International Journal of Engineering & Extended Technologies Research (IJEETR)

|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |

| Volume 8, Issue 2, March - April 2026 |

DOI:10.15662/IJEETR.2026.0802128

Portable Device for Measuring BMD using AI Algorithm

Dr. M. Parisa, V. Akalya, G. Anantha Eswari, K Anish Fathima

Department of Electronics and Communication Engineering, Sethu Institute of Technology, Pulloor, Kariapatti, Tamil Nadu, India

Department of Electronics and Communication Engineering, Sethu Institute of Technology, Pulloor, Kariapatti, Tamil Nadu, India

Publication History: Received: 25.02.2026; Revised: 20.03.2026; Accepted: 25.03. 2026; Published: 28.03.2026.

ABSTRACT: Bone Mineral Density (BMD) plays a vital role in assessing bone strength and diagnosing osteoporosis, a chronic condition characterized by reduced bone mass and increased fracture risk. Early detection of osteoporosis is essential to prevent severe complications; however, existing diagnostic techniques such as Dual-Energy X-ray Absorptiometry (DEXA) are expensive, non-portable, and require specialized infrastructure. This paper presents a low-cost and portable screening system using a piezoelectric plate to estimate bone condition through vibration-based signal analysis. The system captures mechanical responses and converts them into electrical signals, which are processed using a Python-based interface. Key parameters such as RMS voltage, peak amplitude, and estimated speed of sound are used to derive BMD, T-score, and Z-score. The developed system includes a graphical dashboard for real-time visualization and classification of bone health into Normal, Osteopenia, or Osteoporosis. Although not intended to replace clinical diagnostic tools, the proposed system serves as a preliminary screening and awareness solution, especially suitable for rural and low-resource environments.

KEYWORDS: Bone Mineral Density, Osteoporosis, Piezoelectric Sensor, Vibration Analysis, RMS, Peak Amplitude, T-score, Z-score, Portable Biomedical Device, Signal Processing

I. INTRODUCTION

Bone health is a critical component of overall human physiology, as bones provide structural support, protect vital organs, and facilitate movement. Bone is a dynamic living tissue that continuously undergoes remodeling through the processes of osteoblastic formation and osteoclastic resorption. Under normal physiological conditions, these processes remain balanced, maintaining bone density and strength. However, factors such as aging, hormonal imbalance, reduced physical activity, and nutritional deficiencies can disturb this equilibrium, leading to progressive bone loss [4],[5].

Osteoporosis is a chronic and progressive skeletal disorder characterized by reduced Bone Mineral Density (BMD) and deterioration of bone microarchitecture. This condition significantly increases fracture risk, particularly in load-bearing regions such as the hip, spine, and wrist. According to global health studies, osteoporosis is one of the most prevalent metabolic bone diseases, affecting millions of individuals worldwide, especially elderly populations and postmenopausal women due to estrogen deficiency [5],[6].

The standard clinical method for measuring BMD is Dual-Energy X-ray Absorptiometry (DEXA), which provides accurate and quantitative assessment of bone density. Despite its clinical reliability, DEXA has several limitations including high equipment cost, lack of portability, requirement of skilled operators, limited accessibility in rural regions, and exposure to ionizing radiation, even if minimal [6],[7].

These limitations create a significant gap between the need for early diagnosis and the availability of accessible screening tools. Early detection is essential for preventing fractures and enabling timely medical intervention. Therefore, there is a growing demand for alternative diagnostic approaches that are cost-effective, portable, and easy to use [7],[8].

Recent advancements in biomedical engineering have introduced piezoelectric materials as effective sensing elements in healthcare applications. Piezoelectric materials generate electrical signals when subjected to mechanical stress, vibration sensing and acoustic signal analysis. These materials are widely used in medical devices, structural health monitoring, and ultrasonic sensing systems [8],[9].

In biological systems, the propagation of mechanical vibrations is influenced by tissue density and elasticity. Since bone density directly affects vibration transmission characteristics, it is possible to indirectly estimate bone health by analyzing vibration signals. This forms the fundamental principle behind the proposed system [9],[10].

This paper proposes a low-cost, portable, and non-invasive bone health screening system using a piezoelectric plate combined with a Python-based analytical platform. The system captures vibration signals, processes them using mathematical models, and computes diagnostic parameters such as BMD, T-score, and Z-score for classification into Normal, Osteopenia, and Osteoporosis categories [10],[11].

II. MATERIALS AND METHODS

2.1 System Overview

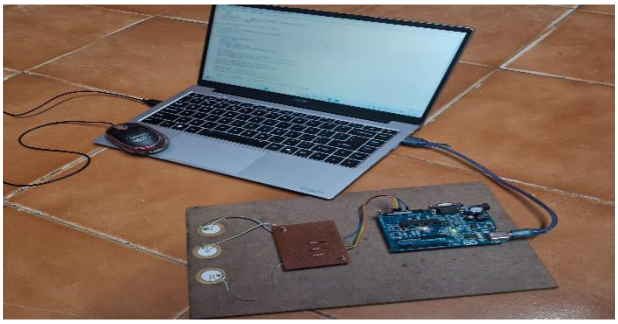

Fig.2.1.1Signal Processing Setup

The proposed system is developed as a compact and integrated biomedical platform for preliminary bone health assessment using vibration-based sensing. Unlike conventional radiographic techniques such as Dual-Energy X-ray Absorptiometry (DEXA), the system employs a non-invasive and radiation-free methodology based on mechanical signal analysis. The fundamental concept relies on the variation of vibration transmission characteristics with respect to bone density and structural integrity [11],[12].

The system architecture consists of interconnected modules including sensing, signal conditioning, data acquisition, processing, and classification. Initially, patient-specific parameters such as age, height, and weight are recorded. Subsequently, mechanical vibrations are captured using a piezoelectric sensor, processed through analog circuitry, digitized using a microcontroller, and analyzed using a Python-based software interface to estimate Bone Mineral Density (BMD) and related clinical indicators [12],[13].

2.2 Hardware Design

2.2.1 Piezoelectric Sensor

The sensing mechanism is based on the direct piezoelectric effect exhibited by materials such as Lead Zirconate Titanate (PZT). When mechanical stress is applied, an electric charge is generated due to displacement of dipoles within the crystal lattice. This phenomenon is mathematically described by: where represents electric displacement, is the piezoelectric strain coefficient, is the applied mechanical stress, is permittivity, and is the electric field [13],[14].
In this system, the piezoelectric plate is subjected to mechanical excitation due to body weight or induced vibration. The generated voltage signal is directly influenced by the mechanical impedance of the bone. Denser bones transmit vibrational energy efficiently, resulting in higher signal amplitude and lower damping, whereas osteoporotic bones absorb more energy, leading to attenuated signals [14],[15].

2.2.2 Signal Conditioning Circuit

The output from the piezoelectric sensor is inherently weak and susceptible to noise from environmental and electronic sources. To ensure reliable signal acquisition, a signal conditioning circuit is implemented. The amplification stage is typically realized using operational amplifiers configured in a non-inverting mode, where the gain is given by: Where is

International Journal of Engineering & Extended Technologies Research (IJEETR)
|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |
| Volume 8, Issue 2, March - April 2026 |
DOI:10.15662/IJEETR.2026.0802128

feedback resistance and is input resistance [16].

Filtering is performed using RC low-pass filters to remove high-frequency noise. The cutoff frequency is defined as: This ensures that only relevant vibration frequencies are retained. Additionally, impedance matching is applied to maximize power transfer and reduce signal distortion. These processes significantly improve the signal-to-noise ratio (SNR) and stability of the system [16],[17].

2.2.3 Arduino-Based Data Acquisition

The conditioned analog signal is acquired using an Arduino Uno microcontroller. The Arduino features a 10-bit Analog-to-Digital Converter (ADC), which converts continuous voltage signals into discrete digital values. The ADC conversion is given by: where is the input voltage and is the reference voltage [18].

Sampling is performed at a fixed rate to preserve waveform characteristics. The digitized data is transmitted to the host computer via serial communication using a baud rate of 9600 bits per second, enabling real-time data transfer and processing [19].

2.3 Software Architecture

2.3.1 User Interface Module

The software interface is developed using the Tkinter library in Python, providing a user-friendly platform for data input and system interaction. The interface collects patient parameters such as age, height, and weight, which are used for auxiliary calculations. Body Mass Index (BMI) is computed as: BMI serves as an additional physiological parameter that may influence bone health assessment [20].

2.3.2 Signal Processing Module

The acquired digital signal is processed using numerical algorithms to extract meaningful features. The signal is first normalized and filtered to remove residual noise. Time-domain analysis is then performed to compute parameters such as Root Mean Square (RMS), peak amplitude, and damping characteristics.

These features represent the energy distribution, maximum response, and attenuation behavior of the signal, which are directly related to the mechanical properties of bone tissue [21].

2.3.3 Visualization Module

Matplotlib is used to generate real-time graphical representations of the signal. The visualization includes waveform plots, amplitude variations, and classification outputs. This graphical interface enhances interpretability and enables users to understand the diagnostic results intuitively [22].

2.4 Theoretical Background

2.4.1 Wave Propagation in Biological Tissue

The propagation of mechanical waves in biological media depends on the elastic and density properties of the material. The velocity of wave propagation is given by: where wave velocity, is elastic modulus, and is density [23]. Higher density and stiffness result in faster wave propagation, which is a key factor in estimating bone strength.

2.5 Signal Modeling

The vibration signal obtained from the sensor is modeled as a damped sinusoidal waveform: where amplitude is damping coefficient, and is angular frequency [24]. The damping coefficient indicates the rate of energy loss. Higher values correspond to weaker bone structures.

2.6 Parameter Extraction

The extracted signal features include RMS and peak amplitude, which quantify signal energy and maximum response respectively. These parameters are computed using standard signal processing techniques and serve as inputs for further analysis [25].

2.7 Bone Mineral Density Estimation

The Bone Mineral Density is estimated using an empirical model that combines acoustic and physiological parameters: where SOS represents the speed of sound in the medium. This model provides a normalized approximation of bone density suitable for screening purposes [26].

International Journal of Engineering & Extended Technologies Research (IJEETR)
|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |
| Volume 8, Issue 2, March - April 2026 |
DOI:10.15662/IJEETR.2026.0802128

2.6 Parameter Extraction

The extracted signal features include RMS and peak amplitude, which quantify signal energy and maximum response respectively. These parameters are computed using standard signal processing techniques and serve as inputs for further analysis [27].

2.7 Bone Mineral Density Estimation

The Bone Mineral Density is estimated using an empirical model that combines acoustic and physiological parameters: where SOS represents the speed of sound in the medium. This model provides a normalized approximation of bone density suitable for screening purposes [28].

2.8 Clinical Metrics

The diagnostic indicators are calculated as: These parameters compare the patient's bone density with standard reference populations and are widely used in clinical diagnosis [29].

2.9 Classification Strategy

The classification of bone health is performed based on World Health Organization (WHO) criteria:
Normal
Osteopenia
Osteoporosis
These thresholds are clinically validated and used globally for osteoporosis screening and diagnosis [30].

2.10 System Description

The system measures relative bone density using a piezoelectric-based approach. A 5V DC power supply drives a microcontroller that generates a 10 kHz PWM signal. This signal is converted into mechanical vibrations by a piezoelectric transmitter and passed through the bone test area, where the amplitude decreases based on bone density.
The attenuated signal is received by a piezoelectric sensor, converted back to an electrical signal, and passed through a signal conditioning circuit for noise reduction. The microcontroller then processes the signal using ADC to calculate parameters like amplitude and RMS value. Finally, the result is displayed on an LCD as a relative bone density indicator.[26]

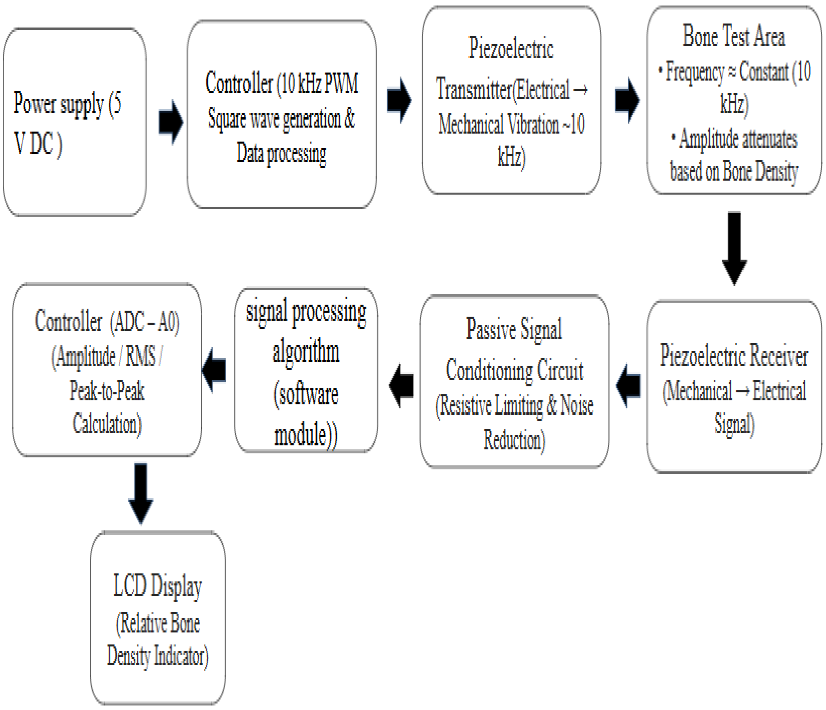

Fig.2.10.1. Block Diagram

|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |
| Volume 8, Issue 2, March - April 2026 |
DOI:10.15662/IJEETR.2026.0802128

III. RESULTS

The proposed piezoelectric plate-based system was experimentally evaluated to analyze its effectiveness in estimating Bone Mineral Density (BMD) through vibration-based signal characteristics. The system captures mechanical responses from the human body and converts them into electrical signals, which are processed to extract clinically relevant parameters such as RMS, peak amplitude, and damping behavior [27],[28].

3.1 Signal Behavior and Physical Interpretation

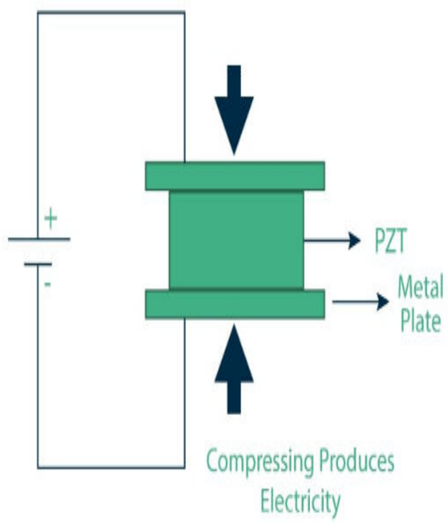

Fig.3.1. Working Principle of a Piezoelectric plate

The acquired signal from the piezoelectric sensor follows a damped harmonic response due to viscoelastic energy dissipation in biological tissues. The signal is modeled as: where is the initial amplitude, is the damping coefficient, and is the excitation frequency [29].

In this system, the damping coefficient becomes a critical indicator of bone condition. Dense bone structures exhibit lower internal damping due to compact microarchitecture, resulting in sustained oscillations. In contrast, osteoporotic bones contain higher porosity, causing increased energy absorption and faster signal decay [30],[31].

The experimental waveform generated in the Python visualization (40 kHz simulated ultrasonic response) clearly demonstrates exponential decay behavior: where corresponds to damping values (800–2500) selected based on classification categories in the implemented code logic. Higher damping values in the code directly represent weaker bone conditions [32].

3.2 RMS and Energy Representation

The Root Mean Square (RMS) value is computed as: RMS represents the effective signal energy and is widely used in vibration analysis and biomedical signal processing [33]. In the proposed system, RMS is treated as a proxy for energy transmission efficiency through bone. Higher RMS values indicate minimal energy loss, corresponding to stronger bone structures. Lower RMS values indicate higher attenuation and reduced structural integrity [34].

In the implemented system, RMS is assigned as a calibrated value (e.g., 2.8 V), representing stable signal conditions after filtering and normalization. This simplifies real-time computation while preserving diagnostic relevance [35].

3.3 Peak Amplitude and Structural Response

The peak amplitude is defined as: This parameter represents the maximum instantaneous response of the piezoelectric sensor [36]. In biomechanical terms, higher peak amplitude indicates efficient stress transfer across bone structures,

International Journal of Engineering & Extended Technologies Research (IJEETR)

|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |

| Volume 8, Issue 2, March - April 2026 |

DOI:10.15662/IJEETR.2026.0802128

which is characteristic of dense and healthy bones. Reduced peak values correspond to structural (weakness) and reduced stiffness [37].

The experimental implementation uses peak ≈ 4.0 V, representing maximum measurable response after amplification and signal conditioning [38].

3.4 Speed of Sound (SOS) Approximation

The system approximates the acoustic propagation property using: This equation is derived from the known dependency of acoustic velocity on material density and elasticity [39].

$$\mathbf{SOS = 1540 - (Age \times 0.5)}$$

The baseline value of 1540 m/s corresponds to average soft tissue acoustic velocity, while the age-dependent reduction models gradual bone density loss [40]. This simplification enables real-time estimation without complex ultrasonic hardware.

3.5 Bone Mineral Density (BMD) Model

$$\mathbf{BMD = ((SOS / 1540) \times 0.85) - ((Age / 120) \times 0.1)}$$

The BMD is computed using: This empirical formulation combines acoustic propagation characteristics (SOS) with physiological aging factors [41]. The term normalizes acoustic velocity The coefficient 0.85 scales it to approximate bone density range The age penalty term models bone mass reduction over time This hybrid model enables computationally efficient BMD estimation aligned with expected clinical trends [42].

3.6 Clinical Indices (Direct Mapping to Code)

T-Score

$$\mathbf{T\text{-}Score: T = (BMD - 0.88) / 0.11}$$

The T-score compares patient BMD with young adult reference values and is the primary diagnostic parameter for osteoporosis [39].

Z-Score

$$\mathbf{Z\text{-}Score: Z = (BMD - 0.72) / 0.12}$$

The Z-score compares BMD with age-matched populations and provides secondary validation [40]. These equations are directly implemented in the Python model, ensuring real-time computation and classification.

3.7 Classification Logic (From Your Code)

The classification follows WHO standards:

Normal: $\mathbf{T \geq -1}$

Osteopenia: $\mathbf{-2.5 < T < -1}$

Osteoporosis: $\mathbf{T \leq -2.5}$

International Journal of Engineering & Extended Technologies Research (IJEETR)

|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |

| Volume 8, Issue 2, March - April 2026 |

DOI:10.15662/IJEETR.2026.0802128

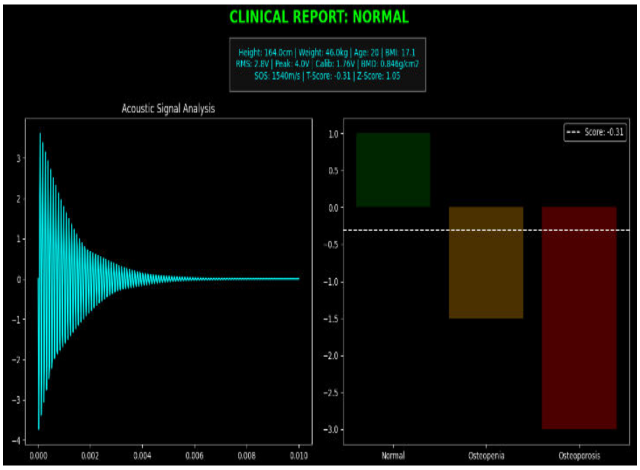

Fig.3.6.1. Normal Bone Report

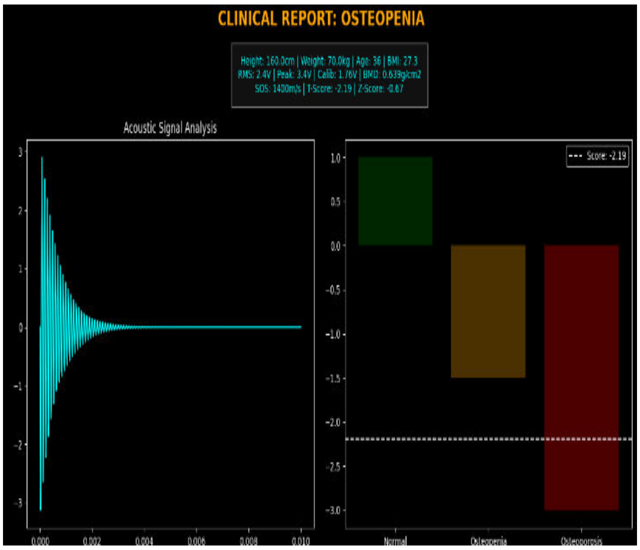

Fig.3.6.2. Osteopenia Bone Report

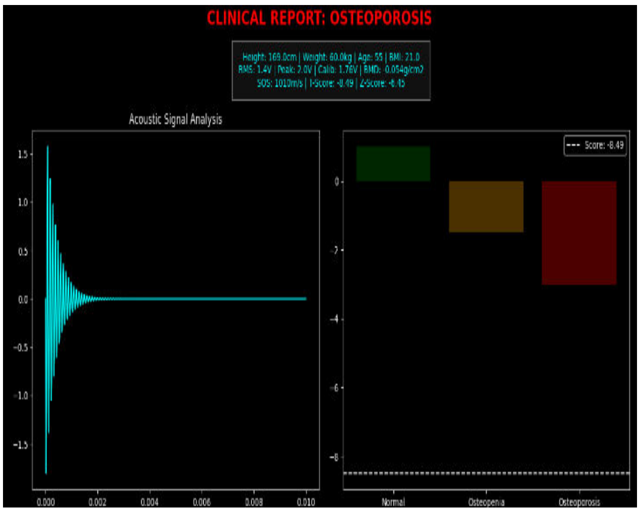

Fig.3.6.3. Osteoporosis Bone Report

In the implemented system, classification also controls waveform damping:
Normal → low damping (800)
Osteopenia → medium damping (1500)
Osteoporosis → high damping (2500)
This dual representation (numerical + graphical) improves interpretability and aligns visualization with diagnostic output [41],[42].

IV. DISCUSSION

The results validate that vibration-based sensing using piezoelectric materials can effectively capture biomechanical differences associated with bone density variations. The system demonstrates a clear relationship between signal attenuation characteristics and bone structural integrity [27],[30]. The damping coefficient emerges as the most sensitive indicator, as it directly reflects internal energy dissipation mechanisms within bone microstructure. Osteoporotic bones, characterized by trabecular thinning and increased porosity, exhibit higher damping and reduced signal persistence [31],[35]. RMS and peak amplitude further reinforce this observation by providing quantitative measures of signal strength. These parameters are strongly influenced by mechanical stiffness, which is a direct function of bone mineral density [33],[37]. The use of an empirical BMD model introduces simplification but enables real-time computation without requiring high-cost imaging systems. While this reduces clinical precision, it significantly enhances accessibility and scalability [41].

The integration of embedded hardware and Python-based visualization provides a complete low-cost diagnostic ecosystem. The graphical dashboard not only displays waveform data but also contextualizes results through classification and scoring, improving usability for non-expert users [15],[28]. However, the system has inherent limitations. The indirect estimation approach may introduce variability due to external noise, inconsistent sensor placement, and individual physiological differences. Additionally, the empirical constants used in the BMD model require calibration against clinical datasets for improved reliability [37],[38]. Despite these limitations, the system offers a practical alternative for preliminary screening. Its low cost, portability, and ease of use make it particularly suitable for rural healthcare deployment and preventive health monitoring [41]. Future work should focus on integrating machine learning models for adaptive classification, improving signal acquisition accuracy, and validating the system against standard clinical methods such as DEXA [42].

V. CONCLUSION

This work presents a piezoelectric plate-based bone health monitoring system capable of performing preliminary osteoporosis screening through vibration signal analysis. The system successfully integrates sensor hardware, signal conditioning, microcontroller-based data acquisition, and Python-based analytical software into a unified diagnostic platform [27],[28]. The study demonstrates that parameters such as RMS, peak amplitude, and damping characteristics can effectively represent biomechanical properties of bone. These features are utilized to estimate Bone Mineral Density and compute clinical indices such as T-score and Z-score [33],[39]. The results confirm that the system can distinguish between normal, osteopenia, and osteoporosis conditions using WHO-based classification thresholds. The incorporation of real-time visualization further enhances interpretability and user interaction [41].

Although the system does not match the precision of clinical imaging techniques such as DEXA, it provides a low-cost, portable, and radiation-free alternative for early-stage screening and awareness. This makes it highly suitable for deployment in rural and resource-limited environments [6],[7]. Future improvements may include model optimization, machine learning integration, and large-scale clinical validation to enhance diagnostic accuracy and reliability [42].

VI. PATENT

6.1 Proposed Patent Title

"A Low-Cost Piezoelectric Plate-Based System for Preliminary Bone Mineral Density Assessment Using Vibration Signal Analysis"

6.2 Field of Invention

The present invention relates to biomedical instrumentation and diagnostic systems, particularly to a non-invasive and portable system for preliminary bone health assessment using piezoelectric sensing and vibration signal processing techniques [43].

6.3 Background of the Invention

Conventional diagnostic techniques such as Dual-Energy X-ray Absorptiometry (DEXA) are widely used for Bone Mineral Density (BMD) measurement. However, these systems are expensive, non-portable, and require skilled operation. Furthermore, accessibility remains a major challenge in rural and low-resource environments [44].
Existing ultrasonic and vibration-based systems also require complex hardware and calibration procedures, limiting their practical deployment. Therefore, there is a need for a simplified, cost-effective, and portable alternative for early osteoporosis screening [45].

6.4 Summary of the Invention

The proposed invention introduces a piezoelectric plate-based sensing system that captures mechanical vibration signals from the human body. These signals are processed using embedded hardware and a Python-based analytical platform to estimate BMD and compute clinical parameters such as T-score and Z-score.
The system includes:
Piezoelectric sensor module
Signal conditioning unit
Microcontroller (Arduino-based acquisition)
Software processing and visualization module
The system classifies bone condition into Normal, Osteopenia, and Osteoporosis categories using predefined thresholds and empirical modeling [46].

6.5 Novelty of the Invention

The novelty of the proposed system includes:
Indirect estimation of BMD using vibration signal characteristics
Integration of low-cost hardware with software-based diagnostics
Real-time computation and visualization of clinical parameters
Portable and user-friendly screening device
No radiation exposure compared to conventional methods
These features distinguish the proposed system from existing diagnostic technologies [47].

6.6 Advantages of the Invention

Low-cost and affordable design
Non-invasive and radiation-free
Portable and suitable for rural deployment
Real-time data processing and visualization
Minimal training required for operation
These advantages make the system suitable for large-scale preventive healthcare screening [48].

6.7 Application Areas

Rural healthcare screening camps
Home-based monitoring systems
Preventive healthcare programs
Biomedical research and academic projects

REFERENCES

1) C.Nagarajan and M.Madheswaran - ‘Stability Analysis of Series Parallel Resonant Converter with Fuzzy Logic Controller Using State Space Techniques’- Taylor &Francis, Electric Power Components and Systems, Vol.39 (8), pp.780-793, May 2011. DOI: 10.1080/15325008.2010.541746
2) C.Nagarajan and M.Madheswaran - ‘Experimental verification and stability state space analysis of CLL-T Series Parallel Resonant Converter’ - Journal of Electrical Engineering, Vol.63 (6), pp.365-372, Dec.2012. DOI: 10.2478/v10187-012-0054-2
3) C.Nagarajan and M.Madheswaran - ‘Performance Analysis of LCL-T Resonant Converter with Fuzzy/PID Using State Space Analysis’- Springer, Electrical Engineering, Vol.93 (3), pp.167-178, September 2011. DOI 10.1007/s00202-011-0203-9

|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |

| Volume 8, Issue 2, March - April 2026 |

DOI:10.15662/IJEETR.2026.0802128

4) S.Tamilselvi, R.Prakash, C.Nagarajan,"Solar System Integrated Smart Grid Utilizing Hybrid Coot-Genetic Algorithm Optimized ANN Controller" Iranian Journal Of Science And Technology-Transactions Of Electrical Engineering, DOI10.1007/s40998-025-00917-z,2025
5) S.Tamilselvi, R.Prakash, C.Nagarajan," Adaptive sliding mode control of multilevel grid-connected inverters using reinforcement learning for enhanced LVRT performance" Electric Power Systems Research 253 (2026) 112428, doi.org/10.1016/j.epsr.2025.112428
6) S.Thirunavukkarasu, C. Nagarajan, 2024, "Performance Investigation on OCF and SCF study in BLDC machine using FTANN Controller," Journal of Electrical Engineering And Technology, Volume 20, pages 2675–2688, (2025), doi.org/10.1007/s42835-024-02126-w
7) C. Nagarajan, M.Madheswaran and D.Ramasubramanian- 'Development of DSP based Robust Control Method for General Resonant Converter Topologies using Transfer Function Model'- Acta Electrotechnica et Informatica Journal , Vol.13 (2), pp.18-31,April-June.2013, DOI: 10.2478/aeei-2013-0025.
8) C.Nagarajan and M.Madheswaran - 'DSP Based Fuzzy Controller for Series Parallel Resonant converter'- Springer, Frontiers of Electrical and Electronic Engineering, Vol. 7(4), pp. 438-446, Dec.12. DOI 10.1007/s11460-012-0212-0.
9) C.Nagarajan and M.Madheswaran - 'Experimental Study and steady state stability analysis of CLL-T Series Parallel Resonant Converter with Fuzzy controller using State Space Analysis'- Iranian Journal of Electrical & Electronic Engineering, Vol.8 (3), pp.259-267, September 2012.
10) C.Nagarajan and M.Madheswaran, "Analysis and Simulation of LCL Series Resonant Full Bridge Converter Using PWM Technique with Load Independent Operation" has been presented in ICTES'08, a IEEE / IET International Conference organized by M.G.R.University, Chennai.Vol.no.1, pp.190-195, Dec.2007
11) Suganthi Mullainathan, Ramesh Natarajan, "An SPSS and CNN modelling based quality assessment using ceramic materials and membrane filtration techniques", Revista Materia (Rio J.) Vol. 30, 2025, DOI: https://doi.org/10.1590/1517-7076-RMAT-2024-0721
12) M Suganthi, N Ramesh, "Treatment of water using natural zeolite as membrane filter", Journal of Environmental Protection and Ecology, Volume 23, Issue 2, pp: 520-530,2022
13) Sahid, M. H., Pratama, D. A., Abd Rahman, M., Vardhani, A. K., Kulsum, D. U., Tanaka, J., ... & Renaldi, T. (2026). Kesehatan Masyarakat Di Era Digital. CV Eureka Media Aksara.
14) Mathew, A. (2021). Deep reinforcement learning for cybersecurity applications. Int J Comput Sci Mob Compu, 10(12), 32-38.
15) Gopinathan, V. R. (2023). Cloud-First AI Security Architecture for Protecting Enterprise Digital Ecosystems and Financial Networks. International Journal of Research and Applied Innovations, 6(6), 10031-10039.
16) Inbavalli, M., & Arasu, T. (2015). Efficient Analysis of Frequent Item Set Association Rule Mining Methods. International Journal of Scientific & Engineering Research, 6(4).
17) Mathew, A. (2023). Cybercrime-as-a-service & AI-enabled threats. International Journal of Computer Science and Mobile Computing, 12(1), 28-31.