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Assessment Of Bone Quality In Osteoporotic Women Through 3t MRI Radiomics Of The Proximal Femur

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Abstract

Background: *Osteoporosis is a systemic skeletal condition characterized by low bone strength, which increases the risk for fragility fractures in particular after menopause. Although traditional assessment through dual-energy X-ray absorptiometry (DXA) provides information about bone mineral density (BMD), it does not assess the microarchitectural integrity that affects true bone quality. The use of high-field magnetic resonance imaging (MRI), especially at 3 Tesla (3T), and radiomics permits non-invasive assessment of trabecular bone and cortical microstructure by extracting quantitative image-based biomarkers. The objective of the current investigation was to assess bone quality in osteoporotic women using the proximal femur in 3T MRI radiomics to correlate radiomic features to BMD based on DXA.*

Materials and Methods: *An observational study was carried out involving 80 postmenopausal women aged between 50 and 75. The participants were classified into two groups, one with 40 women with osteoporosis (T-score ≤ −2.5) and another with 40 age-matched healthy controls. MRI of the proximal femur was obtained on a 3T system using T1-weighted and proton density sequences. The region of interest (ROI) was manually segmented and radiomic features were obtained that included first order statistics, gray-level co-occurrence matrix (GLCM), and gray-level run-length matrix (GLRLM) parameters. Statistical analysis included Pearson correlation between radiomic features and BMD as well as ROC analysis for diagnostic discrimination.*

Results: *Participants with osteoporosis showed significantly increased values for entropy, skewness, and run-length nonuniformity compared to controls ($p < 0.01$), which indicate greater spatial textural heterogeneity. There was a notable decrease in homogeneity and uniformity. Strong negative correlations were noted between BMD and GLCM derived entropy ($r = −0.71$, $p < 0.001$), and positive correlations with uniformity ($r = 0.68$, $p < 0.001$). The best combination of radiomic features was able to classify osteoporotic bone from normal bone with an accuracy of 88%.*

Conclusion: *Using 3T MRI radiomics of the proximal femur, we have developed a non-invasive biomarker-based method to quantitatively measure bone quality in women with osteoporosis. The texture features extracted reflect the constituents of microarchitectural deterioration and have the potential to enhance DXA in the early detection, risk stratification, and monitoring of osteoporosis.*

Keywords: *Osteoporosis; Bone Quality; 3T MRI; Radiomics; Proximal Femur; Bone Mineral Density; Texture Analysis; Microarchitecture; Postmenopausal Women; Diagnostic Imaging*

1. INTRODUCHTION

Osteoporosis is a chronic and progressive skeletal condition that is characterized by decreased bone strength and increased risk of fragility fractures. For example, in postmenopausal women, hip fractures are associated with high morbidity, loss of independence, and increased mortality; thus, the clinician's aim is to identify patients with impaired bone quality as early as possible. Although bone mineral density (BMD) is still the basis for diagnosis and risk assessment in most situations, the risk for fracture is dictated not only by mineral content, but also by the microarchitecture of the trabecular and cortical compartments. A technique which measures these qualitative measures of bone along with mineralization would provide an important link between measured density and actual mechanical competence [1].

Although dual-energy X-ray absorptiometry (DXA) is available in many facilities, it is standardized and

inexpensive, but is essentially a projected, areal measure, which does not distinguish three-dimensional microarchitecture. Therefore, DXA can underestimate risk in individuals with similar BMD but different trabecular connectivity, cortical porosity, or spatial heterogeneity of the bone tissue. The DXA value might also be influenced by body habitus, osteophytes, vascular calcifications, and/or positioning, all of which limit the DXA value as a reflection of intrinsic material and structural characteristics that affect fracture behavior [2].

High-field magnetic resonance imaging (MRI), particularly at 3 Tesla (3T), provides excellent signal-to-noise ratio and spatial resolution without ionizing radiation, enabling depiction of the marrow-bone interface and surrogate features of trabecular organization in vivo. In the proximal femur, 3T MRI can visualize the head, neck, and intertrochanteric regions where fracture risk is clinically most consequential. Beyond simple inspection, the voxel-wise intensity patterns within these regions encode information about the size, spacing, and orientation of trabeculae as well as the uniformity of marrow signal attributes that relate to bone quality even when BMD appears similar across individuals [3].

Radiomics provides a principled framework to harness latent information by transforming routine MR images into voluminous and quantitative descriptors. First-order statistics summarizes over-all intensity distributions; texture matrices (e.g., gray-level co-occurrence and run-length features) delineate spatial relationships and heterogeneity; and shape or morphological indices summarize structured geometries of segmented regions. Deriving features from carefully standardized acquisitions and segmentations may yield imaging biomarkers of microarchitectural degradation, connectivity disruption, and increased complexity consistent with osteoporotic remodeling [4].

The application of radiomics to the proximal femur is compelling because femoral strength is based on the integrity of both the cortex and trabecular tissue, and site-specific microarchitecture determines how loads are distributed during typical and fall activities. A radiomic signature that measures regional heterogeneity or disorganization is an attractive adjunct to BMD because it allows the identification of individuals who have structural fragility even if their T-score deficit is borderline or modest. In addition, a radiomic signature may allow for more personalized tracking of therapeutic response by measuring features specific to microstructure at multiple times [5].

Carrying out research requires very careful methodological rigor. To ensure we derive metrics from imaging that have some degree of biological relevance (versus acquisition, or preprocessing artifact) we will have to critically think about standardized 3T MRI acquisition methods, define our region-of-interest in the femur head(s) and neck, check reproducibility of features, and modeling approaches. Likewise, clinical anchoring is important, as correlating radiomic features with DXA-derived bone mineral density or determining whether a radiomic feature can discriminate osteoporotic and non-osteoporotic bone helps arriving at the additional value of current use cases in screening, or as part of a risk stratification pathway [6].

If successful, an MRI approach with radio-omics would enhance clinical decisions by identifying patients for early intervention, adjusting therapy intensity based on structural vulnerability, and providing a radiation-free process for follow-up with a longitudinal assessment of potential therapy response. This approach aims to promote precision medicine principles while taking advantage of readily available MR technology in tertiary and many secondary care centers.

Therefore, it is of interest to assess bone quality in osteoporotic women through 3T MRI radiomics of the proximal femur, quantify the relationship between radiomic features and DXA-derived BMD, and evaluate the discriminative performance of radiomics-based models for identifying osteoporotic bone.

2. MATERIALS AND METHODS

Study Design and Population: A prospective, cross-sectional analytical study was conducted to assess bone quality among postmenopausal women using 3T MRI radiomics of the proximal femur. The study was carried out in the Department of Radiology in collaboration with the Department of Orthopedics between January 2023 and June 2024. A total of 80 participants were enrolled, including 40 osteoporotic women (T-score ≤ -2.5 as per WHO criteria) and 40 age-matched healthy controls (T-score ≥ -1). Subjects were recruited through outpatient clinics after screening by DXA.

Inclusion Criteria:

1. Postmenopausal women aged 50–75 years.
2. Subjects with recent DXA scans of the hip and lumbar spine.
3. Willingness to undergo 3T MRI evaluation.

Exclusion Criteria:

1. History of metabolic bone disease other than primary osteoporosis.
2. Secondary causes of osteoporosis (e.g., corticosteroid therapy, hyperparathyroidism).
3. Previous hip fractures, metallic implants, or prostheses.
4. Contraindications to MRI (pacemakers, claustrophobia, etc.).

Ethical Approval: The institutional ethics committee has endorsed the study protocol. Prior to MRI examination and data acquisition, all subjects signed written informed consent.

MRI Acquisition Protocol: All MRI scans were conducted on a 3 Tesla system (Siemens Magnetom Skyra, Erlangen, Germany) using an 18-channel dedicated body coil. Participants were placed in a supine position and their lower limbs were stabilized to minimize motion artifacts. The psychological parameters were standardized in the following manner:

Sequence	Orientation	TR/TE (ms)	Slice Thickness (mm)	Matrix	FOV (mm^2)
T1-weighted spin-echo	Coronal	600/12	3.0	320×256	260×260
Proton density (PD)	Axial	2200/30	3.0	256×256	240×240
T2-weighted turbo spin-echo	Sagittal	4000/80	3.0	320×256	260×260

Fat suppression was applied for PD and T2 sequences to improve delineation of marrow trabecular detail.

Image Segmentation and Preprocessing: Two board-certified radiologists, each with more than 10 years of experience in musculoskeletal MRI, manually segmented the proximal femur using ITK-SNAP software without knowledge of the BMD status. The ROI included the femoral head, neck, and intertrochanteric areas but excluded the femur's soft tissues and cortical bone margins. Inter-observer reliability was determined using intraclass correlation coefficients (ICC threshold of >0.85 for acceptable reliability). Furthermore, images were intensity-normalized, and the images were resampled to isotropic voxels (1x1x1 mm^3). Images were processed as per the Image Biomarker Standardization Initiative (IBSI) to ensure consistency and to allow comparison between subjects.

Radiomic Feature Extraction: Quantitative radiomic features were extracted using PyRadiomics v3.1.0 (an open-source Python package). The features involved:

- **First-order statistics:** Mean, variance, skewness, kurtosis, entropy, uniformity.
- **Texture features (GLCM):** Contrast, correlation, homogeneity, energy, dissimilarity, entropy.
- **Texture features (GLRLM):** Short-run emphasis, long-run emphasis, run-length nonuniformity, gray-level nonuniformity.
- **Morphological parameters:** Volume, surface area, compactness, and sphericity.

Each feature was averaged across both femora to minimize laterality bias. Feature reproducibility was validated through repeated extractions.

DXA-Based Bone Mineral Density Assessment: All study participants had a DXA scan (Hologic Discovery Wi) to determine hip and lumbar spine BMD (g/cm^2). T-scores were designated as normal, osteopenic, or osteoporotic, based on WHO definitions. The total hip mean BMD was used in correlational analysis.

Statistical Analysis: Data analyses were carried out using SPSS version 26.0 (IBM Corp., Armonk, NY). The Shapiro-Wilk test was performed to assess normality. For appropriate intergroup comparisons of the radiomic features, independent t-tests or Mann-Whitney U tests were used. Pearson correlation coefficients were computed between the BMD values and radiomic features. Receiver operating characteristic (ROC) curves were created to assess the diagnostic accuracy, and the AUC was calculated to assess performance. Machine learning classification a was used with a logistic regression classifier, which was used in a fivefold cross-validation process to reduce overfitting. A p-value < 0.05 was considered statistically significant.

Outcome Measures: The main outcome was the association between MRI radiomic features and BMD derived from DXA. The secondary outcomes were the differences in the radiomic parameters between the osteoporotic and normal bone groups, as well as the diagnostic performance (AUC, sensitivity, specificity) that included the combined radiomic model to identify osteoporosis.

3. RESULTS

In this study, there were a total of 80 postmenopausal women aged between 50 and 75. Of those total participants, 40 were osteoporotic and 40 were healthy controls. The age of both groups was comparable at

63.2 ± 5.9 years in the osteoporotic group and 61.7 ± 6.4 years among the controls. The two groups were otherwise comparable with regards to anthropometric variables, with the exception of BMI where it was significantly less among the osteoporotic women ($p < 0.05$). The bone mineral density (BMD) was assessed using DXA with significant differences found in the total hip BMD and lumbar spine BMD sufficient to confirm an osteoporotic diagnosis ($p < 0.001$). Radiomic analysis of 3T MRI images provided consistent evidence of significant differences in first order, GLCM and GLRLM parameters relative to variations in the BMD and confirmed the potential of the radiomic features as non-invasive imaging biomarkers of the bone quality. The entropy and run length nonuniformity stood out and were primary markers of trabecular disorganization. Correlation and regression analysis showed significant relationships with radiomic features and the BMD also.

Table 1: Demographic and Anthropometric Characteristics of Study Participants

Table 1 describes the baseline demographic parameters, highlighting comparability between groups and BMI differences associated with osteoporosis.

Parameter	Osteoporotic (n = 40)	Control (n = 40)	p-Value
Mean Age (years)	63.2 ± 5.9	61.7 ± 6.4	0.281
Height (cm)	154.8 ± 5.2	155.6 ± 6.1	0.573
Weight (kg)	56.4 ± 8.7	61.9 ± 9.2	0.011
BMI (kg/m²)	23.4 ± 2.7	25.8 ± 3.1	0.004
Duration of Menopause (years)	12.8 ± 4.5	11.7 ± 5.1	0.412

Significant at $p < 0.05$.

Table 2: Bone Mineral Density (BMD) Measurements by DXA

Table 2 shows significant differences in BMD and T-scores between groups, confirming osteoporosis diagnosis.

Region	Osteoporotic (Mean ± SD)	Control (Mean ± SD)	p-Value
Lumbar Spine BMD (g/cm²)	0.745 ± 0.084	1.032 ± 0.097	<0.001
Total Hip BMD (g/cm²)	0.659 ± 0.072	0.982 ± 0.086	<0.001
Femoral Neck BMD (g/cm²)	0.614 ± 0.068	0.953 ± 0.079	<0.001
Mean T-Score	−2.72 ± 0.21	−0.44 ± 0.33	<0.001

Highly significant at $p < 0.001$.

Table 3: MRI Acquisition Parameters for 3T Imaging of Proximal Femur

Table 3 summarizes standardized MRI parameters ensuring consistency across participants.

Parameter	T1-Weighted	Proton Density	T2-Weighted
TR (ms)	600	2200	4000
TE (ms)	12	30	80
Slice Thickness (mm)	3.0	3.0	3.0
Matrix Size	320×256	256×256	320×256
Field of View (mm²)	260×260	240×240	260×260

Table 4: Inter-Observer Agreement for ROI Segmentation

Table 4 indicates high reproducibility of manual segmentation between two radiologists.

Region of Interest	ICC (95% CI)	Interpretation
Femoral Head	0.89 (0.84–0.93)	Excellent
Femoral Neck	0.87 (0.81–0.91)	Excellent
Intertrochanteric Region	0.90 (0.86–0.94)	Excellent

Table 5: Comparison of First-Order Radiomic Features

Table 5 reveals altered intensity distributions in osteoporotic bone, indicating increased heterogeneity.

Feature	Osteoporotic (Mean ± SD)	Control (Mean ± SD)	p-Value
Mean Intensity	121.5 ± 9.7	126.4 ± 8.3	0.032
Skewness	0.84 ± 0.12	0.59 ± 0.09	<0.001
Kurtosis	3.91 ± 0.44	3.12 ± 0.39	<0.001
Entropy	5.47 ± 0.38	4.82 ± 0.33	<0.001

Uniformity	0.41 ± 0.05	0.53 ± 0.06	<0.001

Table 6: GLCM Texture Features Reflecting Trabecular Microarchitecture

Table 6 demonstrates microarchitectural disorganization in osteoporosis.

GLCM Feature	Osteoporotic (Mean ± SD)	Control (Mean ± SD)	p-Value
Contrast	2.94 ± 0.43	2.15 ± 0.39	<0.001
Correlation	0.52 ± 0.07	0.63 ± 0.06	<0.001
Homogeneity	0.41 ± 0.05	0.52 ± 0.06	<0.001
Energy	0.19 ± 0.04	0.25 ± 0.05	0.002
Entropy	6.11 ± 0.32	5.32 ± 0.28	<0.001

Table 7: GLRLM Features Indicating Textural Nonuniformity

Table 7 identifies significant run-length heterogeneity in osteoporotic bone.

GLRLM Feature	Osteoporotic (Mean ± SD)	Control (Mean ± SD)	p-Value
Short-Run Emphasis	0.69 ± 0.07	0.76 ± 0.08	0.008
Long-Run Emphasis	1.42 ± 0.18	1.15 ± 0.14	<0.001
Run-Length Nonuniformity	0.88 ± 0.09	0.71 ± 0.07	<0.001
Gray-Level Nonuniformity	0.93 ± 0.11	0.78 ± 0.09	<0.001

Table 8: Correlation of Radiomic Features with BMD

Table 8 shows strong correlations between radiomic heterogeneity and DXA-derived BMD.

Feature	Pearson r	p-Value	Direction
GLCM Entropy	−0.71	<0.001	Negative
GLCM Homogeneity	+0.68	<0.001	Positive
GLRLM Nonuniformity	−0.64	<0.001	Negative
Uniformity	+0.66	<0.001	Positive
Kurtosis	−0.57	0.002	Negative

Table 9: Logistic Regression Model for Radiomic Feature Combination

Table 9 summarizes multivariate analysis identifying independent predictors of osteoporosis.

Variable	β-Coefficient	SE	p-Value	Odds Ratio (95% CI)
Entropy	0.82	0.24	0.001	2.27 (1.37–3.61)
Uniformity	−1.15	0.35	0.002	0.32 (0.17–0.61)
Long-Run Emphasis	0.64	0.22	0.004	1.89 (1.23–2.91)

Table 10: Diagnostic Performance of Radiomic Models

Table 10 presents model performance metrics for classification of osteoporosis.

Model	AUC	Sensitivity (%)	Specificity (%)	Accuracy (%)
Entropy + Uniformity	0.88	84	86	85
Entropy + Kurtosis	0.84	80	82	81
Combined Model (All Significant Features)	0.91	86	89	88

Table 11: Feature Reproducibility and Robustness Analysis

Table 11 confirms stability of key radiomic features across repeated extractions.

Feature	ICC	Interpretation
Entropy	0.93	Excellent
Uniformity	0.89	Excellent
Homogeneity	0.90	Excellent
Run-Length Nonuniformity	0.88	Excellent

Table 12: Summary of Radiomic Feature Differences and Clinical Relevance

Table 12 consolidates radiomic trends that characterize osteoporotic bone microarchitecture.

Category	Radiomic Trend in Osteoporosis	Clinical Interpretation
Intensity Distribution	↑ Entropy, ↑ Kurtosis	Reflects disordered trabecular matrix
Texture (GLCM)	↓ Homogeneity, ↓ Energy	Loss of uniform signal and organization
Run-Length (GLRLM)	↑ Nonuniformity, ↑ Long-Run Emphasis	Indicates sparse trabecular connectivity
Overall Signature	Increased heterogeneity, lower uniformity	Microarchitectural fragility and poor bone quality

The research displayed significant differences in microarchitecture, as quantified by MRI radiomics, between osteoporotic and control groups. Baseline differences in the groups' BMI and BMD were shown in Table 1 and Table 2, illustrating lower bone density in the osteoporotic group versus the controls. Imaging consistency and reproducibility of segmentation were demonstrated in Table 3 and Table 4 to establish analytic reliability. Differences in first-order, GLCM, and GLRLM measures were collectively shown in Tables 5 through 7. In the latter, osteoporotic bone displayed increased trabecular heterogeneity and lower uniformity. Table 8 demonstrated substantial correlations of entropy with BMD, suggesting that entropy may have potential use as an imaging based biomarker of bone fragility. Table 9 demonstrated that entropy, uniformity, and long-run emphasis were independent predictors of osteoporosis. Table 10 identified the multifeature model achieved high diagnostic accuracy (AUC = 0.91). Table 11 demonstrated excellent reproducibility of the patient features established in previous tables was needed to support the claims of robust radiomic workflow reliability. Table 12 summarized the established radiomics signature of osteoporosis, which contained high heterogeneity and structural disorganization.

Together, these findings demonstrate that 3T MRI radiomics of the proximal femur provide sensitive, reproducible, and clinically relevant assessments of bone microarchitecture and quality that extend beyond standard measures of BMD.

4. DISCUSSION

This study demonstrates the feasibility of using 3T MRI radiomics to objectively evaluate bone quality in postmenopausal women with osteoporosis as an effective and non-invasive method. By extracting sophisticated features based on texture- and intensity, using radiomics to analyze the proximal femur, provides the ability to identify changes in microarchitecture that standard BMD measures obtained via DXA could not. The study reinforces this ongoing premise; bone strength and risk for fracture is not solely determined by the mineral content but rather dependent on spatial heterogeneity, the orientation of trabecular, and tissue composition, all of which can be measured objectively through radiomic metrics [7].

The demographic factors of the study population revealed that osteoporotic women had significantly lower BMI than controls, consistent with previous evidence that decreased body mass can lead to decreased mechanical loading and reduced bone turnover. This was corroborated with DXA showing a larger difference in BMD at all femoral sites, confirming clinical diagnosis of osteoporosis. Nevertheless, the primary contribution of this study is to demonstrate that radiomic measures from 3T MRI captured microstructural degradation in the bone that was independent of BMD, providing additional information on bone health [8].

The distribution of radiomic parameters most associated with osteoporosis were entropy, uniformity and run-length non-uniformity. Entropy, which implies a measure of randomness or textural complexity, was significantly increased in osteoporotic bone, suggesting disruption of trabecular uniformity and increased textural heterogeneity of marrow signal intensity in the osteoporotic bone. This correlates with reduced trabecular number and increased trabecular spacing histomorphometrically observed in osteoporotic bone. Conversely, uniformity and homogeneity were decreased, representing loss of organized trabecular alignment and increased range of signal variation. Moreover, run-length non-uniformity and long-run emphasis parameters, derived from the gray-level run-length matrix (GLRLM), reaffirm the results with evidence of predominately extended, irregular low-signal runs which is representative of sparse trabecular connectivity [9].

The correlation analyses revealed a significant negative correlation between entropy derived from GLCM and BMD ($r = -0.71$, $p < 0.001$), indicating that increased heterogeneity in trabecular patterns is linked to

decreased bone mineral density. Additionally, the positive relationship between homogeneity and BMD demonstrated that increasing homogeneity is representative of well-organized microarchitecture and equivalently increased strength of the mineralized tissue. Furthermore, these results are in agreement with prior studies employing micro-MRI and HR-pQCT that found similar associations between texture measures and mechanical competence. Aside from the correlation being biologically plausible to suggest that MRI radiomics can be a surrogate measure of microarchitectural integrity [10].

Using multivariate logistic regression, entropy, uniformity, and long-run emphasis were identified as independent predictors of osteoporosis with an overall accuracy of 88% and an AUC of 0.91, reflecting comparable or enhanced diagnostic accuracy versus traditional imaging biomarkers (bone density derived from DXA, trabecular bone score (TBS), ultrasound-based bone quality indices). High reproducibility (ICC > 0.88) of radiomic features demonstrates the credibility of these specific imaging biomarkers in longitudinal and multicenter research. Also, the MRI does not emit ionizing radiation; therefore, MRI can repeatedly and safely monitor disease progression or treatment response—two critical factors compared to traditional imaging (DXA or quantitative computed tomography (QCT)) methods [11].

From a clinical perspective, if MRI radiomics can detect a modification in microstructure before a magnification in the BMD changes it follows that osteoporosis can be diagnosed earlier and patient fracture risk stratified more appropriately. The proximal femur is an anatomical region of concern, as hip fractures are intriguingly some of the most disabling complications of osteoporosis. The sensitivity of radiomic features to small variations in trabecular architecture suggests that sensitivity of radiomic features will provide an early notification that fragility is present in structural architecture. "Even when T scores are in the borderline range.

There were several methodological strengths in this study including standardization of high-field MRI acquisition parameters, adherence to the standards of the Image Biomarker Standardization Initiative (IBSI) framework for extrusion of features, and rigorous cross-validation of both statistical and machine-learning models. All of these parts of the study add to our confidence that the relationships observed between features and behavior reflect a biological truth and not noise, or some sort of technical issue, i.e., systematic variability. Finally, the study employed individuals with experience manually segmenting the regions-of-interest (ROIs) to define the boundaries of the nuclei, alleviating concerns about boundary definition errors that arise in other types of analyses, including texture analysis, and had strong levels of inter-observer agreement (ICC > 0.85) [13].

However, there are a number of limitations worth mentioning. First, while the sample size was sufficient for a primary validation, it limits generalizability; larger multicenter studies will need to be carried out, as the goal is to find reproducibility in different models, as well as in different populations we may encounter. Second, the use of manual segmentation provided anatomical accuracy, it is possible to enhance efficiency and decrease observer dependence by using automated or semi-automated segmentation methods [14]. Third, without direct histopathological comparison, it limits the certainty about the radiomic signatures we are attributing to microstructural changes. In addition, radiomics will ultimately be reliant on variations associated with acquisition parameters " variations in voxel size, S/N ratio, or magnetic field homogeneity can, and do, affect feature stability. Therefore standardized MRI protocols and harmonization principles should be applied prior to translation to clinical practice [15].

In the future, it would be valuable to investigate the integration of radiomic biomarkers with clinical risk factors and biochemical indices to create multimodal predictive models for fracture risk. Furthermore, the combination of features developed from MRI with machine learning and artificial intelligence approaches could improve diagnostic specificity and produce personalized predictions of skeletal fragility. Prospective studies that assess modifications in radiomic parameters over time with respect to anti-osteoporotic treatment can provide an imaging biomarker for treatment effect.

In summary, this research showed that 3T MRI proximal femur radiomics provides a quantitative and reproducible evaluation of bone microarchitecture, and can differentiate between osteoporotic and non-osteoporotic bone. Elevated entropy and nonuniformity and diminished homogeneity reflect the innate disorganization of the trabecular structure associated with bone strength. These features have also shown high correlations with BMD, underscoring their value in risk assessment. Proximal femur radiomics will offer more than just mineral density, and add layers of complexity to microarchitecture that could elevate current diagnostic models and facilitate timely and individualized management of osteoporosis. From this potential, 3T MRI radiomics can be a feasible adjunctive technique for assessing bone quality, and provides opportunities for early identification, non-invasive evaluations, and improved prognostication of bone

quality in women with osteoporosis.

5. CONCLUSION

This study shows that radiomic analysis of the proximal femur using 3T MRI can assess bone microarchitectural degradation among women who are osteoporotic. The texture-based radiomic measurements obtained from MRIs, including entropy, uniformity, and run-length nonuniformity, were strongly correlated with bone mineral density (BMD) measured using dual-energy X-ray absorptiometry (DXA), suggesting the potential use of these measurements as imaging biomarkers of bone quality. Additionally, the multivariate radiomic models developed in the present study demonstrated good diagnostic capacity and indicated the possible application of MRI radiomics for early diagnosis in a clinical setting. Furthermore, using the 3T MRI ribbiome imaging to measure trabecular structure is advantageous because it is non-invasive, involves no radiation exposure, and is reproducible, providing the means to have diagnostic potential above the classical measure of BMD while also providing additional information about the bone organization of trabecular bone and structural fragility. Including radiomics in the routine evaluation of patients will allow for the development of a more sensitive modality for earlier identification of osteoporosis, framed within a personalized patient risk for fragility fracture, and factors included for an innovative method of longitudinal determination of treatment effect and mean longitudinal change variables. By conducting such screening, we would ultimately improve patient-centered outcomes and reduce morbidity associated with fractures.

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