Predicting Osteoporosis Risk in Postmenopausal Women: A Data-Driven Approach for Early Detection Using SMOTE and Explainable AI

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***Abstract*—Osteoporosis is one of the major health risks for elderly people—a condition where the bones become weak, brittle, and easily fractured. The risk is further increased in postmenopausal women because hormonal changes will accelerate the process of bone loss. Hence, its prediction and early detection are of utmost importance. The research paper proposes using data science, in building a predictive model for the likelihood of osteoporosis in postmenopausal women. The process includes data preparation, where cleaning and transformation guarantee the accuracy of the data. Thereafter, different statistical methods are employed to understand the data better, in terms of averages, variations, and other patterns. Then, machine learning techniques are applied to develop a model that can predict the at-risk factors. This would not only help in the early identification of individuals at risk but also make better health-related decisions to improve the quality of life in postmenopausal women.**

***Index Terms*—Osteoporosis, Post menopause, Data Cleaning, Risk Prediction, Machine learning, SMOTE, Explainable AI, LIME, SHAP**

I. Introduction

Osteoporosis is a condition characterized by a decrease in bone mineral density as well as changes within the microarchitecture of the bones and increased fragility of bones. It leads to an increased risk for fractures, especially in the hip, spine, and wrist. In most people, it progresses silently, with symptoms not surfacing until the occurrence of a fracture; hence, it is known as the "silent disease" [1]. The threat of osteoporosis goes up with age and, primarily, in postmenopausal women, as the decline in estrogen levels is directly related to maintaining bone density [2]. Risk factors include gender, age, body size, family history, diet, and lifestyle habits such as exercise.

Osteoporosis is a crucial health concern among postmenopausal women in the USA, where it affects millions due to the natural drop in estrogen levels after menopause. The decline often causes a decrease in bone density, which tends to commonly remain undiagnosed until a fracture occurs, resulting in serious health complications, even as severe as disability and a depreciated quality of life. A machine learning-based prediction model tailored for this demographic, using a dataset of women in the USA, could be highly practical and beneficial. By analyzing predictive factors such as age, BMI, lifestyle factors, medical history, and family's medical history, this project aims to support early detection and personalized risk assessment of osteoporosis.

A model such as the one introduced in this work can play a crucial role in providing a helping hand to healthcare providers in making informed decisions, preventing further complications, and potentially reducing the incidence of fractures. This approach not only helps to enhance clinical care but also allows elder women to take proactive steps in managing their bone health, ultimately improving outcomes for postmenopausal women across the country and enabling them to live healthier lifestyles.

The dataset for this project is derived from a comprehensive survey of postmenopausal women in the USA, which is the NHANES dataset, capturing key variables such as age, BMI, lifestyle habits, and medical history. This data will be utilized to apply various machine learning algorithms to predict the risk of osteoporosis. The proposed approach will address class imbalance in the dataset using the Synthetic Minority Over-sampling Technique. The Synthetic Minority Oversampling Technique (SMOTE) is a statistical way of addressing class imbalance problems in datasets, especially with binary classification tasks [3, 4]. Class imbalance occurs when one of the classes, in this case patients with osteoporosis, is overrepresented inadequately as compared to the other class, that is, healthy individuals. SMOTE achieves this by creating new instances of the minority class based on previous minority class instances [5].

This method works by choosing instances from the minority class, generating new synthetic instances along line segments joining these chosen instances to their nearest neighbors. Richness in the minority class will be achieved by generating new examples that are not observed. With this, model training improves and predictability is enhanced. Applying SMOTE can, therefore, lead to the development of better models for dealing with the prediction of rare events like the case of osteoporosis, thereby developing more effective early detection and intervention strategies. By analyzing these factors, the project aims to provide postmenopausal women with a personalized assessment of their risk for bone-related issues.

In this context, explainable artificial intelligence has to be incorporated to allow clear transparency on how the predictive model derives recommendations. Explainable artificial intelligence (XAI) refers to methods and techniques in artificial intelligence that make the functioning of AI systems understandable to humans. Given this, the overarching goal of XAI is to provide insight into how AI algorithms make decisions, especially in such domains as health care, where knowing something about the reasonableness of decisions may determine if someone trusts the output or is held accountable. An integration of these notions is interpretability, or the ability to ensure that the decisions made by an AI system can be explained in a way that is meaningful to users, such as healthcare providers and patients [6, 7]. This becomes very relevant in medical applications where decisions might influence the outcome of patients, thus demanding assurances that the AI's reasoning would match with clinical knowledge and ethical standards [8].

This proactive approach allows them to take necessary preventive measures based on the results. Given the current lack of machine learning-based risk prediction tools tailored to the lifestyle and health data of women in the USA, this project addresses a significant gap, offering an innovative solution for early detection and management of osteoporosis.

II. LITERATURE SURVEY

Traditional tools for predicting the risk of osteoporosis have usually been the Osteoporosis Self-Assessment Tool for Asians and FRAX, but studies in recent years have increasingly pointed out their shortcomings. For example, the study in [9] illustrates that the FRAX score could achieve an AUROC of only 0.617 in the prediction of osteoporotic fractures. Other machine learning algorithms, however, had more predictive power: gradient boosting, logistic regression, decision trees, and random forests had a range of 0.637 to 0.662 in AUROCs. This thus suggests that conventional models may not hold sufficient predictive accuracy, especially in high-risk populations like postmenopausal women. This view is further supported by the fact that traditional approaches usually have low predictive power, as shown in [10], thereby stressing the need to have more sophisticated predictive models that are population-specific.

The study in [11], building upon the previous literature, has contributed towards this by comparing the performance of different machine learning models such as SVM, RF, ANN, and LoR against the conventional clinical decision tool OSTA. This study targeted, in particular, postmenopausal women to evaluate which of these methods could give a better predictive accuracy for the risk of osteoporosis. The results demonstrated an increased potential of machine learning models over conventional tools in making predictions, hence providing a more reliable measure for the assessment of osteoporosis risk in clinical settings.

Recently, there is growing interest in developing population-specific machine learning models accounting for the characteristics of different demographic groups. The study of [12] investigated the performance of machine learning models on a Taiwanese cohort and concluded that the Random Forest algorithm is far superior to the traditional tool of OSTA, achieving an AUROC of 0.843 for men and 0.811 for women. These results underline the potential of RF as a robust predictive tool that can address the needs of different populations. Another two studies in [13] and [14] consider the application of localized models in postmenopausal women from Korea who are at higher risk of osteoporosis. This stresses the need for machine learning model validation within demographic groups relevant for improved accuracy in clinical practice.

The potential of machine learning in the revolution of risk prediction for osteoporosis is further developed in [15], where advanced machine learning models were constructed based on clinical and medical data from Taiwan and Korea. Such algorithms as ANN, SVM, and KNN have been used, outperforming conventional existing prediction tools in this study. The results indicate that these models provide not only better early detection of osteoporosis but can also be a good basis toward developing individual strategies for treatment. Comparisons between machine-learning models and conventional tools like OSTA further legitimize the superiority of methods like ANN and RF in clinical practice by providing an accurate and customized risk assessment for osteoporosis.

The work done in [16] and [13] places a major emphasis on developing machine learning models for postmenopausal women with a higher risk of osteoporosis. These studies have also been able to identify critical predictors of osteoporosis, such as age, height, weight, and lifestyle habits, without which the model accuracy could not be taken seriously. Evidently, the research in [13] by applying data from the Korea National Health and Nutrition Examination Surveys has demonstrated an ANN model to attain better predictive accuracy and show its promise in clinical applications for postmenopausal women. On the other hand, machine learning was applied in predicting osteoporosis at postmenopausal women in [14], which focused on the identification of people at high risk to enable early detection. These localized models ensure the different population-specific needs are met, and the predictions enhance the clinical utility.

The authors of [17] moved a step further to include personal lifestyle habits and medical history in their predictive model. This paper reviewed some data mining methodologies and pointed out the use of decision trees and neural networks for feature selection, illustrating that personal habits and medical background are very important for constructing an accurate predictive model of osteoporosis. This study took a holistic approach to the prediction of risk, generally improving model accuracy by including more variables; the risk in osteoporosis is multifactorial.

Further information on ANN applications to the prediction of osteoporosis risks can be found in [18]. The proposed methodology considers data from physical examinations, anamnesis, and lifestyle factors to try to enhance the predictive power of ANN models. Their results showed that ANNs can provide significantly better performance than other techniques, especially when different data sources are combined. The work further supports the use of localized data and demographic-based modeling and thus proves ANN as a great potential tool for person-centered predictions of osteoporosis risk in the clinical environment.

However, challenges persist in the translation of these models into clinical practice. A review of major obstacles to this end exists in issues related to the quality of the data and the need for big diverse datasets is stated in [19]. These challenges underscore the complexity of developing general and reliable models. On the other hand, some more advanced approaches are being explored to address these limitations. For instance, the work in [20] introduced relational networks and graph neural networks, which enrich the prediction models by considering complex relationships among various risk factors. These advanced models are the step into improving the machine learning predictive power and the clinical applicability of risk prediction in osteoporosis.

Most of the tools previously available for predicting the risk of osteoporosis, such as Osteoporosis Self-Assessment Tool for Asians (OSTA) and FRAX, have been advocated as having low predictability, particularly for high risk populations like postmenopausal women. The studies showed that the AUROC value of the FRAX score is comparatively less than other machine learning algorithms such as gradient boosting and random forests, which appear to be more accurate than it. The recognition of the importance of machine learning has been encouraging the creation of population-specific models that perform better than conventional tools. In addition, it has been emphasized that lifestyle and medical history be included in the improvement of predictive accuracy because the literature establishes that age, height, weight, and lifestyle are considered critical predictors of osteoporosis.

Despite the actual innovation in the application of machine learning to predict osteoporosis, there are still quite a number of gaps open for further research. One key gap is in the translation of these prediction models into practice, especially on data quality issues as well as the requirement of divergent datasets. The issues above need to be addressed so as to come up with models that are consistent, reproducible, and thus feasible for utilization in diverse healthcare settings. In addition, more complex models such as relational networks and graph neural networks have been further explored, whose effectiveness in the improvement of predictive probability of risk for osteoporosis needs further research.

The potential magnitudes of including the methods of explainable AI and the Synthetic Minority Over-sampling Technique into osteoporosis risk-prediction frameworks are substantial enough to overcome some of these challenges. While machine learning models have been reported to have increased accuracy, the lack of interpretability of their predictions remains one of the crucial barriers to their application in clinics. Though these innovations may enlighten and further ensure confidence by healthcare practitioners, the application of XAI can overcome class distribution imbalances in datasets, thus enhancing predictive performance SMOTE. Validation of machine learning models with such innovative techniques should be focused on subsequent studies to ensure that their specific requirements are met for a given population in clinical practice. Such a consideration calls for further research into improving and refining methods of assessing the risk for osteoporosis.

III. METHODOLOGY

The methodology for the prediction of the existence of osteoporosi sbegins with preprocessing the NHANES data, regarding missing values and outliers. Then, Exploratory Data Analysis and Feature Engineering improve the data, followed by SMOTE to balance it. The best models are trained, evaluated, and explained to ensure transparent predictions. A clear flow from the preprocessing of data to the evaluation of the model is carried out in the system architecture as shown in Fig. 1.

A. Dataset Description

The dataset used in this study includes demographic and health-related information gathered from a government health survey while focusing on osteoporosis prediction.The study examines a dataset obtained by extracting data from the NHANES Survey, targeting postmenopausal women, with features such as age, BMI, liver condition, parental osteoporosis history, and arthritis status. The distribution of the features considered from the NHANES survey before balancing is shown in Fig. 2. This dataset includes the features:

- **Age:** Bone density decreases with age. It drops steeply after menopause because estrogen maintains bones; decreased estrogen after menopause can lead to sharply declining bone density. Age is one of the largest predictors of odds of osteoporosis.
- **BMI:** Higher BMI values correlate with higher bone density, especially as a result of the mechanical load on bones that is associated with greater protection against osteoporosis. Underweight patients are at greater risk.

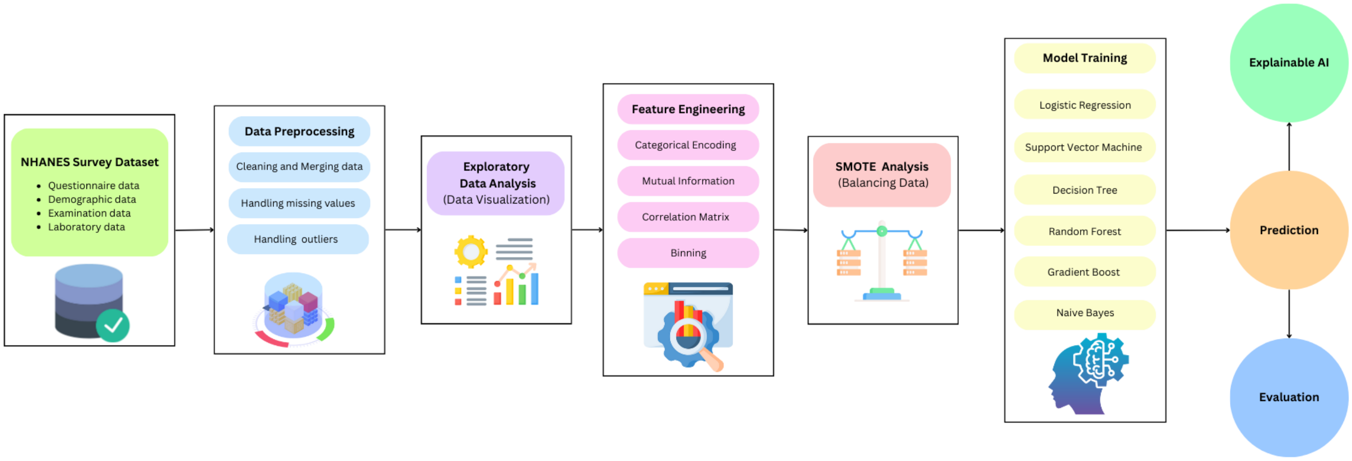

Fig. 1. System Architecture diagram

- **Smoking:** Smoking damages bone by inhibiting calcium absorption and reducing estrogen levels, which increase the possibility of osteoporosis.
- **Heavy Drinking:** Heavy alcohol consumption hinders the process of bone formation and leads to rapid bone loss, thus increasing the risk.
- **Sleep Duration:** Lack or over-sleep can cause disturbances in hormonal balance leading to alteration in bone metabolism. Postmenopausal women with abnormal sleeping patterns may be at higher risk.
- **Arthritis and Liver Condition:**Arthritis can cause erosion of joint and bones, while liver diseases may compromise the metabolism of essential nutrients, contributing to bone loss.
- **Age of Last Menstrual Cycle:** Early menopause leads to a longer period with estrogen deficiency, thus increasing chances of bone density loss.
- **Parental Osteoporosis:** Family history suggests a genetic tendency, women whose parents had osteoporosis are at a significantly higher risk.
- **Used Female Hormones:**Hormone replacement therapy can help to counterbalance the bone loss of post-menopausal women by overcoming estrogen-related levels of deficiency.
- **Osteoporosis status:** The target variable indicating osteoporosis presence or absence.

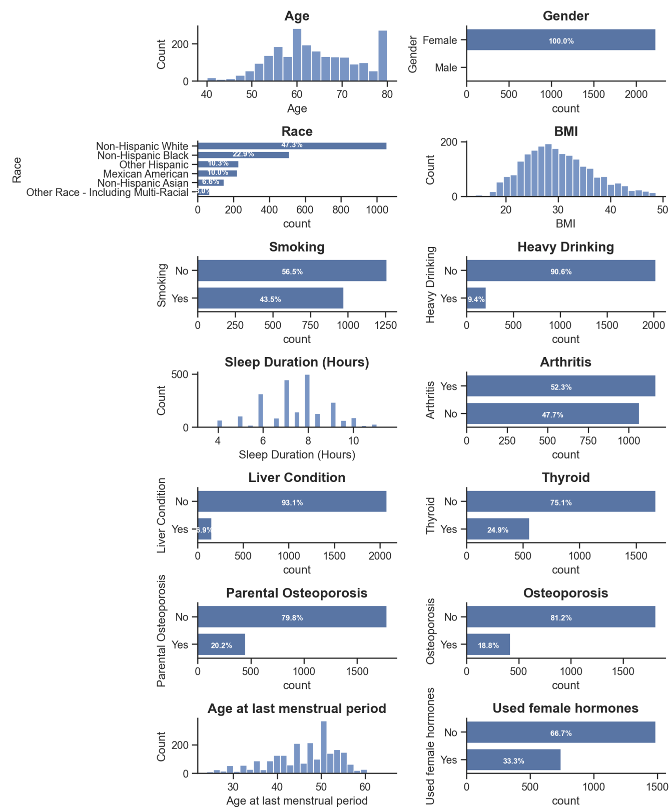

Fig. 2. Distribution of demographic, lifestyle, and health characteristics

B. Data Pre-Processing

Data pre-processing was done to handle missing values, detect and manage outliers, and ensure consistency of data quality throughout the dataset. At first, the dataset was examined for any missing values, which were then addressed to maintain data integrity. The outlier detection methods that were used combined statistical and graphical techniques to identify and manage unusual data points that could create bias within the model. The comparision of all data and outliers for each feature that are considered is depicted in Fig. 3. Initially, box plots and Z-scores were used to visualize and quantify deviations, with box plots flagging values beyond the 1.5 interquartile range and Z-scores marking points over three standard deviations from the mean as potential outliers. The keeping or removal of outliers was decided based on their nature; natural variations were kept, while errors were removed. Furthermore, categorical variables were label-encoded to assign unique integer values to each category, ensuring

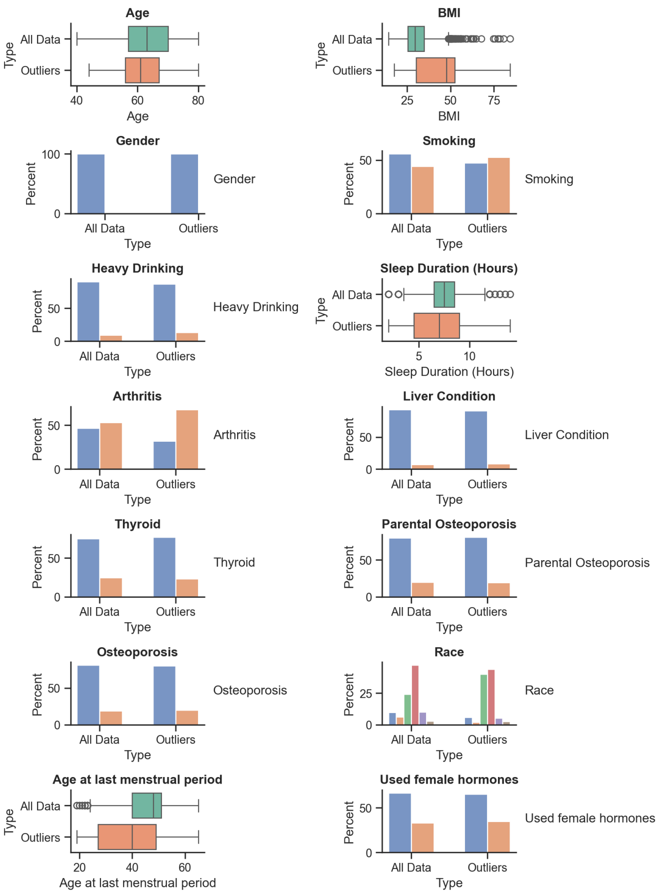

Fig. 3. Histogram plot for All data vs Outliers

compatibility with algorithms. For categorical variables, label encoding was applied to facilitate algorithmic interpretation.

Given the imbalance in osteoporosis outcomes within the extracted dataset the Synthetic Minority Over-sampling Technique (SMOTE) was used to create a balanced dataset, improving model robustness. By concentrating on the interpolation of new examples instead of merely replicating those already present, the method improves the model's ability to generalize and prevents overfitting. The disribusion of data before and after SMOTE is seen in Fig. 4 SMOTE was selected because it can synthesize new data points for the minority class without overfitting and could serve well in raising the recall. The results show that SMOTE reached a recall of 0.702 and an F1 score of 0.494 compared with other methods including ADASYN (recall: 0.667, F1 score: 0.465) and SMOTETomek (recall: 0.702, F1 score: 0.461). Synthetic sampling of SMOTE helped balance the dataset and had the best performance for case detection of osteoporosis (minority case), which is reflected in its higher recall and balanced F1 score. Feature scaling was performed using the Standard Scaler on numerical features, standardizing them to support optimal model performance and convergence. Finally, the dataset was divided into training and testing subsets, with an 80/20 split to ensure reliable model evaluation.

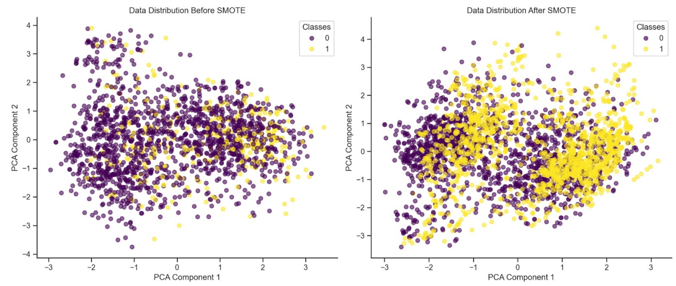

Fig. 4. Class distribution comparision before and after SMOTE

C. Model Training

The study employed a range of machine learning models to evaluate their effectiveness in predicting osteoporosis risk, leveraging each model's unique strengths. Logistic Regression was chosen for its simplicity and accuracy, making it suitable for binary classification tasks. A Decision Tree model was also utilized, with an applied depth limitation to avoid over-fitting and ensure more generalized results. To enhance prediction accuracy even more, Random Forest model was implemented, a method that combines multiple decision trees, reducing variance and increasing stability of the predictions. The Support Vector Machine (SVM) algorithm was included aiming to maximize the margin between classes and improve classification accuracy. Gradient Boosting was also utilized, which iteratively improved predictions by focusing on residual errors from previous iterations. The Naive Bayes classifier, which uses a probabilistic approach, was included, offering efficiency in scenarios with highly dimensional data.

D. Model Evaluation

After training, each model underwent comprehensive model evaluation, with metrics such as accuracy, precision, recall, F1-score, and ROC-AUC calculated to capture each model's strengths and weaknesses. These metrics provided detailed insights into the models' ability to correctly identify osteoporosis cases and reduce false positives, allowing for an informed assessment of areas for further improvement. This evaluation process was essential to selecting the most reliable model for predicting osteoporosis risk in the study cohort.

IV. RESULT AND DISCUSSION

This section presents the results based on performance metrics from the machine learning models applied to the risk prediction dataset. The study effectively demonstrates a machine learning approach for predicting osteoporosis risk using clinical and demographic data. It includes data collection and preprocessing, feature selection, model training, and evaluation. Data is cleaned, scaled, and processed to modify missing values before the features are selected through methods of feature selection that identify most important predictors for osteoporosis. The study trains on multiple models, such as Logistic Regression, Decision Tree, Random Forest, Support Vector Machine (SVM), and evaluate them using accuracy, precision, recall, F1-score, and AUC-ROC to check the performance as depicted in I. The ROC Curves Comparing Performance of Various Machine Learning Models for Risk Prediction is shown in Fig. 5 The study also integrates Explainable AI techniques like SHAP and LIME into the top-performing model to provide insights about the decision-making process.

TABLE I
MODEL EVALUATION METRICS

Model	Accuracy	Precision	Recall	F1 Score	AUC
Logistic Regression	0.715	0.359	0.655	0.464	0.759
LDA	0.706	0.352	0.667	0.461	0.760
Naive Bayes	0.682	0.321	0.619	0.423	0.709
Gradient Boost	0.794	0.443	0.369	0.403	0.720
SVM	0.711	0.323	0.488	0.389	0.696
K-Nearest Neighbors	0.673	0.299	0.548	0.387	0.636
Gaussian Process	0.717	0.322	0.452	0.376	0.638
CatBoost	0.796	0.429	0.250	0.316	0.684
Decision Tree	0.742	0.313	0.310	0.311	0.575
AdaBoost	0.742	0.313	0.310	0.311	0.707
Random Forest	0.780	0.379	0.262	0.310	0.692
Extra Trees	0.778	0.368	0.250	0.298	0.660
XGBoost	0.762	0.323	0.238	0.274	0.668

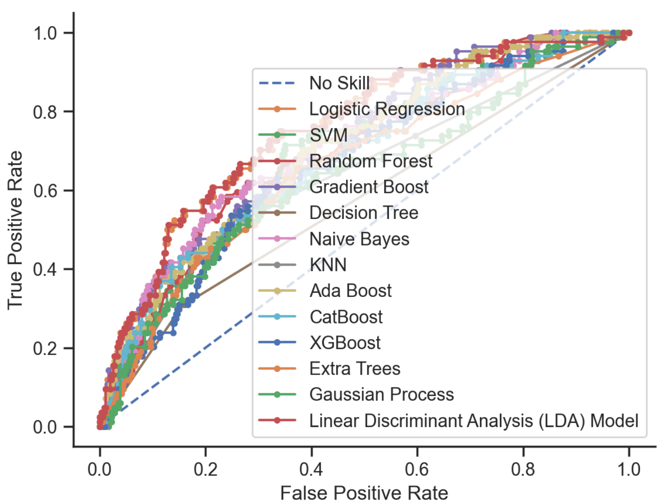

Fig. 5. ROC Curves Comparing Performance of Various ML Models.

Logistic Regression outperformed the rest as it had the best fit and AUC-ROC score Fig. 7 and Fig. 8 also show the confusion matrix and ROC plot for the same. Feature importance also proved age and parental osteoporosis are the most important predictors and well-known risk factors of osteoporosis as shown in Fig. 6. Confusion matrix analysis shows that the Logistic regression model has a low false-negative rate, which is vital in medical diagnostics to minimize missed cases.

A. Hypothesis Testing

Hypothesis testing was used to analyze the relationship between specific factors and osteoporosis risk in women. T-tests that were performed on continuous variables showed that

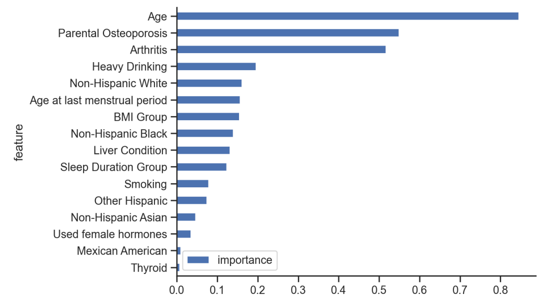

Fig. 6. Feature Importance Graph

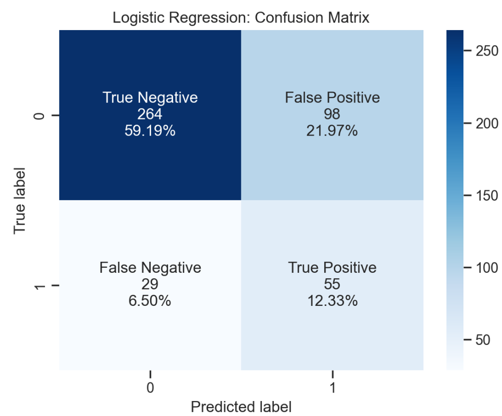

Fig. 7. Confusion Matrix for Logistic Regression

age (p-value = 1.05e-31), age at last menstrual period (p-value = 0.015), and BMI (p-value = 0.039) were significantly different between women with and without osteoporosis, suggesting these factors are important for predicting osteoporosis risk. On the other hand, sleep duration had a high p-value of 0.627, indicating that there is no significant difference, meaning it most likely does not impact osteoporosis risk. These results help to understand to prioritize the features: age, age at last menstrual period, and BMI for inclusion in predictive modeling, while sleep duration may be less relevant.

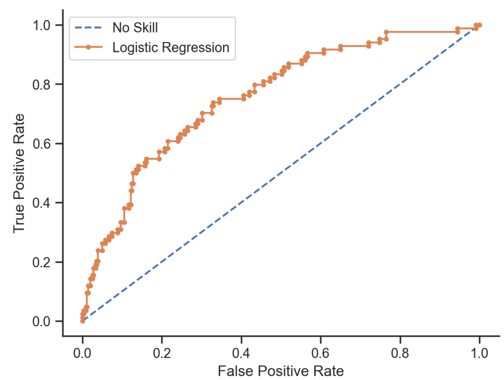

Fig. 8. ROC Plot for Logistic Regression

B. Explainable AI

To improve the clinical interpretability of the predictive model, Explainable AI (XAI) methods like LIME and SHAP were used. The tools shed light on how the models make decisions, making them more transparent and trustworthy for healthcare providers. Explainable AI bridges the gap between model complexity and user understanding, making the system actionable for clinical decision-making.

1) LIME: Using Local Interpretable Model-Agnostic Explanations (LIME), individual predictions were analyzed to understand which features contributed most to the model's decision for specific cases. The model predicts an 86% probability of "No Osteoporosis" and highlights the key factors influencing this decision. Strong contributors toward "No Osteoporosis" include low age and absence of family history, with minor factors pushing towards "Osteoporosis" including heavy drinking and hormone use, though they have lesser impacts. The output efficiently explains the model's decision-making process by identifying the most impactful factors like age and family history, which could guide further analysis or public health efforts.

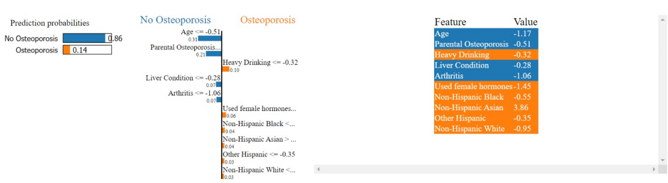

Fig. 9. LIME prediction probability

2) SHAP: SHAP (SHapley Additive exPlanations) results provide more insight into how individual features influence the values of the osteoporosis prediction model. Age stands out as the most important factor as seen in Fig. 10, with older age generally increasing the risk of osteoporosis, though its impact can vary from person to person. BMI and arthritis are also key factors—higher BMI tends to lower the risk, while arthritis significantly raises it. Family history of osteoporosis, age at last menstrual period, and sleep duration also play important roles, with their effects depending on individual values.

Ethnicity plays a role too as seen from Fig. 10, with Non-Hispanic Black and Non-Hispanic Asian groups showing a lower risk but, in the case of Non-Hispanic White and Other Hispanic groups, only a smaller, though more varied effect. Lifestyle habits, including smoking and heavy drinking, increase risk; use of female hormones provides partial protection. Health conditions like thyroid disease and liver disorders increase risk.

SHAP makes the process of decision-making clearer with visualization of how each factor contributes toward the model prediction. It thus helps in the identification of major risk factors and gives useful insight in the management of osteoporosis.

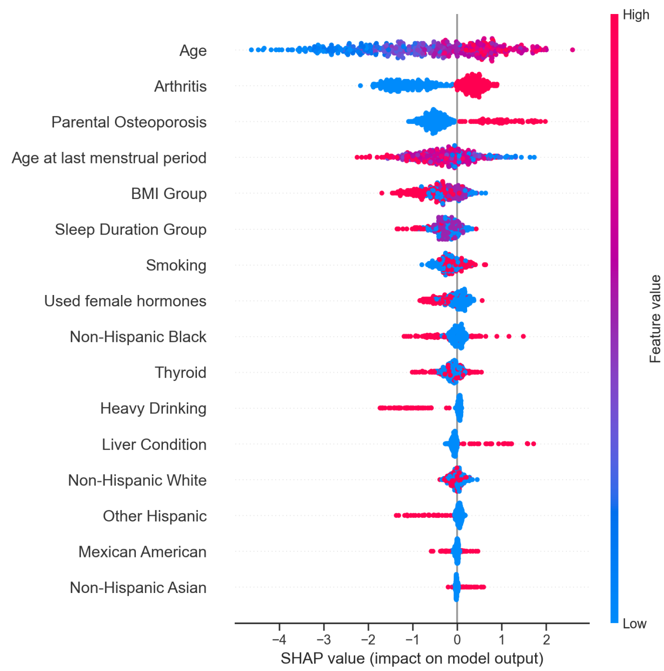

Fig. 10. Summary Plot

V. Conclusion

The paper proposes a data-driven approach for early detection of osteoporosis risk in postmenopausal women using SMOTE with machine learning in conjunction with XAI methods. The Logistic regression model is the best algorithm, outperforming other algorithms, with the highest value of ROC-AUC and the lowest false negative rate, as it increases the lowest chance of missed diagnosis. Feature importance analysis showed that age, BMI and parental history of osteoporosis were the most important predictors. The preprocessing steps for missing data, outliers, and class imbalance contributed the most to making the model more robust. In addition, XAI tools like SHAP and LIME were added for interpretability at both the global and local levels, making the model more trustworthy and usable by healthcare professionals.

Although the results suggest promise in improved risk stratification and clinical decision support, the study highlights some limitations—standing validation in different populations and exploration of more complex machine learning architectures, such as graph neural networks. This methodology represents a balanced approach in terms of predictivity, precision, and interpretability in providing a reliable tool for the early diagnosis and individualized treatment of osteoporosis in postmenopausal women.

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