Journal of Scientific & Industrial Research
Vol. 84, August 2025, pp. 862-870
DOI: 10.56042/jsir.v84i8.16731

Predictive Modelling of Bone Mineral Density: An ANN and Regression-based Approach

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Received 28 January 2025; revised 23 June 2025; accepted 08 July 2025

In recent years, the development of predictive models using Multi-Variable Regression (MVR) and Artificial Neural Networks (ANN) has become a focal point in health research, particularly in predicting Bone Mineral Density (BMD) for the early detection of osteoporosis. This study compares the performance of MVR and ANN models using a clinical dataset comprising patient attributes such as age, weight, height, and BMD. The primary objective is to predict BMD values of the femur bone and evaluate the potential risks of osteoporosis. ANN demonstrated superior predictive accuracy with a correlation coefficient (R^2) of 0.8823 compared to 0.6087 for MVR, highlighting its capability to capture data linearity and complex patterns effectively. The study used filtered and validated datasets, including results from BMD tests on two dry intact femurs, sourced from Kaggle. Performance metrics such as regression accuracy and Mean Square Error (MSE) were calculated, showing that ANN with a hidden layer of 12 neurons provided the best results. The findings indicate that ANN not only outperforms MVR in predictive accuracy but also avoids the need for experiments on real human femurs, providing a non-invasive, data-driven alternative for medical diagnostics. A secondary goal was to develop a practical model for clinical use in predicting bone density. The study also explores the integration of ANN outputs with Genetic Algorithms (GA) to optimize the prediction process. This hybrid strategy reduces the number of simulations and computation time, offering a robust framework for global optimization. The combination of ANN and GA demonstrates the potential to enhance diagnostic precision and streamline decision-making processes in orthopedic and medical technology. In conclusion, this study emphasizes the applicability of ANN for accurate BMD predictions, paving the way for advanced diagnostic tools in healthcare. Future research could focus on expanding datasets and exploring hybrid optimization techniques to further improve prediction accuracy and clinical utility.

Keywords: Artificial neural networks, Genetic algorithms, Machine learning, Medical diagnostics, Multi-variable regression

Introduction

Predictive modelling in healthcare, particularly in assessing Bone Mineral Density (BMD) for early osteoporosis detection, has seen significant advancements with the rise of sophisticated techniques like Multiple Linear Regression (MLR) and Artificial Neural Networks (ANN). MLR, a statistical method, explores cause-and-effect relationships between variables, while ANNs, inspired by the human brain, excel at pattern recognition and prediction. These tools are crucial for analyzing complex medical data and informing clinical decisions. Osteoporosis, characterized by weakened bones and increased fracture risk, poses a significant global health challenge. Accurate BMD prediction is

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essential for early intervention and prevention of debilitating fractures. Traditional methods often rely on invasive procedures, highlighting the need for non-invasive, data-driven approaches.

Predictive modelling of BMD has been explored through various approaches, including ANN and regression-based methods, to enhance early diagnosis and treatment of osteoporosis. A study by Li *et al*. developed a deep learning model using CT images to predict BMD, achieving high diagnostic accuracy and a strong correlation with standard Quantitative Computed Tomography (QCT) measurements, indicating its potential for automatic BMD assessment and osteoporosis prediction.[1] Similarly, Bezerra *et al*. employed machine learning techniques, including regression algorithms, to predict BMD using anthropometric and demographic data, demonstrating good performance with low mean absolute errors, thus offering a cost-effective alternative to traditional methods like Dual-energy X-ray Absorptiometry (DXA).[2,3] In another study, Wenhua *et al*. utilized NHANES data to develop interpretable machine learning models for predicting femoral neck BMD in elderly men, with the random forest regressor showing the best performance, highlighting the importance of factors such as age, Body Mass Index (BMI), and serum calcium.[4] Additionally, Li *et al*. applied neural networks and nomograms to identify risk factors for BMD abnormalities, emphasizing the influence of diet and electrolytes, and achieving high predictive accuracy, which underscores the model's clinical applicability.[5] These studies collectively illustrate the efficacy of ANN and regression-based models in predicting BMD, offering valuable tools for early osteoporosis detection and management, thereby potentially improving patient outcomes and reducing healthcare burdens associated with bone health issues. The proposed approach utilizes clinical Computational Tomography (CT) scan images taken for other medical indications to predict BMD without incurring additional costs, time, or radiation exposure. This method employs image processing and an ANN to analyze DICOM image properties from QCT scans, aiming to assist clinicians in early identification of osteoporosis and the development of strategies to enhance BMD.[6] provides a comprehensive overview of various Artificial Intelligence algorithms that can be utilized for detecting osteoporosis by measuring bone mineral density, highlighting the application of advanced Python algorithms such as K-Means, KNN, and Random Forest Classifier among others.[7] The research utilizes a deep learning model trained on a large dataset collected from multiple hospitals, incorporating patient demographics (age and sex) and imaging data (chest X-rays) to enhance predictive performance for BMD and T-score classification, demonstrating significant correlation and classification accuracy in identifying patients at risk for osteoporosis.[8] The study investigates the use of deep learning models to classify osteoporosis and predict bone density from opportunistic CT scans, demonstrating high accuracy and a strong correlation with QCT results. This suggests that deep learning can effectively enhance osteoporosis screening processes.[9] It is noted that conventional radiography is more effective for screening osteoporosis rather than for definitive diagnosis, as only experienced physicians can detect osteoporosis on radiographs. The research explores the potential of using a deep learning algorithm, specifically a Convolutional Neural Network (CNN), to predict BMD from plain pelvis X-ray images, aiming to improve the diagnostic process.[10] The study addresses the challenge of measuring BMD in clinical settings, where DXA is typically required, leading to additional radiation exposure. The research highlights the limitations of using CT for BMD assessment due to technical difficulties, which has resulted in a lack of BMD information from CT in clinical practice.[11] It is noted that despite the availability of various therapeutic options, approximately one-fourth of osteoporosis patients do not experience improvement in BMD, indicating a high failure rate of treatment responses. This failure is attributed not only to the treatment regimens and dosages but also to other clinical factors, emphasizing the need for personalized treatment approaches based on individual patient profiles.[12] The study explores the integration of Optical Bone Densitometry (OBD) and Machine Learning (ML) techniques to enhance the early detection and screening of osteoporosis, indicating a growing trend in utilizing advanced technology for medical diagnostics.[13] The paper discusses the limitations of existing methods for estimating BMD from x-ray images, which typically require large training datasets due to significant intensity variations in the images. It highlights the need for a more efficient approach that does not rely on extensive data collection.[14] The literature indicates that BMD is a critical factor in assessing the risk of osteoporosis, particularly in patients with Rheumatoid Arthritis (RA), who are known to be at higher risk for osteoporotic fractures. Previous studies have established a correlation between BMD and the 2nd Metacarpal Cortical Index (2MCI), suggesting that 2MCI can serve as a useful screening tool for identifying patients at risk of low bone density.[15] The systematic review and meta-analysis examined studies published between 2014 and 2024 that focused on the application of deep learning models to multimodal imaging data for early osteoporosis detection. This review highlighted the differences in accuracy and effectiveness among various predictive models.[16] The study focuses on the development of a Machine Learning based predictive model aimed at screening individuals at high risk of osteoporosis by utilizing chronic disease data, which is crucial for early detection and personalized management of the condition.[17]

The central problem addressed in the study is the accurate and non-invasive prediction of BMD to identify individuals at risk of osteoporosis, particularly focusing on early detection methods that avoid costly and radiation-based diagnostic techniques like DXA and CT scans. This issue is critical in healthcare because osteoporosis leads to bone fragility and fractures, which are significant causes of morbidity, especially among aging populations. Traditional diagnostic approaches are often invasive, expensive, and not always accessible.

The study emphasizes the development and comparison of predictive models using MVR and ANN, aiming to create a robust tool that can estimate BMD using simple patient attributes (age, weight, height). This is important for improving early intervention strategies, minimizing fracture risks, and enabling cost-effective, scalable, and personalized healthcare solutions, especially in resource-limited or high-risk populations.

This study aims to compare the predictive performance of MLR and ANN models in predicting BMD using a clinical dataset. By analyzing patient attributes such as age, weight, and height, the study seeks to develop a robust and accurate model for clinical use. The research explores the potential of ANNs to capture complex non-linear relationships within the data, potentially surpassing the predictive capabilities of MLR. Furthermore, the study investigates the integration of ANNs with optimization techniques like GA to enhance prediction accuracy and efficiency. The findings of this research have the potential to revolutionize BMD prediction, leading to more accurate and timely diagnoses, improved patient outcomes, and a significant reduction in the burden of osteoporosis. Early detection and prevention of osteoporosis are critical public health concerns, especially in aging populations. Current diagnostic approaches primarily rely on measuring BMD using techniques like DXA and CT scans. However, these methods have limitations. Most studies focus on women, neglecting the significant risk in men. Additionally, BMD predictions are often hindered by small sample sizes and a lack of crucial data, such as daily physical activity levels. Furthermore, the use of neural networks for BMD prediction faces challenges related to optimizing learning rules, algorithms, and network architectures. Addressing these gaps is essential for developing more inclusive and accurate predictive models, enabling personalized risk assessments, and improving the efficiency and cost-effectiveness of osteoporosis diagnosis.

Methodology

The study used clinical data of 89 patients, processed through normalization and filtering. It developed and compared MVR and ANN models, with the ANN trained in MATLAB and optimized using a neuron independence study. The study offers a detailed comparative analysis between MVR and ANN for predicting BMD, with the goal of identifying which model provides superior predictive accuracy and practical applicability in clinical settings.

Multi-Variable Linear Regression (MLR)

MLR serves as a widely-used statistical method for examining the associations between multiple independent variables and a single dependent variable. While statistical and mathematical approaches are prevalent, empirical studies can also contribute valuable insights. This study investigates the influence of age, weight, and height on BMD. To achieve this, a multi-variable regression model was developed and evaluated using a dataset of 89 patients. Normalized data for age, weight, and height were entered as independent variables, while BMD was designated as the dependent variable.

The analysis was conducted using Data Fit 9.1 software, employing the regression equation:

$$y = a + b_1x_1 + b_2x_2 + b_3x_3 \quad \ldots (1)$$

where, y = dependent variable; a = intercept; x1, x2, x3 = independent variable; b1, b2, b3 = slope coefficients

This equation was utilized to determine the correlation between the predictor variables and the measured BMD values, enabling the calculation of the intercept and slope coefficients.

Artificial Neural Network (ANN)

ANNs have emerged as a powerful tool for problem-solving, particularly within engineering and medicine, due to their speed and computational efficiency. Inspired by the human brain, ANNs comprise interconnected neurons organized into layers. These networks learn by adjusting the weights of connections between neurons during training, aiming to minimize the difference between the actual output and the network's predicted output. This study utilizes a Feed-Forward Back Propagation algorithm with a single hidden layer for training the ANN. The Tan-Sigmoid and Levenberg-Marquardt algorithms are employed to update the network's bias values and weights. The neural network toolbox in MATLAB 2021 was used for training. The dataset includes three input variables (features) crucial for BMD diagnosis. The network is efficiently trained based on the combined influence of these features. These features can encompass symptoms of osteoporosis and other relevant information that contribute to bone density prediction. To determine the optimal network architecture, a sensitivity analysis was conducted by varying the number of neurons in the hidden layer from 2 to 20. The optimal network was identified based on the minimum Root Mean Square Error (RMSE) and Mean Relative Error (MRE), and the maximum Regression Coefficient (R^2).

Following medical examination and filtration, the dataset was validated by comparing it with BMD measurements obtained from DEXA scans of 2 dry, intact femur bones. This validation demonstrated good agreement between the dataset and actual BMD values.

Multi-variable regression analysis, conducted using Data Fit software, a widely-used statistical tool in engineering and medical fields, yielded the following coefficients: a = 0.0935, b1 = −0.2677, b2 = 0.3469, and b3 = 0.4083. These coefficients were then used in Equation 1 to predict BMD values. The error between actual and predicted BMD values was 123, and the R-squared value was 0.6087.

For the ANN model, the dataset was divided into training (70%) and testing (30%) sets, comprising 62 and 27 data points, respectively. The dataset was sourced from Kaggle and included additional validation using BMD values from DEXA scans of two dry femur bones. The network architecture and algorithms employed are detailed in the methodology section. To optimize the model, multiple training iterations were performed until satisfactory results were achieved. An independent neuron analysis was carried out to identify the optimal number of neurons in the hidden layer, with the range varying from 2 to 20, detailed in Table 1. This table summarizes the performance of the ANN model for predicting BMD based on varying numbers of neurons in the hidden layer. The model was trained using clinical data, and the optimum configuration (12 neurons) yielded the lowest MSE = 0.00188 and highest R^2 = 0.8823, indicating the best predictive accuracy.

The optimal network, identified by its maximum R-squared value of 0.8823, is shown in Fig. 1. The trend demonstrates how both under fitting and overfitting can negatively impact prediction performance. The

Table 1 — Neuron Independence Study: Effect of Varying Hidden Layer Neurons on ANN Performance in BMD Prediction

Sr. No.	No. of Neurons	MSE	R-Squares
1	2	0.001267	0.8122
2	4	0.003975	0.8214
3	6	0.001210	0.8535
4	10	0.003510	0.8759
5	12	0.001880	0.8823
6	14	0.000914	0.8430
7	16	0.001053	0.8764
8	20	0.002996	0.8536

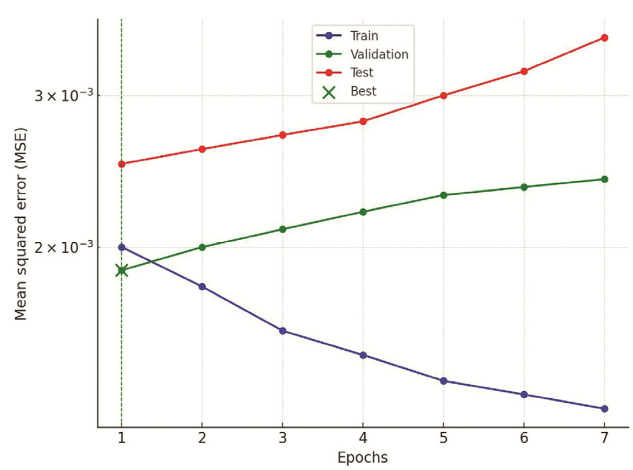

Fig. 1 — ANN Training Progress: MSE Trends Across Epochs Showing Optimal Performance at Epoch 1

optimal balance is achieved at 12 neurons, selected for final model development. The lowest validation error (0.00188) is observed at epoch 1, marked by a green 'X', indicating the best generalization capability of the model. The increasing test and validation errors beyond epoch 1 suggest the beginning of overfitting, justifying the selection of epoch 1 for final model deployment.

The Artificial Neural Network (ANN) model was designed with three input neurons representing age, weight, and height, one hidden layer containing 12 neurons selected through performance optimization, and a single output neuron predicting the Bone Mineral Density (BMD) value. The network was trained using a feed-forward back propagation algorithm with a Tan-Sigmoid activation function and Levenberg-Marquardt optimization. This configuration yielded the highest prediction accuracy with an R^2 value of 0.8823 and a minimal MSE of 0.00188. This ANN architecture, illustrating the connection between input features, hidden neurons, and output has illustrated in Fig. 2.

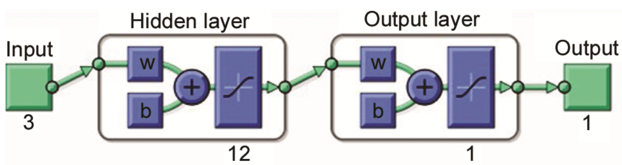

Fig. 2 — ANN Architect for 12 neurons

Results and Discussion

This study demonstrates the feasibility of predicting human BMD based on readily available attributes such as age, weight, and height. Given that BMD significantly influences bone strength, accurate prediction of BMD values holds significant potential for enhancing the prevention and management of osteoporosis and fractures in both men and women.

The four regression plots in the Fig. 3 provide insight into the performance of the ANN model

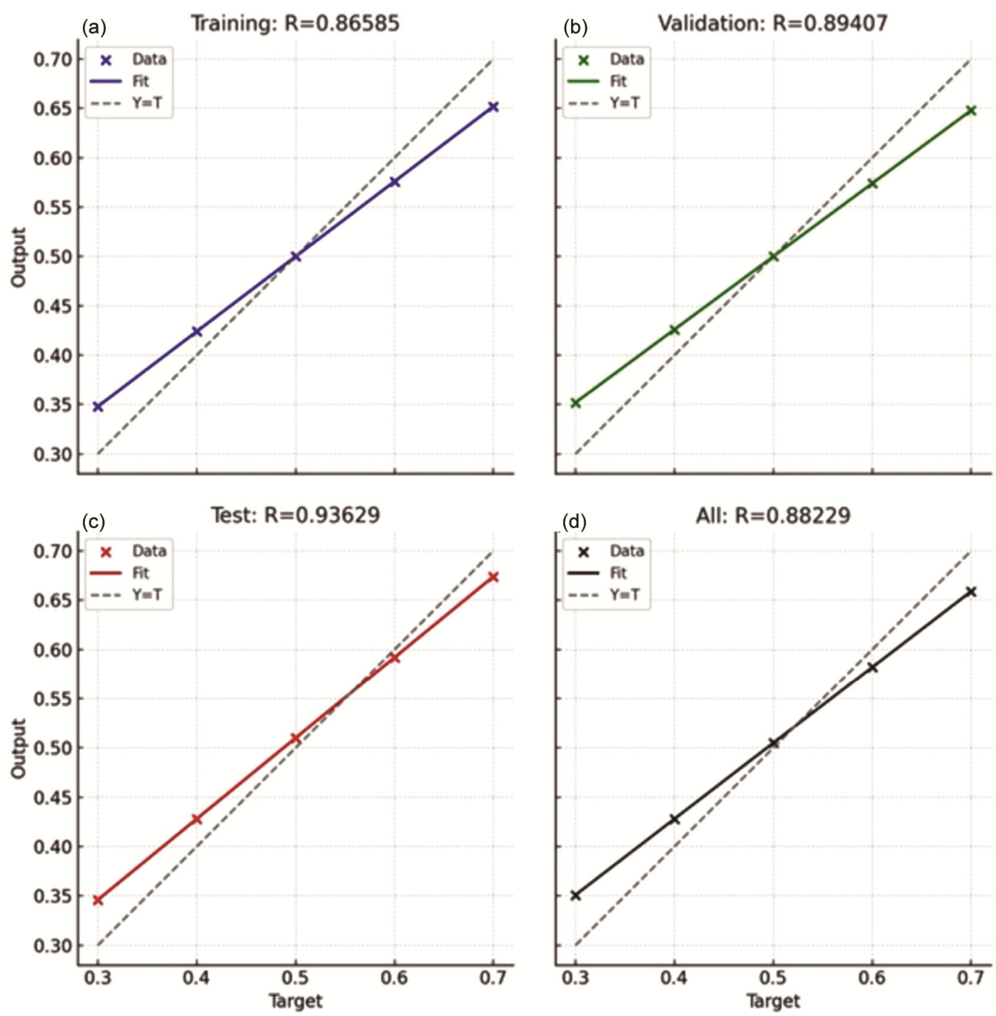

Fig. 3 — Regression result of ANN at R values (a) 0.86585, (b) 0.89407, (c) 0.93629 and (d) 0.88229

developed for BMD prediction. The top-left plot, representing the training phase, shows a correlation coefficient (R) of 0.86585, indicating that the model has successfully learned the underlying relationships within the training dataset. The predicted values closely align with the actual BMD values, as evidenced by the proximity of the data points to the ideal diagonal line (Y = T).

In the top-right plot, the validation results reveal an even higher R value of 0.89407, demonstrating that the model generalizes well to unseen data without overfitting. The bottom-left plot highlights the test phase performance, yielding the highest R value of 0.93629. This signifies exceptional predictive accuracy when the model is applied to entirely new data, reflecting its potential reliability in real-world clinical settings. The bottom-right plot consolidates all data subsets—training, validation, and testing—and presents an overall R value of 0.88229, confirming the model's robustness and consistency. The Regression plots showing the ANN model's performance during training (R = 0.86585), validation (R = 0.89407), testing (R = 0.93629), and combined evaluation (R = 0.88229). The closeness of the data points to the Y = T diagonal line in all four plots indicates strong predictive agreement between actual and predicted BMD values.

A comparative analysis was conducted between multivariate regression and ANNs to evaluate their predictive accuracy. The results unequivocally demonstrate the superior performance of the ANN model, achieving a correlation coefficient of nearly 0.8823, surpassing the R-squared value of 0.6087 obtained from the regression model. While the regression model exhibited reasonable linearity in data representation, the ANN model demonstrated superior linearity. The inherent resemblance of ANNs to the human brain offers a distinct advantage in medical applications, facilitating "prediction" without the complexities often associated with traditional mathematical models.

A comparative analysis presented in Fig. 4 clearly illustrates the superior predictive performance of the ANN model, exhibiting lower prediction errors compared to the regression model. The inherent flexibility and robustness of ANNs, particularly their ability to generalize input data and effectively handle noisy or incomplete data, render them well-suited for modelling complex, non-linear relationships characteristic of biological systems. However, the development of optimal ANN architectures remains a challenge due to the lack of a standardized design methodology. The feed-forward backpropagation network, a widely utilized ANN architecture, was employed in this research.

The ANN model significantly outperforms MVR in terms of predictive accuracy, robustness, and its ability to model non-linear and complex relationships between variables. It also generalizes better across datasets, as shown by regression results on training, validation, and test sets (Fig. 3 and Table 2). The regression model, while more interpretable, shows limitations in capturing intricate patterns inherent in biological data like BMD. Hence, the study concludes that ANN is a more effective and practical tool for non-invasive, data-driven prediction of BMD, with potential applications in early diagnosis and management of osteoporosis in clinical settings.

The outcomes of this research could significantly influence clinical practice by offering a non-invasive, accurate, and data-driven alternative to traditional BMD assessment methods like DEXA scans. By demonstrating that ANNs can predict BMD with high accuracy (R^2 = 0.8823), the study supports the integration of machine learning models into diagnostic workflows. This can enable early identification of osteoporosis, especially in at-risk populations, and help clinicians make timely intervention decisions.

Moreover, the findings encourage the development of intelligent diagnostic tools that require minimal patient data inputs (age, weight, height) to generate clinically reliable BMD estimates. Such tools can be deployed in resource-limited settings where advanced imaging technologies are unavailable. Overall, the research paves the way for cost-effective, scalable, and personalized healthcare solutions, enhancing preventive care and reducing the burden of osteoporotic fractures.

Limitations and Future Scope

Despite the promising outcomes of the present study, several limitations were identified that may affect the generalizability and clinical applicability of the findings. First and foremost, the dataset used comprised only 89 patient records, which, while useful for initial model development, may not be representative of broader, more diverse populations.

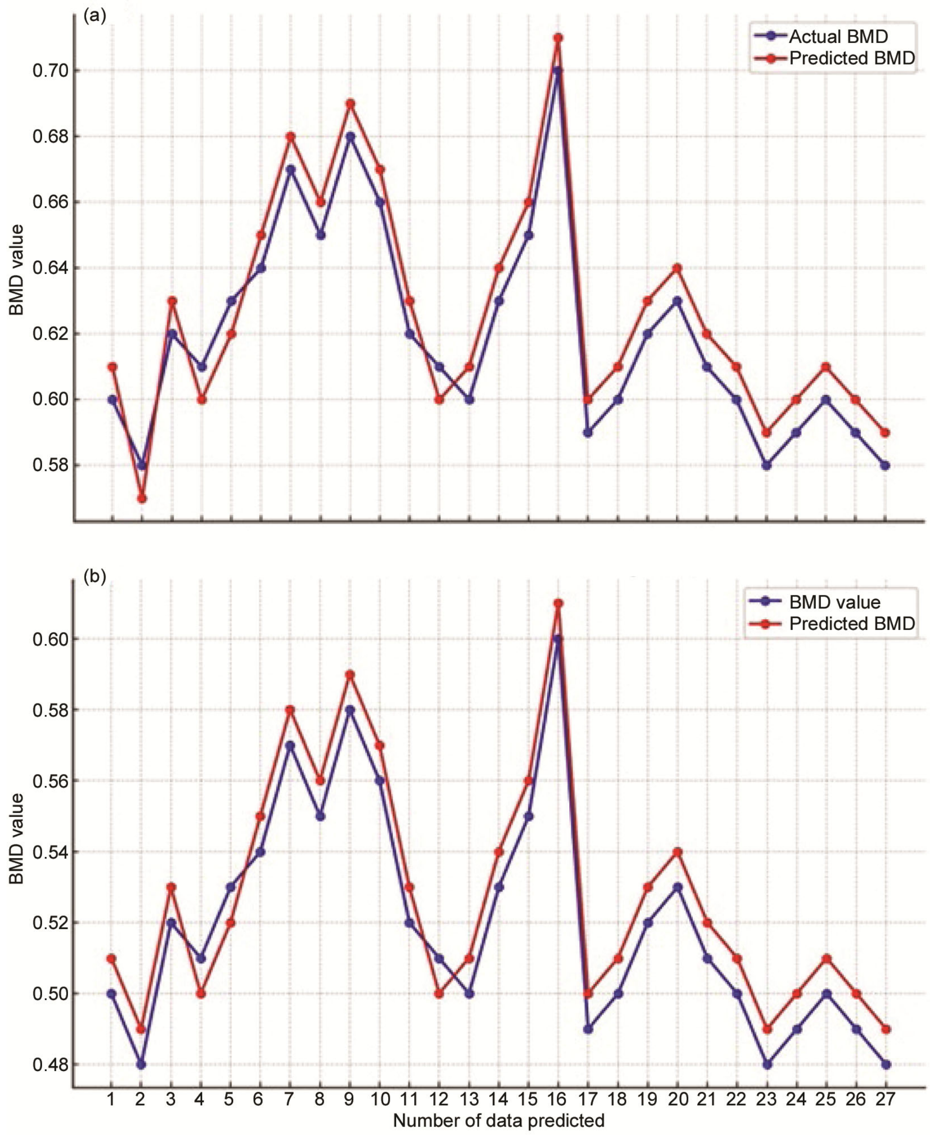

Fig. 4 — Results of Actual v/s Predicted BMD value by: (a) multi-variable regression, (b) ANN

Table 2 — Comparison of MVR and ANN for BMD Prediction

Aspect	Multi-variable regression (MVR)	Artificial neural network (ANN)
Model type	Linear statistical model	Non-linear, biologically inspired computational model
Input variables	Age, weight, height	Age, weight, height
Output	BMD value prediction	BMD value prediction
Performance (R^2 value)	0.6087	0.8823
Error metric (MSE)	Higher than ANN (exact value not specified)	0.00188 at optimal configuration
Network complexity	Simple equation-based model	Feed-forward backpropagation network with 12 hidden neurons
Handling non-linearity	Limited to linear relationships	Capable of modeling complex, non-linear patterns
Tool used	Data Fit 9.1	MATLAB neural network toolbox
Validation method	Compared with actual BMD data from DEXA scans	Same dataset used, validated using regression coefficient and MSE

This restricted sample size can lead to overfitting and limits the robustness of the models when applied to real-world clinical scenarios. Additionally, the study considered only three input variables—age, weight, and height—ignoring other significant factors such as gender, dietary habits, physical activity levels, bone structure, hormonal status, and comorbidities, all of which can have a substantial impact on BMD. Another constraint lies in the model validation process, which was restricted to comparisons with DEXA scans of two dry femur bones, limiting its applicability to in vivo clinical environments. Furthermore, while the ANN model outperformed the MVR model in accuracy, it inherently lacks transparency and interpretability, which are essential for clinical decision-making. The empirical approach to selecting ANN architecture, particularly the number of hidden neurons, also points to the need for more systematic optimization techniques.

To address the current limitations and further improve the predictive framework, several future research directions are proposed. First, expanding the dataset by incorporating records from multiple hospitals, regions, and demographics would enhance the model's generalization capabilities and statistical significance. Future models should also consider a more comprehensive set of input features, including bone-related biomarkers, genetic predisposition, lifestyle factors, and prior fracture history to capture the multifactorial nature of osteoporosis. Another important direction is the integration of hybrid models—specifically combining ANN with optimization algorithms like GA, Particle Swarm Optimization (PSO), or Ant Colony Optimization (ACO)—to automate architecture tuning and improve computational efficiency. Development of real-time, user-friendly diagnostic software or mobile applications based on ANN outputs could bridge the gap between machine learning research and its implementation in healthcare facilities, especially in low-resource settings. Finally, prospective clinical validation through longitudinal studies and clinical trials will be essential to assess the reliability, usability, and ethical implications of deploying such AI-driven tools in routine osteoporosis screening and diagnosis.

Conclusions

This study concludes that Artificial Neural Networks (ANN), particularly with a 12-neuron hidden layer, significantly outperform Multi-variable Regression (MVR) models in predicting Bone Mineral Density (BMD) using basic clinical attributes—age, weight, and height. The ANN model achieved high predictive accuracy (R^2 = 0.8823, MSE = 0.00188), demonstrating its capacity to capture non-linear relationships and deliver reliable results for early osteoporosis detection. However, limitations such as the small dataset size, limited input variables, and validation using only dry femur scans may affect the generalizability of the findings. Future research should include larger, more diverse datasets and incorporate additional clinical factors such as gender, lifestyle, and biomarkers. Integration of ANN with optimization algorithms like Genetic Algorithms (GA) or Particle Swarm Optimization (PSO) is also recommended to improve model performance and automation. These findings lay the groundwork for developing non-invasive, AI-based diagnostic tools that are scalable, cost-effective, and applicable in real-world clinical and resource-limited settings.

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