An Approach for Prediction of Osteoporosis and Its Association with Osteoporotic Fracture Risk Using Machine Learning

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***Abstract*—** *Osteoporosis is a prevalent condition characterized by decreased bone mineral density and increased fracture risk, representing a significant global health concern, especially in aging populations. Early detection and risk stratification are critical for preventing fractures and reducing healthcare burdens associated with osteoporosis. A dataset of 1,958 individuals with demographic, lifestyle, and clinical features is analyzed, with the data explicitly split into 75% for training and 25% for testing. Three machine learning models—Random Forest, Decision Tree, and Multilayer Perceptron (MLP)—are developed and evaluated by using accuracy, precision, recall, F1-score, ROC-AUC, and balanced accuracy. The Decision Tree model achieved the highest accuracy (0.884) and perfect precision (1.0), while Random Forest and MLP models demonstrated competitive performance with ROC-AUC values of 0.876 and 0.875, respectively. Feature importance analysis confirmed age as the most influential predictor, with prior fractures, low BMI, glucocorticoid use, and smoking contributing to osteoporosis risk classification. On another side, to determine the degrees of fracture risks and their categories using the Fracture Risk Assessment Tool (FRAX) medical tool.*

***Keywords*— Osteoporosis; Machine Learning; DEXA; Osteoporotic fracture; FRAX tool; Big Data.**

I. INTRODUCTION

As people age, their risk of developing diseases increases. One of the most prominent of these diseases is osteoporosis, which affects the skeletal system and leads to a loss of bone mass, erosion of fine bone tissue, and a decrease in its quality, leading to an increased risk of fracture. [1] According to the International Osteoporosis Foundation, one-third of elderly women and one-fifth of elderly men suffer from osteoporotic fractures. [2] This leads to an increase in cases of disability and death resulting from this disease. According to the World Health Organization, osteoporosis is the second largest medical problem after cardiovascular diseases. The consequences of this disease are significant, as the patient requires continuous medical care in the hospital. Those afflicted with this disease are exposed to the risk of fractures, such as hip fracture, which increases the risk of death, as 25% of patients die within one year. Early detection of this disease can reduce the likelihood of fractures and avoid the medical costs of surgical operations [3]. With age, the likelihood of developing this disease increases, as about 10% of women at the age of sixty are afflicted with it, while the percentage increases to 20% at the age of seventy, 40% at the age of eighty, and two-thirds of women at the age of ninety. Half of fractures occur at the age of seventy-five [4]. There are many reasons that can lead to developing this disease, such as the use of certain medications or smoking, hormonal imbalance, calcium deficiency, vitamin D deficiency, physical activity, gastrointestinal diseases, kidney patients, genetic factors, and rheumatoid arthritis [3]. One of the most prominent tools used in the diagnostic process is bone mineral density using dual-energy X-ray absorptiometry in the lumbar spine and bilateral hip joint, where the results are as follows:

$$T \leq -2.5 \text{ osteoporosis}, -2.5 < T \leq -1 \text{ osteopenia}, T > -1 \text{ Normal} \quad (1)$$

However, the relative availability and usefulness of DEXA in diagnosing osteoporosis is low [5]. This method is characterized by being unsuitable for early detection, in addition to the high purchase price of the device and its expensive maintenance, which makes it impractical in many healthcare institutions. There were many alternative methods, such as "quantitative computed tomography" and "radio absorptiometry", although they are still expensive and costly [6]. Also, the relationship between these diseases and their association makes prediction difficult and complex using traditional statistical methods [3]. From this standpoint, we

thought of developing a prediction system through prediction algorithms for osteoporosis cases through historical data derived from medical results and by adopting machine learning algorithms: decision tree (DT), random forest (RF), and MLP [7].

To demonstrate the importance of the topic of osteoporosis, we can do so through statistics. [8] In the year 2000, the number of fractures around the world due to osteoporosis was nine million cases, 1.6 million of which were in the hip, 1.7 million fractures in the forearm, and 1.4 million fractures in the vertebrae [9] with Europe constituting the largest proportion at 35% of the total number. These cases generated a burden estimated at nearly six million years of disability-adjusted life years (DLAYS). They constitute a critical health challenge that requires prevention and treatment strategies that surpass many common diseases [10].

Osteoporosis diagnosis and fracture risk assessment are confronted with several challenges. Despite DEXA being the gold standard for measuring bone mineral density (BMD), it faces barriers such as high equipment costs, the need for specialized devices and trained professionals, limited availability in rural or resource-constrained areas, and delays in diagnosis. Alternative methods also present limitations: conventional X-rays can detect fractures but fail to measure bone density or enable early detection; quantitative ultrasound (QUS) provides indirect assessments of bone quality but lacks reliability and often requires DEXA confirmation; peripheral DEXA devices are more accessible but less predictive of fracture risk and inadequate for monitoring treatment; and laboratory tests, while useful for evaluating metabolic factors, cannot independently diagnose osteoporosis. Furthermore, fracture risk assessment based solely on BMD has its own shortcomings, including incomplete evaluation of risk by neglecting critical clinical factors, limited predictive accuracy since fractures often occur above the osteoporosis threshold, continued accessibility and cost issues, and the absence of systematic integration of demographic, lifestyle, and clinical risk variables. These challenges collectively emphasize the pressing need for alternative, accessible, and comprehensive methods to improve the early prediction of osteoporosis and associated fracture risks. Where the study aims to apply specific machine learning algorithms to a historical dataset and evaluated their predictive results for those with and without osteoporosis (normal, abnormal cases) for determined the best of them, as a first step in developing a future model for using with other datasets by specialists. Then divide the fracture risk of participants in the data set through extracted values and the threshold into three categories: high risk, medium risk, and low risk.

II. LITERATURE REVIEW

In this section, we will review the latest findings in our research field, which include the topic of osteoporosis prediction using machine learning techniques. The most important of these studies are as follows:

Lin et al. (2022) conducted a study using machine learning techniques to develop predictive methods for the outcomes of drug treatment for osteoporosis. This study aimed to support treatment decisions and improve treatment effectiveness. The study relied on electronic data from Wanfang Hospital between 2011 and 2018, using the T-score index. This study relied on the application of four main algorithms: random forest (RF), artificial neural network (ANN), logistic regression, and support vector mechanism (SVM). This algorithm relied on 12-18 relevant genetic traits from 33 clinical variables. The models were trained using cross-validation and further evaluated on a separate test dataset. Model performance was evaluated using evaluation metrics (precision, recall, F1 score, Auroc, etc.). The study concluded that machine learning-based models show promise as effective tools to support personalized drug therapy in osteoporosis, which may lead to improved treatment outcomes and reduced disease progression. The researchers concluded that more diverse data from multiple centers should be collected and extensive external validation of the models should be performed [11].

Bui et al. (2022) developed machine learning predictors of osteoporosis risk using a study of Vietnamese women over the age of 50. The researchers used cross-sectional clinical data and four common algorithms, such as SVM, RF, neural network, and LR. The researchers tested two cases, using original continuous variables and binary transformed features to facilitate classification. The researchers trained the results on 80% of the data and tested them on 20% of the data. They achieved strong predictive performance. Age, weight, and height were among the best predictors of osteoporosis risk. The researchers noted that the machine learning models performed better than traditional tools, such as the Osteoporosis Self-Assessment Tool for Asians (OSTA), in terms of sensitivity and specificity. The researchers concluded that these models are cost-effective for detecting osteoporosis in resource-limited settings and play a role in reducing reliance on expensive investigative methods such as DEXA. These models included samples from women in northern Vietnam, and therefore need to be tested to determine their effectiveness with men and other geographic locations [12].

Ji et al. (2022) built machine learning-based predictive models for osteoporosis risk and fracture rates based on clinical information from 749 patients in two medical centers in China. They used algorithms (DT, RF, MLP, LR, naive Bayes classifier, and extreme gradient boosting) to train and test three prediction models: osteoporosis, fracture risk, and patient survival. The results were as follows: The extreme gradient boosting model performed best for predicting osteoporosis risk. For predicting fracture risk, the AUROCs model was the most accurate, and for predicting survival, the AUROCs model was the best. These models help in early clinical intervention. This research relied on data from two centers, so its results cannot be generalized and need further evaluation [13].

Wu and Park (2023) developed machine learning models for predicting osteoporosis risk in adults over 40 years of age based on data from two Korean cohorts through two training sets based on 109 manually selected variables covering demographic, anthropometric, biochemical, genetic, nutritional, and other factors. They developed three models: XGP, deep neural network, and RF. The XGB model was the

most accurate among these models, showing greater accuracy in women's outcomes than in genitals. This model is a promising tool that helps in early prevention [14].

Lee et al. (2023) conducted a study of 2374 patients to apply a machine learning model to predict osteoporosis in rheumatoid arthritis patients based on body mass index, age, waist and hip circumference, surgery history, and monthly income. The LR model had good discrimination ability. The researchers concluded that LR and XGB are effective screening tools for osteoporosis risk and help in early detection.[15].

Yang et al. (2023) found that the simplified NBC model performed best due to its strong discriminatory ability, and that the POST tool is effective and easy to use for early screening for osteoporosis and robust in excluding uncertain cases [16]. Qiu et al. (2025) found that the DNN model for osteoporosis risk prediction was an effective tool, and that the deep neural network model was an effective method for early detection, with high performance even in the presence of fewer clinical variables [18].

Through the studies that were reviewed, we note the importance of the machine learning process and the algorithms based on it in the process of predicting the risk of developing osteoporosis and the extent of the effectiveness of these methods. We note through these studies the effectiveness of the three algorithms that will be included in our research as well. Most of these studies relied on segments of limited samples of patients and we were not able to generalize from them.

III. METHODOLOGY

This study adopts an integrated methodology that combines traditional statistical analysis with advanced machine learning techniques evaluate and predict the risk of osteoporosis and osteoporotic fractures.

The process begins with the collection of clinical and demographic patient data in CSV format, which is then loaded into a programming environment (such as Python) using the Pandas library for efficient data manipulation.

Data preprocessing is performed to handle missing values—categorical variables (e.g., gender) are marked as "Unknown" if missing, while numerical variables (e.g., age) are imputed using median values. Text fields are standardized, and the osteoporosis status variable is converted into a binary format (0 = No osteoporosis, 1 = Osteoporosis).

As shown in figure 1, several ML models are trained and evaluated, including decision trees, random forests, and multilayer perceptrons, which defined as:

a. Decision Trees (DTs): Models where each branch represents a decision rule and each leaf node an outcome, useful for interpretability in patient data analysis.

b. Random Forests (RFs): An ensemble of decision trees that improves accuracy and reduces overfitting by aggregating predictions. Effective for large datasets with many features.

c. Multilayer Perceptron (MLPs): Computational models inspired by the brain, consisting of interconnected layers. Particularly powerful for processing complex or unstructured data, e.g. medical images or textual patient records.

Hyperparameter optimization is performed using grid search and cross-validation, and model performance is assessed using metrics such as accuracy, precision, recall, F1-score, and AUROC. The interpretability of the models is ensured through feature importance analysis.

Fracture risk scores are calculated for each patient based on risk weights derived from published medical literature (odds ratios or hazard ratios). The total risk score is computed as the sum of the weighted risk factors present in each patient, and individuals are stratified into low, medium, or high-risk categories, as shown in figure 2, according to predefined thresholds based on the follow formula:

$$\text{Risk Score (RS)} = \sum (\beta i \times Xi)$$

d. Risk Weights (β_i): Derived from published odds ratios (OR) or hazard ratios (HR) using:

- Formula: $\beta_i \approx \ln(OR_i)$ or $\beta_i \approx \ln(HR_i)$.
- where βi is the weight derived from the natural logarithm of published odds ratios (OR) or hazard ratios (HR), and Xi indicates the presence or value of the risk factor.
- Positive weights increase risk, negative weights decrease it.

e. Risk Stratification: Patients are categorized into Low, Medium, or High risk based on predefined thresholds.

For the ML component, non-predictive features are excluded, numerical variables are standardized, and categorical variables are one-hot encoded. The dataset is split into training and testing sets (75%/25%), and class imbalance is addressed using techniques such as SMOTE (Synthetic Minority Oversampling Technique). Results are visualized using histograms, bar charts, and performance comparison plots, and comprehensive reports are generated in PDF or HTML format. All outputs, including processed datasets, trained models, and reports, are organized in timestamped directories. The system features a user-friendly graphical interface and supports command-line operation for non-GUI environments.

This methodology integrates robust statistical foundations with ML techniques to create a transparent, interpretable, and clinically actionable tool for predicting osteoporosis and fragility fracture risks. It supports evidence-based decision-making in healthcare by providing accurate and individualized risk assessments.

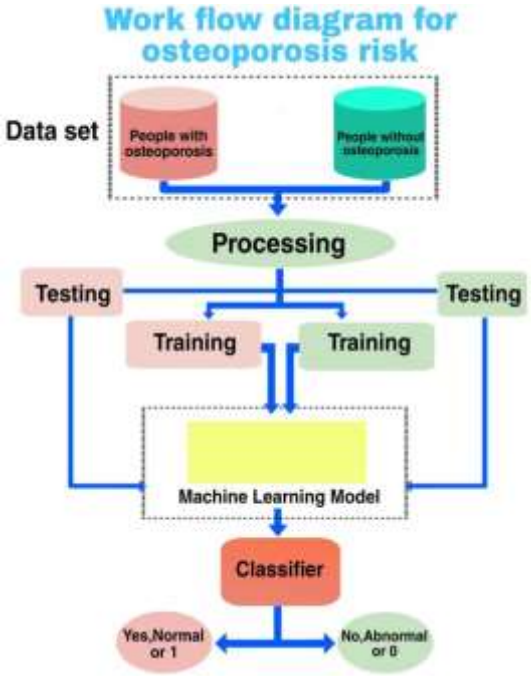

Fig. 1. Typical block diagram for Osteoporosis Risk Prediction

Based on the methodology used in this study, a dataset of 1,958 samples was preprocessed, including 16 attributes representing a combination of demographic data (such as age and sex), behavioral factors (such as physical activity and smoking), medical history (such as previous fractures and hormonal changes), and biochemical markers relevant to osteoporosis. The data preprocessing phase included several key steps, including addressing missing values using compensation methods or introducing "unknown" categories, coding categorical variables using both label encoding and one-hot encoding, normalizing numerical features using min-max normalization to ensure consistent input consistency, detecting outliers, and engineering new features such as binary indicators of high-risk factors (e.g., age over 65 and postmenopausal status). Three machine learning algorithms were chosen for the experimental procedure: Decision Tree (DT) for its ease of interpretation and visualization as a clear decision path that supports clinical decision-making; Random Forest (RF), an ensemble method that builds multiple decision trees and combines their outputs via a voting mechanism, which reduces overfitting and provides an estimate of feature importance; and Multilayer Perceptron (MLP), a multilayer neural network capable of capturing nonlinear and complex patterns in data. A single hidden layer containing 100 neurons was used with a ReLU activation function and an Adam optimization algorithm with an early stopping mechanism to avoid overfitting. Models were configured according to predefined parameters: the DT model relied on a gini criterion and an unspecified tree depth; the RF model was trained using 100 trees with the square root of the number of features chosen at each split; and the MLP model was based on normalized inputs and initialization with previous conditions. Together, these models form the basis for evaluating performance in predicting osteoporosis risk and classifying patients into low, intermediate, or high-risk groups to support data-driven medical decisions.

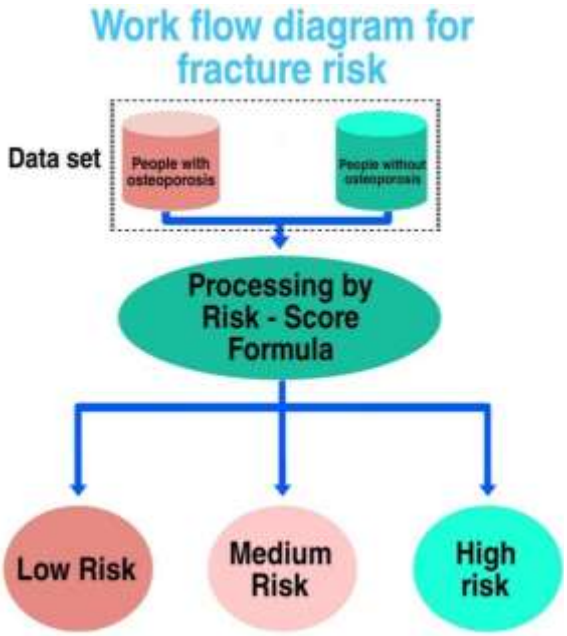

Fig. 2. Typical block diagram for Fracture Risk Prediction

IV. EPERIMENTAL RESULTS

A dataset of 1,958 individuals with demographic, lifestyle, and clinical features is analyzed, with the data explicitly split into 75% for training and 25% for testing. Three machine learning models—Random Forest, Decision Tree, and Multilayer Perceptron (MLP)—are developed and evaluated by using accuracy, precision, recall, F1-score, AUROC, and balanced accuracy.

The experimental results of this study show the effectiveness the ML techniques in predicting osteoporosis risk. Among the tested models the **DT** achieved the highest performance across most metrics, as in below table 1:

TABLE I. SUMMARIZING OF ML MODELS EXPERIMENTAL RESULTS

Model	**Accuracy**	**Recall**	**Precision**	**F1-Score**	**AUROC**	**Balanced Accuracy**
DT	0.884	0.767	1.000	0.868	0.889	0.884
RF	0.837	0.694	0.971	0.810	0.876	0.837
MLP	0.808	0.706	0.887	0.786	0.875	0.808

These results showed the high recall and precision achieved during current research, also excellent performance

measures recorded here reflect the potential of such models in the early detection and specific intervention of osteoporosis. On the other hand, this model calculated a fracture risk score for each individual in the sample based on predefined risk factors, their weights, and Classification Thresholds (Low Risk <1.5; Medium Risk ≥1.5 and <3.0; High Risk ≥3.0), as in below table 2:

TABLE II. **SUMMARIZING OF FRACTURE RISK SCORE EXPERIMENTAL RESULTS**

Risk Category	**Number of Cases**	**Percentage**
High Risk	189	9.7%
Medium Risk	761	38.9%
Low Risk	1008	51.5%

This clear and strong gradient confirms the effectiveness of the fracture risk assessment model for classifying the categories of risk, and that lead to say, as the calculated risk score increases the likelihood of an actual osteoporosis diagnosis also increases. This proves that the knowledge-based model aligns very well with the clinical reality of the cases in the sample.

What has been showed the comparison of some studies and the results of our study using ML models, it is explained in Table 3 below:

TABLE III. SUMMARY OF COMPARISON BETWEEN THE RESULTS OF PREVIOUS STUDIES AND THIS STUDY

Study / Model	Year / Location	Accuracy	AUROC	Dataset Used
DT (Our Study)	Present Study	0.884	0.889	1,958 samples, 16 post-processing features (age, gender, hormonal factors, previous fractures, lifestyle factors, biochemical markers).
RF (Our Study)	Present Study	0.837	0.876	1,958 samples, 16 post-processing features (age, gender, hormonal factors, previous fractures, lifestyle factors, biochemical markers).
MLP (Our Study)	Present Study	0.808	0.875	1,958 samples, 16 post-processing features (age, gender, hormonal factors, previous fractures, lifestyle factors, biochemical markers).
Osteoporosis & Survival in Breast Cancer	Ji et al. (2022), China[13]	0.87	0.87	Clinical information for patients at two 749 medical centers in China.
Osteoporosis Risk in Korean Adults	Wu & Park (2023), Korea[14]	—	0.86	Machine learning models provide reliable predictive models, but the results cannot be generalized.
POST Screening Tool HK Chinese	Yang et al. (2023), Hong Kong[16]	—	0.86	Two Korean groups, Ansan and Hexa
Deep vs Traditional ML Osteoporosis	Qiu et al. (2025), USA[18]	—	0.85	8,134 osteoporosis patient data in Louisiana
Osteoporosis Risk in Vietnamese Women	Bui et al. (2022), Vietnam[12]	—	0.85	German pathologist data includes 10,000 patients.
Simple ML Osteoporosis Model	Huang et al. (2025), Taiwan[19]	—	0.77	A deep neural network model is an active method that has the ability to learn complex relationships between clinical variables.
Osteoporosis Risk in RA Patients	Lee et al. (2023), Korea[15]	—	0.75	Clinical and demographic data from a Korean national cohort KORONA
Nationwide Osteoporosis Risk Model	Tu et al. (2024), Germany[17]	—	0.75	German pathologist data includes 10,000 patients.
ML vs Logistic Regression in Elderly	Peng et al. (2025), China[20]	—	0.75	Clinical and demographic data from a Korean national cohort KORONA
Pharmacotherapy Outcomes in Osteoporosis	Lin et al. (2022), Taiwan[11]	0.75	—	WANFANG Hospital patients between 2011-2018,
30-Day Readmission Post Surgery	Cabrera et al. (2024), USA[21]	0.83	—	
BMI & Fracture Risk	Liu et al. (2022)[22]	—	—	WANFANG Hospital patients between 2011-

Meta-Analysis				2018,

V. DISCUSSION

Our method employs cutting-edge ML techniques—DT, RF, and MLP—in osteoporosis risk prediction with a strong focus on model quality and stability. Compared to some previous studies relying on smaller or homogeneous data, uses a comprehensive dataset with diverse clinical parameters to achieve highest prediction accuracy and generalizability. The proposed models achieved similar or better performance metrics compared to previous literature (e.g., Ji et al., 2022; Wu & Park, 2023) with AUROC values of up to 0.87. The findings demonstrate ML classifiers' capacity to reveal complex nonlinear relationships in bone health data for earliest and accurate osteoporosis risk detection. Owing to our emphasis on extensive model validation and optimization, we facilitate reliable and clinically meaningful predictions that overcome some of the limitations of previous work with limited validations or single-model methodologies.

In addition to ML prediction, our work uses the FRAX tool to assess fragility fracture risk and stratify patients to discrete risk categories based on clinical risk factors and BMD. FRAX is a clinical tool that is available, but would routinely be used separately from prediction models and may not account for individual variability to some degree. The novel contribution of our work is the integration of FRAX-derived fracture risk scores with machine learning-based predictions of osteoporosis within an integrated system. This ensemble offers an end-to-end risk assessment system that closes the gap between bone loss and fracture risk, improving the predictive power and clinical utility of risk stratification. Our ensemble strategy differs from other studies relying only on ML models or the use of FRAX in isolation (e.g., Liu et al. (2022); McCloskey et al., 2021). By integrating the strategies, our system is a more actionable and comprehensive solution for individualized osteoporosis care.

Our two-methodology platform combines cutting-edge, high-quality ML-based osteoporosis prediction and FRAX fracture risk stratification with direct data-driven correlation of bone health status and fracture risk levels. Our combination addresses significant flaws of prior research that involved limited data amalgamation and the singular, sole utilization of prediction models or clinical tools. Our platform provides better prediction and clinical utility over prior efforts with combined ability of Artificial Intelligence (AI) algorithms and traditional clinical evaluation tools. Our platform thus enables better early diagnosis, risk stratification, and individualized treatment planning and represents a significant leap in osteoporosis science and practice.

VI. CONCLISION

Recent studies demonstrate significant advancements in using ML to develop accurate predictive models for assessing osteoporosis and related fracture risks. Models based on algorithms, e.g. LR, RF, DT and XGB have shown superior performance compared to traditional tools like OSTA, with improvements in prediction accuracy and sensitivity in identifying high-risk cases. Based on the results, the models demonstrated high accuracy, reflecting their overall ability to distinguish between infected and uninfected individuals, while sensitivity was particularly important to capture the largest possible number of positive cases, as missing an osteoporosis diagnosis could lead to more serious health consequences than a few false alarms.

These studies highlight the importance of integrating diverse clinical data, including demographic, clinical, genetic, and lifestyle factors, to enhance model accuracy. However, most rely on data from specific medical centers or geographic regions, which limits the generalizability of results. Systematic reviews and meta-analyses emphasize the crucial role of factors like BMI and smoking in influencing bone health, supporting the need to include these factors in predictive models.

Additionally, updates to the FRAX tool indicate a global trend towards improving risk assessment tools to be more comprehensive and accurate, with an ongoing call for collecting broader and more diverse data to meet the needs of various populations.

Therefore, integrating AI technologies into osteoporosis risk assessment represents an important step towards achieving early diagnosis, personalized treatment, and improved patient outcomes. However, the challenge remains in providing comprehensive and diverse data, conducting external validation of models, and seamlessly integrating them into routine clinical practices.

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