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A COMPREHENSIVE FRAMEWORK FOR ULTRASONIC BONE DENSITY ASSESSMENT: THE CONVERGENCE OF FINITE ELEMENT MODELING AND DEEP LEARNING

[1]Ahmed Aiham Abbas, [2]Yaghoub Farjami

[1]information technology engineering university of qom, Iran

ayhamahmed68877@gmail.com

[2]Ph.D. Professor (Associate) at University of Qom

farjami@gmail.com

Abstract

Background: The accurate, non-invasive assessment of bone mineral density (BMD) is critical for diagnosing osteoporosis and preventing fragility fractures. While conventional methods like Dual-Energy X-ray Absorptiometry (DXA) are effective, their reliance on ionizing radiation limits their use for frequent screening. Quantitative Ultrasound (QUS) offers a safe alternative, but traditional parameters like Speed of Sound (SOS) and Broadband Ultrasound Attenuation (BUA) often lack sufficient diagnostic accuracy because they fail to fully exploit the rich information encoded in the complex wave-bone interaction.

Proposed Framework: We propose a comprehensive computational framework designed to overcome these limitations by synergistically combining high-fidelity physics simulation with advanced artificial intelligence. The framework leverages the Finite Element Method (FEM) to accurately model the diffraction of ultrasonic waves through complex trabecular bone microarchitecture, generating a large-scale synthetic dataset. This data is then used to train a deep Convolutional Neural Network (CNN) for end-to-end prediction of bone density directly from the raw ultrasonic signals.

Proof-of-Concept & Perspective: A proof-of-concept study based on this framework demonstrated exceptional predictive power, achieving a coefficient of determination (R^2) of 0.94 on a synthetic test set. This result validates the proposed methodology and establishes a powerful new paradigm for bone sonometry. This paper reviews the state-of-the-art that motivates this approach and presents a future perspective on how this convergence of simulation and AI can pave the way for a new generation of safer, more accessible, and highly accurate tools for bone health assessment.

Keywords: Bone Density, Quantitative Ultrasound (QUS), Finite Element Method (FEM), Deep Learning, Convolutional Neural Networks (CNN), Osteoporosis, Non-invasive Diagnostics, Computational Modeling.

1. Introduction

The progressive aging of the global population has brought a number of public health challenges to the forefront, among which the rising prevalence of osteoporosis is a primary

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concern. Osteoporosis is a systemic skeletal disease characterized by a reduction in bone mass and a deterioration of the microarchitectural integrity of bone tissue, leading to a marked increase in bone fragility and fracture susceptibility [1, 2]. These fragility fractures, most commonly occurring at the hip, spine, and wrist, are not merely acute injuries but are sentinel events that often precipitate a devastating decline in health, leading to chronic pain, loss of mobility and independence, and a significant increase in mortality rates [3]. The immense societal and economic burden of osteoporosis, encompassing massive direct healthcare costs and indirect losses in productivity and quality of life, underscores the urgent and unmet clinical need for diagnostic methodologies that are accurate, safe, and accessible enough for widespread, population-level screening and monitoring [4].

The current clinical gold standard for the diagnosis of osteoporosis and the assessment of fracture risk is Dual-Energy X-ray Absorptiometry (DXA). This technique provides a quantitative measure of areal bone mineral density (aBMD) and has been extensively validated in large-scale prospective studies [5]. However, the utility of DXA is fundamentally constrained by its reliance on ionizing radiation. This inherent safety concern makes it unsuitable for frequent, longitudinal monitoring, particularly in younger or radiation-sensitive populations, and precludes its use in true point-of-care settings. Furthermore, other high-resolution imaging modalities like quantitative computed tomography (QCT), while capable of providing true volumetric BMD and distinguishing between cortical and trabecular compartments, impart an even higher radiation dose and are significantly more costly, largely restricting their use to research applications [6].

In response to these limitations, the field of Quantitative Ultrasound (QUS) has emerged over the past several decades as a promising radiation-free alternative. Conventional QUS devices, typically measuring the heel bone, have established a role in clinical practice by demonstrating a clear ability to predict fracture risk [7, 8]. These systems, however, are predicated on the measurement of two simple, scalar parameters: the Speed of Sound (SOS) and the Broadband Ultrasound Attenuation (BUA). While correlated with bone health, these metrics represent a profound reduction of information. They attempt to summarize the entire, complex interaction between an ultrasonic wave and the intricate three-dimensional structure of bone into just two numbers. This "information bottleneck" is a primary reason why conventional QUS has historically struggled to match the diagnostic precision of DXA and has been unable to provide specific insights into the architectural nature of bone degradation [9]. A fundamental leap forward requires a new approach that can move beyond these simple metrics and begin to decode the wealth of information latent within the full ultrasonic waveform.

This paper proposes such a new approach: a comprehensive computational framework for bone density assessment that synergistically combines high-fidelity physics simulation with advanced artificial intelligence. We will first provide a critical review of the state-of-the-art in bone sonometry to establish the context and motivation for this work. We will then detail the proposed framework, which leverages the Finite Element Method (FEM) to accurately model the diffraction of ultrasonic waves through bone and uses a Convolutional Neural Network (CNN) to learn the mapping from these complex signals to bone density. We will present key

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results from a proof-of-concept study that validates the efficacy of this framework and conclude with a perspective on how this convergence of simulation and AI represents a powerful and promising path toward the next generation of bone health diagnostics.

2. The State-of-the-Art in Bone Ultrasonometry: A Critical Review

The field of quantitative ultrasound for bone assessment has been characterized by a continuous search for more informative physical parameters and more sophisticated methods of signal interpretation. This evolution can be understood as a progression away from simple, integrated metrics towards techniques that can probe the finer details of bone's material properties and microarchitecture. A critical review of this landscape reveals a clear trajectory that motivates the development of a new, more comprehensive framework.

2.1 From Conventional Metrics to Advanced Experimental Techniques

As introduced, conventional QUS is defined by the measurement of Speed of Sound (SOS) and Broadband Ultrasound Attenuation (BUA) in a through-transmission configuration, typically at the calcaneus. SOS is primarily sensitive to the elastic modulus and density of the bone, reflecting the properties of the fastest wave path through the trabecular network [10]. BUA, conversely, is an integrated measure of energy loss due to both absorption and scattering, and is thought to be more reflective of the overall porosity and trabecular number [11]. While their combination into indices like the Stiffness Index has proven effective for fracture risk stratification [7], these parameters are fundamentally limited. They are single scalar values that discard the vast majority of the information contained in the complex, received waveform, thereby limiting their diagnostic specificity [9].

Recognizing these limitations, researchers have explored several advanced techniques to extract more detail. Ultrasonic backscatter analysis uses a pulse-echo configuration to analyze the energy scattered back from the trabeculae. The backscatter coefficient has been shown to be strongly correlated with bone density and is sensitive to the number and size of trabecular scatterers [12, 13]. However, this approach is technically challenged by the need for accurate attenuation compensation, a difficult problem that has hindered its clinical translation. For assessing long bones, the axial transmission method has been developed to analyze ultrasonic guided waves that propagate along the cortical shell. By analyzing the dispersive properties of these waves, it is possible to estimate critical parameters like cortical thickness and elasticity [14, 15]. While powerful for cortical bone, this technique is not applicable to trabecular-rich sites like the spine or hip. More complex methods like ultrasonic tomography aim to reconstruct 2D images of sound speed and attenuation, but are often limited by ray-based assumptions that ignore diffraction effects, leading to artifacts [16]. The most advanced approach, Full-Waveform Inversion (FWI), addresses this by using the full wave equation but at an immense computational cost that makes it currently infeasible for routine clinical use [17].

2.2 The Role of Computational Modeling and Signal Interpretation

Running parallel to these experimental advances has been the development of computational tools to model and interpret the data. Numerical simulation has become an indispensable part

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of QUS research, providing a "virtual laboratory" to study wave-bone interactions with perfect control [18]. Two primary methods dominate: the Finite-Difference Time-Domain (FDTD) method, which is computationally efficient but struggles with complex geometries, and the Finite Element Method (FEM), which is more computationally demanding but offers superior accuracy in representing the curved, intricate microarchitecture of trabecular bone [19, 20]. This geometric fidelity is paramount when studying phenomena like scattering and diffraction.

In terms of signal interpretation, the field has seen a clear evolution. Early approaches relied on traditional machine learning models, such as Support Vector Machines (SVMs), which were trained on a small set of hand-crafted features manually extracted from the ultrasonic signal [21]. While these methods showed modest improvements over SOS/BUA alone, their performance was fundamentally capped by the quality of the engineered features, a process that is both subjective and prone to information loss.

The recent revolution in deep learning, particularly the advent of Convolutional Neural Networks (CNNs), has offered a new path forward. CNNs are capable of learning optimal, hierarchical features automatically and directly from raw data, such as images or time-series signals [22]. This "end-to-end" learning approach has proven exceptionally powerful for complex pattern recognition tasks. Its application to medical ultrasound is growing rapidly, with studies demonstrating its success in analyzing guided waves for cortical bone characterization [23] and in other diagnostic imaging tasks [24].

2.3 The Identified Gap in the Literature

This critical review reveals a clear and compelling research gap at the intersection of these domains. Despite decades of progress, no existing methodology has synergistically combined the most powerful tools from each area into a single, cohesive framework. Specifically:

1. The rich diagnostic information contained within the forward-diffracted ultrasonic wavefield remains largely unexplored, with most research focusing on bulk transmission, backscatter, or guided waves.
2. While high-fidelity FEM simulations are capable of accurately modeling these diffraction effects, they have not been systematically used to generate the large-scale, perfectly-labeled synthetic datasets required to train modern deep learning models.
3. While CNNs are the ideal tool for decoding complex waveform patterns, their application to QUS has been limited and has not been specifically targeted at learning from diffraction phenomena in a simulation-driven context.

The framework proposed in this paper is designed to fill this precise gap, integrating these three key components-diffraction analysis, FEM simulation, and CNN interpretation-to create a new and more powerful approach for bone density assessment.

3. A Proposed Methodological Framework for Diffracted Pulse Analysis

To address the limitations identified in the existing literature, we propose a novel and comprehensive methodological framework for bone density assessment. This framework is engineered to maximize the extraction of diagnostically relevant information from the

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ultrasound-bone interaction by focusing on the analysis of the forward-diffracted wavefield. The core principle is a synergistic integration of high-fidelity physical modeling and advanced, data-driven interpretation via deep learning. The framework can be deconstructed into three primary conceptual components: the guiding physical principle, a simulation engine for data generation, and an interpretation engine for diagnostic prediction.

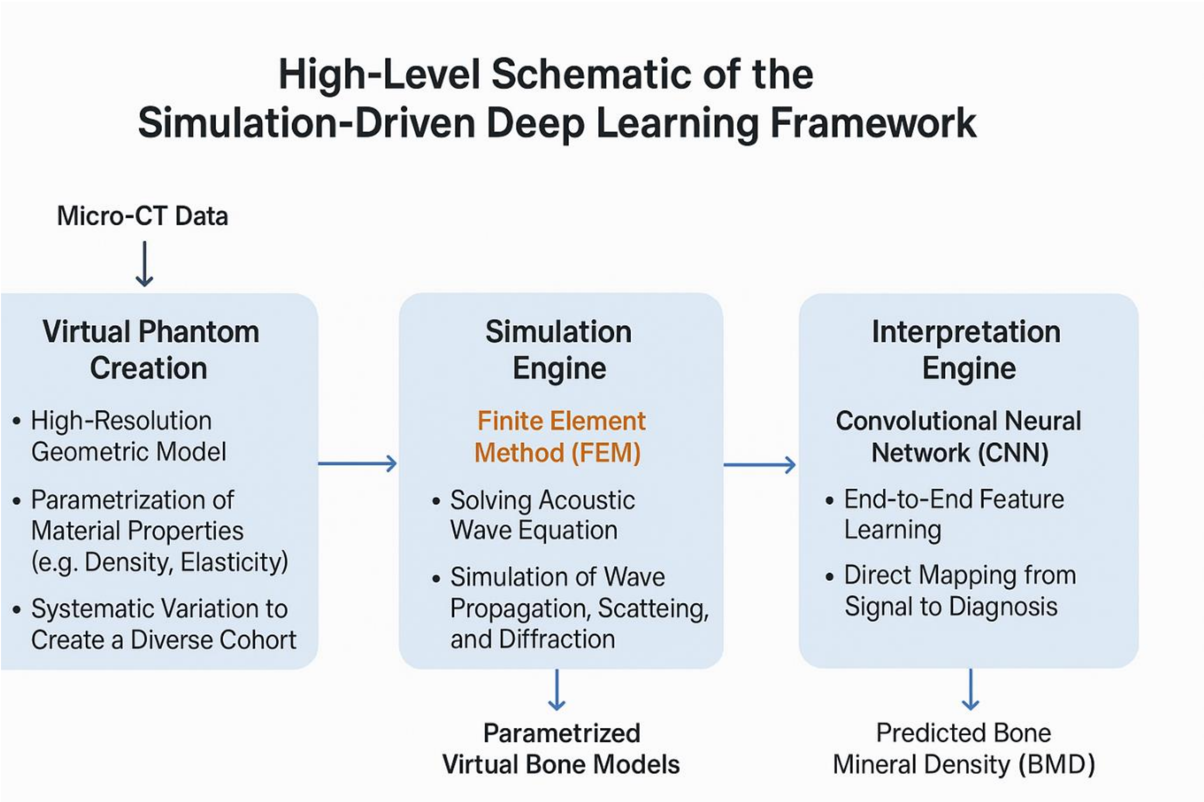

Figure 1: High-Level Schematic of the Simulation-Driven Deep Learning Framework

3.1 The Core Principle: Harnessing Diffraction for Architectural Sensitivity

The central physical premise of our framework is that the phenomenon of diffraction provides a richer source of information about bone microarchitecture than conventional acoustic parameters. As an ultrasonic wave propagates through the porous labyrinth of trabecular bone, the network of mineralized trabeculae and marrow-filled spaces acts as a complex, three-dimensional diffraction grating. According to the Huygens-Fresnel principle, the wave bends and interferes as it passes through this structure, creating a complex spatial and temporal pattern in the forward-propagating wavefield [25].

The characteristics of this diffraction pattern are intrinsically linked to the geometric properties of the grating that created it. The angular spread of the diffracted energy is related to the size of the apertures (the pores), while the angular separation of interference maxima is determined by the periodic spacing of the grating elements (the trabeculae) [26]. Therefore, the progressive architectural decay seen in osteoporosis-the thinning of trabeculae, the increase in trabecular spacing, and the loss of connectivity-will necessarily imprint a unique and detectable signature onto the diffracted wavefield. By shifting the analytical focus from simple time-of-flight or

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bulk attenuation to the detailed analysis of these complex diffraction patterns, we can develop a technique that is fundamentally more sensitive to the microstructural changes that underpin bone fragility.

3.2 The Simulation Engine: High-Fidelity Forward Modeling

To effectively analyze these diffraction patterns, a method is needed to generate clean, perfectly-labeled, and physically realistic data. Our framework accomplishes this through a Simulation Engine based on the Finite Element Method (FEM). This in silico approach serves as a "virtual laboratory", allowing us to model the entire physical interaction with high fidelity and control.

The simulation process begins with a high-resolution digital model of bone microarchitecture, typically derived from a micro-computed tomography (micro-CT) scan. This detailed geometry is then meshed using an unstructured grid of tetrahedral or triangular elements, which, unlike the Cartesian grids used in FDTD, can conform precisely to the curved surfaces of the trabeculae. This geometric accuracy is paramount for correctly modeling the diffraction and scattering phenomena at the heart of our approach [19]. The acoustic wave equation is then solved numerically on this mesh using a time-domain solver. By systematically varying the material properties (e.g., density, elasticity) of the bone and marrow components in the model across a clinically relevant range, we can simulate a large and diverse set of wave-bone interactions. The output of this engine is a comprehensive synthetic dataset, where each entry consists of the raw, time-domain pressure signals recorded at multiple receiver locations, each one perfectly labeled with the "ground truth" bone density used in that specific simulation. This methodology provides the vast amount of high-quality, labeled data necessary to train a robust deep learning model, a task that would be logistically and financially prohibitive to achieve through physical experimentation alone [27].

3.3 The Interpretation Engine: End-to-End Deep Learning

The final component of the framework is the Interpretation Engine, which is responsible for decoding the complex, high-dimensional output of the Simulation Engine. We posit that a Convolutional Neural Network (CNN) is the optimal tool for this task. The traditional approach of manually engineering a few features (e.g., peak amplitude, center frequency) from the signal inevitably discards a vast amount of subtle information contained in the waveform's morphology.

Our proposed end-to-end learning approach bypasses this limitation. The CNN is trained to learn the direct mapping from the raw (or minimally processed) time-domain signal to the final bone density prediction. The architecture of a 1D CNN is exceptionally well-suited for this purpose. Its convolutional layers act as a bank of learnable filters, automatically discovering the most salient morphological patterns and features within the diffracted waveform-patterns that may not be obvious to a human observer or captured by simple mathematical descriptors [22]. The hierarchical nature of the network allows it to build up progressively more abstract representations of the signal, while its inherent properties of parameter sharing and local connectivity make it highly efficient and robust to small shifts or distortions in the signal [28].

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By training on the large, clean dataset generated by the Simulation Engine, the CNN can learn the intricate, non-linear relationship between the diffraction pattern and bone density, effectively serving as a powerful, data-driven "physics decoder".

4 .Proof-of-Concept: A Case Study in Bone Density Prediction

To validate the efficacy and potential of the proposed methodological framework, a comprehensive proof-of-concept study was conducted. This study implemented the full simulation-to-AI pipeline to address the specific challenge of predicting bone mineral density (BMD) from ultrasonic signals. This section summarizes the methodology and key findings of that investigation, providing empirical support for the framework's validity. A full, detailed account of this study, including extensive methodological details and results, is the subject of a separate publication.

4.1 Implementation of the Framework

The study was executed by following the three core components of the framework. First, a two-dimensional Finite Element Model was constructed in COMSOL Multiphysics® to represent a cross-section of bone tissue, incorporating both cortical and trabecular regions. A synthetic dataset comprising 1,000 unique virtual bone samples was generated by systematically varying the key material properties of these regions-namely density and speed of sound-within clinically-reported ranges for healthy and osteoporotic bone. For each of the 1,000 virtual samples, a time-domain simulation was performed, modeling the propagation of a 1 MHz ultrasonic pulse through the structure. The resulting raw, time-domain pressure signals, which encapsulate the complex diffraction and scattering effects, were recorded at multiple receiver points.

Second, these 1,000 labeled waveforms constituted the dataset for the Interpretation Engine. The dataset was partitioned into training (80%) and testing (20%) sets. A 1D Convolutional Neural Network (CNN) was designed and implemented using the TensorFlow and Keras libraries. The CNN architecture was specifically tailored for time-series signal analysis, comprising convolutional layers for feature extraction, max-pooling layers for downsampling, and fully connected layers for the final regression task of predicting the continuous BMD value. The model was trained end-to-end, learning directly from the raw signal data to minimize the mean squared error between its predictions and the ground-truth BMD values.

4.2 Key Performance and Interpretability Results

The performance of the trained CNN model was rigorously evaluated on the unseen test set. The model demonstrated exceptional predictive power, achieving a coefficient of determination (R^2) of 0.94, indicating that the features learned by the CNN from the diffracted waveforms could explain 94% of the variance in the bone density data. The Mean Absolute Error (MAE) was found to be 0.045 g/cm^3, signifying a very high degree of accuracy. As illustrated in Figure 2, a scatter plot of the predicted BMD versus the actual BMD values reveals a tight clustering of data points along the line of identity, visually confirming the model's high accuracy and reliability. For benchmarking purposes, the CNN significantly outperformed several traditional

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machine learning models (including Linear Regression, Support Vector Regression, and Random Forest) that were trained on the same dataset using a set of hand-crafted features.

To ensure the model had learned physically meaningful relationships, an Explainable AI (XAI) analysis was performed using Shapley Additive Explanations (SHAP). The analysis quantified the influence of different input parameters on the model's output. The results clearly indicated that the model's predictions were most heavily influenced by the wave speed, followed by signal amplitude and time-of-flight. This finding aligns perfectly with the underlying physics of acoustics, where the velocity of a wave is fundamentally linked to the density and stiffness of the medium it traverses. This provides strong evidence that the CNN did not learn spurious correlations but instead successfully identified and prioritized the most physically relevant information within the complex signals.

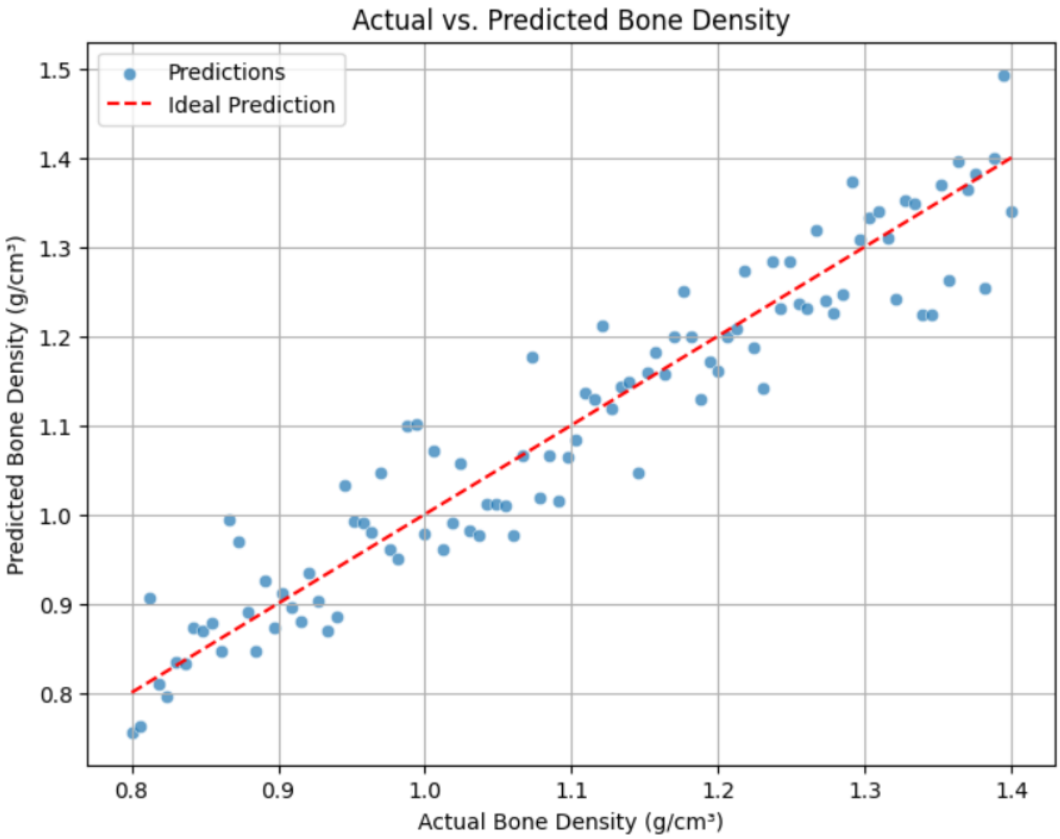

Figure 2: Predicted BMD vs. Actual BMD

4.3 Validation Summary

In summary, this proof-of-concept study provides a strong and compelling validation of the proposed framework. The successful implementation of the simulation-to-AI pipeline and the resulting high-accuracy predictions confirm that: (a) FEM simulation can effectively generate realistic, high-fidelity data representing wave diffraction in bone; and (b) a CNN is capable of decoding this complex information to produce highly accurate diagnostic predictions. These findings provide the necessary empirical foundation to discuss the broader implications and future perspective of this methodological paradigm.

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5. Discussion and Future Perspective

The successful validation of our proposed framework in the proof-of-concept study provides a strong foundation for discussing its broader implications for the field of bone sonometry and its potential future trajectory towards clinical application. The high predictive accuracy achieved is not merely a numerical result; it is an affirmation of the core principles upon which the framework is built and offers a new perspective on how to approach the challenge of non-invasive bone assessment.

5.1 Interpretation and Scientific Significance

The exceptional performance of the simulation-driven CNN stems from its ability to overcome the two primary bottlenecks that have historically limited quantitative ultrasound: information loss and feature-set fragility. Conventional methods, by reducing the entire ultrasonic waveform to just one or two scalar parameters like SOS and BUA, discard the vast majority of the rich morphological and phase information encoded in the signal. Our framework, by feeding the raw (or minimally processed) waveform directly into a CNN, circumvents this information loss. The Interpretation Engine is thus able to exploit subtle patterns in the diffracted wavefield-patterns related to phase cancellations, frequency dispersion, and the spatial distribution of energy-that are invisible to traditional metrics.

Furthermore, the framework overcomes the fragility of manual feature engineering. Instead of relying on human intuition to define a limited set of potentially sub-optimal features, the CNN learns the optimal feature representation automatically, driven by the singular goal of predicting bone density. The subsequent XAI analysis confirmed the scientific validity of this learned representation, showing that the model's decisions are anchored in physically meaningful parameters like wave speed. This synergy is the key to the framework's power: the Simulation Engine provides a physically accurate, high-fidelity representation of the wave-bone interaction, and the Interpretation Engine provides a mathematically powerful and unbiased tool to decode it. This represents a significant step towards a more holistic and physically complete method of ultrasonic signal analysis.

5.2 A Roadmap for Clinical Translation

While the results from our synthetic data are highly encouraging, the translation of this framework from a computational proof-of-concept to a clinical reality requires a deliberate, multi-stage research and development roadmap. This future work can be envisioned in four key phases:

1) Ex Vivo Validation: The immediate and most critical next step is to validate the framework using physical measurements. This involves acquiring ultrasonic data from ex vivo bone samples (e.g., human cadaveric calcanei or femora) and correlating the model's predictions with a gold-standard measurement of BMD and microarchitecture from micro-CT scans of the same samples. This phase will be crucial for assessing the "sim-to-real" gap-the degree to which the idealized simulation captures the complexities of real-world tissue and measurement artifacts.

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2) Hardware Development and Optimization: The current framework is agnostic to the specific hardware configuration. A dedicated research effort is needed to design and prototype an optimal transducer array for capturing the forward-diffracted wavefield in vivo. Simulations from our framework can be used to guide this process, virtually testing different transducer sizes, placements, and frequencies to maximize the acquisition of diffraction-sensitive information while considering the anatomical constraints of clinical sites like the heel or distal radius.

3) Refining the AI with Transfer Learning: A model trained exclusively on synthetic data may not perform optimally on noisy, complex experimental data. Transfer learning will be a key technique to bridge this gap [29]. The CNN, pre-trained on the vast synthetic dataset to learn the fundamental physics of diffraction, can then be fine-tuned on a smaller, more limited set of ex vivo or in vivo experimental data. This approach leverages the best of both worlds, allowing the model to generalize from the clean physics of the simulation while adapting to the specific noise and characteristics of a real-world measurement system [30].

4) In Vivo Studies and Clinical Trials: The final phase involves conducting human studies. Initial in vivo studies will focus on establishing the technique's safety, reproducibility, and correlation with DXA in healthy volunteers. This would be followed by larger-scale clinical trials involving patient populations to assess the technique's diagnostic accuracy for osteoporosis and its ability to predict fracture risk prospectively.

5.3 Broader Implications and Future Vision

The vision for this research extends beyond the specific application of bone density assessment. The methodological paradigm presented here-synergistically combining high-fidelity, physics-based simulation with deep learning for end-to-end interpretation-is a powerful and generalizable approach. It can be adapted to a wide range of challenging problems in medical diagnostics, non-destructive material evaluation, and geophysical exploration where complex wave phenomena are used to probe the internal structure of an opaque medium.

For bone health, the ultimate goal is to develop a new generation of diagnostic devices that are not only as accurate as DXA but are also fundamentally safer, more affordable, and more accessible. We envision a future where a portable, handheld device based on this AI-driven ultrasonic framework could be used in a primary care physician's office, at a patient's bedside, or in remote and resource-limited communities. Such a tool would enable widespread, cost-effective screening, facilitate the frequent monitoring of treatment efficacy, and empower a proactive, preventative approach to managing the global challenge of osteoporosis. This research represents a foundational step towards realizing that future.

6. Conclusion

The pressing clinical need for a safe, accessible, and accurate method for bone density assessment has driven decades of research in quantitative ultrasound. However, the progress of conventional QUS has been fundamentally constrained by its reliance on overly simplified metrics that fail to capture the rich information encoded in the complex interaction between

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ultrasound and bone microarchitecture. To overcome this longstanding barrier, a new methodological paradigm is required.

In this paper, we have reviewed the state-of-the-art in bone sonometry and have proposed a comprehensive, simulation-driven deep learning framework designed to unlock the diagnostic potential of ultrasonic diffraction analysis. By integrating the geometric accuracy of the Finite Element Method to generate high-fidelity training data with the powerful pattern recognition capabilities of a Convolutional Neural Network, our framework enables an end-to-end interpretation of complex wave phenomena. The success of our proof-of-concept study, which predicted bone density from synthetic diffracted signals with an R^2 of 0.94, provides strong validation for this approach.

This convergence of physics-based simulation and artificial intelligence represents a significant step forward. It moves the field beyond the limitations of hand-crafted features and low-dimensional parameters, creating a robust and adaptable methodology for decoding complex physical signals. While the path to clinical translation will require dedicated future work in experimental validation and hardware development, the framework presented here establishes a powerful and promising new direction for research. It lays the scientific and computational groundwork for a future generation of diagnostic tools that could revolutionize the management of osteoporosis and improve skeletal health for millions worldwide.

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