

Early Detection and Prediction of Osteopenia: A Pathway to Enhanced Bone Health using Machine Learning

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Abstract: Early identification of osteopenia, an easy indicator of osteoporosis, is essential for fracture preventative measures and the restoration of long-term bone wellness. This research sets up and assesses a machine learning screening framework designed for detecting the beginning of osteopenia, utilizing enhanced clinical datasets that include demographic, medical, and bone health variables. The Custom Weighted Ensemble Model, through a comparative analysis with different classification algorithms, obtained the highest accuracy of 98.69%, surpassing standard models including Random Forest and Gradient Boosting, both at 98.48%. The ensemble approach demonstrates enhanced precision and F1-scores, underscoring its effectiveness in balancing both precision and sensitivity compared with prior research which concentrates primarily on osteoporosis. This investigation demonstrates the initial stage of osteopenia detection along with it suggests that optimized ensemble strategies significantly improve predictive performance. The findings indicate the potential of data-driven models to enhance preventive bone health care and decrease the risk of future fractured bones. Early recognition of osteopenia—widely noticed as the impassive initial level for osteoporosis—is essential for safeguarding the health of bones and avoiding severe fractures. This paper presents a detailed review of existing methodologies for diagnosing and predicting osteopenia, with a focus on the comprehensive overview of machine learning (ML). By combining insights from significant studies on osteoporosis prediction and choosing a comprehensive dataset incorporating with demographic, medical, and bone health parameters, we reveal essential predictive factors. Additionally, we offer a state-of-the-art framework for creating reliable machine learning models specifically suited for early detection. This study highlights how data-driven innovation can improve clinical care, slow the progression of osteopenia, and pave the way for a future free of fractures.

Index Terms: Osteopenia, Bone Mineral Density, Custom Weighted Ensembled Algorithm, Machine Learning, Osteopenia.

1. Introduction

Between normal bone health and osteoporosis, a medical disorder marked by lower-than-normal bone mineral density (BMD) is called osteopenia. Whereas osteopenia cannot always result in fractures, it significantly raises the chances of acquiring osteoporosis, a severe disorder that is linked to fractured bones and an increased chance of fractures. Early detection of osteopenia is essential for putting preventative measures in place that may slow down or even rectify the loss of bone density.

1.1. T-Score and Bone Density Classification

Bone density can often be measured by DXA (dual-energy X-ray absorptiometry). Bone density is measured using

the T-score, which compares the person's BMD to the average maximum BMD of a healthy young adult. The WHO (World Health Organization) categorizes bone health into the following categories based on T-scores: Osteopenia: T-score between -1.0 and -2.5; Osteoporosis: T-score < -2.5; Normal bone density: T-score > -1.0. A measurement of statistical significance known as the T-score analyzes an individual's bone mineral density (BMD) to the typical average maximum BMD of an adult young person of the same sex who is in good health and usually comes in between the ages of 20 and 30. Standard deviations (SDs) from the reference mean are used to express it.

The T-score is often determined by the following formula:

$$\text{T-Score} = (\text{Patient's BMD} - \text{Mean BMD of Young Adults}) / \text{Standard Deviation of Young Adult BMD}$$



Fig. 1. Graphical illustration of Bone health

A graphical comparison of different bone disorders illustrates the morphological differences between osteopenia, osteoporosis, and healthy bones. Normal bone possesses a dense and well-connected trabecular structure; meanwhile, osteopenia bone shows moderate porosity, and osteoporotic bone produces severe porosity, fragility, and thinning of bone trabeculae.

1.2. Challenges in Osteopenia Diagnosis

Despite osteopenia's clinical importance, detecting it is difficult. DXA scans are used, which are expensive, difficult to get, and need specialist equipment. Even though conventional models, such as the FRAX (Fracture Risk Assessment Tool), aid in estimating fracture risk, they frequently fall short in accurately predicting a person's propensity to osteopenia.

1.3. Machine Learning for Osteopenia Prediction

With the use of clinical, lifestyle, and demographic data, machine learning (ML) provides a more accurate way to predict the risk of osteopenia. More efficiently analyzing large data sets than standard statistical methods, machine learning (ML) techniques can also identify complex relationships between various risk factors. These may include age, BMI, smoking, alcohol use, and BMD values in order to enhance the precision of predictions. Early identification of those who run a risk will enable immediate action. This work aims to generate and assess supervised machine learning models while trying to figure out the osteopenia risk. Among the approaches under comparison are random forest (RF), logistic regression (LR), support vector machine (SVM) and gradient boosting method (GBM). The primary goal is to enhance early diagnosis and a preventive measure by identifying the most effective model and determining the important risk variables linked to osteopenia. The goal of this work is to improve clinical decision-making along with improved bone health care through the integration of machine learning (ML) into osteopenia evaluation in a feasible, scalable, and data-driven manner.

1.4. Diagnostic Approaches

DXA (Dual-energy X-ray absorptiometry), used to measure BMD (bone mineral density) at essential skeletal regions, is the conventional approach used to identify osteopenia. However, DXA has a number of limitations, including high prices, restricted accessibility in environments with limited resources, and a focus on through bone health rather than the estimation of risks. More accessible and cost-effective options have been made available by recent developments, including portable RF-based tools [1] and optical bone densitometry [2]. In addition, through analysis of clinical and imaging data for early detection, machine learning-based decision-support technologies are being created to

improve osteoporosis risk prediction [3].

1.5. Risk Factor Analysis

Age, gender, family history, and lifestyle variables including smoking and inactivity contribute to the risk of osteopenia. These factors correlate with other general studies on osteoporosis, which underline the serious consequences of dietary deficiencies, especially those in calcium and vitamin D [4]. Moreover, it has been specified that long-term illnesses such as diabetes, high blood pressure, and chronic renal disease are major causes of the decline in bone health [5]. Such variables have been shown to have predictive value in recent machine learning evaluations, with models successfully using comorbidity data to evaluate the risk of osteoporosis. In an interesting work, [6] employed GAN-based augmentation strategies to enhance CNN performance in DXA-based osteoporosis classification. Meanwhile, CNNs are used in conjunction with classical image processing techniques to diagnose osteoporosis in its early phases [7].

1.6. Machine Learning in Predictive Diagnostics

Healthcare's predictive and diagnostic capacities have significantly increased because of innovations in machine learning (ML). Neural networks, gradient boosting models (XGBoost, CatBoost), decision trees, support vector machines (SVM), and other techniques can be employed to analyze high-dimensional medical data and find patterns that conventional statistical models would detect. Recent studies have highlighted that machine learning models outperform the typical Osteoporosis Self-Assessment Tool (OSTA) for Asians [8]. Regarding the potential of ML in osteoporosis prediction, deep learning models using hip radiographs achieved 81.2% accuracy in predicting osteoporosis [9] and Regression-based approaches have been successfully applied to predict T-scores using optical densitometry. CNNs and R-CNNs have shown promise in early osteoporosis detection through imaging. Multi-modal AI models integrating clinical records and imaging data have been explored for osteoporosis screening. Sharma et al. also consider ML algorithms, including logistic regression, in forecasting heart disease, diabetes, and COVID-19, with high accuracy in early prediction and screening [10]. Additionally, ensemble learning techniques have further enhanced predictive performance. For instance, a multi-level stacking approach proposed by Khanna et al. achieved 89% accuracy in osteoporosis risk prediction. These models utilize advanced feature selection techniques like RFE - recursive feature elimination, mutual information selection, and particle swarm optimization, to refine predictions.

1.7. Machine Learning in Healthcare-Applications of Bone

Machine learning has shown great potential in predicting osteoporosis and fracture risk, with several approaches emerging to enhance diagnostic accuracy. Convolutional Neural Networks (CNNs) have been used to analyze radiographic images for bone quality assessment [11]. Hybrid AI frameworks combining CNNs with ensemble learning have improved osteoporosis prediction, particularly in aging populations [12]. Ensemble methods like Random Forest and AdaBoost have been successfully applied to integrate clinical and genetic data for osteoporosis risk stratification. Feature-augmented predictive models have demonstrated the effectiveness of AI in analyzing dietary patterns and their correlation with bone density [13], underscoring the broader potential of deep learning in enhancing osteoporosis diagnosis and risk assessment [14]. Additionally, studies leveraging large-scale chronic disease datasets have highlighted key risk factors, including lipid metabolism disorders, chronic conditions, and lifestyle influences. A deep neural network (DNN) model, trained with gene expression information, accurately predicted bone metastasis (BM) in a study [15], with 92.11% accuracy, an AUC, and performance in a variety of datasets; therefore, its application could go a long way in becoming a general predictive model for BM in a range of types of cancer, a study claims. The model performed with success, with its success attributable to its consideration of 34 important genes, most of which are involved in processes concerning BM, and its observations regarding metastasis molecular drivers.

Another approach involves using ML algorithms to integrate imaging features from MRI and PET/CT scans [16] and [17]. The model can predict development of metastasis in experimental samples even when undetectable with traditional imaging modalities. Application of an avNNet model enables subjects to be grouped in terms of metastasis development propensity with high accuracy and with ease in accommodation with any ML algorithm. These findings emphasize the role of machine learning in automatic risk assessment and ultimately improving patient outcomes.

1.8. Clinical Integration

Develop user-friendly tools, such as web-based applications or EHR-integrated systems, for clinical use. Conduct prospective studies to validate the model in real-world settings. Building on existing research into osteoporosis prediction, such as the use of electromagnetic wave-based devices and machine learning models to detect low BMD, convolutional neural networks (Jang et al.), ANN (Artificial Neural Network) classifier-Based Computer-Aided Diagnostic system for early and accurate detection of osteoporosis [18] and chronic disease datasets, this paper highlights the need for a tailored approach to osteopenia. The dataset used in this study includes 40 variables, such as demographic attributes (Gender, Age, Height, Weight, BMI), bone health metrics (L1-4, FN, TL), and clinical risk factors (e.g., Hyperuricemia, Fracture, Smoking, Drinking).

The intention of this research is actually to design and evaluate many Machine Learning (ML) classifiers that accurately predict a patient's risk of osteopenia. Because choosing the best features significantly improves predicted

accuracy, feature engineering is important for improving classifier performance. In order to enhance the accuracy of classification, a customized weighted ensemble model is established as well. This ensemble method increases accuracy and durability by combining predictions from several classifiers while allocating each model appropriate weights. This approach provides a balanced and improved prediction strategy in comparison to standard black-box classifiers by employing the benefits of several models. Feature selection helps enhance the efficiency of machine learning models by removing irrelevant or redundant variables. This study determined traits that most significantly associated with osteopenia risk by use of RFE (Recursive Feature Elimination). RFE is a wrapper-based feature selection method which gradually removes the least significant features depending on model performance. This method improves interpretability, reduces overfitting, and offers Model-Based Ranking among various additional advantages.

Even though there have been advancements in osteoporosis detection by applying ML, current approaches for osteopenia prediction remain limited. Many current models are more focused on advanced bone loss than on finding early signs of danger, which makes them less useful for prevention. Also, many popular models have problems with overfitting because they utilize small sample sizes, don't test their results in a wide range of populations, or employ variables that aren't usually gathered in clinical settings. Moreover, there isn't actually any consensus on the best feature sets and algorithms to use, and it's still unusual for them to be used in real-world clinical processes. These gaps reveal that we need models that are specifically designed for early identification of osteopenia and that are easy to understand and use in clinical settings.

2. Existing Studies and Approaches

Low density in the bone as well as microarchitectural degradation of the bone tissue characterize the systemic skeletal disease known as osteoporosis, which raises fracture risk and renders bones more sensitive [19]. Moreover, early detection and therapy are crucial for preventing fractures and improving the quality of life for persons who are at danger [20]. Emphasizing techniques for imaging, machine learning applications, and other diagnostic approaches, this review of the literature looks at many options for identifying and predicting osteoporosis. Machine learning (ML) techniques have recently attracted recognition as possible tools for osteoporosis risk prediction (Wen-Yu Ou Yang et al.). Large amounts of information may be filtered using ML in search of trends otherwise missed by more traditional methods. These models could incorporate a range of clinical data, imaging features, and other relevant factors to offer more exact and unique risk estimates.

Several research investigations have examined the application of machine learning techniques for osteoporosis prediction using clinical diagnostic data. Wen-Yu Ou Yang et al. designed prediction models using Artificial Neural Network, Support Vector Machine, Random Forest, K-Nearest Neighbor, and Logistic Regression in order to project the development of osteoporosis in individuals over fifty. Men's and women's models were produced independently, and the findings demonstrated that ML algorithms outperformed conventional techniques in osteoporosis detection. The Osteoporosis Self-Assessment Tool for Asians technique was substantially outperformed by the ANN, SVM, and RF techniques.

Later, for the purpose of identifying the possible signs of osteoporosis, K.A. Ullah et al. [21] also suggested a better prediction model that makes use of machine learning strategies. They used various machine learning techniques using Taiwanese clinical test data sets and Korean postmenopausal women's medical reports. A method for predicting bone problems in females has been established using K-nearest neighbor methodologies, Support Vector Machine, and Artificial Neural Networks. When compared to the Osteoporosis Self-Assessment Tool for Asians, the outcomes of the ML-based models were considerably better and more accurate.

Then, according to [22], Deep learning structures have demonstrated important promise in the analysis of imaging data for the identification of osteoporosis. Using lumbar spine MR (Magnetic Resonance) and CT (Computed Tomography) images, Yasemin Kkilolu et al. created unimodal and multimodal deep-learning models to predict bone mineral loss. The study demonstrated that deep learning models can reliably predict osteoporosis from pictures by achieving high balanced accuracy for MRI, CT, and mixed datasets. The authors recommended that these technologies might be used in clinical practice with more prospective trials with a greater number of patients, and the created technique enhanced osteoporosis prediction.

Furthermore, to estimate bone mineral density (BMD) from hip X-ray images, Shang-Wen Feng et al. [23] developed a segmentation recognition classification model utilizing deep learning techniques. The model consisted of segmented pictures of the Wards triangle, greater trochanter, femoral neck and whole hip using a U-Net framework. The results show that the built model generated positive BMD prediction, which indicates that hip X-ray interpretation and BMD prediction in patients might be accomplished through convolutional neural network models. For the purpose to improve the accuracy as well as robustness of osteoporosis prediction models [24], some studies are concentrating on ensemble learning together with feature selection methods. Pallavi Hallappanavar Basavaraja and Shanmugarathinam developed early osteoporosis diagnosis for X-ray pictures by use of an ensemble-of-classifiers approach. Osteoporosis detection, feature extraction, appropriate feature selection, and pre-processing were all included in the model. The best features from the recovered characteristics were selected using the CGHFA (cat guided hummingbird foraging algorithm), a novel hybrid optimization approach.

In the osteoporosis detection phase, these carefully chosen characteristics were utilized to train the Deep Learning

classifiers. The outcome results demonstrated that the suggested deep ensemble model +CGHFA outperformed the current models with respect to accuracy in detecting. The actual fact that many machine learning models are developed and evaluated using certain datasets may restrict their relevance across other demographics [25]. It is crucial for building models that are accurate and efficient in a variety of clinical situations and demographic groupings.

Several previous research investigations have explored the application of machine learning to osteoporosis risk prediction. In particular, Feng et al. and Jang et al. employed deep learning models developed on hip X-ray images to estimate BMD and fracture risk, and they were quite good at it. But because they depend on imaging data, they can't be used in situations with few resources or for preventative screening. Tu et al. and [26] employed ML on structured clinical data; however, they mostly looked at advanced osteoporosis instead of early-stage osteopenia. Also, most studies don't have mechanisms to validate their results in the actual world or integrate them into real life. The current study, on the other hand, creates a Custom Weighted Ensemble Model that is particularly designed to find osteopenia utilising clinical and demographic data that is already accessible. This method makes it easier to use in general practice and helps with early management before bone loss becomes serious.

The structure of this document is as follows: In Section 2, relevant research on machine learning-based osteopenia and osteoporosis prediction is reviewed. The dataset, feature selection method, and model construction procedure are all covered in Section 3. The experimental findings are shown in Section 4, along with comparisons between classifiers and performance measures. Clinical consequences, restrictions, and possible uses are covered in Section 5. The work is finally concluded and future research possibilities are outlined in Section 6.

Literature Review Approach

This paper possesses a narrative literature review that provides the proposed machine learning model's development in perspective as well. We came across relevant publications by looking for databases like PubMed and Google Scholar for specific keywords like "osteopenia prediction", "bone mineral density", and "machine learning". The selection process comprises papers that were published in English and peer-reviewed between 2010 and 2024. There is no PRISMA checklist, bias rating, or formal inclusion/exclusion methodology used because this is a narrative review. We chose studies based on how clear and relevant their methods were.

3. Proposed Framework for Early Prediction of Osteopenia

This paper proposes a conceptual framework to guide the development of ML-based models for osteopenia prediction. Python utilities such as NumPy, Pandas, Scikit-learn, and SciPy were used for machine learning model development, data manipulation, and modeling. This paper provides a machine learning approach to predict osteopenia early using easily obtained clinical and demographic data. This strategy targets early-stage bone loss using interpretable elements from structured medical records, unlike previous research that focused on osteoporosis identification or data from imaging studies like DXA scans. In order to mitigate both variance and bias and increase prediction accuracy, a Custom Weighted Ensemble model was created. Early risk classification in resource-limited settings and electronic health system integration are the main goals. The model performs well, but dataset generalizability and prospective clinical validation are issues.

3.1. Custom Weighted Ensemble Model and Overall System Architecture

The fig. 2 indicates the whole machine learning pipeline, commencing with data preprocessing through final model evaluation. Then, the dataset goes through cleaning and feature selection, during which duplicates are removed, and unrelated columns (such as 'Status') are eliminated. subsequently, data is standardized using StandardScaler, maintaining uniform feature distributions, accompanied by a train-test split (70-30) to separate the data for training and validation. In the framework's training phase, multiple classifiers—including Support Vector Machine, Logistic Regression, Decision Tree, Random Forest, Gradient Boosting, AdaBoost, K-Nearest Neighbors, Multi-Layer Perceptron (MLP), and a Sequential Neural Network—are trained on the dataset. Every framework involves the assessment using metrics such as accuracy score, classification report, confusion matrix, and ROC curve analysis, providing insights into their predictive performance.

The fig. 3 addresses on the Custom Weighted Ensemble Model, an advanced approach developed to enhance predictive accuracy by integrating the two best-performing models: Random Forest (RF) and Gradient Boosting Classifier (GBC). Instead of depending on a single model, this ensemble technique assigns weights to the probability derived from RF and GBC, with 40% weight given to RF and 60% to GBC, expressing their individual performances. The final predictions can be obtained by applying a threshold (0.5) on the combined probability scores. This weighted ensemble approach strengthens the generalization of models and consistency, ensuring enhanced accuracy in prediction compared to individual classifiers.

The final assessment phase includes a precision comparison, confusion matrix visualization, and ROC curve comparison to confirm the superiority of the ensemble model over standalone classifiers. The outcome demonstrates the fact that the Custom Weighted Ensemble Model efficiently balances bias and variance, achieving optimized classification performance.

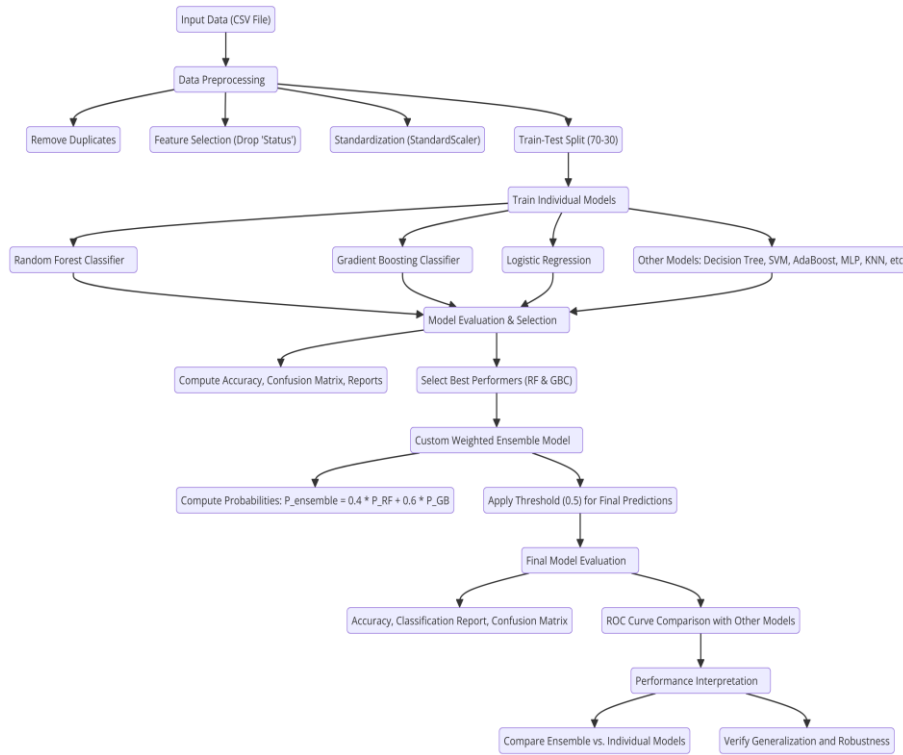


Fig. 2. Overall system architecture

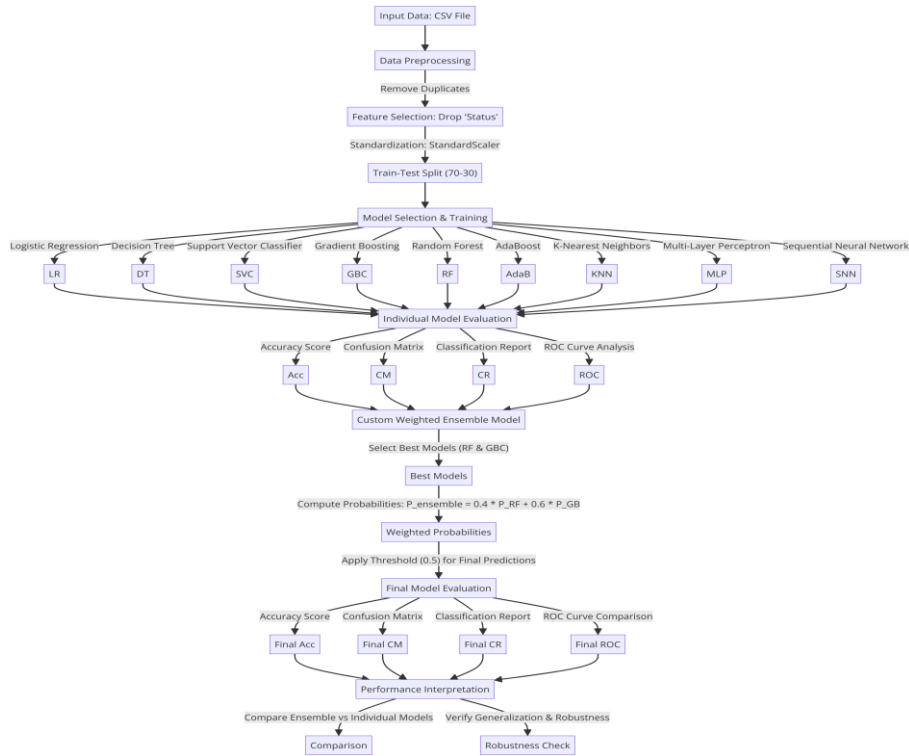


Fig. 3. Custom weighted ensemble model architecture

3.2. Data Collection

The open-source 'Bone Mineral Density' dataset, released by He and Linfeng [27] and accessible on Harvard Dataverse, was used in this investigation. The content of this document has been released under a CC0 public domain license, enabling unrestricted use for research purposes. The data set included 40 variables and 1,537 occurrences in the original dataset. The key variable in this study was L1-4T, which stands for the Lumbar 1–4 (L1-4) DXA T-score. 'Status' is a new derived variable that can be calculated based on the L1-4T T-score and determines bone mineral density as either osteopenia or normal. Additional analysis has been constructed based on this classification.

Five of the 39 attributes that remained reflected extra bone density and Thoracolumbar (TL) T-scores and Femoral Neck (FN) bones T-scores. Hematological and biochemical profiles were recorded by eleven characteristics, including renal markers such as Blood Urea Nitrogen (BUN), Phosphorus (P), Calcium (Ca), Magnesium (Mg), Uric Acid (URIC), and Creatinine (CREA). ALT (ALanine Transaminase) and AST (aspartate amino-transferase) were part of the hepatic panel, while HDL-C and LDL-C were part of the lipid profile. Additionally, Fasting Blood Glucose (FBG) was measured.

Four variables also include information on the use of particular medications, such as calcium intake, calcitonin, calcitriol, and bisphosphonate. Eleven additional factors recorded conditions that relate to osteoporosis, and two characteristics indicated information about the patient's drinking and smoking patterns. Lastly, five variables—height, gender, age, Body Mass Index (BMI) and weight—represented anthropometric and demographic data. In order to gain valuable insights, this study particularly examined the relationships among osteoporosis-related disorders, lifestyle variables, biochemical markers, and bone mineral density (L1-4T T-score).

3.3. Data Pre-Processing

In this research, during this process we found the data that had missing values. Variables which are Height, Age, Weight, BMI, ALT, AST, BUN, CREA, FBG, Ca, HDL-C, Mg, LDL-C and P had missing values. These missing data can be filled along with the feature median technique [28]. A pair plot has been generated for the purpose of analyzing the relationships between the dataset's different numerical variables. The pair plot 4 helps explain feature mutual dependence and separability between the two classes (Status: 0 or 1) by providing a thorough illustration of paired feature distributions and interactions. Using the Kernel Density Estimation (KDE), each diagonal element of the pair plot demonstrates the distribution of distinct characteristics, emphasizing variations between the two classes. The scatter plots that show the associations between feature pairs are shown in the off-diagonal elements. Patterns like linear correlations, clusters, or separability between the two groups can be found using these scatter plots.

The visualization indicates possible multicollinearity because some feature pairs, like height and weight and BMI and weight, show strong correlations. Certain characteristics, such as FN and IL-4, had variations in distribution in the two groups, which suggests that they may be important for classification. In scatter plots, features where the two classes are well separated might be important predictors for training the model. In general, the pair plot is used as an early feature selection phase which helps in locating unimportant features and identifying relevant variables that might improve model performance.

Table 1. Summary statistics of numerical attributes

S. No	Attrib-Utes	Data Type	Missing Values	Mean	Std	Min	25%	50%	75%	Max
1	Gender	Numerical	0	1.39	0.49	1.00	1.00	1.00	2.00	2.00
2	Height	Numerical	34	165.82	8.09	141.00	160.00	167.00	172.00	187.00
3	Age	Numerical	36	59.85	12.94	28.60	51.00	57.00	67.30	99.80
4	BMI	Numerical	34	24.31	3.32	9.21	22.07	24.22	26.36	37.26
5	Weight	Numerical	34	67.15	11.99	23.00	59.00	67.00	75.00	113.00
6	L1-4	Numerical	0	1.14	0.19	0.76	1.00	1.12	1.26	1.94
7	L1.4T	Numerical	0	-0.55	1.53	-3.50	-1.60	-0.70	0.40	6.00
8	FN	Numerical	0	0.87	0.15	0.33	0.77	0.86	0.96	1.42
9	FNT	Numerical	0	-1.30	1.11	-5.05	-2.05	-1.40	-0.55	2.70
10	TL	Numerical	0	based on the L1-4T T-score and 0 ty 0.93	0.15	0.31	0.84	0.93	1.04	1.46
11	AST	Numerical	2	22.66	9.46	9.00	17.00	21.00	25.00	128.00
12	BUN	Numerical	1	5.62	3.32	1.74	4.34	5.18	6.20	69.80
13	TLT	Numerical	0	-0.93	1.15	-4.80	-1.70	-1.00	-0.20	3.10
14	ALT	Numerical	2	23.55	16.62	4.00	14.00	19.00	28.00	181.00
15	FBG	Numerical	16	5.33	1.54	3.13	4.58	4.96	5.53	24.65
16	HDL-C	Numerical	17	1.25	0.38	0.45	1.01	1.19	1.44	5.46
17	CREA	Numerical	3	73.97	25.70	5.86	60.00	70.60	81.57	381.20
18	LDL-C	Numerical	14	2.60	0.90	0.14	1.92	2.55	3.18	6.65
19	Ca	Numerical	2	2.24	0.16	1.78	2.16	2.23	2.31	5.84
20	P	Numerical	5	1.04	0.21	0.56	0.92	1.02	1.13	4.41
21	Mg	Numerical	3	0.87	0.10	0.10	0.81	0.87	0.93	1.73
22	Calcium	Numerical	0	0.15	0.35	0.00	0.00	0.00	0.00	1.00

23	Calcitriol	Numerical	0	0.17	0.38	0.00	0.00	0.00	0.00	1.00
24	Bisphosphonate	Numerical	0	0.06	0.24	0.0	0.0	0.0	0.0	1.0
25	Calcitonin	Numerical	0	0.06	0.23	0.0	0.0	0.0	0.0	1.0
26	HTN	Numerical	0	0.55	0.5	0.0	0.0	1.0	1.0	1.0
27	COPD	Numerical	0	0.25	0.43	0.0	0.0	0.0	0.0	1.0
28	DM	Numerical	0	0.33	0.47	0.0	0.0	0.0	1.0	1.0
29	Hyperlipidaemia	Numerical	0	0.39	0.49	0.0	0.0	0.0	1.0	1.0
30	Hyperuricemia	Numerical	0	0.17	0.38	0.0	0.0	0.0	0.0	1.0
31	AS	Numerical	0	0.75	0.43	0.0	0.0	1.0	1.0	1.0
32	VT	Numerical	0	0.02	0.14	0.0	0.0	0.0	0.0	1.0
33	VD	Numerical	0	0.07	0.26	0.0	0.0	0.0	0.0	1.0
34	OP	Numerical	0	0.37	0.48	0.0	0.0	0.0	1.0	1.0
35	CAD	Numerical	0	0.2	0.4	0.0	0.0	0.0	0.0	1.0
36	CKD	Numerical	0	0.04	0.19	0.0	0.0	0.0	0.0	1.0
37	Fracture	Numerical	0	0.02	0.14	0.0	0.0	0.0	0.0	1.0
38	Smoking	Numerical	0	0.26	0.44	0.0	0.0	0.0	1.0	1.0
39	Drinking	Numerical	0	0.23	0.42	0.0	0.0	0.0	0.0	1.0

3.4. Feature Selection

The RFE (Recursive Feature Elimination) has been employed in the process of selecting features to identify which characteristics were most important for classification. Height, Age, Weight, BMI, L1-4, HDL-C, FBG, LDL-C, and P were the parameters that were ultimately shown to be the most significant after the RFE algorithm systematically eliminated less significant variables using a Random Forest Classifier. In order to ensure that only the most significant qualities contribute to predicted performance, these variables were kept for future model development.

By integrating these techniques—RFE for feature selection, correlation analysis during redundancy detection, along with mutual information for significance assessment—we ensure our model is built on the most essential and non-redundant features. This approach improves performance and interpretability, which helps make AI-driven decision-making easier to understand. In our model, those attributes are highly linked to the risk of osteopenia, but it's essential to remember that these links are not causal. To prove causality, research studies or logical investigations would need to be done.

3.5. Model Development

Following an overview of the previous sections, we now describe the models used in the present study, that incorporate both linear and non-linear machine learning techniques. Tree-based methods, boosting techniques, and conventional models of statistics were among the several types of classifiers applied to guarantee effective performance research. These linear models include Support Vector Classifier (SVC) with a linear kernel and Logistic Regression (LR) capable of establishing decision limits based on linear relationships within the dataset. On the other hand, non-linear models, which capture complex relationships and correlations among characteristics, include AdaBoost, K-Nearest Neighbors (KNN), Decision Tree (DT), Random Forest (RF), Gradient Boosting Classifier (GBC), Multi-Layer Perceptron (MLP). For the purpose to enhance the prediction accuracy, an ensemble learning method also was employed. The Random Forest Classifier and the Gradient Boosting Classifier are connected using a custom-weighted ensemble technique. The probability estimates obtained from RF and GBC were especially assigned certain weights (RF: 0.4, GBC: 0.6) to provide an accurate final estimate. The final prediction was computed using a threshold, hence outputs above five percent are classified as positive cases. Moreover, a unique sequential model including many classifiers in a hierarchical structure was generated. This approach provides the best decision-making process by utilizing the various strengths of multiple algorithms.

This work aimed to build a strong and effective classification structure capable of handling various data patterns by combining a weighted ensemble technique with tree-based models, neural network models, and conventional approaches.

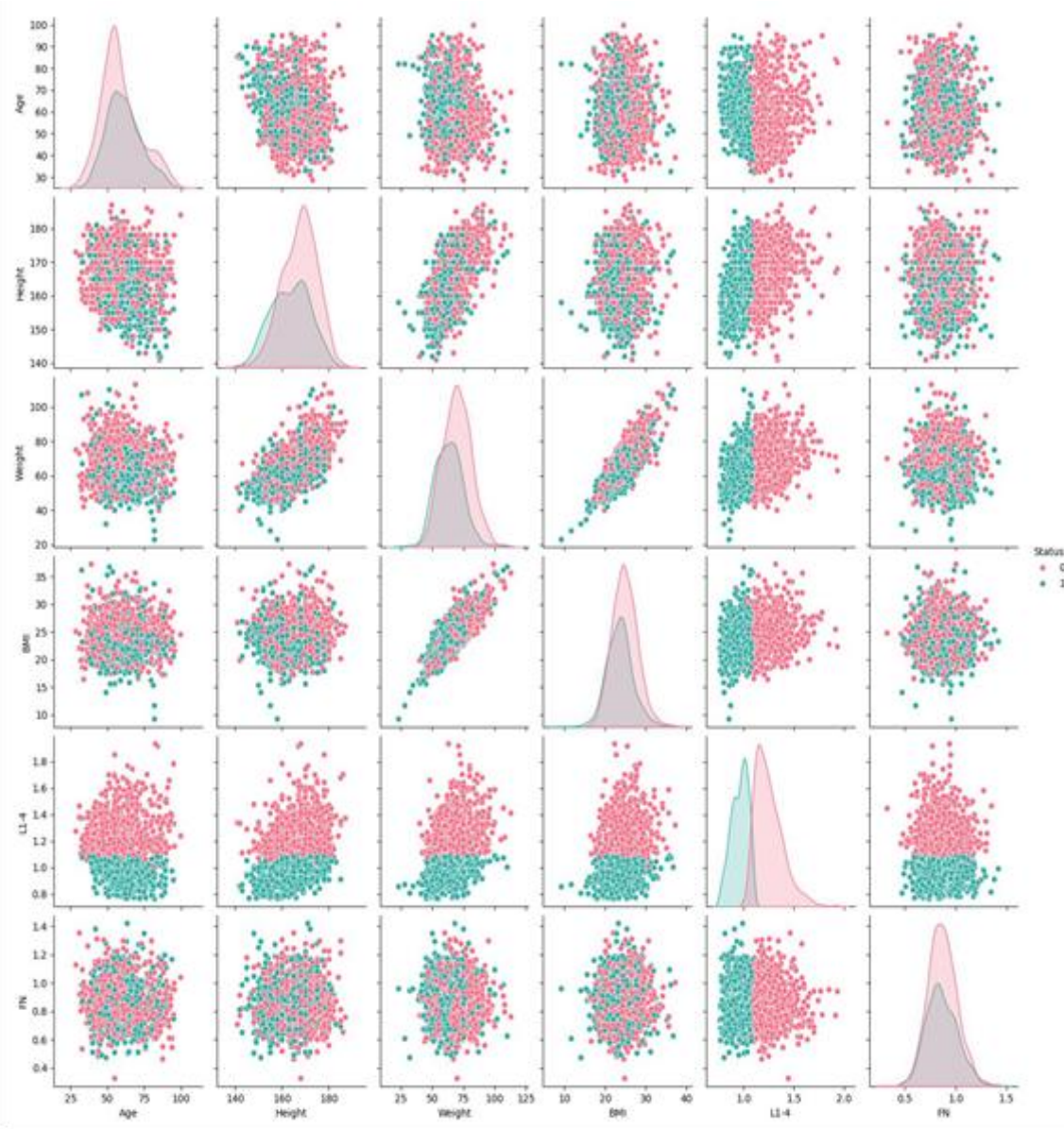


Fig. 4. Pairwise feature visualization for exploratory data analysis

3.5.1. Algorithm

Algorithm 1 Custom Weighted Ensemble Model Algorithm

1. Input: DataSet $D = \{(x, y) : x \in \mathbb{R}^{n \times p}, y \in \mathbb{R}_n\}$ which has n samples and p attributes
 2. Initialization process: Set k base learning algorithms
 3. for $j = 1$ to k do
 - a. for $i = 1$ to m do

Do m -fold cross-validation

 - i. Split D as D_i^{train}, D_i^{test}
 - ii. Train base learner j on D_i^{train}
 - iii. Obtain predictions P_{ij} on D_i^{test}
 - b. End for
 - c. Construct the prediction vector $\hat{Y}_j = (P_{1j}, \dots, P_{mj})$
 4. end for
- Solve optimization problem to compute the optimal weight vector w_j for each base learner by minimizing the MSE
- Combine base learners using weights $w_1, \dots, w_k$.
- Output: Optimal object values (MSE*), optimal weights ($w_1^*, \dots, w_k^*$), final prediction ($\hat{Y}^*$)

The input data set is $D = \{(x, y): x \in R^{n \times p}, y \in R^n\}$. The input basis learners are k base learners $W(\hat{Y}_j)$. The most appropriate weights (w_j^*) are used to integrate j base learners and create predictions ($\hat{Y}^*$).

The Custom Weighted Ensembled algorithm is displayed as follows:

Ensemble learning has become a powerful machine learning method that utilizes multiple base learners to improve predictive performance. This document presents a Custom Weighted Ensemble Model Algorithm, which optimally combines multiple base learners using weighted optimization. The method leverages cross-validation to produce out-of-bag assumptions, that are then utilized for determining optimal weights. Several base learners (k) are trained using various data subsets. Cross-Validation and Out-of-Bag Predictions: Data and Base Learners: The input dataset includes target values $y \in R^n$ and feature vectors $x \in R^{n \times p}$. The algorithm follows m -fold cross-validation in order to divide the collection of data into sets for training as well as testing. Each base learner is trained on a training set and then makes predictions on the test set. These predictions develop an out-of-bag dataset $\hat{Y}_j$. Optimization and Weight Calculation: The predictions with all base learners can be employed as inputs to an optimization problem. This optimization procedure decides the best weights w_j^* for leveraging base learners to minimize an objective function, which means as Mean Squared Error (MSE). Final Ensemble Prediction: The weighted arrangement of base learner predictions produces the final ensemble prediction $\hat{Y}^*$, acquiring improved functionality compared to individual learners. The Custom Weighted Ensemble Model Algorithm precisely incorporates multiple base learners through optimal weights obtained from cross-validation-based predictions. This methodology enhances the reliability as well as precision of machine learning models.

4. Result and Discussions

A correlation matrix fig.5 has been generated for the purpose to validate and evaluate the relationships among these selected characteristics. All features' linear relationships are shown in the matrix, where repetition may be demonstrated through strongly connected features. More importantly, the L1-4 variable shows a strong negative correlation (-0.77), suggesting significant classification connection. The model's selection for additional factors such as age and BMI is confirmed by their weak to moderate relationships with other features.

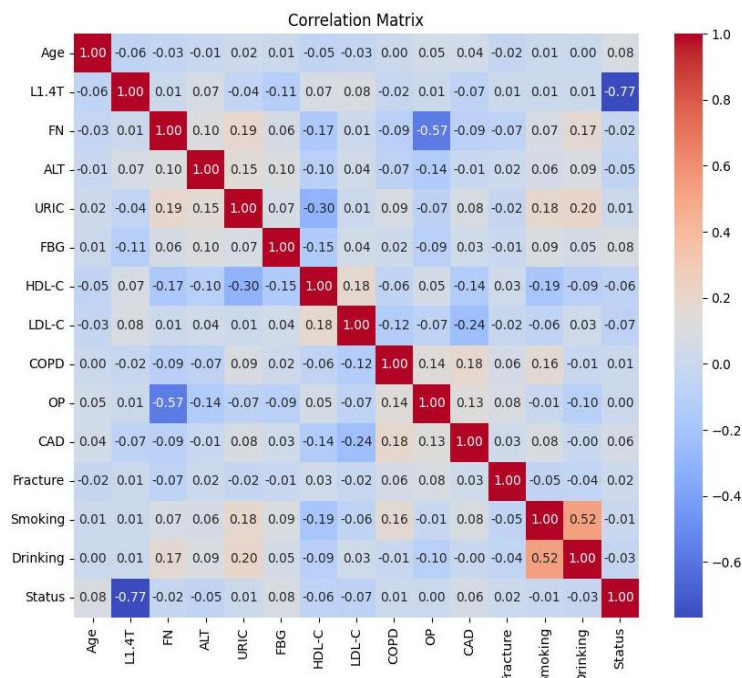


Fig. 5. Correlation matrix

Additionally, a mutual-information-based feature importance analysis (Fig. 6) was carried out to reinforce the findings. L1-4 has the most insights gain, based to the data, followed by weight, AST, height, and BMI. These results demonstrate the importance of the RFE-selected features. However, certain attributes like AST and P are included in the mutual information ranking but have been ignored by RFE, which suggests a potential difference in feature evaluation criteria between the two methods.

There are a number of important measures for assessing a model's performance in machine learning classification issues, including recall, accuracy, and precision. These metrics assist in determining the system's capacity to recognize the differences between various categories. Detailed definitions, calculations, and a comparison of the several models employed in this study are provided in the section which follows.

Table 2. Model evaluation results

Model Name	Accuracy	Precision	Recall	F1-Score
Custom Weighted Ensemble	98.69%	0.99	0.99	0.99
Sequential	96.31%	0.96	0.96	0.96
MLP Classifier	96.75%	0.97	0.97	0.97
K-Nearest Neighbors	89.15%	0.89	0.88	0.89
AdaBoost Classifier	97.83%	0.98	0.98	0.98
Logistic Regression	96.96%	0.97	0.97	0.97
Decision Tree	98.05%	0.98	0.98	0.98
Support Vector Classifier	94.79%	0.95	0.95	0.95
Gradient Boosting Classifier	98.48%	0.98	0.98	0.98
Random Forest Classifier	98.48%	0.99	0.98	0.98

The Table 2 represents the analysis results of different models of classification used in this research. The performance of each model is evaluated using important classification variables in this Table 2. With an accuracy of 98.69%, the Custom Weighted Ensemble Model performed better than the other models. With an accuracy of 98.48%, the Random Forest and Gradient Boosting Classifiers scored in second and third, respectively, indicating that they are capable in classification tasks. With a minimum precision of 89.15%, K-Nearest Neighbors (KNN) may be able to manage more complicated decision boundaries.

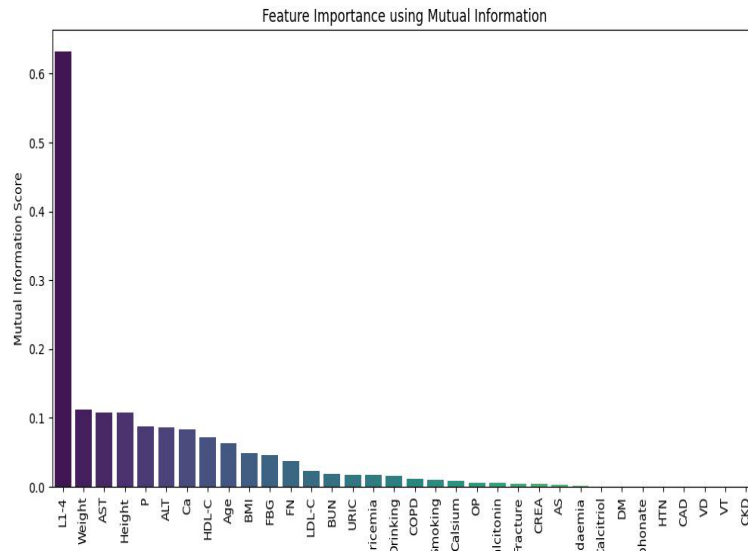


Fig. 6. Feature importance selection

The effective use of ensemble-based approaches like AdaBoost and Gradient Boosting is further shown by the F1-score, which achieves a balance between precision and recall. The models' accuracy in forecasting positive cases can be seen by their precision and recall values. Whereas conventional models such as Logistic Regression and Decision Tree handled well but were less effective than ensemble approaches, ensemble models like Custom Weighted Ensemble and AdaBoost were shown to be somewhat effective overall. These findings reveal that classification performance may be greatly improved by combining many models with optimal weighting. The ROC curve in fig. 7 describes that the Custom Weighted Ensemble, Random Forest, and Gradient Boosting classifiers obtained high AUC values, with curves close to the top-left corner, representing more effective classification performance. This figure represents the Receiver Operating Characteristic (ROC) curve, which illustrates the way various classification models perform in distinguishing throughout classes. The relationship between sensitivity and specificity for each model is displayed by the ROC curve, which shows the True Positive Rate (TPR) versus the False Positive Rate (FPR) across a range of threshold values. The fig. 7 Receiver Operating Characteristic (ROC) Curve demonstrates the ability of various classification models to differentiate between classes. The ROC curve displays the trade-off among sensitivity and specificity for every model by showing the TPR (True Positive Rate) against the FPR (False Positive Rate) over the range of threshold values. This framework is designed for use by clinicians and screening programs in both primary care and specialist settings. By leveraging routinely collected clinical and demographic data, the model can assist in early identification of patients at risk for osteopenia. It can be embedded within Electronic Health Record (EHR) systems as a decision-support tool or adapted for community-based screening programs. In future iterations, integration with wearable health devices may be explored to enable continuous risk monitoring in at-risk populations.

5. Conclusions

The present research provides the effectiveness of machine learning, specifically ensemble-based models, helping with the early detection of osteopenia, a significant but frequently under-diagnosed precursor to osteoporosis. The constructed Custom Weighted Ensemble Model, incorporating readily available clinical as well as demographic data, obtained a predicted accuracy of 98.69%, presenting a non-invasive and scalable alternative to DXA-based screening in primary care environments.

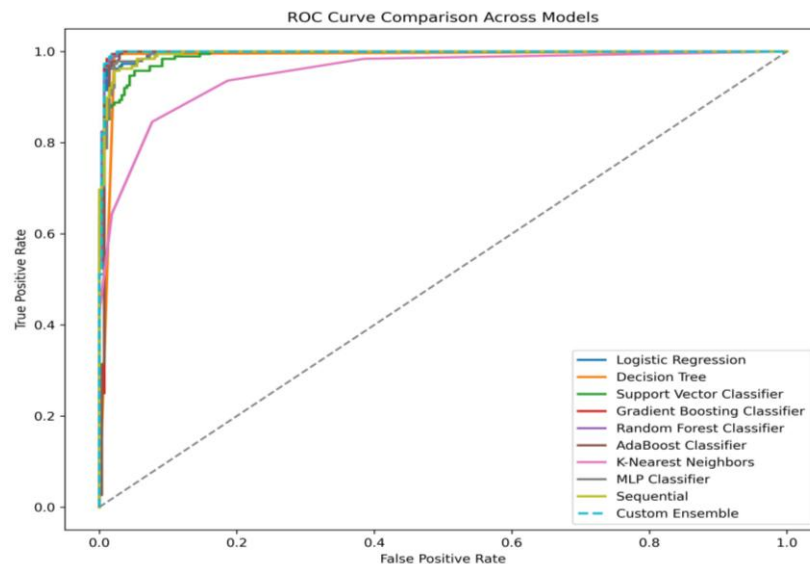


Fig. 7. Feature importance selection

In addition to the technical performance, our findings emphasize the practical importance of machine learning models that are capable of interpretation compatible with electronic health records, and designed for real-world integration. Tree-based and ensemble classifiers showed robust performance metrics while facilitating transparency in decision-making, an essential factor for clinical trials adoption. This study adds to the expanding field of AI-driven preventive medical services and underscores the significance of meticulous feature selection in enhancing classification results.

Meanwhile, the current study also points out the importance of additional research in model generalization, clinical evaluation, and ethical risk reduction particularly with regard to false negatives in early assessment. The effective implementation of these models necessitates collaboration across data scientists, clinicians, and healthcare system designers. This study establishes a foundation for intelligent, data-driven decision support in bone health care. Future research should expand upon this groundwork by utilizing larger datasets, hybrid modelling strategies, and conducting real-world clinical trials.

6. Limitations and Future Work

The proposed machine learning structure revealed strong predictive performance; however, certain limitations must be recognized; the dataset, while comprehensive, is derived from a single source and may not adequately reflect the diversity of global populations, thereby constraining generalizability. The model has not yet been subjected to prospective clinical validation in a real-world healthcare context. Moreover, while ensemble methods showed strong performance, there is possible risk of overfitting associated with the high accuracy metrics, necessary for careful interpretation.

Future research will be focused on performing external validation studies across various clinical settings for determining predictability. Collaboration along with medical personnel and interdisciplinary teams, including clinicians, data engineers, and software developers, is crucial for incorporating the model into electronic health records (EHRs) to assess its usability in live clinical workflows. The goal of this project is to establish a robust, interpretable, and scalable tool that facilitates early diagnosis and specific preventive care for osteopenia.

Moreover, clinical implementation needs to take into consideration both practical and moral issues. One reason we are working on this is that DXA scans are hard to get in remote or low-resource areas. Our approach tries to solve this by delivering a non-invasive, data-driven screening option. We picked interpretable classifiers, including decision trees and ensemble approaches, that show clearly how important each characteristic is and how decisions are made. This makes it simpler for doctors to comprehend and accept the results. Furthermore, we recognize the moral issues that come with false negatives in a screening model: cases of early osteopenia that are missed may not be treated right away.

Future deployments should thus put a strong priority on high sensitivity and assist clinical monitoring to lower the hazards that might happen.

All the Declarations and Statements

Author Contributions Statement

Nanda Kumar R.: Conceptualization, Methodology, data curation, software implementation, writing: Proposed research ideas, constructed overall framework, data acquisition, data preprocessing, drafted the initial manuscript, documented the technical background study.

Kumar N.: Conceptualization, supervision, formal analysis, writing: Proposed research idea, supervised project execution, performed in-depth analysis, reviewed and edited the manuscript, ensured the clarity and coherence, and helped coordinate the project milestones.

All authors have read and agreed to the published version of the manuscript.

Conflict of Interest Statement

The authors declare no conflicts of interest.

Funding Declaration

The authors declare that no funding was received for this research.

Data Availability Statement

This study analyzed publicly available datasets. The results obtained and datasets can be found in [27].

Ethical Declarations

This study does not involve human participants or animals. Therefore, ethical approval was not required.

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Declaration of Generative AI in Scholarly Writing

During the preparation of this work, the authors did not use any Generative AI or AI-assisted technologies.

Abbreviations

The following abbreviations are used in this manuscript:

ML - Machine Learning
BMD - Bone Mineral Density
DXA - Dual Energy X-ray Absorptiometry
WHO - World Health Organization
FRAX - Fracture Risk Assessment Tool
LR - Logistic Regression
SVM - Support Vector Machine
GBM - Gradient Boosting Machine
RF - Random Forest
DT - Decision Tree
MLP - Multi Layer Perceptron
GBC - Gradient Boosting Classifier
DNN - Deep Neural Network
BM - Bone Metastasis
ANN - Artificial Neural Network
RFE - Recursive Feature Elimination

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