

AI-Driven Predictive Model for Osteoporosis Risk Assessment

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ABSTRACT: Bone mass and bone structure are both diminished during the course of osteoporosis, a degenerative bone disease. For millions of individuals all around the globe, it is the primary source of suffering. In order to intervene and treat osteoporosis in a timely manner, early prognosis of the disease is crucial. The suggested method entails creating a system for assessing the risk of osteoporosis by machine learning (ML). This system uses the Osteoporosis Risk Prediction dataset comprising 14 demographic and clinical variables and 1,958 patient records. Various methods were performed to improve the data and to make it balanced between the classes. Label encoding, Missing value imputation, Procedures for removing duplicates, handling outliers, imputation of missing values, and SMOTE (Sequential Minority Oversampling Technique). For the goal of osteoporosis prediction, four ML models were evaluated: Decision Tree, XGBoost, K-Nearest Neighbours (KNN), LightGBM (LGBM), and Random Forest (RF). In comparison to the other models, the Random Forest model had the best results in terms of accuracy (ACC) (93%), precision (PRE) (92%), recall (REC) (93%), and F1-score (F1) (92%). Characteristic importance analysis also helped identify the key risk variables for osteoporosis prediction. The results indicate that the proposed random forest-based method is accurate and reliable in early osteoporosis diagnosis and it could assist health-care providers to make clinical decisions and diagnose osteoporosis at an early stage.

KEYWORDS: Osteoporosis, Post-menopausal women, Artificial Intelligence, Risk prediction, Model validation, Bone mineral density, machine learning.

1. Introduction

Healthy bones are essential for sustaining mobility, independence, and quality of life. The global burden of fractures and healthcare costs can be substantially reduced with early detection and prevention of bone abnormalities. Low bone mineral density (BMD), decreased bone microarchitecture, and an increased risk of fracture are the hallmarks of osteoporosis, a metabolic bone disease that worsens over time. There are around 8.9 million fractures every year and over 200 million people affected by it, making it one of the most frequent skeletal disorders globally [1]. Hormones change with age and the disease tends to be more prevalent in older adults, especially post-menopausal women, who have a greater risk of fracture[2][3]. High morbidity, high health care expenses, and lower quality of life are the effects of osteoporosis, which is sometimes referred to as the "silent disease" due to its stealthy progression until a fracture happens [4][5].

The factors associated with osteoporosis include: age, gender, body mass index (BMI), family history, physical inactivity, poor nutrition, calcium and vitamin D deficiency, and other endocrine disorders [6][7]. Early

identification of individuals at risk at a young age stage is necessary to initiate interventions to prevent progression of the disease and to reduce the incidence of fractures [8][9]. Thus, reliable osteoporosis risk assessment techniques are very important for enhancing clinical result and facilitating preventive health care plan [10][11].

Currently, the gold standard for diagnosing osteoporosis and evaluating bone mineral density is Dual-Energy X-ray Absorptiometry, more often known as DXA [12]. The high cost, limited availability and lack of complete representation of bone quality [13] are the limitations of widespread DXA use [14]. Traditional approaches to risk assessment, including clinical risk factors used in combination with BMD measurements, have been developed to estimate fracture risk, but some populations may be over- or under-assessed with these techniques and in many cases clinical resources are required for these methods to be used [15]. Therefore, it is increasingly important to identify efficient, easy to access, and data-driven methods to screen and predict osteoporosis [16][17].

Healthcare prediction and decision support have been

utterly transformed by the recent developments in AI, ML, and DL. ML algorithms can also be used to detect complex and non-linear relationships between demographic, laboratory, and clinical variables from large-scale clinical datasets that have proven difficult to model using traditional statistics [18][19]. In the same way, DL models have shown to provide remarkable performance in extracting meaningful patterns from the health care information which can be used to predict the diseases and risk stratification. A number of AI-based approaches have shown promise in improving the PRE, efficacy, and scalability of osteoporosis risk assessment, leading to more reliable prediction solutions [20][21][2].

Motivation and Contribution

The motivation behind this study is the growing prevalence of osteoporosis and the increasing number of fracture-related complications that significantly affect public health worldwide. There is an urgent need for early and accurate risk prediction tools because osteoporosis is often undiagnosed until a fracture. Traditional diagnostic methods can be expensive and not readily available in all health care environments. This project's research therefore focuses on a data-driven approach to early risk factors and preventative health support for osteoporosis. The researchers aim to construct this system by utilizing methods related to DL, ML, and AI. Several significant contributions are made by this work, as can be shown below:

- Utilized demographic and clinical data to build a ML system for early risk prediction of osteoporosis.
- Utilized the Osteoporosis Risk Prediction dataset comprising 1,958 patient records and 14 input features for comprehensive risk assessment.
- Implemented and compared multiple ML models, namely DT, KNN, XGBoost, LightGBM (LGBM), and RF.
- Identified RF as the best-performing model for osteoporosis risk prediction.
- Using feature importance analysis, determined which characteristics significantly impact the risk of osteoporosis.
- Developed a trustworthy decision-support system that medical providers may use to better identify and prevent osteoporosis in its early stages.

The rising prevalence of osteoporosis and the need for early risk assessment techniques that are valid, accurate, cost-effective, and able to minimize fracture consequences warrant this investigation. The novelty of the proposed work is the usage of comprehensive data preprocessing methods, such as the missing value imputation, outlier treatment, normalization and class

balancing using SMOTE in conjunction with a comparative analysis of various ML techniques for the risk prediction of osteoporosis. Moreover, the study incorporates feature importance analysis to improve model interpretability and finds that the RF model is the best model in terms of predicting early osteoporosis risk.

Organization of the Paper

The paper is organized as follows: In Section II, examine the relevant literature, In Section III, offer the dataset and the approach that used, the experimental results are discussed in Section IV, and the study is concluded with suggestions for further research in Section V.

Literature Review

A detailed review and critical analysis of existing research on the early detection of osteoporosis risk were carried out to provide a strong foundation for the development and evaluation of the proposed study.

Mirza et al. (2026) perform three-class osteoporosis risk classification (normal, osteopenia, and osteoporosis) from anteroposterior lumbar DXA images using contemporary DL models. Multiple backbones were trained and evaluated under a unified experimental protocol to enable fair comparison across model families. In terms of overall performance on the held-out test set, ConvNeXtV2-Base was the most effective with an ACC of 88.89%, macro precision of 89.18%, macro-REC of 89.20%, macro-specificity of 94.24%, and macro-F1 of 89.13%. The best performing model achieved a macro-averaged ROC-AUC of 0.971. The picture areas that contributed the most to the predictions were visualized using explainable AI [22].

Padmanabha and Pai (2025) AI system that accounts for data limitations and model interpretability in predicting the likelihood of osteoporosis. A high-quality synthetic dataset is generated using Conditional Tabular Generative Adversarial Networks (CTGAN), which improves upon restricted clinical datasets and maintains statistical characteristics and patient privacy. A Random Forest classifier with 75% ACC and an AUC-ROC of 0.82 is trained on the synthetic-enhanced dataset. To improve clinical applicability, SHAP (SHapley Additive explanations) values are incorporated to provide transparent, feature-level explanations for individual risk predictions [23].

Aburomman et al. (2025) presents an interpretable DL model for classifying knee osteoporosis using X-ray images. Leveraging transfer learning, this research fine-tuned several pre-trained CNN architectures, with DenseNet121 achieving the highest classification ACC of 92.50% on the Multi-Class Knee Osteoporosis X-Ray dataset. Using Gradient-weighted Class Activation

Mapping (Grad-CAM) to highlight the most important areas in the X-ray pictures that were used to make predictions by the model, the suggested study improved interpretability [24].

Hidar et al. (2024) examines the effects of image preprocessing methods on pretrained convolutional neural networks that can automatically identify osteoporosis in knee X-ray pictures. When combined with Bilateral Filtering and CLAHE, VGG16 achieved better results than ResNet-50, ResNet-101, and VGG19, with an ACC of 78.39%, PRE of 80.00%, and REC of 76.02% [25].

Shetty et al. (2023) Diagnostic tests for osteoporosis include measurements of bone mineral density (BMD) taken with imaging modalities as pQCT, DXA scans, or quantitative ultrasound (QUS). Provide a neural network-based osteoporosis prediction model with L2 regularization to overcome the aforementioned challenge and increase the ACC of predictions. Many

prominent ML algorithms are tested against this model to see how it performs. These include KNN, SVM, LR, XGBoost, and RF. An analysis is conducted using the NHANES dataset, which considers demographics and living circumstances. The 87.2% ACC rate of proposed model for osteoporosis prediction is evidence of its efficacy [26].

Varalakshmi et al. (2022) determined the most effective model for osteoporosis risk prediction using DEXA scan pictures. Denoising, image augmentation, and thresholding are pre-processed on the scan pictures to increase the diagnostic PRE and ACC. In order to find the most effective model, train and test various CNN and hybrid models, then graph their performance. In terms of ACC (92.05%), specificity (90.37%), sensitivity (93.87%), PRE (89.97%), and F1 (91.88%), the experimental results demonstrate that the suggested method of image pre-processing, data augmentation, sampling using the SMOTE, and the Inception v3 CNN model achieves the best results [27].

Table I summarizes recent studies on the early detection of osteoporosis risk, highlighting the proposed methodologies, datasets employed, key outcomes achieved, and the limitations or challenges identified in each study.

Author	Proposed Work	Dataset	Findings	Limitations & Future Work
Mirza et al., (2026)	Multi-class osteoporosis classification using deep learning models on lumbar DXA images with XAI.	Lumbar DXA images	ConvNeXtV2-Base achieved 88.89% accuracy and ROC-AUC of 0.971.	Requires larger and multi-center datasets for better generalization and clinical validation.
Padmanabha and Pai, (2025)	CTGAN-based synthetic data generation with Random Forest and SHAP for interpretable osteoporosis prediction.	Clinical tabular dataset	Achieved 75% accuracy and AUC-ROC of 0.82 with improved interpretability.	Limited prediction performance; future work should explore hybrid deep learning models and real-world validation.
Abuomman et al., (2025)	Transfer learning-based knee osteoporosis classification using CNNs with Grad-CAM explanations.	Multi-Class Knee Osteoporosis X-ray dataset	DenseNet121 achieved 92.50% accuracy with interpretable predictions.	Performance should be validated on larger and more diverse datasets.
Hidar et al., (2024)	Pretrained CNNs with image preprocessing techniques for osteoporosis detection from knee X-rays.	Knee X-ray images	VGG16 with Bilateral Filtering and CLAHE achieved 78.39% accuracy.	Moderate accuracy; future studies should investigate advanced architectures and larger datasets.
Shetty et al., (2023)	Neural network with L2 regularization compared with conventional ML models for osteoporosis prediction.	NHANES dataset	Proposed model achieved 87.2% accuracy.	Limited to demographic and lifestyle features; multimodal clinical data can improve prediction performance.
Varalakshmi et al., (2022)	CNN and hybrid models with image preprocessing, augmentation, and SMOTE for DEXA image analysis.	DEXA scan images	Inception-v3 achieved 92.05% accuracy and 93.87% sensitivity.	Future work should focus on explainable AI and real-time clinical deployment.

Research gaps: Existing osteoporosis prediction studies predominantly depend on medical imaging datasets, which require specialized equipment and increase computational complexity. The proposed models are not necessarily generalizable to other populations because they are trained based on a limited

number of samples or based on specific domain data. Furthermore, relatively few studies focus on readily accessible clinical and demographic data for early assessment of osteoporosis risk. Osteoporosis risk may be accurately predicted using commonly available healthcare data, so a cost-effective, interpretable, and ML framework is required.

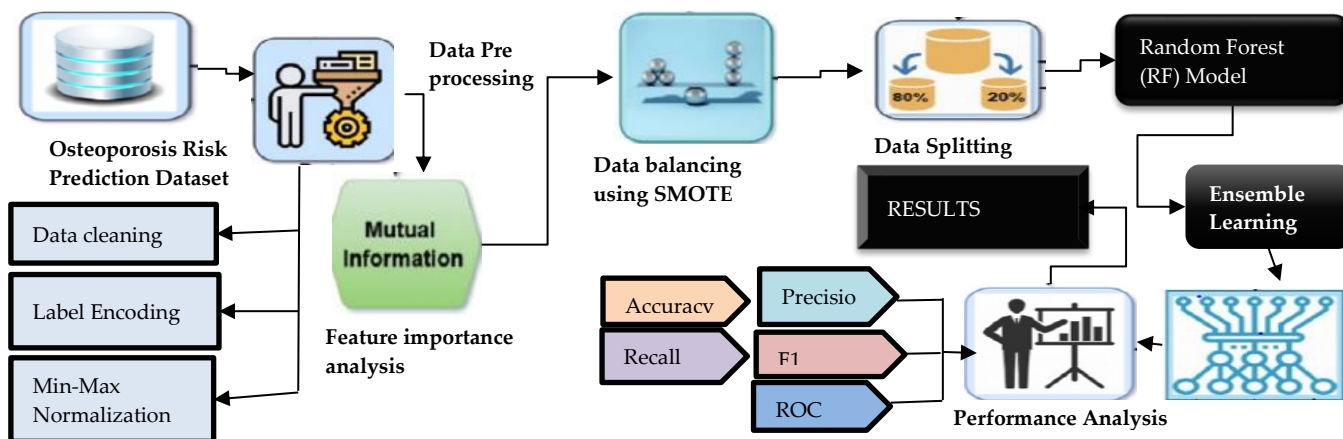


Fig. 1. Proposed Flowchart for Early Detection of Osteoporosis Risk Using Machine Learning

III. Research Methodology

The 1958 patient records that make up the Osteoporosis Risk Prediction Dataset are used in conjunction with preprocessing techniques such as normalization, label encoding, outlier treatment, missing value imputation, and SMOTE-based data balancing by this methodology. Osteoporosis risk prediction using a RF classifier may be achieved by dividing the processed data into 80% training and 20% testing. To find the most important risk factors, feature significance analysis is utilized. To test how well the model worked, ROC curve analysis, F1, ACC, PRE, and REC are employed. The proposed flowchart for early risk assessment of osteoporosis using ML is shown in

Figure 1.

The following section should contain the data source, pre-processing information, and ML models that were utilized:

A. Data Gathering and Analysis

The 14 input features of the Osteoporosis Risk Prediction Dataset are utilized in this study. Two kinds of characteristics are taken into consideration: numerical and category. Binary variables are used as output features. A total of 1958 patients have had their data recorded. The distribution of attacks and the correlations between attributes were some of the elements that informed the creation of these data visualizations, which comprise bar graphs and heatmaps:

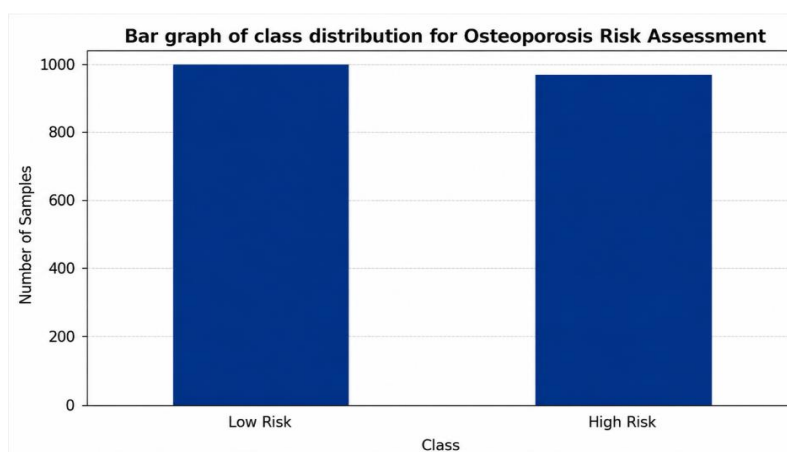


Fig. 2. Bar Graph of Class Distribution

Table II displays the sample distribution for the data set's osteoporosis risk classes. The bar graph shows that both classes, Low Risk and High Risk, contain a comparable number of instances, indicating a relatively

balanced dataset. Such a balanced class distribution minimizes prediction bias and leads to the creation of a reliable osteoporosis risk assessment model.

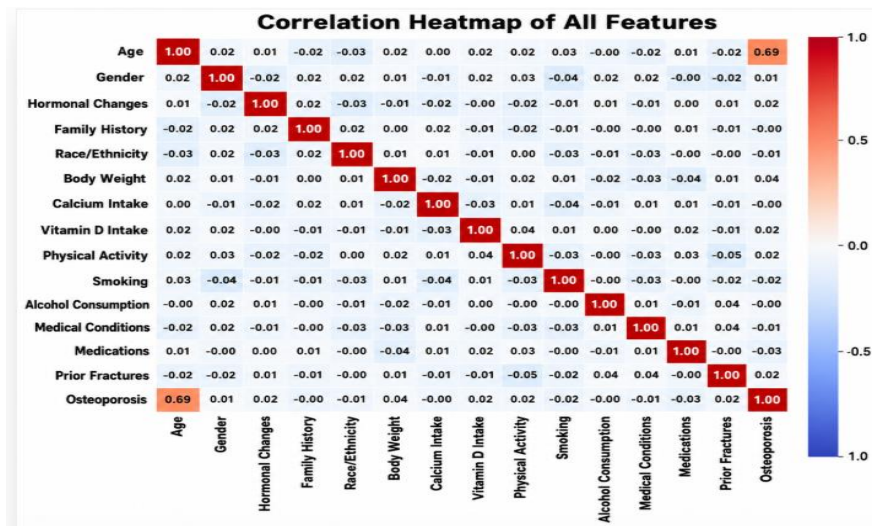


Fig. 3. Correlation Matrix Heatmap

The correlation matrix heatmap of features used for osteoporosis risk assessment is shown in Figure 3. The

correlations of most features are relatively weak and therefore low multicollinearity, and age is relatively strongly positively correlated with osteoporosis risk.

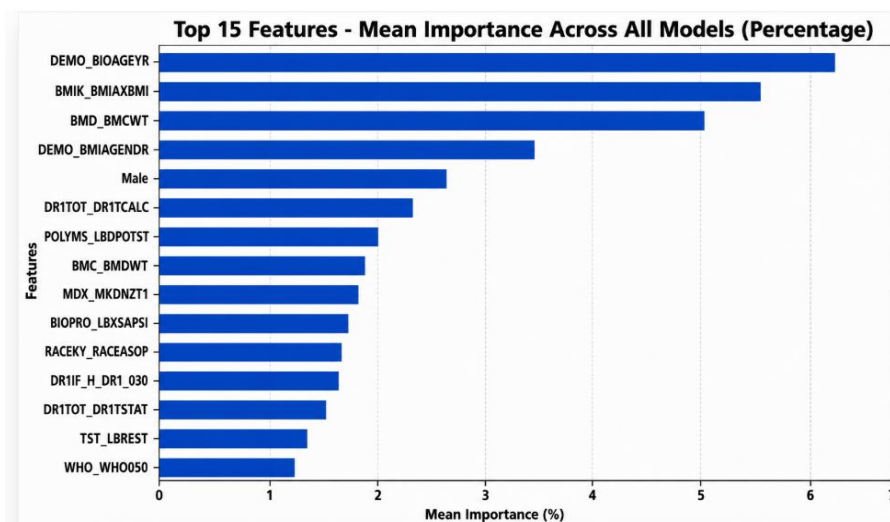


Fig. 4. Feature Importance Analysis

Feature relevant for osteoporosis prediction is displayed in Figure 4. The most impact characteristics are those that are directly related to age and BMD. The remaining variables have a small influence, but they all help to explain the model and identify the most important risk factors.

B. Data Pre-Processing

Data was cleaned and engineered to be consistent and of high quality, as per the Osteoporosis Risk Prediction Dataset. Data preprocessing techniques involved in the process of handling missing values, removing duplicate values, detecting and treating outliers. Finally, data labeling and normalization were applied to transform the dataset into a suitable format for accurate osteoporosis risk prediction:

- **Missing value imputation:** Missing values were detected and filled to complete the data set. The numeric attributes, age, BMI, and vitamin D levels,

were filled with the median value of the attribute, and the categorical attributes, type of source, type of health care, and type of health care provider were filled with the mode value of the attribute.

- **Duplicate Record Removal:** There was data duplication in the data set; this was identified and removed from the data set to reduce bias in modelling. This step helped to ensure equal contribution from each patient record and ensured that patient records were unique.
- **Outlier Detection and Treatment:** Outliers in variables with clinical measurements were detected by the Interquartile Range (IQR) method. Extreme observations were investigated and treated for their impact on model performance, particularly for BMI and laboratory measurements.
- **Label Encoding:** Used LabelEncoder from scikit-learn rather than one-hot encoding for categorical

data encoding. LabelEncoder encodes categorical variables into sequences of integers: {0, ..., n_classes-1} with n_classes being the number of different categories for the given variable.

C. Min-Max Normalization

The min-max technique was used to normalize the records from 0 to 1. The goal was to improve the classifiers' performance and reduce the influence of outliers. The following mathematical formula was used to do the normalisation Equation (1):

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Here, X stands for the feature's initial value, X' for its normalised value, X_{min} for its minimum value, and X_{max} for its maximum value.

D. Feature Importance Analysis

The built-in feature importance in the ensemble model was used to analyze the feature importance in this study. In order to compare and identify the most significant factors impacting osteoporosis risk prediction, measured and normalised the proportional contribution of each predictor as a percentage (Fig. 4). The feature importance was calculated using Equation. (2):

$$I(f) = \sum_i \left(\frac{\Delta i(f)}{M} \right) \quad (2)$$

E. Data Balancing Using SMOTE

Data balancing is the answer to class imbalance. To improve dataset balance, this study used the SMOTE approach to create synthetic samples for minority groups. Using the distance between instances of the minority class and their neighbors as a measure, SMOTE creates synthetic samples.

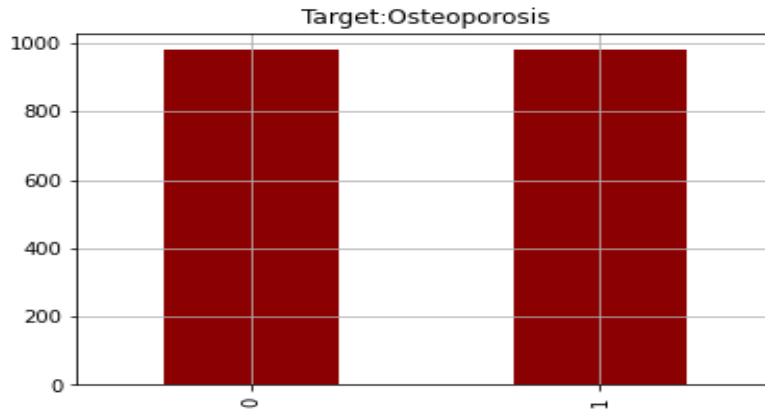


Fig. 5. Bar Graph of Class Distribution After SMOTE

The class distribution of the osteoporosis dataset after applying the SMOTE is shown in Figure 5. The graph indicates that there is no class imbalance and that both classes have the same number of samples. This is a balanced distribution and help learning models, reduce prediction bias and enhance confidence in the osteoporosis risk classification.

F. Data Splitting

Training data and testing data are the two halves of the dataset that are being considered here. The conventional method calls for training the model using 80% of the data and testing it with 20%.

G. Proposed Random Forest (RF) Model

The early risk of osteoporosis was predicted using an RF model. One ensemble learning method, RF, uses a large number of DTs trained on different sets of data and characteristics to improve prediction ACC. The final prediction is obtained by using Gini impurity to quantify the quality of splits at each node and majority voting. It is possible to determine the Gini impurity at node (N) by applying Equation (3):

$$g(N) = \sum_{i \neq j} P(w_i)P(w_j) \quad (3)$$

where P(w_i) is the percentage of the population that belongs to class i. One other approach to assess the split's quality is to examine its Shannon entropy. It computes the degree to which the data is disorganised. One way in which decision trees quantify the unpredictability of data stored in individual nodes is by calculating their Shannon entropy. This metric quantifies the degree to which a node's population is diverse. Using Equation (4) as follows, may determine the entropy in node N.

$$H(N) = \sum_{i=1}^d P(w_i) \log_2(Pw_i) \quad (4)$$

where d is the number of classes that are being looked at and P(w_i) is the percentage of the population that is labelled as i. With an equal distribution of classes inside the node, the entropy is maximum. This is at its lowest when a node is pure, meaning it has exactly one class. When deciding on a splitting option at a node, the most apparent heuristic is to go for the one that minimises impurity. When comparing splits, the better one have the most information gain or impurity reduction. Find the information gain from a split using Equation (5):

$$\Delta IN = IN - PL * INL - PR * INL \quad (5)$$

The left and right children of node N are denoted as N_L and N_R, respectively, and the impurity measure of node N is denoted as I(N). The percentage of the population of node N that go to the left and right children of N after the split are denoted as P_L and P_R, respectively, and N_L and N_R are the children of N.

The RF model was suggested with these parameters: n_estimators = 200, max_depth = 15, min_samples_split = 5, min_samples_leaf = 2, max_features = 'sqrt', and random_state = 42. These hyperparameter values were utilised to enhance generalisation performance, minimise overfitting, and boost classification ACC for osteoporosis risk prediction. The improved RF model outperformed every other ML technique that was evaluated in terms of prediction ACC.

H. Evaluation Metrics

The proposed model for assessing the risk of osteoporosis was evaluated using a bunch of classification metrics. Confusion matrices were created as the initial stage in assessing the prediction outcomes. With this matrix, and can shows how the projected and actual class labels line up. Total number of TPs, TNs, FPs, and FNs were provided by the confusion matrix. In order to evaluate the classification model's performance and reliability, these data were utilised to calculate associated evaluation metrics such as REC, ACC, PRE, and F1:

Accuracy: A dataset's ACC may be calculated by dividing the total number of occurrences by the number of correct classifications. The trained model's total performance, spanning both positive and negative classifications, is evaluated using it. Equation (6) is used to compute the ACC-

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (6)$$

Precision: One technique to assess the accuracy of the model's predictions is to divide the total number of correct predictions by the actual number of correct forecasts. It measures the model's ability to decrease the number of FP predictions and is indicative of the ACC of the positive classifications. That equation is the basis of the PRE Equation (7).

$$Precision = \frac{TP}{TP+FP} \quad (7)$$

Recall: A higher proportion of actual positives are genuine positives. The goal is to find out how well the classifier can distinguish between true positives and FN. Equation (8) shows the mathematical formulation of recollection-

$$Recall = \frac{TP}{TP+FN} \quad (8)$$

F1 score: The F1 is an all-encompassing metric for evaluating a model's performance; it is the harmonic mean of the REC and your ACC. At the point where FP and negatives are of equal significance, it becomes significantly more valuable. The mathematical expression of F1 is given by Equation (9), and its value can take on a range from 0 to 1, with higher scores translating to better classification performance

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (9)$$

Receiver Operating Characteristic Curve (ROC): A ROC curve is a chart that shows how well a binary classifier or other binary classification model does over a range of decision criteria. It plots the TPR also known as sensitivity or REC, against the FPR that is mathematically computed as 1- specificity.

IV. Results and Discussion

An Intel Core i7 CPU, 16 GB of RAM, a 512 GB solid-state drive, and an NVIDIA RTX 3060 GPU (CUDA toolkit supported) are the optimum hardware configurations for high-performance ML analysis and model training. Python 3.8 and Jupyter Notebooks served as the foundation for the software environment.

A. Experimental Results

This section showcases the suggested model's efficacy and efficient processing in identifying early osteoporosis risk, as well as its performance on several evaluation measures. Table II provides a synopsis of the training and assessment conducted on the Osteoporosis Risk Prediction Dataset for the suggested model. The metrics used for evaluation include ACC, PRE, REC, and F1. With a 93% ACC rate, 92% PRE rate, 93% REC rate, and 92% F1, the model clearly possesses strong and well-balanced categorization skills. The suggested approach shows promise for the accurate identification of the patients who may be susceptible to osteoporosis, with reliable forecasting performance.

TABLE II. Classification Results of Proposed Model for Early Detection of Osteoporosis Risk

Matrix	Testing
Accuracy	93
Precision	92
Recall	93
F1-score	92

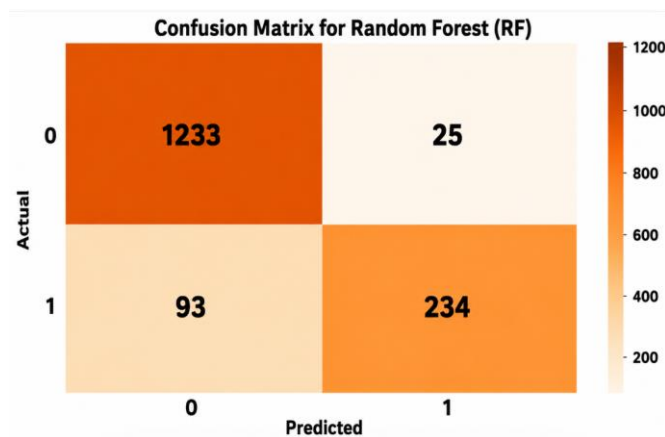


Fig. 6. Confusion Matrix for the Random Forest (RF) Model

The confusion matrix for RF model is shown in Figure 6, which shows that the model performs well in classification tasks with a high number of correct

predictions and few misclassifications. The RF model's capacity to distinguish between the two classes is demonstrated by the darker diagonal cells, which indicate instances that were appropriately categorized.

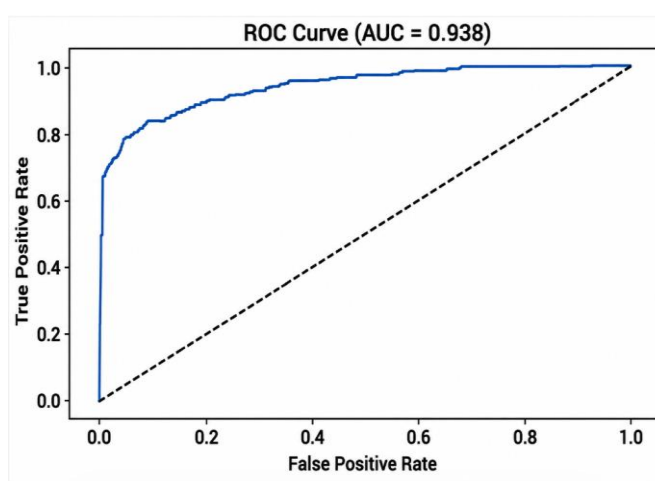


Fig. 7. ROC Curve for Random Forest (RF) Model

Figure 7 below shows the RF model's ROC curve. There is a high TPR and a low FPR because the curve is densely packed at the top left corner. Good discriminative performance and overall data accuracy were shown by the RF model's AUC score of 0.938.

B. Comparative Analysis

The efficiency of the suggested model is tested by comparing it with other existing models in Table III. With an ACC of 93% in ACC, PRE, REC, and F1, the

suggested RF model clearly outperforms the competition. The ACC for the other algorithms was 82.9 percent for DT, 82.8 percent for XGBoost, 88.5 percent for KNN, and 90.5 percent for LightGBM (LGBM) accordingly. The RF model's superior performance illustrates its effectiveness in capturing the intricate patterns present in the Osteoporosis Risk Prediction Dataset, thereby serving as a dependable method for early detection of osteoporosis risk.

Table III. Comparison of Different Machine Learning Models for Early Detection of Osteoporosis Risk

Model	Accuracy	Precision	Recall	F1-score
Decision tree (DT)[28]	82.8	-	-	-
XGBoost[29]	88	89	88	88
KNN[30]	89	-	-	-
LightGBM (LGBM)[31]	90.05	91	90	90
RF	93	92	93	92

The proposed early osteoporosis risk detection model Random Forest (RF) possesses several

advantages. Multiple decision trees can be run simultaneously with RF, which enables it to capture complex interactions among clinical characteristics

without overfitting. The model performed well and exhibited a high ACC of 93% and was able to perform better than other models. Furthermore, it demonstrates high PRE, REC, and F1, which signify solid classification performance, churning it into a strong instrument for osteoporosis risk assessment.

V. Conclusion and Future Study

Osteoporosis is an increasing problem and there is a need for simple and accessible ways of predicting osteoporosis risk. In this study, the researchers have created an AI-based ML system using clinical and demographical data of 1958 patients, for the early assessment of osteoporosis risk. The use of comprehensive preparation methods such as missing value imputation, outlier treatment, label encoding, and SMOTE data balancing enhanced data quality and the robustness of models. Multiple algorithms such as Decision Tree, KNN, XGBoost, LightGBM and RF were tested. With 93% ACC, 92% PRE, 93% REC, 92% F1, and 0.938 AUC, the RF model had the best performance in the experiments. The feature importance analysis also determined the most important risk factors linked with osteoporosis. These results suggest the proposed framework is valid, reliable and can be used by health care practitioners to make early predictions about risk of osteoporosis and clinical decisions.

Future research will involve the inclusion of larger and multi-center datasets for better generalizability of the model. Furthermore, combining multimodal healthcare data, explainable AI methods and DL algorithms could further improve the ACC of predictions, interpretability and real time clinical utility of osteoporosis risk assessment.

References

1. X. Tong et al., "The Effect of Exercise on the Prevention of Osteoporosis and Bone Angiogenesis," *Biomed Res. Int.*, vol. 2019, pp. 1–8, Apr. 2019, doi: 10.1155/2019/8171897.
2. A. V. S. R. Dantuluri, "A Scalable Deep Learning Analytics Pipeline for Converting Longitudinal Real-World Data Into Predictive Disease Trajectories," in *IEEE Access*, IEEE, 2026, pp. 24871–24878, February. doi: 10.1109/ACCESS.2026.3663571.
3. K. K. Mohammed, "A Survey on Digital Health Care Data Analysis Techniques for Developing Machine Learning Models," *Int. J. Softw. Eng. Technol.*, vol. 13, no. 5, pp. 158, October, 2025, doi: 10.5281/zenodo.17339813.
4. J. A. Clowes, B. L. Riggs, and S. Khosla, "The role of the immune system in the pathophysiology of osteoporosis," *Immunol. Rev.*, vol. 208, no. 1, pp. 207–227, Dec. 2005, doi: 10.1111/j.0105-2896.2005.00334.x.
5. [5] N. E. Lane, "Epidemiology, etiology, and diagnosis of osteoporosis," *Am. J. Obstet. Gynecol.*, vol. 194, no. 2, pp. S3–S11, Feb. 2006, doi: 10.1016/j.ajog.2005.08.047.
6. [6] A. Warriar and K. Abhilash, "Autonomous Agentic AI for Clinical Workflow Orchestration: Self-Managing Healthcare Operations," in *2025 6th International Conference on IoT Based Control Networks and Intelligent Systems (ICICNIS)*, Bengaluru, India: IEEE, 2025, pp. 1450–1457, December. doi: 10.1109/ICICNIS66685.2025.11315712.
7. [7] J. S. Ramos, J. G. Maciel, M. T. Cazzolato, C. Traina, M. H. Nogueira-Barbosa, and A. J. M. Traina, "BEAUT: a radiomic approach to identify potential lumbar fractures in magnetic resonance imaging," in *2021 IEEE 34th International Symposium on Computer-Based Medical Systems (CBMS)*, IEEE, Jun. 2021, pp. 389–394. doi: 10.1109/CBMS52027.2021.00089.
8. [8] A. Naseri et al., "Hip structural analysis, trabecular bone score, and bone mineral density in post-menopausal women with type-2 diabetes mellitus: a multi-center cross-sectional study in the south of Iran," *Arch. Osteoporos.*, vol. 18, no. 1, p. 98, Jul. 2023, doi: 10.1007/s11657-023-01310-1.
9. [9] V. Chaturvedi, "Disease Diagnostic Systems based on AI-Applications in Healthcare: Models, Challenges, and Future Directions," *Int. J. Emerg. Res. Eng. Technol.*, vol. 6, no. 4, pp. 207–217, Dec. 2025, doi: 10.63282/3050-922X.IJERET-V6I4P125.
10. [10] J. Deshpande and C. K. Singh, "Development and Validation of an AI-Based Risk Prediction Model for Osteoporosis in Post-Menopausal Women," *BioMed Target J.*, vol. 3, no. 1, pp. 76–83, 2025, doi: 10.59786/bmtj.317.
11. [11] J. Smets, E. Shevroja, T. Hügler, W. D. Leslie, and D. Hans, "Machine Learning Solutions for Osteoporosis—A Review," *J. Bone Miner. Res.*, vol. 36, no. 5, pp. 833–851, Dec. 2020, doi: 10.1002/jbmr.4292.
12. [12] C. E. Harris and S. Makrogiannis, "Sparse Analysis of Block-Boosted Deep Features for Osteoporosis Classification," in *2022 IEEE 14th Image, Video, and Multidimensional Signal Processing Workshop (IVMSP)*, IEEE, Jun. 2022, pp. 1–5. doi: 10.1109/IVMSP54334.2022.9816199.
13. [13] E. Shevroja, F. P. Cafarelli, G. Guglielmi,

- and D. Hans, "DXA parameters, Trabecular Bone Score (TBS) and Bone Mineral Density (BMD), in fracture risk prediction in endocrine-mediated secondary osteoporosis," *Endocrine*, vol. 74, no. 1, pp. 20–28, Oct. 2021, doi: 10.1007/s12020-021-02806-x.
14. S. K. Madishetty, "Cyber Resilience and DevOps in Operating Rooms: Securing Connected Embedded Medical Devices in High Risk Clinical Environments," *J. Electr. Syst.*, vol. 19, no. 3, pp. 244–253, Jan. 2024, doi: 10.52783/jes.9597.
 15. S. Mahmud, K. K. Mohammed, V. R. Jain, and S. A. Shah, "Artificial Intelligence-Driven Predictive Models for Identifying Risk Factors of Chronic Diseases," in *14th International Symposium on Digital Forensics and Security (ISDFS)*, Boston, MA, USA: IEEE, 2026, pp. 01–06, April. doi: 10.1109/ISDFS69419.2026.11459003.
 16. N. Sollmann and T. Baum, "Editorial on Special Issue 'Spine Imaging: Novel Image Acquisition Techniques and Analysis Tools,'" *Diagnostics*, vol. 12, no. 6, p. 1361, Jun. 2022, doi: 10.3390/diagnostics12061361.
 17. U. Ferizi, S. Honig, and G. Chang, "Artificial intelligence, osteoporosis and fragility fractures," *Curr. Opin. Rheumatol.*, vol. 31, no. 4, pp. 368–375, Jul. 2019, doi: 10.1097/BOR.0000000000000607.
 18. Y. He, J. Lin, S. Zhu, J. Zhu, and Z. Xu, "Deep learning in the radiologic diagnosis of osteoporosis: a literature review," *J. Int. Med. Res.*, vol. 52, no. 4, Apr. 2024, doi: 10.1177/03000605241244754.
 19. M. Almohaimeed, "Enhancing Prediction of Osteoporosis Using Supervised and Unsupervised Learning: New Approach to Disease Subtyping," *Intell. Inf. Manag.*, vol. 17, no. 02, pp. 31–47, 2025, doi: 10.4236/iim.2025.172002.
 20. M. L. T. Alfianti and R. Supriyanto, "Perbandingan Kinerja Algoritma Random Forest, AdaBoost, dan XGBoost Dalam Memprediksi Resiko Penyakit Osteoporosis," *J. Ilmu Komput. dan Agri-Informatika*, vol. 11, no. 2, pp. 172–184, Nov. 2024, doi: 10.29244/jika.11.2.172-184.
 21. C. Huang et al., "Application of deep learning model based on unenhanced chest CT for opportunistic screening of osteoporosis: a multicenter retrospective cohort study," *Insights Imaging*, vol. 16, no. 1, p. 10, Jan. 2025, doi: 10.1186/s13244-024-01817-2.
 22. A. K. M. Mirza, W. A. Hafiz, A. S. Rajab, S. A. Albargi, and A. Duru, "Osteoporosis Risk Classification from Lumbar Spine DXA Images," in *2026 8th International Congress on Human-Computer Interaction, Optimization and Robotic Applications (ICHORA)*, IEEE, May 2026, pp. 1–7. doi: 10.1109/ICHORA69329.2026.11537181.
 23. S. Padmanabha and R. M. Pai, "Explainable AI for Osteoporosis Risk Modeling: Random Forest and SHAP Interpretation on CTGAN-Enhanced Data," in *2025 2nd Asia Pacific Conference on Innovation in Technology (APCIT)*, IEEE, Sep. 2025, pp. 1–6. doi: 10.1109/APCIT65661.2025.11410996.
 24. A. Aburomman, K. Hamad, S. Abuowaida, A. Al-Momani, R. Al-Azaidah, and O. Alidmat, "Explainable Deep Transfer Learning for Multi-Class Knee Osteoporosis Diagnosis Using Grad-CAM and DenseNet121," in *2025 26th International Arab Conference on Information Technology (ACIT)*, IEEE, Dec. 2025, pp. 40–47. doi: 10.1109/ACIT68900.2025.11510591.
 25. W. A. Hidar, A. S. Mubarak, L. R. David, A. J. Hyssian, H. M. Tawfik, and D. U. Ozsahin, "Classification of Osteoporosis in Knee X-ray using Transfer Learning and Random Forest," in *2024 17th International Conference on Development in eSystem Engineering (DeSE)*, IEEE, Nov. 2024, pp. 328–333. doi: 10.1109/DeSE63988.2024.10912021.
 26. S. Shetty, S. Shetty, A. Masurekar, V. Sarbhukan, and R. Pawar, "Neural Network-Based Model for Osteoporosis Prediction: A Novel Approach for Enhanced Accuracy," in *2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, IEEE, Jul. 2023, pp. 1–6. doi: 10.1109/ICCCNT56998.2023.10308187.
 27. P. Varalakshmi, S. Sathyamoorthy, V. Darshan, V. Ramanujan, and S. J. S. Rajasekar, "Detection of Osteoporosis with DEXA Scan Images using Deep Learning Models," in *2022 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI)*, IEEE, Jan. 2022, pp. 1–6. doi: 10.1109/ACCAI53970.2022.9752533.
 28. B. Ogunmiloro, "AI-Based Predictive Analysis of Osteoporosis: A Machine Learning Approach for Early Diagnosis," *Med. J. Zambia*, vol. 52, no. 3, pp. 434–442, Jun. 2025, doi: 10.55320/mjz.52.3.690.
 29. I. Irmawati, E. Herdit Juningsih, and Y. Yanto, "Predictive Modeling of Osteoporosis Risk Factors using XGBoost and Bagging Ensemble Technique," *J. Med. Informatics Technol.*, pp. 6–10, Mar. 2024, doi: 10.37034/medinftech.v2i1.27.
 30. R. Khushal and U. Fatima, "Fuzzy machine learning logic utilization on hormonal imbalance dataset,"

Comput. Biol. Med., vol. 174, p. 108429, May 2024,
doi: 10.1016/j.compbiomed.2024.108429.

31. F. Elias, M. S. Reza, M. Z. Mahmud, S. Islam, and S. R. Alve, "Machine Learning Meets Transparency in Osteoporosis Risk Assessment: A Comparative Study of ML and Explainability Analysis," 2025.