

# Assessment of trabecular bone stiffness using radiomics and deep-learning features

Qian Cao, Ran Yan, Sriharsha Marupudi, Ravi Samala, Nicholas Petrick  
CDRH/OSEL/DIDSR, AI/ML Program



## Abstract

Evaluation of bone fracture risk is important for the diagnosis and treatment of osteoporosis. Bone stiffness is one major factor in determining bone strength and fracture risk. With recent improvements in the spatial resolution of computed tomography (CT) imaging systems, it is possible to visualize bone microstructure and extract texture features. These texture features can be used to construct artificial intelligence/machine learning (AI/ML) models to predict bone stiffness.

**Hypothesis:** Bone texture from high-resolution CT can be used to improve the assessment of bone strength compared to using bone mineral density (BMD) alone.

## Introduction

Conventionally, bone health can be assessed with BMD measured from dual-energy absorptiometry (DXA) or quantitative CT (qCT). In this work, we develop models utilizing texture features to estimate trabecular bone stiffness from simulated high-resolution CT. These features may be useful as part of a novel imaging-based biomarkers for osteoporosis therapy studies, potentially streamlining clinical trial designs.

We used micro-finite element ( $\mu$ FE) analysis to characterize the stiffness of trabecular bone specimens imaged with micro-CT ( $\mu$ CT). The same analysis cannot be applied to clinical CT images directly due to the lower image quality. We then simulated the appearance of the specimens in high-resolution CT. We profile the effectiveness of 3 features sets at estimating the  $\mu$ FE-derived stiffness: radiomics, gradient structure tensors (GST), and features derived from a deep learning model (DL).

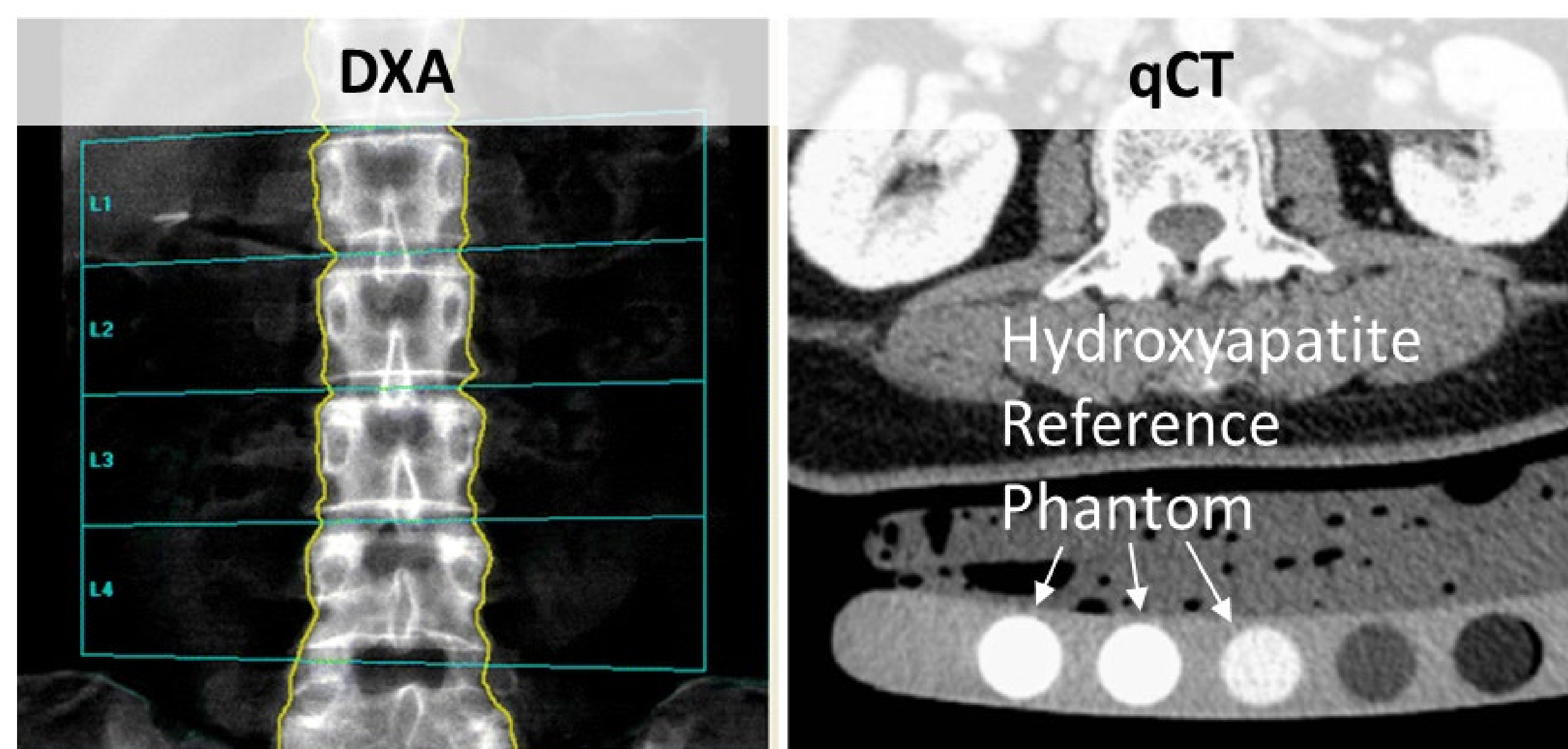


Figure 1. Examples of conventional image-based assessment of bone health.

## Materials and Methods

- Dataset:** 70  $\mu$ CT images of individual lumbar vertebrae cadaver specimens with voxel size of 51  $\mu$ m partitioned into training (40), tuning (15), and testing (15) datasets. Ten trabecular bone ROIs were extracted per vertebral body.
- Imaging Simulation:** Blur, correlated noise, and resampling were applied to segmented  $\mu$ CT images to simulate the appearance of trabecular bone in high resolution CT.
- Mechanical Analysis:** Linear  $\mu$ FE simulating uniaxial compression using elastic modulus of 17 GPa and Poisson ratio of 0.3.
- Model Development:** A random forest regressor trained and tested using combinations of radiomics, GST, and DL features. Performance measured with RMSE and  $r^2$ .

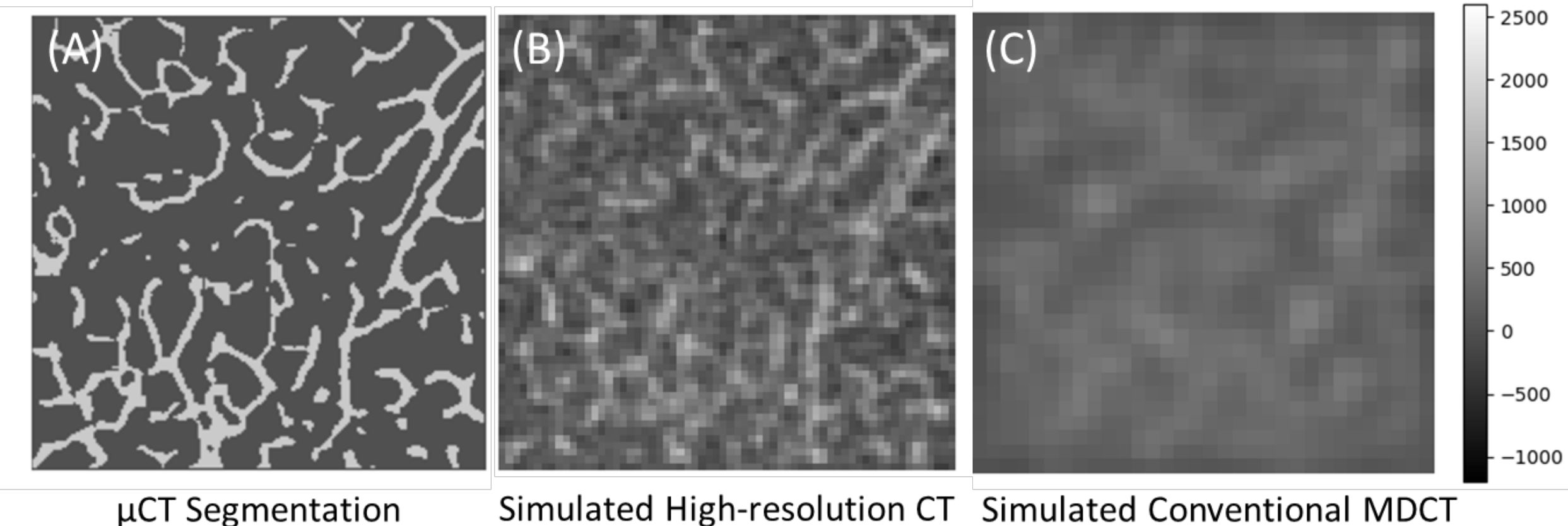


Figure 2. Example images simulated from  $\mu$ CT. Images simulated using a (B) high-resolution CT configuration were used in this work.

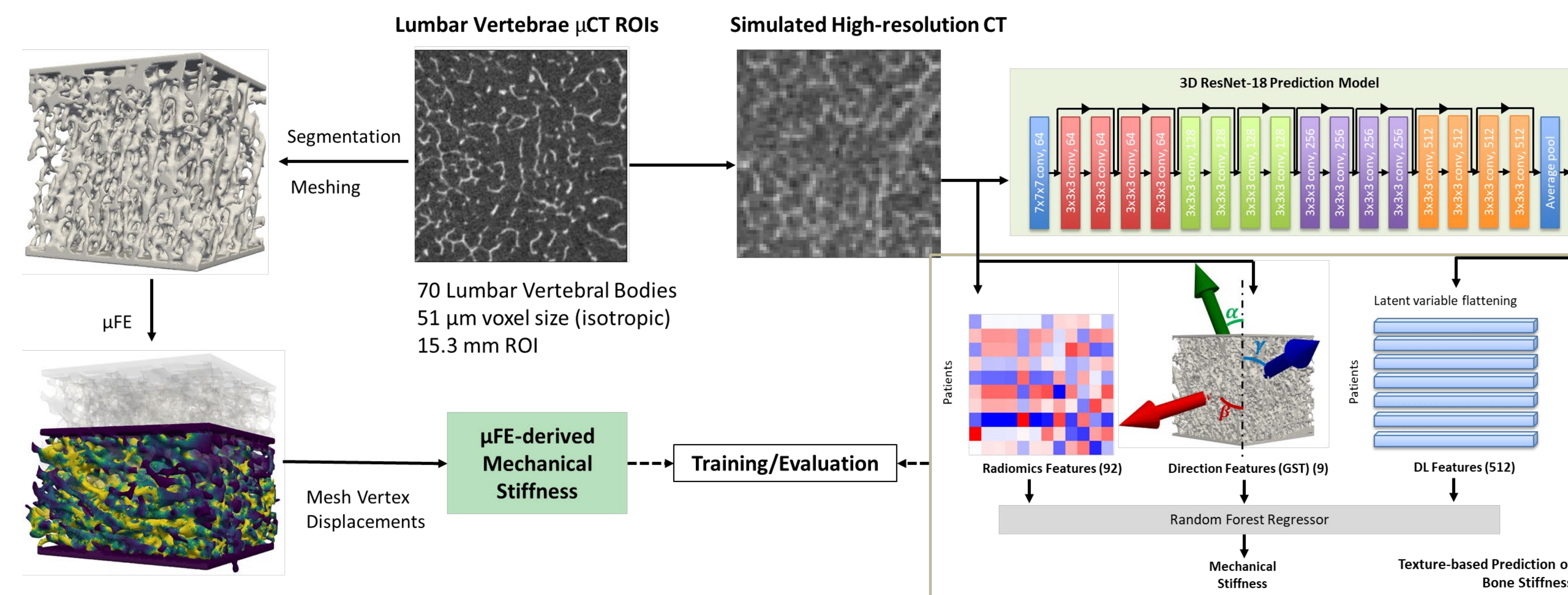


Figure 3. Overview of mechanical evaluation and model development for texture features.

## Results and Discussion

For our dataset, models based on DL features achieved RMSE  $\sim 2.64$  N/ $\mu$ m and  $r^2$  above 0.880, which outperforms models using the other feature sets. As a baseline model, Model 9 based on only BMD shows the worst performance. Figure 4 compares the results utilizing DL and radiomics features with direction features. DL features showed better performance than radiomics and BMD-only for our dataset. This suggests that in trabecular bone, there are higher-order features that our batch of radiomics features did not capture.

	GST	Radiomics	DL	Training		Testing	
				RMSE (N/ $\mu$ m)	$R^2$	RMSE (N/ $\mu$ m)	$R^2$
<b>Models with DL features</b>							
Model 1	+	+	+	0.360	0.997	2.646	0.881
Model 2	+	+	+	0.362	0.997	2.646	0.881
Model 3			+	0.356	0.998	2.648	0.880
Model 4		+	+	0.365	0.997	2.649	0.880
<b>Models without DL features</b>							
Model 5	+	BMD*		1.455	0.958	3.451	0.688
Model 6	+	+		1.341	0.964	3.628	0.691
Model 7		+		1.431	0.959	3.703	0.687
Model 8	+			1.550	0.951	3.752	0.636
Model 9			BMD*	3.957	0.683	5.340	0.317

Table 1. Summary of performance for different models and features used.

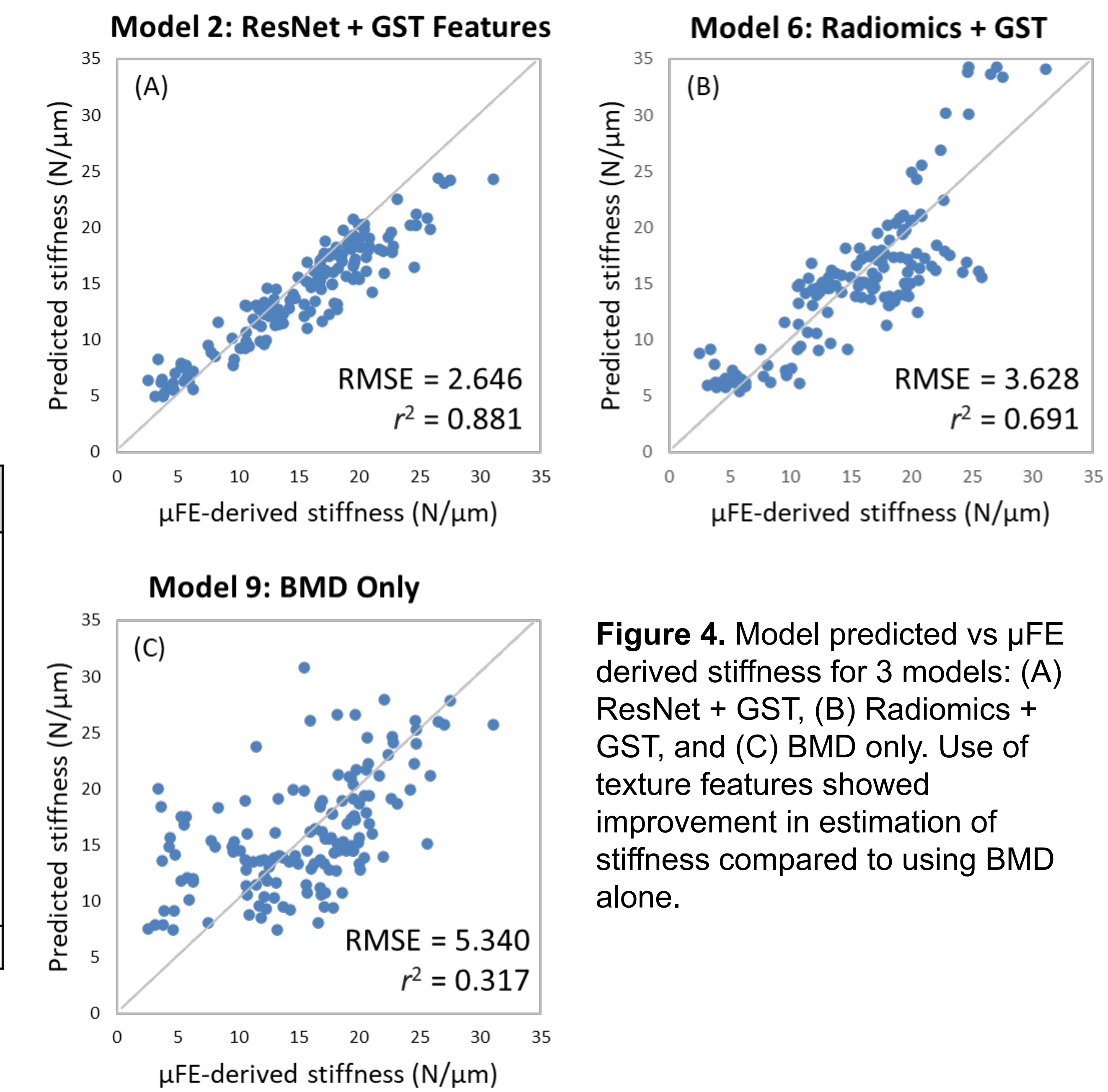


Figure 4. Model predicted vs  $\mu$ FE derived stiffness for 3 models: (A) ResNet + GST, (B) Radiomics + GST, and (C) BMD only. Use of texture features showed improvement in estimation of stiffness compared to using BMD alone.

## Conclusion

We have shown that image-based texture features have the potential to improve the characterization of bone health compared to using BMD alone. We have developed regression models for  $\mu$ FE-derived bone stiffness prediction using DL, radiomics, and GST features from simulated high-resolution CT images. Texture features can be extracted using both DL approaches and feature-engineering (radiomics). For our dataset, DL features provided better stiffness prediction compared with radiomic features and BMD.

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