Diagnosing Osteoporosis in Postmenopausal Females Using Machine Learning and AdaBoostM1 Algorithm Based on Bone Mineral Density

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Received: January 20 2024; Revised: March 17 2024; Accepted: March 17 2024; Published Online: May 18 2024

ABSTRACT

Osteoporosis, also known as low bone mineral density (BMD), is a serious health concern, especially for women who have gone through menopause in community settings. This condition weakens the bones and increases the risk of fractures. Women who have gone through menopause are more susceptible to osteoporosis due to hormonal changes. Therefore, it is crucial to identify the condition early to start preventive treatments and reduce the risk of fractures. To address the challenges of diagnosing low BMD in postmenopausal women in community settings, this study proposes a method that combines machine learning with the AdaBoostM1 algorithm, which has shown promising results. Data acquisition, data preprocessing, data training, model testing, and model prediction and evaluation are integral phases of the operational dynamics of our model in osteoporosis diagnosis. This approach recommends increasing screening initiatives and educating patients as strategies to improve early detection and management of the disease. The analysis method used achieved an impressive accuracy rate of approximately 88.8% on the dataset it was applied to. The area under the curve was 0.87, the true positive rate was 88%, and the F1 measure was 0.88. By using accurate diagnostic techniques and providing proactive community care, the incidence of osteoporotic fractures can be significantly reduced, thus improving the quality of life for this vulnerable population.

KEYWORDS

bone mineral density, osteoporosis, machine learning, true positive rate, diagnosis of osteoporosis, disease classification, AdaBoostM1 algorithm, community healthcare, postmenopausal women, medical imaging analysis, bone fracture

INTRODUCTION

Osteoporosis is a common condition becoming more prevalent as the world’s population ages. This disorder leads to low bone mineral density (BMD) and a degradation of the bone’s microstructure, increasing the risk of fractures (Friedman, 2006). BMD measures the amount of calcium and phosphorus in bone, used to diagnose osteoporosis, assess treatment effectiveness, and predict fracture risk, with low density. Osteoporosis-related hip, spine, and wrist fractures can cause diseases that reduce the patient’s quality of life and, in severe cases, increase the risk of mortality (Dempster, 2011). Due to the rising global population and life expectancy, osteoporosis is becoming a more serious issue. Over 200 million people worldwide are believed to suffer from osteoporosis, and recent data from the International Osteoporosis Foundation indicate that one in three women and one in five men over the age of 50 are likely to experience osteoporotic fractures (Shevroja et al., 2023). This disease progresses silently, often beginning with a low-energy fracture of a long bone or vertebrae. Early signs are often overlooked, leaving the disease undiagnosed and untreated, which is expected to continue given the asymptomatic early stages of the disease. To determine BMD, dual-energy x-ray absorptiometry is commonly used, which provides a T-score to indicate the BMD values (Long et al., 2023). However, despite being the most reliable method, it is not often used in community settings due to its high cost and operational complexity.

Recent research has shown that dental panoramic radiographs (DPRs) can be a cost-effective option for digital
imaging-based osteoporosis screenings. This is particularly important as women have a high-risk ratio for the lifetime probability of fracture, as Table 1 indicates (Long et al., 2023). Several studies have demonstrated the feasibility of using DPRs for BMD assessment and osteoporosis screening. Additionally, panoramic radiation is frequently used in dental treatments for elderly patients (Wong et al., 2022). Traditional methods for identifying osteoporosis have relied on manually classified feature indexes, but this approach has limitations due to the low-order representation of the heterogeneous patterns in radiographic images.

In the field of image classification, traditional machine learning (ML) algorithms such as support vector machine (SVM) and fuzzy classifiers require a lot of preprocessing tasks such as image normalization and area of interest (ROI) segmentation (Caffarelli et al., 2022). This creates doubts about the repeatability of the classification process. Artificial intelligence (AI) is a vast field built on a foundation of mathematical and scientific disciplines. ML is a notable subset of AI that aims to enable machines to learn through feedback, experience, and input datasets. This subset further divides into deep learning (DL) and neural networks, with the ultimate goal of developing systems that can accurately process new and untouched datasets (Ullah et al., 2022).

The use of ML in analyzing medical images has emerged as a promising and rapidly growing subset of AI. This field has a wide range of applications in image processing, which helps in detecting illnesses, aiding in computer-aided diagnostics, and advancing computer vision techniques (Santos et al., 2019). The development of new imaging technologies such as multi-slice computed tomography, positron emission tomography, tomosynthesis, magnetic resonance imaging, tomography, and diffuse optical tomography necessitates the use of sophisticated ML techniques to further the analysis of medical images.

ML works on a collection of methods that are tailored to identify patterns in data autonomously, thereby aiding in making informed decisions in ambiguous situations and anticipating future data trends. This methodology relies on a data-driven decision-making process, which significantly reduces the need for human intervention by utilizing training data analysis to make predictions on new data inputs (Tantalaki et al., 2019). In recent years, various ML strategies have been deployed to predict and identify diseases. For instance, natural language processing is used to analyze electronic health records to extract valuable data for disease forecasting and identification (Van Vleck et al., 2019).

In the medical field, it is important to have transparency in decision-making. Explainable AI techniques such as SHapley Additive exPlanations help in understanding the predictions given by ML models. Additionally, generative models such as generative adversarial networks can be used to create artificial medical images, which can improve the accuracy of results. These techniques can work together to address specific issues and datasets (Ahmed et al., 2020).

AI technology plays a crucial role in the medical domain, especially in image data analysis. It helps with disease detection, prediction, diagnosis, and classification, enables informed decision-making, and optimizes treatment strategies (Sebastian and Peter, 2022). For instance, AI can detect tumors from medical imagery and facilitate early intervention. AI-based diagnostic models can identify underdiagnosed or undertreated individuals and recognize rare diseases (Rabaan et al., 2022).

A study by Singh et al. has shown that ML algorithms such as SVM, k-nearest neighbors, Naïve Bayes, and decision tree are useful in detecting and diagnosing diseases such as cancer, diabetes, and heart attacks (Singh et al., 2021). Another study found that DL technology can be applied to disease diagnosis categorization, using five attributes to improve decision analysis in illness diagnostics (Hussain et al., 2023). Further research has demonstrated the effectiveness of ML techniques in identifying and classifying bone fractures, achieving an accuracy rate of 85% and a 0.86 area under the curve (AUC) through various DL approaches including detection, enumeration, and localization strategies (Sahin, 2023).

This research aims to diagnose osteoporosis in postmenopausal women using BMD. Below are the contributions of our research:

- This study aims to increase awareness of osteoporosis in postmenopausal women and highlights the unique challenges and risks faced by this demographic. Diagnostic frameworks and strategies will be developed specifically for community healthcare settings to achieve this objective. These frameworks will emphasize the crucial role of readily available methods such as clinical risk assessments and fracture risk prediction models, especially in resource-strained areas.

- In addition, this research will focus on innovative diagnostic techniques, encouraging the use of automated detection and refined risk assessment models to improve diagnostic capabilities. The study will also underscore the importance of patient education in raising awareness among postmenopausal women about osteoporosis, its risk factors, and the critical role of early detection and management.

- Finally, this study seeks to alleviate the societal and economic burden associated with osteoporotic fractures by promoting timely diagnosis and intervention in local settings. Its findings will have significant public health implications.

### Table 1: Remaining lifetime probability of fracture (%) in men and women risk ratio.

<table>
<thead>
<tr>
<th>Type of fracture</th>
<th>Women</th>
<th>At 50 years</th>
<th>Risk ratio</th>
<th>Women</th>
<th>At 80 years</th>
<th>Risk ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hip</td>
<td>10.7</td>
<td>22.9</td>
<td>2.1</td>
<td>19.3</td>
<td>9.1</td>
<td>2.1</td>
</tr>
<tr>
<td>Forearm</td>
<td>4.6</td>
<td>20.8</td>
<td>4.5</td>
<td>8.9</td>
<td>1.6</td>
<td>5.6</td>
</tr>
<tr>
<td>Proximal humerus</td>
<td>4.1</td>
<td>12.9</td>
<td>3.1</td>
<td>7.7</td>
<td>2.5</td>
<td>3.1</td>
</tr>
<tr>
<td>Spine</td>
<td>8.3</td>
<td>15.1</td>
<td>1.8</td>
<td>8.7</td>
<td>4.7</td>
<td>1.9</td>
</tr>
<tr>
<td>Any of these</td>
<td>22.4</td>
<td>46.4</td>
<td>2.1</td>
<td>31.7</td>
<td>15.3</td>
<td>2.1</td>
</tr>
</tbody>
</table>
The article is organized into several sections. The Materials and Methods section reviews the related works in the field and provides details on the methodology of the proposed system. The Results and Discussion and Comparative Discussion sections delve into the results and discussion based on the research findings. Finally, the Conclusion and Future Work section offers the conclusion drawn from the study and outlines potential avenues for future work.

**MATERIAL AND METHODS**

**BMD based on ML**

The high-level architecture of a model is illustrated in Figure 1. It uses ML to determine BMD. The model consists of three layers, each with three modules.

The first layer begins with the dataset module, which contains all relevant information on bone fractures. The next module, data preprocessing, is crucial to the study as it is responsible for cleaning and annotating the data. The final module in this layer focuses on data training, where the dataset is trained and prepared for the next layer. In the second layer, we start with data testing by analyzing the dataset based on the training data. The data are then transferred to the model module where predictions are made based on previously established patterns. To ensure the model’s effectiveness and reliability, it is essential to rigorously evaluate its performance using a standardized dataset. Our analysis utilized a publicly available dataset from Kaggle specializing in bone detection (Kaggle, 2024).

The dataset provided is divided into two folders, one containing control data and the other containing data for various circumstances. The comma separated values files in each folder record the details of each patient, including their ID, age, fracture details, weight, height, and medication history. The actigraphy records have been compiled over several years, making this dataset a rich repository of patient information. The process of creating an ML model for osteoporosis diagnosis is presented in Figure 2, in the form of a knowledge process diagram. This diagram showcases the integral phases of data preparation, model training, and model assessment, providing a conceptual roadmap for medical professionals to better understand the operational dynamics of these models in osteoporosis diagnosis. Detailed
Stage 1—data acquisition

The first step in studying BMD and osteoporosis is to collect relevant data such as age, gender, and medical history. This can be done through clinical research, surveys, and examination of medical records. For our study, we obtained the necessary data from Kaggle, a well-known open-source dataset archive. This dataset includes 169 rows and 9 columns of various attributes, including a unique ID for each patient, age, a classification label indicating whether the patient has experienced a fracture, weight in kilograms, and height in centimeters. Other details such as medication, waiting time, and BMD values were also included, providing a comprehensive insight into each patient’s health status. We created a graphical representation of gender-wise BMD distributions in Figure 3, where blue dots represent male data points and pink dots represent female data points. The graph highlights a discernible pattern: females are more affected by BMD variation than males, particularly postmenopausal females. This underscores the serious impact of osteoporosis in this demographic.

Stage 2—data preprocessing

The next step in the ML process is data preprocessing, which is a crucial step that involves cleaning the dataset by removing outliers and transforming the data into a format suitable for ML algorithms. This stage includes several techniques, such as data cleaning, data transformation, data integration, and dimensionality reduction. Data cleaning involves removing noisy and irrelevant information from the dataset to ensure more accurate analyses. Data transformation involves converting data values from one format to another to ensure consistency and compatibility with the analytical tools used. The data integration technique is applied to eliminate data duplication, ensuring a single and correct representation of each data point. Dimensionality reduction, on the other hand, simplifies the data representation by converting three-dimensional data into two-dimensional data, while maintaining the essential characteristics and reducing complexity and storage requirements. Figure 4 illustrates the workflow of the data preprocessing stage, showing the systematic progression from the raw data to a refined format ready for analysis.

Stage 3—data training

During this stage, the data that have been preprocessed go through training using a chosen ML algorithm. There are many ML algorithms available, each with its strengths and weaknesses. The choice of algorithm, in this case, AdaBoostM1, depends on the specifics of the dataset and the analysis objectives. This crucial step involves inputting the preprocessed data into the algorithm, allowing it to learn the complex relationships between BMD and osteoporosis indicators. The chosen attributes within the dataset play a critical role in determining the effectiveness of the ML algorithm and, consequently, the accuracy of the osteoporosis identification process. Figure 5 demonstrates the importance of selecting attributes that are directly aligned to accurately identify osteoporosis through analysis.

Stage 4—model testing

It is crucial to ensure the performance of an ML algorithm. This can be accomplished by conducting a thorough evaluation using a separate dataset that is not used during the

![Figure 3: Gender-wise BMD distributions. Abbreviation: BMD, bone mineral density.](image)

![Figure 4: Data preprocessing steps.](image)
training phase. This approach helps to prevent overfitting to the training data and enables the model to perform well on new and unseen data.

**Stage 5—model prediction and evaluation**

After the testing phase, the ML algorithm has been validated and is now ready to be deployed in a clinical setting to help identify osteoporosis. Fine-tuning the algorithm is critical, and it involves adjusting hyperparameters, which are the settings that control the algorithm’s behavior. These adjustments can significantly improve the algorithm’s performance, leading to a more accurate diagnosis of osteoporosis. The field of ML is continually evolving, and with advancements, there are improved capabilities for detecting osteoporosis. This facilitates the development of novel and more effective strategies for identifying and managing the condition.

**RESULTS AND DISCUSSION**

The data obtained from this process can help medical professionals make more informed decisions about the care and treatment of their patients. These data can be used as a precise tool to distinguish between individuals with fractures and those without. Ultimately, it can lead to a higher standard of medical care and better patient outcomes. In Figure 6, a graph shows the correlation between age and the likelihood of fractures. The x-axis represents age, while the y-axis shows the risk of experiencing a fracture. The graph illustrates the increasing probability of fractures with age, with the red zone indicating higher risk. According to the study, the risk of fractures increases with age. For example, a 19-year-old has a 35.81% risk, while a 76-year-old has a substantial 88.75% risk.

This is because as people age, their bones become more brittle and weaker, making them more susceptible to fractures in the case of falls and other injuries. As a result, senior citizens are at an increased risk of experiencing bone fractures.

The line graph shown in Figure 7 displays the relationship between true positive rate (TPR) and false positive rate (FPR) at various thresholds. TPR indicates the percentage of correctly identified positive cases, while FPR indicates the percentage of negative cases that are incorrectly identified. The graph reveals that increasing the threshold correlates with an increase in TPR, which improves the model’s accuracy in identifying positive cases. However, raising the threshold also increases the FPR, which means that the model is more likely to label negative instances inaccurately. Therefore, establishing the optimal threshold is crucial to achieving a balance between TPR and FPR, thereby enhancing the model’s ability to distinguish between positive and negative cases.

In this scenario, a threshold of 0.5 is found to be appropriate for instructing the model to classify a case as positive. This means that the model will classify a case as positive if the probability of it being positive exceeds 0.5. This mechanism is closely related to precision and recall. Precision refers to the ratio of correctly identified positive instances, while recall represents the fraction of total positive instances that have been correctly identified.

As shown in Figure 8, the cost curve represents the performance of a binary classifier in evaluating the financial implications of diagnostic errors. There are two kinds of incorrect diagnoses: false positives, where individuals are incorrectly identified as having a fracture, and false negatives, where individuals who have a fracture are erroneously declared fracture-free. Each type of error has
associated costs. The analysis of the cost curve reveals that, for this model, the financial consequences of false positives are less severe than those of false negatives. This suggests that the model is more likely to inaccurately identify individuals as fracture patients rather than falsely clearing individuals who have a fracture.

The following analysis has revealed that the model used tends to be overly cautious in its predictions, which may result in false alerts. Improving the model’s specificity can enhance its predictive capabilities, reducing unnecessary alerts and focusing on actual fracture cases. By fine-tuning the model, accurate and cost-effective BMD assessments can be conducted for osteoporosis diagnosis.

Figure 9 displays the results of a non-parametric statistical method called the Nemenyi test, which compares the means across different groups to identify significant differences. This test is crucial for understanding the pairwise comparisons among various groups. The diagram shows a value 1 along the diagonal line, indicating an equivalence between the values represented on the x and y axes. This analytical tool was used to evaluate the BMD dataset, comparing individual columns to determine their accuracy.

Figure 7: Relationship between true positive rate (TPR) and false positive rate (FPR).

Figure 8: Cost curves used for performance evaluation.
in identifying the essential characteristics for osteoporosis diagnosis. The test provides an invaluable landscape of the efficacy of different features in osteoporosis detection, serving as a compass to identify the most potent identifiers in the dataset.

The receiver operating characteristic (ROC) curve, shown in Figure 10, is a tool used to evaluate binary classifiers’ effectiveness in distinguishing between two categories—in this case, fractures and no fractures. The curve is based on TPR and FPR. TPR measures the proportion of positive instances that are correctly identified, while FPR represents the proportion of negative instances that are incorrectly classified as positive.

Ideally, a perfect classifier would achieve a TPR of 1 without any false positives, resulting in an FPR of 0. However, this equilibrium is practically impossible due to the inherent trade-off between TPR and FPR. The AUC, which represents the model’s overall performance, is 0.855 in this case. An AUC of 1 indicates a perfect classifier, while an AUC of 0.5 represents a random classifier. An AUC of 0.855 indicates a highly capable classifier, although there is still room for improvement. This could potentially be achieved by focusing on reducing the FPR to improve the model’s specificity in identifying fractures.

Figure 11 displays a scatter plot illustrating the relationship between BMD and fracture status. Blue points represent individuals without fractures, while red points represent individuals with fractures. The decision boundary, a delineating line used by the model to determine an individual’s fracture status, is at the center of the plot. Analyzing the plot reveals that the model has effectively predicted the fracture status of most individuals. However, there are instances of
misclassification: the model incorrectly attributed fracture status to 9 individuals who did not have fractures (false positives) and failed to identify fractures in 11 individuals who did have them (false negatives).

The overall accuracy rate is about 88.1657%, which means that over 88% of the population analyzed has been predicted correctly. Although the accuracy rate is high, there is still room for improvement in reducing the number of false positive and false negative rates. One can adjust the classification algorithm’s parameters to improve the model’s accuracy in identifying fractures accurately to enhance its sensitivity and specificity. Depending on the application of this model, different approaches to tuning these parameters could be more beneficial to optimize the model’s predictive accuracy.

The graph shown in Figure 12 demonstrates the relationship between the decision threshold and the predicted probability of a positive classification for a logistic regression model. In this case, the positive classification refers to patients with fractures, while the negative classification refers to those without fractures. The x-axis represents the decision threshold, while the y-axis represents the probability of a positive classification.
predicted probability of a positive classification. The curve in the graph was generated using a threshold of 0.4743. This means that patients were classified as having a fracture if the predicted probability equaled or exceeded this value.

The graph shows that the model correctly identified a significant number of fracture cases. However, there were still some instances of misdiagnosis, which suggests that the decision threshold may not be optimal. The test results provide further insights into the model’s effectiveness. The classification accuracy was found to be 88.1657%, indicating that over 88% of patients were correctly classified. The data also showed that the model had a sensitivity of 63.91% and a specificity of 99.2308%. This means that the model correctly identified 63.91% of patients with fractures and 99.2308% of those without.

Although the model’s specificity is commendably high, indicating the accurate classification of negative cases, there is still considerable room for improving its sensitivity to classify more positive cases correctly. This would augment the model’s overall efficacy.

Figure 13 presents a confusion matrix that is a potent tool in medical diagnostics. The values classified under “a” represent cases without fractures, while those categorized under “b” signify cases with fractures. Specifically, we observe 109 and 10 instances under category “a,” alongside 9 and 41 instances recorded under category “b.” This detailed breakdown gives healthcare professionals critical insights for informed analysis and decision-making.

Figure 14 presents the results of an ML test designed to divide patients into two groups: those with fractures and those without. To determine whether a patient has a fracture, a threshold of 0.4743 was established, which was optimized to improve the cost–benefit curve. This curve balances between accurately identifying patients with fractures (true positives) and mistakenly flagging patients without fractures (false positives). The confusion matrix shows the actual versus predicted classifications for the patients in the test group. The diagonal cells indicate successful classifications, while the off-diagonal cells show classification errors. The accompanying cost matrix shows the financial consequences of each type of misclassification, indicating that misdiagnosing a patient with a fracture could be 20 times more expensive than correctly identifying them as fracture-free.

The model achieved a classification accuracy of 88.1657% in terms of performance metrics, indicating the proportion of patients classified correctly. It demonstrated a sensitivity rate of 63.91%, indicating the correctly identified fracture
cases, and an impressive specificity of 99.2308%, which refers to the correct identifications of non-fracture cases. The results confirm the model’s ability to identify patients who do not have fractures, highlighting its significant aptitude in this criterion. However, there is still room for improvement. Reducing the occurrence of false positives would increase the model’s accuracy further.

Figure 15 depicts a bubble chart that shows the connections between BMD, gender, medication usage, and the risk of sustaining fractures. Each bubble in the chart represents a unique patient, with the size of the bubble indicating the number of patients falling into a particular category. The chart’s color coding uses red to indicate patients who have suffered fractures and green for those who have not, making it easy to see each patient’s fracture status.

The chart directly correlates decreasing BMD levels and increasing fracture risks. It means that as BMD levels decrease, the likelihood of experiencing a fracture goes up. The chart also shows that women are more likely to experience fractures than men, which could be due to generally lower BMD levels in women.

Moreover, the chart highlights the significant role of medication in reducing fracture risks. Patients under medication show a reduced propensity for fractures, presumably due to the medication’s effectiveness in increasing BMD and slowing bone degradation. The insights from this chart highlight that BMD, gender, and medication are critical factors that influence fracture risks. Healthcare professionals can use these data to develop preventive strategies and identify individuals with a higher risk of fractures, leading to a more informed and proactive approach to patient care.

Table 2 provides a detailed breakdown of the accuracy by class, which is essential for evaluating the performance of the classification model. The table assesses the ability of the model to distinguish between cases labeled as “fracture” and “no fracture.” The model shows a high TPR of 0.916 and a low FPR of 0.18 for the “no fracture” classification, resulting in a precision score of 0.924 and a recall score of 0.916. Currently, the F-measure, which is also known as the precision-to-recall ratio, is at 0.92.

The ROC area shown in Figure 16 represents the model’s overall performance, with a score of 0.87. The weighted average across all classes indicates an accuracy rate of 0.888, demonstrating that the model accurately identifies “fracture” and “no fracture” scenarios. These metrics provide valuable insights into the model’s performance, making it an essential tool for clinical decision-making.

Table 2: Detailed accuracy by class.

<table>
<thead>
<tr>
<th>Attribute</th>
<th>TP rate</th>
<th>FP rate</th>
<th>Precision</th>
<th>Recall</th>
<th>F-measure</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>No fracture</td>
<td>0.916</td>
<td>0.18</td>
<td>0.924</td>
<td>0.916</td>
<td>0.92</td>
<td>0.87</td>
</tr>
<tr>
<td>Fracture</td>
<td>0.82</td>
<td>0.084</td>
<td>0.804</td>
<td>0.82</td>
<td>0.812</td>
<td>0.87</td>
</tr>
<tr>
<td>Weighted average</td>
<td>0.888</td>
<td>0.152</td>
<td>0.888</td>
<td>0.888</td>
<td>0.888</td>
<td>0.87</td>
</tr>
</tbody>
</table>

Abbreviations: AUC, area under the curve; FP, false positive; TP, true positive.
CONCLUSION AND FUTURE WORK

This study examines the characteristics of osteoporosis, a systemic disease that weakens bone strength and increases the risk of fractures, especially in the hips, spine, and wrists, due to the degradation of BMD. This not only triggers other illnesses but also reduces the quality of life, and in severe cases, it can even increase the mortality rate. In community settings, it is essential to address the critical healthcare challenge of detecting osteoporosis and low BMD in

Table 3: Comparison of osteoporosis screening results with existing techniques.

<table>
<thead>
<tr>
<th>Author</th>
<th>Technique</th>
<th>AUC</th>
<th>F-measure</th>
<th>TPR (%)</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shi et al. (2021)</td>
<td>CNN</td>
<td>0.61</td>
<td>—</td>
<td>—</td>
<td>85</td>
</tr>
<tr>
<td>Dzierzak and Omiotek (2022)</td>
<td>Radial function</td>
<td>0.829</td>
<td>—</td>
<td>51.0</td>
<td>83.3</td>
</tr>
<tr>
<td>Wu et al. (2023)</td>
<td>AdaBoost</td>
<td>0.814</td>
<td>0.679</td>
<td>—</td>
<td>74.4</td>
</tr>
<tr>
<td>Abedi et al. (2022)</td>
<td>CART</td>
<td>0.868</td>
<td>—</td>
<td>—</td>
<td>86</td>
</tr>
<tr>
<td>Liu et al. (2022)</td>
<td>VGG16</td>
<td>0.74</td>
<td>—</td>
<td>—</td>
<td>80</td>
</tr>
<tr>
<td>Wu et al. (2023)</td>
<td>KNN</td>
<td>0.632</td>
<td>0.518</td>
<td>—</td>
<td>65</td>
</tr>
<tr>
<td>Jang et al. (2021)</td>
<td>VGG16</td>
<td>0.74</td>
<td>—</td>
<td>91.1</td>
<td>81.2</td>
</tr>
<tr>
<td>Proposed model</td>
<td>VGG16</td>
<td>0.875</td>
<td>0.888</td>
<td>88</td>
<td>88.75</td>
</tr>
</tbody>
</table>

Abbreviations: AUC, area under the curve; KNN, k-nearest neighbors; TPR, true positive rate.
postmenopausal women. The proposed model aims to be a robust tool in predicting osteoporotic fractures, which will significantly positively impact an individual’s quality of life.

Innovative solutions such as telemedicine and mobile screening units can enhance accessibility to screenings. Community-based osteoporosis screening initiatives can promote greater awareness and facilitate the early identification of at-risk individuals. Additionally, developing and validating more accurate and personalized risk assessment models remains a priority. Incorporating elements beyond the conventional clinical criteria, such as genetic markers and lifestyle factors, can be a prospective pathway for advancement in early detection strategies. The proposed system can be upgraded with the Modified MixNet Model (Ahoor et al., 2023) to create an automated classification system for osteoporosis in postmenopausal females. Pre- and postmenopausal women are also prone to ovarian cancer (Ziyambe et al., 2023). This study project can be extended to address this issue as well.

**FUNDING**
The authors extend their appreciation to the King Salman Center for Disability Research (funder ID: http://dx.doi.org/10.13039/501100019345) for funding this work through Research Group no. KSRG-2023-443.

**SOURCE/DATA AVAILABILITY**
The dataset is secondary data and is available online at https://www.kaggle.com/datasets/amarsharma768/bmd-data.

**ACKNOWLEDGMENTS**
The authors extend their appreciation to the King Salman Center for Disability Research (funder ID: http://dx.doi.org/10.13039/501100019345) for funding this work.
REFERENCES


