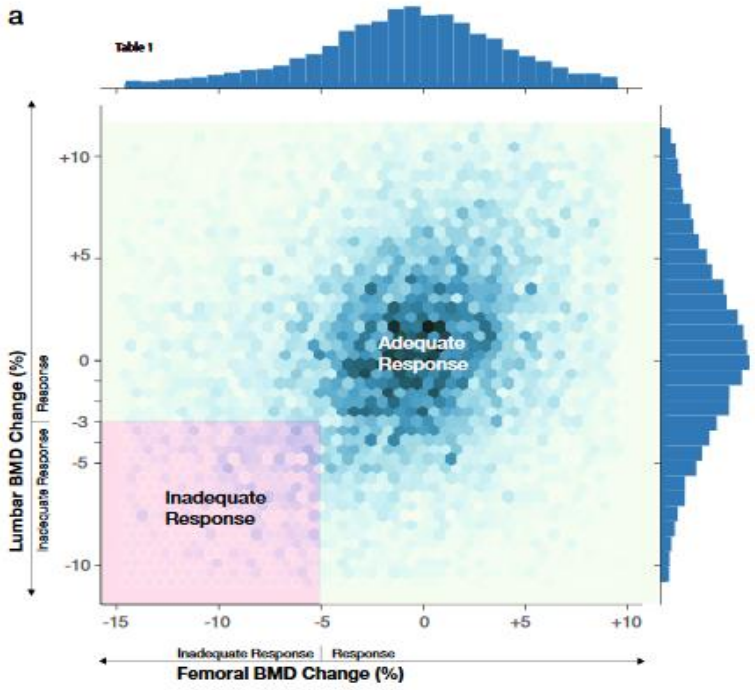
a great challenge to achieve the goals is how to select the best treatment regimen for individual patients

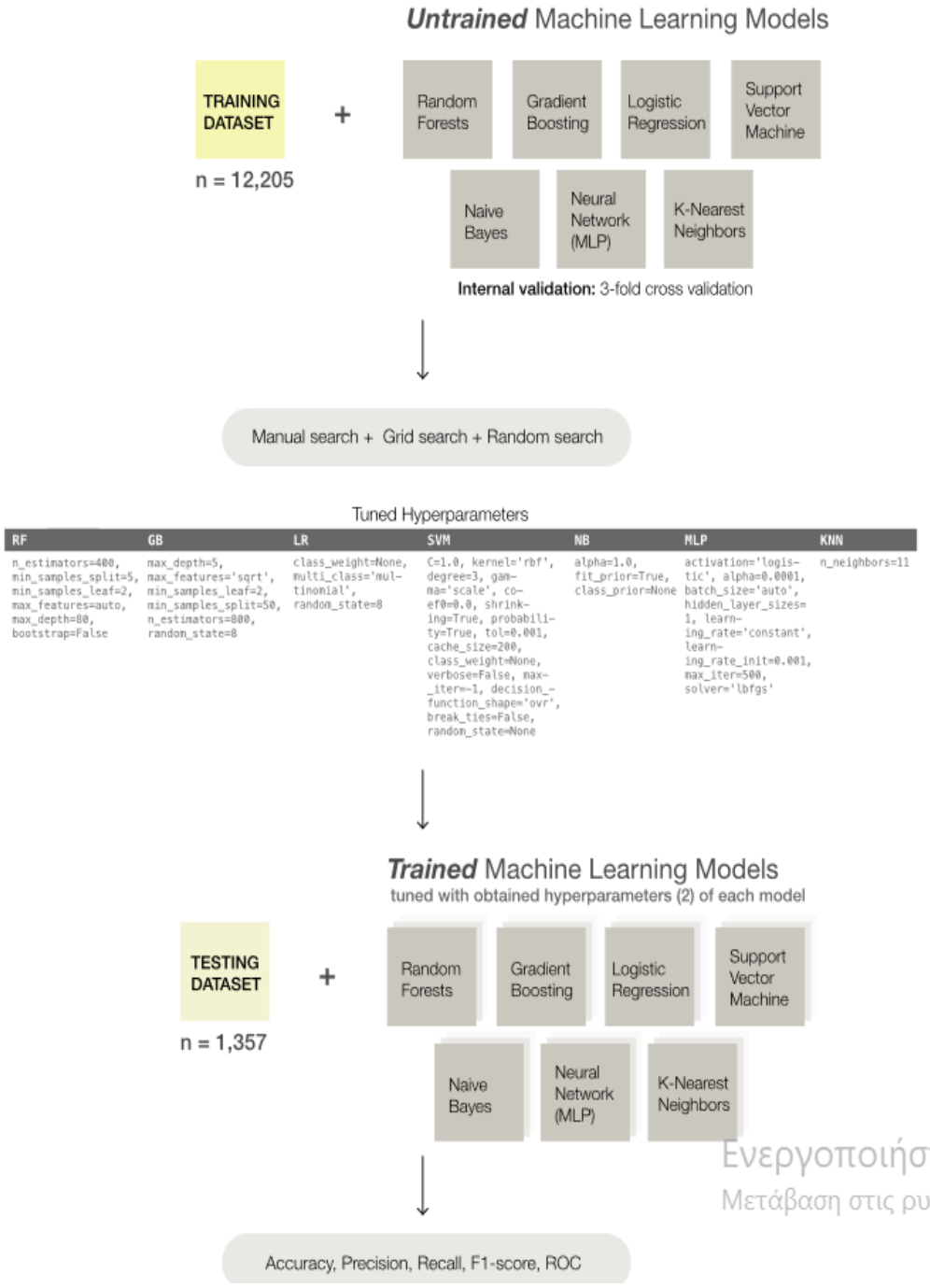
- a computational model from 8981 clinical variables, including demographic data, diagnoses, laboratory results, medications, and initial BMD results, taken from 10-year period of electronic medical records to predict BMD response after treatment
- trained 7 machine learning models with 13,562 osteoporosis treatment instances [comprising 5080 (37.46%) inadequate treatment responses and 8482 (62.54%) adequate responses] and selected the best model
- Individually predict treatment responses of 11 therapeutic regimens, then selected the best predicted regimen to compare with the actual regimen

Aside from any relevant clinical information, a typical printout of this AI-based software also provides a list of potentially eligible drugs, including information on which of these drugs would most likely be associated with the highest BMD increase

Variables	Total	Inadequate response	Response	*p* value
Treatment profile, n (%)	13,562	5080 (37.46%)	8482 (62.54%)	
Age (mean ± SD) years	62.23 ± 10.76	63.36 ± 10.87	64.75 ± 10.66	*< 0.01*
Sex, n (%)				
Women	12,731 (93.87%)	4790 (37.62%)	7941 (62.38%)	0.12
Men	831 (6.13%)	290 (34.90%)	541 (65.10%)	0.12
Medical history, n (%)				
Hypertension	483 (3.56%)	182 (37.68%)	301 (62.32%)	0.96
Diabetes	194 (1.43%)	81 (41.75%)	113 (58.25%)	0.24
Dyslipidemia	367 (2.71%)	137 (37.95%)	230 (63.71%)	1.00
Gout	9 (0.07%)	6 (66.67%)	3 (33.33%)	0.14
Laboratory (mean ± SD)				
Calcium	9.48 ± 1.46	9.47 ± 0.54	9.48 ± 1.80	0.61
Phosphate	4.00 ± 0.54	4.00 ± 0.21	4.00 ± 0.66	0.57
Albumin	4.30 ± 1.75	4.28 ± 1.27	4.30 ± 1.99	0.43
ALP	69.90 ± 15.95	70.42 ± 19.38	69.58 ± 13.48	*< 0.01*
BUN	14.29 ± 3.16	14.34 ± 3.33	14.26 ± 3.06	0.13
Creatinine	0.98 ± 0.83	0.99 ± 0.85	0.97 ± 0.81	0.26
Hemoglobin	12.24 ± 0.94	12.23 ± 0.97	12.25 ± 0.91	0.24
Fracture history, n (%)				
S32* Vertebral fractures	28 (0.21%)	9 (32.14%)	19 (67.86%)	0.70
Non-vertebral fractures				
S42* Shoulder and upper arm	25 (0.18%)	9 (36%)	64 (72.73%)	1.00
S52* Forearm	62 (0.46%)	14 (22.58%)	48 (77.42%)	0.02
S72* Hip and Femur	62 (0.46%)	18 (29.03%)	44 (70.97%)	0.21
S82* Lower leg and ankle	16 (0.12%)	8 (50%)	8 (50%)	0.44
Treatment regimens, n (%)				
Calcium	10,285 (75.84%)	3776 (36.71%)	6509 (63.29%)	*< 0.01*
Vitamin D	9939 (73.29%)	3558 (35.80%)	6381 (64.20%)	*< 0.01*
Calcitonin	282 (2.08%)	110 (39.01%)	172 (60.99%)	0.63
Menatetrenone	2819 (20.79%)	1091 (38.70%)	1728 (61.30%)	0.13
Anti-osteoporosis drug	7179 (52.93%)	2126 (29.61%)	5053 (70.39%)	*< 0.01*
Weak antiresorptive agents				
Daily oral regimens				
Raloxifene (60 mg)	420 (3.10%)	187 (44.52%)	233 (55.48%)	*< 0.01*
Strontium (2 g)	1188 (8.76%)	313 (26.35%)	875 (73.65%)	*< 0.01*
Potent antiresorptive agents				
Weekly oral regimens				
Alendronate (70 mg)	2383 (17.57%)	649 (27.23%)	1734 (72.77%)	*< 0.01*
Risedronate (35 mg)	1064 (7.85%)	356 (33.46%)	708 (66.55%)	*< 0.01*
Monthly oral regimens				
Risedronate (150 mg)	87 (0.64%)	23 (26.44%)	64 (73.56%)	*0.04*
Ibandronate (150 mg)	1,711 (12.62%)	529 (41.15%)	1182 (58.85%)	*< 0.01*
Injection regimens				
3-Month Ibandronate (3 mg)	48 (0.35%)	15 (31.25%)	33 (68.75%)	0.46
6-Month Denosumab (60 mg)	176 (1.30%)	32 (18.18%)	144 (81.82%)	*< 0.01*
12-Month Zoledronic acid (5 mg)	809 (5.97%)	218 (26.95%)	591 (73.05%)	*< 0.01*
Anabolic agent				
Injection regimen				
Daily teriparatide (20 mcg/dose)	295 (2.18%)	88 (29.83%)	207 (70.17%)	*< 0.01*
Initial femoral BMD (mean ± SD)	0.61 ± 0.13	0.65 ± 0.14	0.60 ± 0.11	*< 0.01*
Initial lumbar BMD (mean ± SD)	0.79 ± 0.14	0.81 ± 0.15	0.78 ± 0.14	*< 0.01*
Femoral BMD changes (mean ± SD)	−0.82% ± 0.12	−6.09% ± 8.24	2.33% ± 11.06	*< 0.01*
Lumbar BMD changes (mean ± SD)	−0.87% ± 0.18	−8.65% ± 22.89	3.80% ± 6.83	*< 0.01*

Features	Mean	sd	hdi-2.5%	hdi-97.5%	Interpretation
Intercept	4.778	0.648	3.498	5.947	–
BMD (Femur)	− 3.796	0.352	− 4.473	− 3.146	Lower
Anti-osteoporosis agent	0.657	0.048	0.569	0.752	Higher
BMD (Lumbar)	− 0.696	0.547	− 1.745	0.313	Not different
Age	− 0.017	0.003	− 0.023	− 0.013	Lower
Lumbar T-score	0.289	0.069	0.169	0.423	Higher
Lumbar Z-score	− 0.302	0.056	− 0.407	− 0.120	Lower
Femur Z-score	0.554	0.054	0.448	0.649	Higher
Radius T-score	0.133	0.038	0.059	0.201	Higher
Femur T-score	− 0.402	0.057	− 0.509	− 0.295	Lower
Radius Z-score	− 0.105	0.042	− 0.189	− 0.030	Lower
Calcium (oral)	− 0.39	0.073	− 0.524	− 0.253	Lower
Ibandronate (oral, monthly)	0.488	0.065	0.357	0.601	Higher
Lab Alkaline Phosphatase (ALP)	− 0.003	0.001	− 0.005	− 0.002	Lower
Weight	0.003	0.001	0.001	0.005	Higher
Analgesic Balm	− 0.446	0.079	− 0.605	− 0.304	Lower
Risedronate (oral, weekly)	− 0.127	0.08	− 0.278	0.016	Not different
Calcium 600 mg (oral)	0.094	0.065	− 0.023	0.211	Not different
Tramadol + acetaminophen	0.061	0.057	− 0.041	0.172	Not different
Prednisolone 5 mg	− 0.044	0.079	− 0.193	0.097	Not different
Codiene + acetaminophen	− 0.189	0.079	− 0.342	− 0.043	Lower



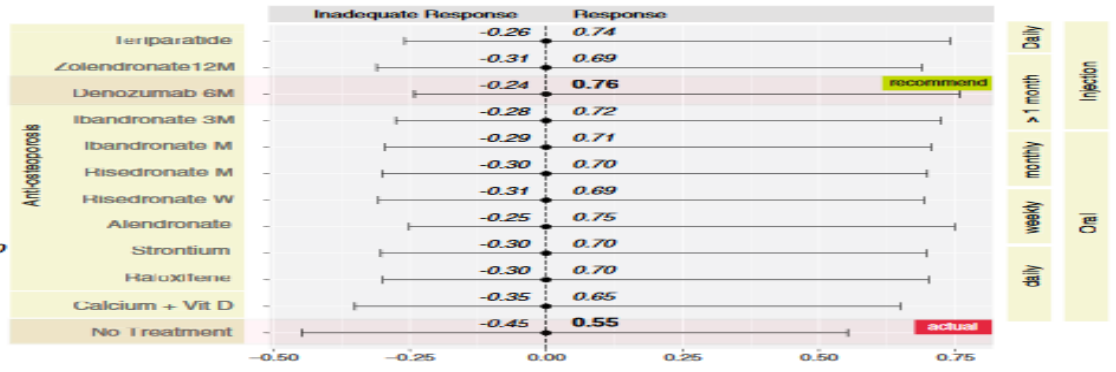


Ενεργοποιήστ
Μετάβαση στις ρυθ

Conclusion

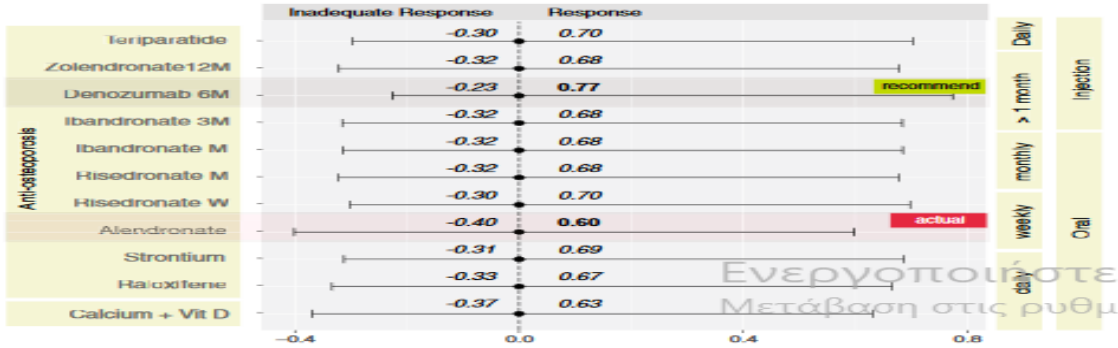
Patient #1 (Inadequate Response)

80 year-old ♀
T-Score (before treatment)
Lumbar -3.7
Femur -2.5
BMD (before treatment)
Lumbar 0.583
Femur 0.534
BMD (after treatment)
Lumbar 0.585 (+0.34%)
Femur 0.506 (-5.24%)
Comorbidity
E11. 9 - Type 2 Diabetes mellitus w/o complications
H25. 9 - Unspecified age-related cataract
Medication
Glipizide 5 mg
Metformin and Sitagliptin 50/500
Metformin 850 mg
Multivitamin
Lab
ALP 55 U/L
BUN 12.5 mg/dL
Creatinine 0.875 mg/dL
Hemoglobin 12.2 g/dL
Total Calcium 9.48 mg/dL
Albumin 4.5 g/dL



Patient #2 (Response)

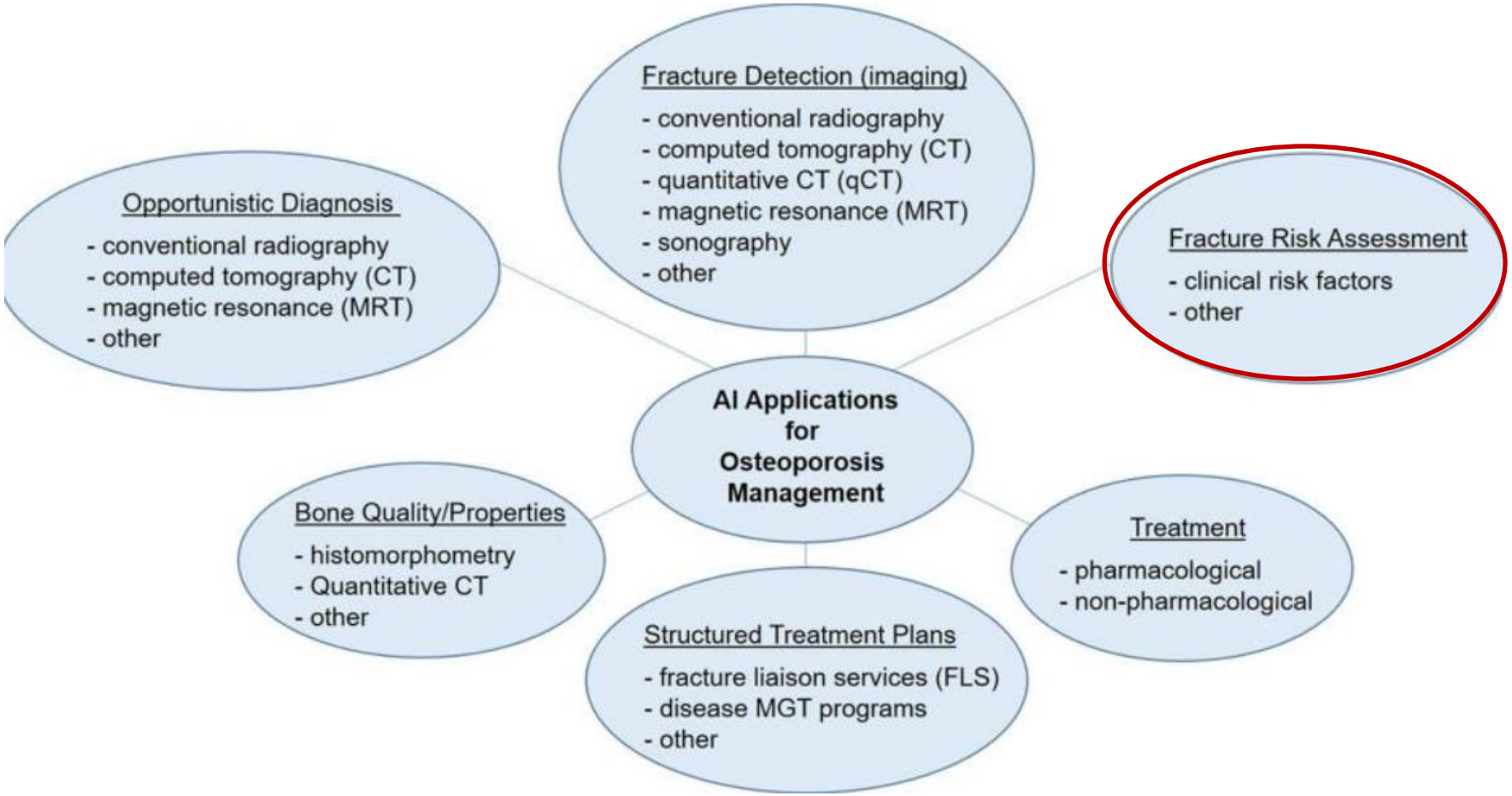
71 year-old ♂
T-Score (before treatment)
Lumbar -3
Femur -2.7
BMD (before treatment)
Lumbar 0.66
Femur 0.515
BMD (after treatment)
Lumbar 0.663 (0.45%)
Femur 0.539 (4.66%)
Comorbidity -
Medication
Vitamin B1-6-12 tab
Atorvastatin Tab 20 mg
Omeprazole Cap 20 mg
Esomeprazole Tab 20 mg
AmlodipineTab 5 mg
Lab
ALP 49 U/L
BUN 14.29 mg/dL
Creatinine 0.6 mg/dL
Hemoglobin 12.24 g/dL
Total Calcium 9.48 mg/dL
Albumin 4.7 g/dL



Ενεργοποιήστε
Μετάβαση στις ρυθμί

✓ It is feasible to use a combination of EMR-derived information to develop a machine learning algorithm to predict a BMD response following osteoporosis treatment

➢ This alternative approach can aid physicians to select an optimal therapeutic regimen in order to maximize a patient-specific treatment outcome


Fracture Detection (imaging)
- conventional radiography
- computed tomography (CT)
- quantitative CT (qCT)
- magnetic resonance (MRT)
- sonography
- other
Opportunistic Diagnosis
- conventional radiography
- computed tomography (CT)
- magnetic resonance (MRT)
- other
Fracture Risk Assessment
- clinical risk factors
- other
AI Applications for Osteoporosis Management
Bone Quality/Properties
- histomorphometry
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Treatment
- pharmacological
- non-pharmacological
Structured Treatment Plans
- fracture liaison services (FLS)
- disease MGT programs
- other

> J Bone Miner Res. 2023 Jun;38(6):887-895. doi: 10.1002/jbmr.4814. Epub 2023 May 4.

Deep-Learning-Based Detection of Vertebral Fracture and Osteoporosis Using Lateral Spine X-Ray Radiography

Namki Hong [1], Sang Wouk Cho [2], Sungjae Shin [1], Seunghyun Lee [1], Seol A Jang [3], Seunghyun Roh [1], Young Han Lee [4], Yumie Rhee [1], Steven R Cummings [5] [6], Hwiyoung Kim [7], Kyoung Min Kim [3]

- Patients aged 50 years or older who underwent lateral spine radiography in Severance Hospital, Korea, from January 2007 to December 2018

- Providing a total of 26,299 lateral spine plain X-rays for 9276 patients

(VF prevalence 18.6% osteoporosis prevalence 40.3%)

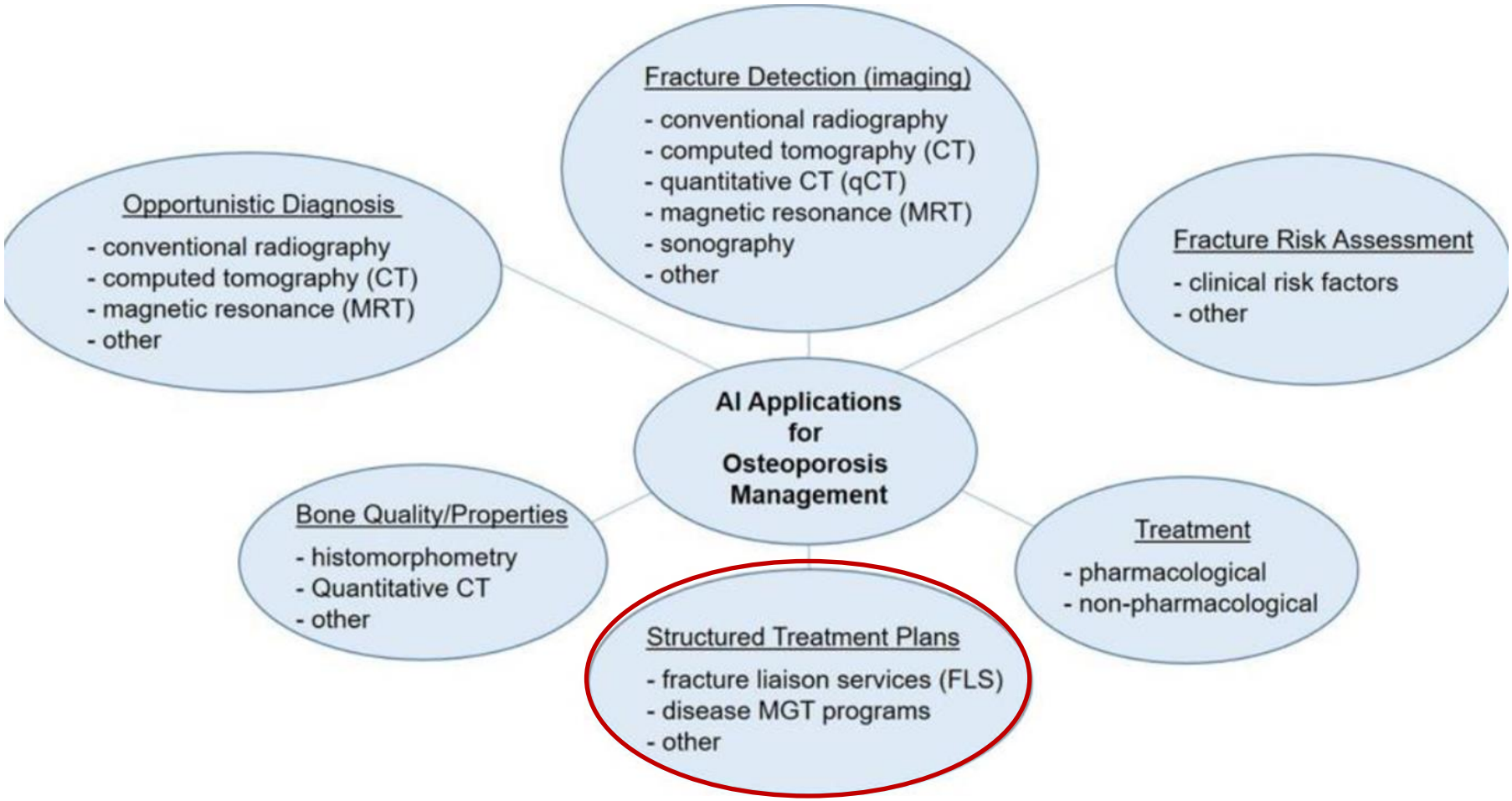
1. Clinical Characteristics of Study Participants

Characteristic	Derivation cohort				External test cohort
	Overall (n = 9276)	Train set (n = 5568, 60%)	Validation set (n = 1856, 20%)	Test set (n = 1852, 20%)	External test set (n = 234)
Women, n (%)	6105 (66)	1219 (66)	1220 (66)	3666 (66)	204 (87)
Age (years), mean ± SD	65.7 ± 8.5	65.7 ± 8.5	65.8 ± 8.5	65.7 ± 8.5	68.5 ± 9.2
Height (cm), mean ± SD	159.1 ± 8.5	159.2 ± 8.5	159.2 ± 8.4	158.8 ± 8.6	155.7 ± 7.1
Weight (kg), mean ± SD	61.1 ± 10.6	61.1 ± 10.6	61.2 ± 10.6	61.0 ± 10.3	56.3 ± 9.2
BMI (kg/m^2), mean ± SD	24.0 ± 3.2	24.0 ± 3.2	24.1 ± 3.3	24.1 ± 3.2	23.2 ± 3.4
Lumbar spine BMD (g/cm^2), mean ± SD[a]	0.895 ± 0.212	0.894 ± 0.215	0.894 ± 0.209	0.899 ± 0.221	0.827 ± 0.162
Lumbar score T-score, mean ± SD[a,b]	−1.4 ± 1.9	−1.4 ± 1.9	−1.3 ± 2.0	−1.4 ± 2.0	−1.9 ± 1.5
Femoral neck BMD (g/cm^2), mean ± SD[a]	0.654 ± 0.138	0.650 ± 0.138	0.654 ± 0.137	0.657 ± 0.141	0.616 ± 0.116
Femoral neck T-score, mean ± SD[a,b]	−1.7 ± 1.2	−1.7 ± 1.1	−1.7 ± 1.2	−1.7 ± 1.2	−2.0 ± 1.0
Total hip BMD (g/cm^2), mean ± SD[a]	0.792 ± 0.155	0.788 ± 0.153	0.792 ± 0.154	0.795 ± 0.159	0.762 ± 0.126
Total hip T-score, mean ± SD[a,b]	−1.2 ± 1.3	−1.2 ± 1.3	−1.2 ± 1.3	−1.2 ± 1.3	−1.5 ± 1.0
Osteoporosis, n (%)[a]	2649 (40.3)	1590 (40.3)	533 (40.1)	526 (40.1)	133 (56.8)
Morphometric vertebral fracture, n (%)	1723 (18.6)	1035 (18.6)	349 (18.8)	339 (18.3)	40 (15.8)
History of fracture (clinical), n (%)	682 (7.4)	426 (7.7)	124 (6.7)	132 (7.1)	22 (9.4)
Glucocorticoid users, n (%)	437 (4.7)	250 (4.5)	86 (4.6)	101 (5.5)	13 (5.6)
Rheumatoid arthritis, n (%)	252 (2.7)	145 (2.6)	46 (2.5)	61 (3.3)	3 (1.3)
Secondary osteoporosis, n (%)[c]	188 (2.0)	119 (2.1)	31 (1.7)	38 (2.1)	8 (3.4)

Table 3. Net Reclassification Improvement by VERTE-X pVF and VERTE-X Osteo Scores to Detect Individuals with Osteoporosis over Clinical DXA Testing Indications

Parameter	With osteoporosis			Without osteoporosis		
	Spine X-ray scores or clinical indications for DXA testing[b]			Spine X-ray scores or clinical indications for DXA testing[b]		
DXA-available internal test set (n = 1313)						
Clinical indications for DXA testing[a]	Not recommend	Recommend	Total	Not recommend	Recommend	Total
Not recommend	56	77	133	369	34	403
Recommend	0	393	393	0	384	384
Total	56	470	526	369	418	787
NRI: 0.10 (95% CI 0.07–0.14, p < 0.001)						
DXA-available external test set (n = 234)						
Clinical indications for DXA testing[a]	Not recommend	Recommend	Total	Not recommend	Recommend	Total
Not recommend	14	24	38	30	4	34
Recommend	0	95	95	0	67	67
Total	14	119	133	30	71	101
NRI: 0.14 (95% CI 0.06–0.22, p < 0.001)						

The proposed method could detect prevalent VFs and osteoporosis, and it improved referral of individuals at high risk of fracture to DXA testing more than clinical indications alone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Structured Treatment Plans
- fracture liaison services (FLS)
- disease MGT programs
- other

biosensors

MDPI

Article

Explainable Artificial Intelligence and Wearable Sensor-Based Gait Analysis to Identify Patients with Osteopenia and Sarcopenia in Daily Life

Jeong-Kyun Kim [1,2], Myung-Nam Bae [2], Kangbok Lee [2], Jae-Chul Kim [2] and Sang Gi Hong [1,2,*]

[1] Department of Computer Software, University of Science and Technology, Daejeon 34113, Korea; kim.jk@etri.re.kr

[2] Intelligent Convergence Research Laboratory, Electronics and Telecommunications Research Institute, Daejeon 34129, Korea; mnbae@etri.re.kr (M.-N.B.); kblee@etri.re.kr (K.L.); kimjc@etri.re.kr (J.-C.K.)

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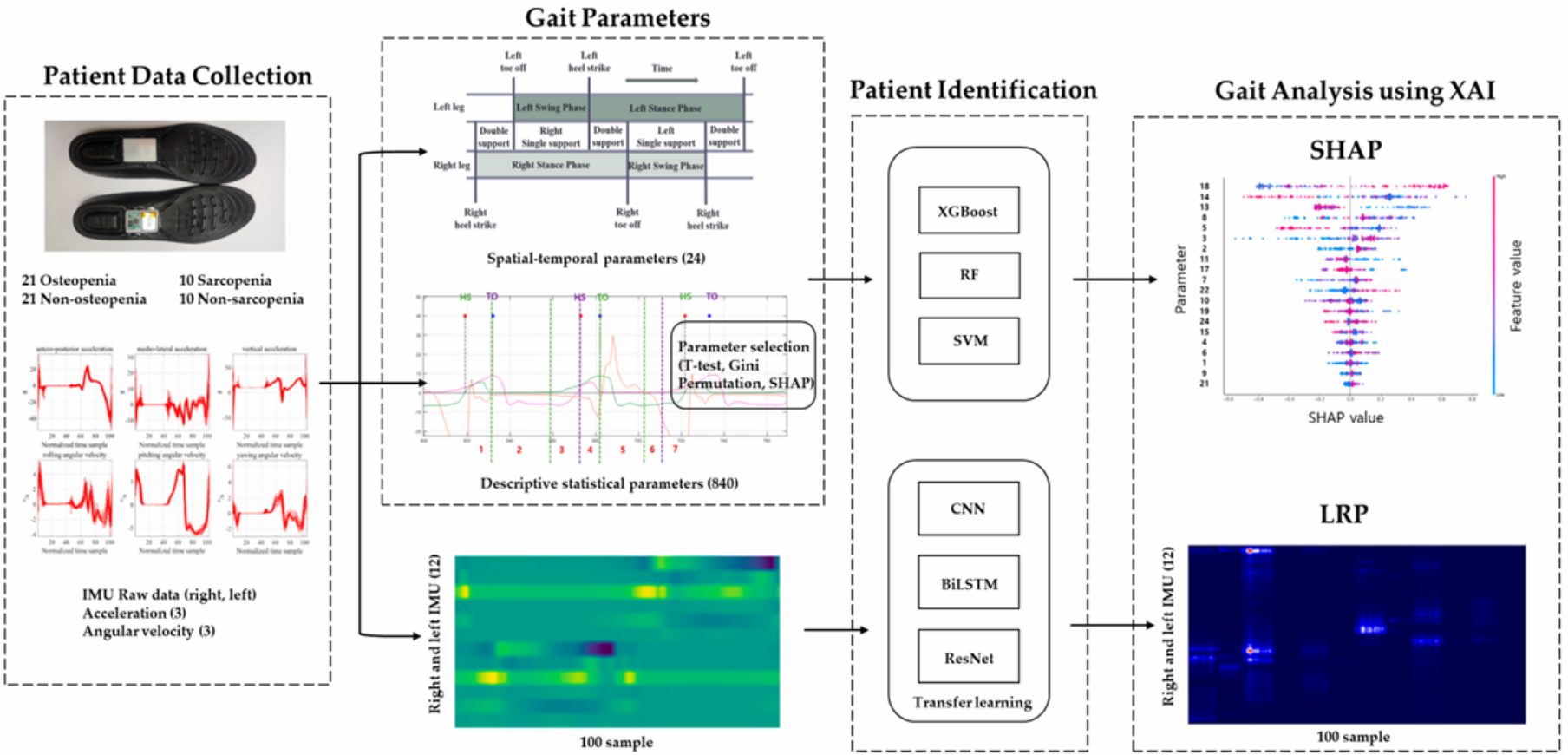


Figure 1. Gait analysis flowchart.

- Gait signals of 42 women over 65 years of age were obtained to analyze the gait characteristics for osteopenia and sarcopenia
- Among the 42 subjects, there were 21 patients with osteopenia and 21 patients without osteopenia
- Additionally,10 sarcopenia and 10 non-sarcopenia patients were selected among the 42 subjects

- All participants wore the same sneaker model and walked the 27m corridor four times in a straight line
- The clinical system consisted of 10 cameras (Vicon,OxfordMetrics,Oxford,UK) and 4 force plates(Advanced Mechanical Technology,MA,USA)

Table 2. Group population statistics for osteopenia and sarcopenia groups.

Parameter	Osteopenia	Non-Osteopenia	Osteopenia *p*-Value	Sarcopenia	Non-Sarcopenia	Sarcopenia *p*-Value
Age (years)	70.48 ± 2.36	70.33 ± 2.56	0.852	71.10 ± 2.13	69.50 ± 3.14	0.199
Height (cm)	153.65 ± 4.83	152.80 ± 5.93	0.614	150.87 ± 4.66	153.10 ± 4.36	0.283
Weight (kg)	57.75 ± 6.12	59.57 ± 7.12	0.379	53.55 ± 5.62	61.20 ± 5.07	0.005
Feet_size (mm)	236.91 ± 7.66	238.57 ± 6.55	0.453	232.00 ± 5.87	239.50 ± 6.43	0.014
MMSE	27.62 ± 1.77	28.19 ± 1.78	0.303	27.80 ± 1.40	27.30 ± 2.16	0.547
SARC-F	3.19 ± 2.40	3.86 ± 2.15	0.349	2.90 ± 1.52	2.90 ± 2.85	1.000
MFS	23.10±17.92	26.43 ± 16.59	0.535	13.50 ± 12.92	23.50 ± 12.70	0.098
BBS	42.38 ± 8.48	42.19 ± 6.85	0.937	43.10 ± 6.26	41.90 ± 9.47	0.742
3m TUG	10.96 ± 1.64	11.50 ± 2.87	0.464	11.71 ± 1.62	9.85 ± 1.92	0.031
Grasp_right (kg)	17.29 ± 5.42	18.77 ± 4.71	0.351	14.42 ± 3.65	22.57 ± 2.73	0.000
Grasp_left (kg)	17.61 ± 4.67	18.04 ± 4.40	0.761	14.15 ± 3.97	22.17 ± 3.02	0.000
T_score (DEXA)	−1.85 ± 0.74	0.69 ± 1.49	0.000	−0.49 ± 2.08	−0.64 ± 2.03	0.872
SMI(ASM/height)	5.37 ± 0.55	5.38 ± 0.65	0.961	4.58 ± 0.32	5.93 ± 0.35	0.000

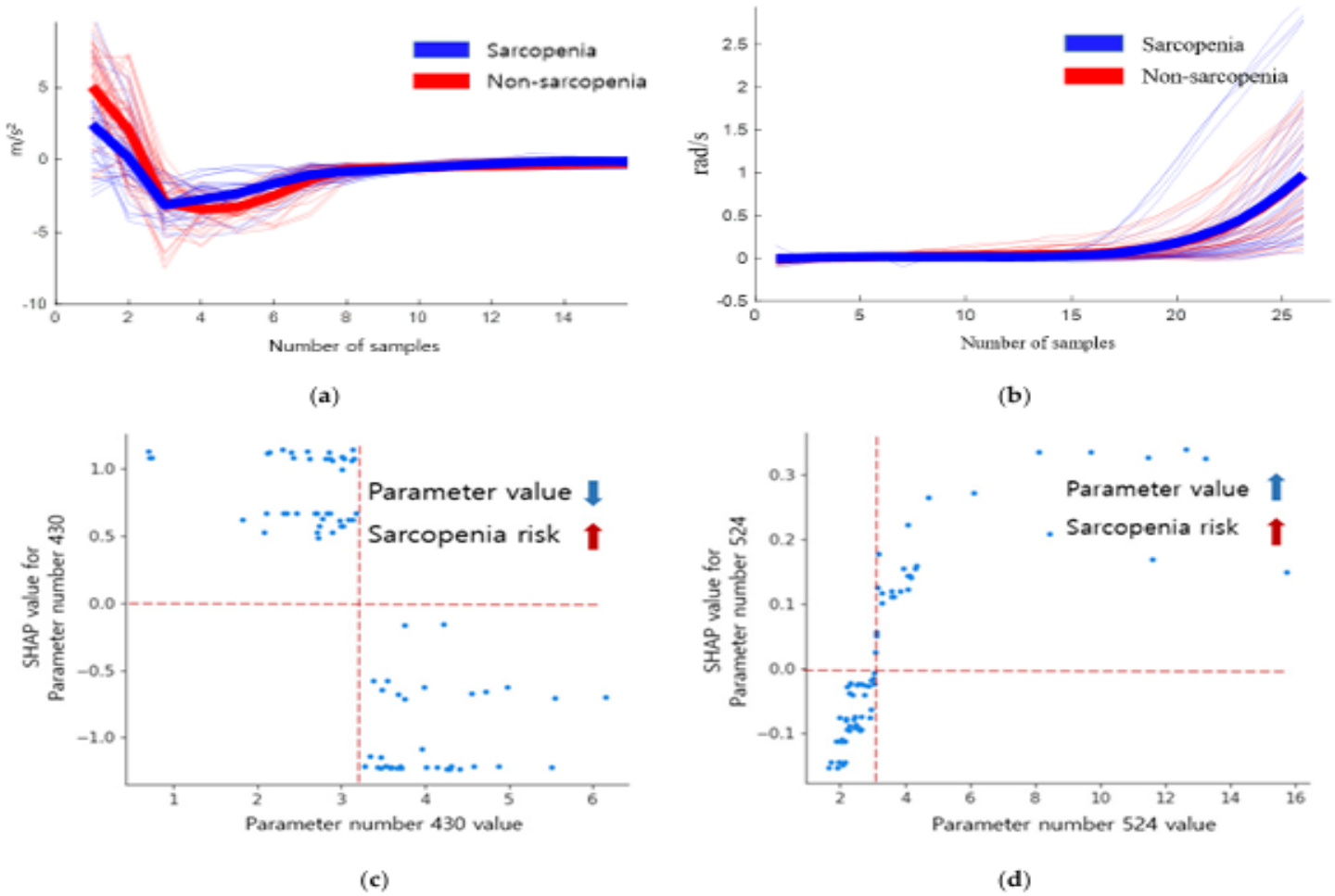


Figure 6. Inertial signals and SHAP dependence plots of descriptive statistical parameters 430 and 524 of sarcopenia. (**a**) Inertial signal 430. (**b**) Inertial signal 524. (**c**) SHAP dependence plot 430. (**d**) SHAP dependence plot 524.

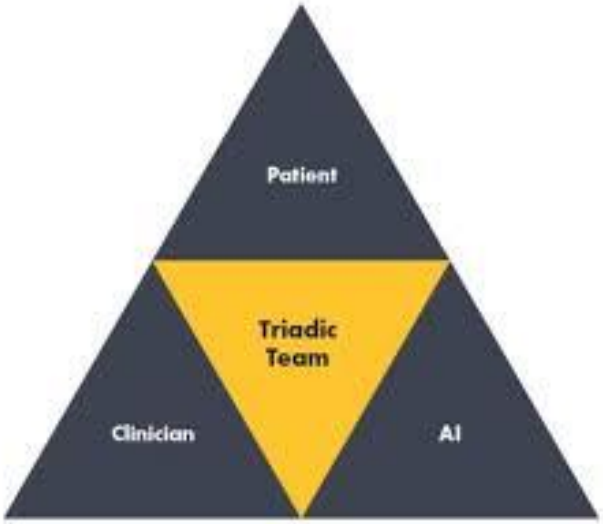
Conclusion

- ✓ A large number of AI algorithms have been developed in the past few years to facilitate the management of osteoporosis including diagnosis, fracture risk assessment, fracture detection, bone quality assessment, and treatment decision

- ✓ Performance comparison between such solutions and human physician experts show similar results or are even in favor of the AI algorithm

- ✓ Specifically, radiomics including AI-supported opportunistic methods for BMD assessment together with clinical data appear to have a great potential for early detection of patients who are at increased risk of fracture

Conclusion

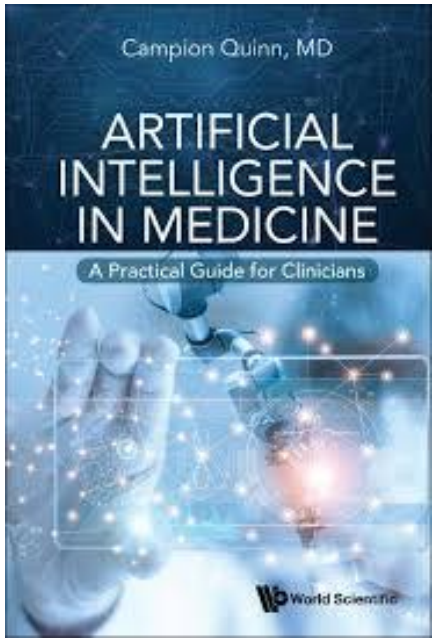


However

- ✓ even if study results appear promising at a first glance, methodological approaches behind a newly developed AI algorithm should always be carefully read and critically appraised

- ✓ it is not always evident that the AI algorithm chosen or developed would result in a performance superior to that of simple traditional statistical methods

Conclusion



There is a clear need for high-quality clinical research in the field of AI in osteoporosis management

- ✓ *This could be achieved by, eg, establishing an internationally consented best practice framework that considers AI developers, osteoporosis experts, and their respective scientific societies as well as healthcare authorities including those involved in approval processes*

ΝΤΕΜΗΣ ΧΑΣΑΜΠΗΣ: ΣΕ 10 ΧΡΟΝΙΑ Η ΑΙ ΘΑ ΜΠΟΡΕΙ ΝΑ ΚΑΝΕΙ ΤΑ ΠΑΝΤΑ

ECONOMIA 18.03.25 10:27

CEO της Google DeepMind

«Νομίζω ότι τα σημερινά συστήματα είναι πολύ παθητικά και εξακολουθούν να υπάρχουν πολλά πράγματα που δεν μπορούν να κάνουν. Όμως, τα επόμενα πέντε με δέκα χρόνια, πολλές δυνατότητες θα αρχίσουν να αναδύονται, και θα αρχίσουμε να κινούμαστε προς την τεχνητή γενική νοημοσύνη», είπε ο Χασάμπης, ορίζοντας την AGI ως «ένα σύστημα ικανό να επιδεικνύει όλες τις σύνθετες ικανότητες που διαθέτουν οι άνθρωποι».

«Δεν έχουμε φτάσει ακόμα εκεί. Αυτά τα συστήματα είναι εντυπωσιακά σε ορισμένα πράγματα, αλλά υπάρχουν και άλλα που δεν μπορούν να κάνουν ακόμα, και μένει ακόμη πολλή έρευνα να διεξάγουμε μέχρι να φτάσουμε εκεί», παραδέχθηκε.

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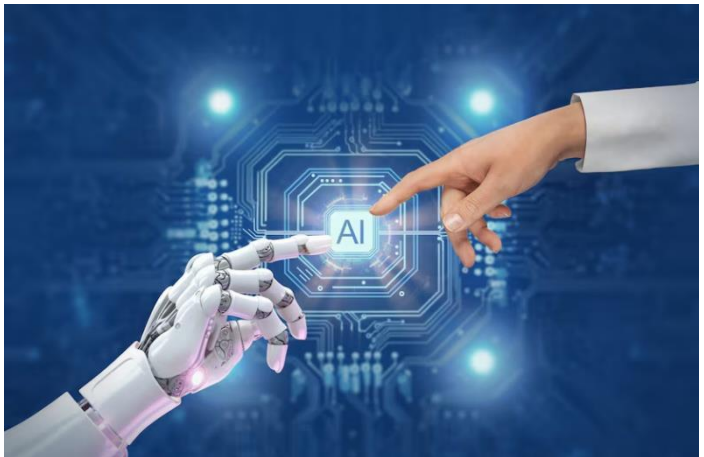
AI

Thank you