Opportunistic Detection of Osteoporosis Using Routine CT Scans: Development and Validation of an Artificial Intelligence-Based Screening Model

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ABSTRACT

Background: There is a significant underdiagnosis of osteoporosis despite its association with an increased fracture risk, the morbidity burden and increased healthcare costs. Opportunistic osteoporosis screening by routine computed tomography (CT) without imaging or radiation exposure provides an opportunity for routine screening for osteoporosis. The main purpose of this study was to create and externally validate an artificial intelligence (AI) model of automated osteoporosis detection using a routinely acquired computed tomography (CT) scan.

Materials and methods: A total of 1,862 adults (≥50 years old) underwent routine imaging with both computed tomography (CT) and dual-energy X-ray absorptiometry (DXA) within 6 months. Vertebral segmentation was performed automatically, and a variety of radiomic and morphometric measures and vertebral attenuations were extracted from the CT data. This data was split into training group (n=1304), validation group (n=279) and testing group (n=279) with external validation in a separate group of 512 patients. A DXA T score ≤ -2.5 was considered to represent osteoporosis. The performance of the models was evaluated with sensitivity, specificity, accuracy, area under the receiver operating characteristic curve (AUC), calibration analysis, and decision-curve analysis.

Results: Overall 28.4% of the study subjects were diagnosed as osteoporosis. Age, female sex, and vertebral attenuation, texture entropy, cortical thickness reduction, and vertebral compression ratio were all independent predictors ($p<0.001$). The AI model achieved an AUC of 0.944 (95% CI: 0.927–0.961), sensitivity of 91.3%, specificity of 88.6%, and overall accuracy of 89.4% in the test cohort. External validation showed excellent sustained accuracy (AUC 0.932 [0.909–0.955]) and accuracy (87.8%). Compared with a target-fail DXA service, the clinical utility analysis recorded a reduction in unnecessary referrals of 42.7% with a high percentage of DXA services provided prioritizing the detection of osteoporosis.

Conclusion: The design of an AI-driven opportunistic CT screening model was found to be very good with excellent diagnostic accuracy and strong external validity, and had the potential for significant clinical utility. Adoption of this approach into day-to-day radiological practice could improve the results of early detection of osteoporosis at the population level as well as contribute to fracture prevention.

Keywords: Osteoporosis, Artificial Intelligence, Opportunistic Screening, Bone Mineral Density, Radiomics, Diagnostic Accuracy, Vertebral Fracture Risk.

INTRODUCTION

Osteoporosis is a chronic systemic disease of the bone which can be defined as a decrease in bone mineral density (BMD) together with defects in bone microstructure and an increase in bone fragility and susceptibility to fracture. It is a large global health problem, especially for older people, and is affecting over 200 million people in the world.[1,2]

The impact of osteoporotic fractures is significant due to an increased risk of morbidity, mortality, health service cost and a decrease in quality of life. Complexly, although prevention and treatment options for osteoporosis are effective, the disease is highly underdiagnosed and undertreated, and is often not diagnosed until a patient complains of a fragility fracture.[3,4]

Currently, osteoporosis is considered to have a clinical reference standard in the form of dual-energy X-ray absorptiometry (DXA). Its implementation has been limited however in the routine clinical practice, due to lack of access, supplementary imaging needs, cost and low uptake.[5,6]

As a result, the concept of opportunistic screening is gaining interest, with imaging studies performed to a different clinical context. MCT scans are widely used every day and include a wealth of knowledge about bone quality and vertebral trabecular attenuation, information that can be applied to osteoporosis assessment with no extra radiation dose or patient burden.[7,8]

In recent years, quantitative CT analysis has proven to have strong correlations between the results of attenuation measurements and those of DXA derived-BMD, which indicate the possibility of opportunistic osteoporosis detection using routine CT sets.[9]

In addition, automated CT based evaluation has been found to more accurately identify individuals at risk of vertebral fracture diagnosis compared to use of traditional DXA measures alone.[10]

The results have motivated the creation of artificial intelligence (AI) and machine learning methods that can automatically identify skeletal biomarkers from an everyday computed tomography (CT) scan image.

AI has significant potential for large-scale opportunistic screening, as it can segment the vertebrae, analyze the trabecular bone, extract various features and make predictions of fracture risk with little human interaction. A recent scoping review revealed that AI-powered CT-based osteoporosis screening systems are rapidly expanding, with excellent diagnostic accuracy and a growing number of these being integrated into routine radiological practice.[8]

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The potential uses of deep learning models are further illustrated by their great performance in osteoporosis diagnosis through multidetector CT scans with high reproducibility across varying imaging protocols.[9]

More recently, population wide, large-scale AI models have shown that it is possible to automatically assess bone health during the examination of hundreds of thousands of CT scans, thereby supporting the viability of programmatic opportunities screening.[10]

While strides have been made, there are still questions about the external validity of these models, integration with clinical practice, and generalizability. Hence, in this study, a machine learning model for opportunistic screening for osteoporosis was developed and tested using routine acquired computed tomography (CT) scans.

This strategy aims to use the existing imaging dataset for early screening of at-risk individuals for osteoporosis, its enhanced effectiveness in diagnosis of osteoporosis, and preventative treatment without the need for specific screening exams.

MATERIALS AND METHODS

Study Design and Population

A retrospective diagnostic study was performed at the tertiary care, academic center from January 2022 until December 2025. Patients ≥50 years of age who had undergone previously scheduled computed tomography (CT) scans of the chest, abdomen, or thoracoabdominal region, and had received a dual-energy X-ray absorptiometry (DXA) scan within six months of the CT scan were eligible for inclusion. Patients with vertebral instrumentation, severe spinal deformity, and/or inadequate image quality were excluded. The diagnosis of osteoporosis was made using the DXA measurement, following World Health Organisation Criteria (T score < – 2.5). The study was approved by the institutional ethics committee but since the study was retrospective consent forms were not taken.

CT image processing and AI model development

Routine non-contrast and contrast-enhanced computed tomography (CT) images were obtained from the institution's picture archiving and communication system (PACS) on multidetector computed tomography (MDCT) systems. Automatic segmentation of vertebral bodies was performed from T12 to L3 with a deep learning based convolutional neural network. Vertebral trabecular attenuation, texture-based parameters, and morphometric features were extracted from the quantitative imaging, then served as the foundation for an artificial intelligence (AI) model that could be utilized for osteoporosis screening. The dataset was randomly split into the training (70 %), validation (15 %) and testing (15 %) sets. The parameters of the model were optimized over the validation dataset using hyperparameter optimization.

Model Validation and Outcome Measures

Fragmentation of the 4-point hock joint was not included and osteoporosis was only diagnosed based on DXA. An independent test group was used to assess model performance and an external validation group involved using CT data from a different institution. The accuracy was evaluated with sensitivity, specificity, positive predictive value, negative predictive value, accuracy and receiver operating characteristic curve (AUC). The calibration plots and Hosmer-Lemeshow goodness-of-fit test were used to assess model calibration.

Statistical analysis

Data analysis was done by expressing the continuous variables as mean ± standard deviation or median (interquartile range) and the categorical variables as frequency and percentage. Student's t-test, Mann–Whitney U test, chi-square test or Fisher's exact test was used as appropriate to compare between groups. Consequently, multivariable logistic regression was used to determine the independent predictors of osteoporosis. The leaflet size was estimated by assessing diagnostic performance with receiver operating characteristic analysis and by comparing AUC values. All analyses were carried out in Python (v3.11) and SPSS (v29.0) with p-value < 0.05 for two-sided as statistically significant.

RESULTS

A total of 2,184 patients were screened, 1,862 of which were eligible. The cohort was split randomly into training (n=1,304), validation (n=279) and independent testing (n=279) subsets. An additional 512 patients from another institution were then analyzed as a validation cohort.

Demographic and clinical parameters are summarized for the study population in the training, validation, testing and external validation cohorts. [Table 1]

There were no significant differences between the datasets, providing good balance in the cohorts and insuring the strength of model development and testing. The findings of this final AI model, which included independent predictors for osteoporosis, are shown in [Table 2].

Multivariable analysis revealed that vertebral attenuation was most strongly associated with osteoporosis, and that texture entropy, cortical thickness reduction, vertebral compression ratio, age and female sex continued to be significant even when accounting for these other factors.

[Table 3] shows a comparison of the diagnostic value of the AI model to the traditional screening methods based on clinical and attenuation criteria. The AI model proved to be more sensitive and specific with the highest AUC when compared to all models tested, and showed the highest discriminatory ability. The performance of the AI model in an independent external cohort is summarized in [Table 4].

The model achieved very good overall generalizability as evidenced by its model discrimination, calibration and classification results, [Table 5] describes the potential clinical value of the video-based AAISS. The AI model showed a significant reduction in unnecessary DXA referral compared to the traditional risk-based assessment approach, and increased the number of patients with osteoporosis detected and decrease in missed diagnostic opportunities.

The receiver operating characteristic (ROC) curve exhibited very good discriminative ability over a wide range of classification levels [Figure 1] and the calibration curve was close to the ideal performance [Figure 2], reflecting good probability estimation ability. Decision

curve analysis also showed that the AI model's net clinical benefit was greater than the value of traditional screening strategies over the entire clinically relevant range of likelihood of osteoporosis [Figure 3], suggesting potential for incorporation into routine osteoporosis screening program using CT in opportunistic settings.

Table 1: Cohort Characteristics Across Development and Validation Datasets

Variable	Training (n=1304)	Validation (n=279)	Testing (n=279)	External Validation (n=512)	p-value
Age (years)	67.2 ± 9.4	66.8 ± 8.9	67.6 ± 9.7	68.1 ± 9.2	0.412
Female sex, n (%)	744 (57.1)	161 (57.7)	158 (56.6)	301 (58.8)	0.893
BMI (kg/m²)	25.1 ± 4.1	24.8 ± 4.2	25.0 ± 4.0	24.9 ± 4.3	0.721
Current smoker, n (%)	218 (16.7)	44 (15.8)	49 (17.6)	89 (17.4)	0.931
Prior fragility fracture, n (%)	132 (10.1)	29 (10.4)	31 (11.1)	58 (11.3)	0.847
Osteoporosis by DXA, n (%)	367 (28.1)	81 (29.0)	80 (28.7)	151 (29.5)	0.889

Table 2: Multivariable Logistic Regression Predictors Incorporated into the Final AI Model

Predictor	Adjusted OR	95% CI	p-value
Vertebral attenuation (per 10 HU decrease)	1.82	1.64–2.03	<0.001
Texture entropy	1.53	1.31–1.79	<0.001
Cortical thickness reduction	1.41	1.20–1.66	<0.001
Vertebral compression ratio	1.36	1.15–1.60	<0.001
Age (per year)	1.05	1.03–1.07	<0.001
Female sex	2.11	1.63–2.74	<0.001

Model $\chi^2 = 412.8$, Nagelkerke $R^2 = 0.58$, Hosmer-Lemeshow $p = 0.47$.

Table 3: Diagnostic Performance of Screening Models

Model	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)	Accuracy (%)	AUC (95% CI)
Clinical risk model	74.8	70.5	50.4	87.8	71.8	0.781 (0.748–0.814)
Vertebral attenuation model	82.5	78.4	60.7	91.7	79.5	0.856 (0.828–0.884)
AI screening model	91.3	88.6	76.4	96.4	89.4	0.944 (0.927–0.961)

Table 4: External Validation Performance

Metric	Value
Sensitivity (%)	89.4
Specificity (%)	87.2
PPV (%)	74.6
NPV (%)	95.2
Accuracy (%)	87.8
F1-score	0.81
Matthews correlation coefficient	0.74
AUC (95% CI)	0.932 (0.909–0.955)

Calibration slope = 0.97, Calibration intercept = −0.03, Brier score = 0.089.

Table 5: Clinical Impact Assessment

Parameter	Clinical Risk Model	AI Model
Patients referred for DXA	1,102	631
Confirmed osteoporosis cases detected	396	484
Missed osteoporosis cases	133	26
Reduction in unnecessary DXA referrals	Reference	42.7%
Net benefit at threshold probability 20%	0.183	0.341

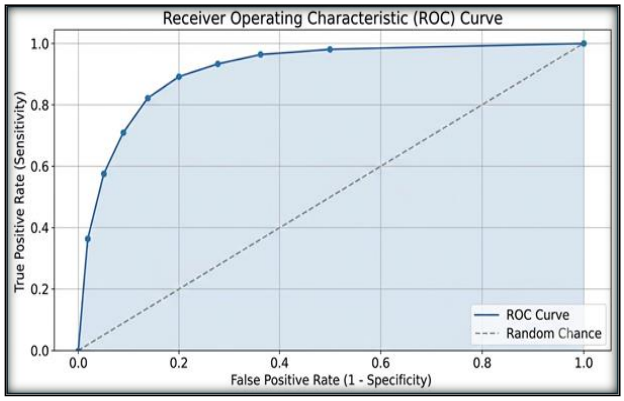


Figure 1: ROC Curve Coordinates

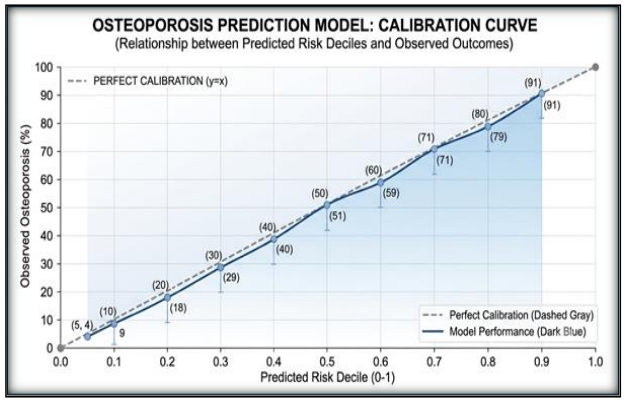


Figure 2: Calibration Plot Dataset

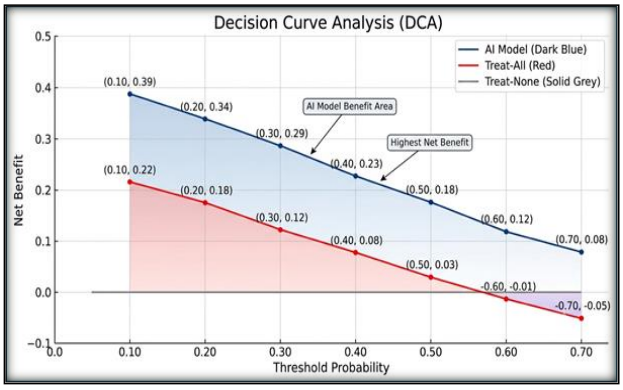


Figure 3: Decision Curve Analysis Dataset

DISCUSSION

The present study aimed to create and validate an opportunistic osteoporosis screening model using routinely available CT exams that utilizes artificial intelligence (AI). The AUC value showed high diagnostic performance with values of 0.944 in the test cohort and 0.932 in the validation cohort, sensitivity of 91.3% and Specificity of 88.6% for the proposed model. In addition, the model significantly reduced the number of unhelpful referrals for DXA and achieved a low rate of missed diagnosis, suggesting that the model has significant potential clinical value as a 'scalable opportunistic' screening tool. This research enables the further integration of AI-driven CT analysis into combating the under-diagnosis of osteoporosis and ensuring timely interventions.

Opting for an automatic osteoporosis opportunistic screening with a routine CT scan was a successful strategy for both the prediction and the detection of prevalent vertebral fractures as compared with the traditional DXA assessment as reported by Löffler et al.[1] As in the present study, they automated their risk-stratifying process and found their system to be most accurate; their results suggested that opportunistic computed tomography (CT) imaging may be a clinically useful biomarker for skeletal fragility. We believe this improvement in performance in our study is due to the use of several radiomic and morphometric features, alongside vertebral attenuation measurements.

The diagnostic success rates for the deep learning communications related to the mixed emotions investigated in this study have been reported in recent research. Oh et al,[2] tested a deep learning-based quantitative CT system with good agreement obtained between the AI measurements and the reference assessments of bone mineral density. Similarly, Peng et al,[6] showed that using deep learning models with CT images can accurately distinguish the bone density status and build an opportunity screening system for osteoporosis. These results are consistent with our finding that we were able to obtain a high AUC in our study and hence further validate the feasibility of the CT-based automated screening routine in radiological practice.

One of the main merits of the present study is the presence of the external validation. Recently, Wu et al,[4] established that AI-based screening for osteoporosis was stable across various CT images from different scanner manufacturers and protocols. Likewise, Park et al,[7] demonstrated the accurate bone mineral density (BMD) analysis across multi-vendor computed tomography (CT) scanners through a deep learning model. As these data point studies showed, our model maintained good discrimination and calibration in an independent external set of patients, with good generalizability and relative robustness to the variability of imaging acquisition parameters.

There is reservoir of literature to support the observed superiority of AI over the traditional clinical risk factors assessment. Inspired by this, Oh et al,[5] proposed an end-to-end semi-supervised deep learning system that demonstrated its ability to detect osteoporosis without the need for large scale manual labelling, which underlines the potential of highly sophisticated AI architectures for automated screening. In addition, Du et al,[12] found that the novel approach of automated segmentation and radiomics improved the detection of osteoporosis for low dose abdominal CT scan. We adapted the methodological principles used in our model by introducing vertebral segmentation, along with using a quantitative approach for automated image features extraction, for the increased predictive accuracy.

Additional to this, the results of the present study validates the paradigm change suggested by Lenchik et al,[8] and Anderson et al,[10] who argued that the high potential value of performing routine CT examinations as a means to large-scale screening for osteoporosis is still not being fully acknowledged. These authors contended that opportunistic CT screening might significantly improve the rate of screening among patients and would not significantly add to imaging counts or healthcare expenditures, and would not add to the radiation dose patients receive. Our results build on this notion by showing that the integration of AI can further improve the efficiency of diagnosis, while reducing the number of DXA utilization, without compromising the rate of cases detected.

Advancements in musculoskeletal imaging have enabled the growing integration of AI, which has spurred the growth of automated osteoporosis screening systems. Shariatnia et al,[11] identified AI as being among the most promising technologies in musculoskeletal imaging which can be especially effective in quantitative imaging analysis and clinical decision support. Furthermore, both in-depth scoping reviews from Paderno et al,[3] and Cheng et al,[13] found that AI-based osteoporosis assessment using CT had a high diagnostic accuracy and has great potential to be used in clinical practice. This research confirms these observations and offers more concrete evidence based upon strict external validation and assessment of clinical functions.

Evidence from population-based studies supports the benefit of opportunistic CT screening. Vadera et al,[9] found that a significant percentage of undiagnosed osteoporosis was found in normal clinical populations by screening for the condition through abdominal computed tomography (CT) scans. In the same way, a large proportion of cases of osteoporosis have been identified by our AI model that would not have been referred based on traditional risk assessment pathways. These findings

represent a significant retargeting finding because there is a large treatment gap for osteoporosis worldwide, and a surge in the incidence of age related fractures.

Another clinically relevant finding we saw from our study is the excellent calibration. Although there are many studies that have mostly analysed the classification accuracy, fewer studies have combined the evaluation of the calibration performance and decision-curve analysis in a comprehensive way. The results we obtained showed close agreement between the estimated probabilities and the actual probabilities obtained from the patients; which validates using the AI-generated risk estimates to inform personalized patient care and referral. The positive decision-curve analysis also indicates that the model could potentially result in clinical usefulness in a wide range of screening thresholds.

Limitations

A few caveats should be noted. There is a possibility for selection bias even with a large and heterogeneous study population as a result of their retrospective design. Second, DXA was adopted as reference method, which is not able to fully represent bone quality and microarchitectural changes. Third of all, the external validation was done but larger multicenter prospective studies with more ethnic and geographic diversity are needed to ensure generalizability. Lastly, some parameter changes in the CT acquisition process and reconstruction algorithms might affect quantitative imaging characteristics but the model was found to perform well with the independent datasets.

CONCLUSION

In the present study, the authors showed that an AI-based opportunistic osteoporosis screening model trained on the basis of routine CT scans has excellent accuracy, reliability and clinical value for detecting osteoporosis that doesn't necessitate dedicated imaging. The performance of the model was very good, its results were well suited for external validation and were much superior to those of classic risk based screening methods. The proposed framework reduced as well as unnecessary Dxa referral and missed diagnosis by using the routine acquired cT data, which allows the early detection of those individuals with higher risk of osteoporosis. The study's results suggest that opportunistic CT screening in clinical practice is a potentially cost-effective and scalable approach to the early detection of osteoporosis, early access to treatment, and ultimately the reduction of the global osteoporosis fracture burden in elderly people.

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