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Original Article

Osteoporosis Disease Prediction Using Machine Learning Algorithms

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Abstract

Osteoporosis is a long-term bone condition in which reduced mineral density weakens skeletal strength and increases susceptibility to fracture-related complications. In addition, accurate and early identification of osteoporosis can significantly decrease disease-related complications and enhance overall patient outcomes. This paper compares three machine learning methods without tree-based approaches, namely Logistic Regression, Support Vector Machine, and K-Nearest Neighbors, for the prediction of osteoporosis disease. Feature normalization and standard scaling were performed as preprocessing techniques to optimize model performance. Accuracy, precision, recall, F1-score, and receiver operating characteristic-area under the curve metrics are considered to evaluate the efficiency of the proposed models. Experimental results illustrate that the Logistic Regression model achieved the highest prediction accuracy, 98.56%, and outperformed other models in disease prediction. Support Vector Machine showed very stable and robust classification performance with an accuracy of 98.12%. On the other hand, K-Nearest Neighbors provided moderate performance with an accuracy of 94.13%. Thus, it is clear that machine learning models are both effective and computationally efficient in the prediction of osteoporosis disease and support clinical decision-making systems.

Categories: Predictive Analytics, Data Mining, Machine Learning (ML)

Keywords: machine learning, logistic regression, support vector machine, k-nearest neighbors, clinical decision support, osteoporosis prediction

Introduction

Osteoporosis is a progressive metabolic bone condition associated with decreased mineral density and structural deterioration of skeletal tissue. Often increased bone risk is due to the occurrence of fractures. Osteoporosis is considered to be one of the key major bone diseases found all over the world. Fractures affecting the hip, spine, and wrist regions frequently result in severe pain and long-term limitations in physical mobility. An increased risk of mortality has been associated. The onset of the condition is painless and has shown important socioeconomic issues. Early diagnosis of the condition has become the key because the condition is painless [1-3]. Bone mineral density (BMD) assessment using dual-energy X-ray absorptiometry (DEXA) is commonly applied in clinical practice to identify osteoporosis cases. While DEXA has been regarded as the clinical gold standard, it entails several disadvantages: high costs, limited availability in rural and resource-poor environments, radiation exposure, and inability to fully capture complex clinical risk factors. In addition, most traditional risk assessment methods are threshold-dependent and fail to model nonlinear interactions between specific patient attributes [2,4].

All the techniques of machine learning have gained widespread attention over the years in healthcare due to their ability to process a huge amount of data in the clinical environment to find hidden patterns. The models of predictive analysis are very helpful in increasing the rate of accuracy in diagnosis in healthcare through machine learning techniques in understanding the complex relationship among various factors like age, sex, body mass index, lifestyle habit, and biochemical markers. The methodology of data-driven techniques has tremendous possibilities in automating the task of osteoporosis prediction [1,4].

Most existing studies focus on learning methods associated with trees, which, although accurate, face problems related to complexities. On the other hand, studies that are not associated with trees are most effective in terms of their generalization and processing. Hence, it was planned to analyze three simple models associated with machine learning, which are not associated with trees, and are used commonly. They include Logistic Regression (LR), Support Vector Machine (SVM), and K-Nearest Neighbor (KNN) [5,6].

The significant contributions of the current research work can be briefed as follows. First, a comparative analysis is conducted using LR, SVM, and KNN algorithms for the prediction of the osteoporosis disease. Second, the experiments will be conducted using the above-stated techniques in terms of significant assessment factors such as accuracy, precision, recall, F1 measure, and receiver operating characteristic-area under the curve (ROC-AUC) scores. Third, relying upon the prediction accuracy and computational overhead of the algorithm, the most suitably validated algorithm of the relevant learning technique for the prediction of osteoporosis will be obtained. The results of the current research work will assist in formulating an efficient prediction system for osteoporosis using the learning algorithm technique [7].

Related work

Osteoporosis Diagnosis Techniques

The diagnosis of osteoporosis has conventionally been based on the evaluation of BMD. This has been determined using DEXA. BMD assessment is considered the golden standard for the diagnosis of osteoporosis as well as estimation of the risk of fracture. Patients are categorized as either normal, osteopenic, or osteoporotic depending on the predefined values of the T-score. Although much used, there are drawbacks to BMD evaluation, which include its high cost, unavailability, particularly in rural settings, exposure to low-doses of ionizing radiation, and poor ability to detect patients with early stages of bone degradation. BMD, on its own, may not accurately portray the complexity of patients with osteoporosis as it does not consider other risk factors for this condition [2,4]. To overcome such limitations, various clinical risk calculators such as FRAX and QFracture have been developed that can calculate the likelihood of fracture based on several demographic and clinical and lifestyle parameters. Though they do better in tailoring the accuracy of fracture probability, they mostly depend on statistical and threshold scores based on their established models. Consequently, they might not perform very well in identifying complex interactions between several variables of fracture probability in osteoporosis patients [7].

Machine Learning in Medical Prediction

The machine learning techniques have, in turn, been increasingly applied to medical diagnosis and disease prediction due to their capability of handling large and heterogeneous datasets. Models involving LR, SVM, and ANN have been able to perform accurately for different cardiovascular disease, diabetes, and cancer prediction over a wide range of clinical applications. LR is preferred mainly because of its simplicity and interpretability, making it suitable for baseline medical decision-making. While SVM has demonstrated strong generalization capability through maximizing the margin between classes, ANN-based models have turned out to handle superior performance in capturing complex nonlinear relationships within the medical data [5,6,8]. Some latest studies have also revealed the precision achieved by decision trees and ensemble techniques, such as Decision Trees and Random Forest, in the process of disease categorization. Even though techniques such as these prove helpful in precision, the problem pertaining to these techniques is that they tend to suffer from the problem of overfitting, tend to be computing resource-intensive, and tend to be non-interpretable, particularly in the case of limited healthcare datasets, such as imbalanced datasets in the healthcare industry [9].

Research gap

Although machine learning has been widely investigated for the prediction of osteoporosis, as well as other diseases, most of the current studies focus on tree-based or ensemble models. Only a few comparison studies have been conducted, which focus on non-tree-based machine learning algorithms. Furthermore, the trade-offs among predictive performance, computational efficiency, and interpretability have rarely been explored. This sets the motivation for a systematic comparison between efficient and interpretable non-tree-based models. The current study fills this gap by investigating and comparing LR, SVM, and KNN models for the prediction of osteoporosis disease.

Materials And Methods

Under this section, we give a mention about the dataset used for predictive modeling for the osteoporosis disease and preprocessing activities performed for cleaning data as well as system workflow methodology adopted for carrying out this research work. The adopted methodology allows for ensuring the quality of data and improvement in models for a comparative perspective regarding appropriate machine learning models for selection.

Dataset description

An ultrasonometer system was used to collect 3,008 instances and achieve a comprehensive data set including details of patients: age, sex, weight, height, and BMD, and T-score and patient ID. Then, samples are divided into three categories based on their severity of osteoporosis-normal, at the borderline of osteoporotic stage, also known as "Osteopenia", or Osteoporosis. Care has been taken that the data is valid and the distribution is equal so that effective learning and performance take place by models.

Data preprocessing

The purpose of data preprocessing is to improve machine learning systems, especially when working with a large database. Since healthcare data is susceptible to noise, the first step is to check for missing or inconsistent entries in the dataset [10]. When there are gaps in the database due to missing information, other methods (mean or median) are applied to substitute for the missing data. To normalize the features, we applied the standard scaler method [11]. The standard scaler permits each feature column to be represented on the same relative scale, with a zero mean and unit variance. This normalization process is critical for a number of learning algorithms, including LR, SVM, and KNN, as the scale of the input attributes has a large influence on the behavior of these algorithms. Normalization also ensures that all attributes are balanced by giving them the same weight in the training process and preventing an attribute with a large numerical range from dominating the other attributes. After normalizing the attributes, we used the conventional method of dividing the input dataset into two separate datasets for training and evaluating different machine learning models developed for predictive analysis, using a ratio of 70% of the data for training and 30% for evaluation [12].

System workflow

A general idea about the total workflow of the proposed osteoporosis disease prediction system is presented in a sequential manner through a three-stage pipeline. In the first stage, the clinical data input undergoes preprocessing in a manner that deals with missing values in the dataset and normalizes all features in a standardized form of the dataset. In the second stage, the preprocessed dataset is employed for the selection of the machine learning models: LR, SVM, and KNN classification technique using the training dataset. In the third stage of the pipeline, the trained models are then tested using the testing dataset in order to estimate their accuracy in predictive analytics. Some standard parameters of accuracy in most machine learning techniques used in the literature - accuracy, precision, recall, F1 Score, and AUROC - can be utilized in a comprehensive manner for a renewed assessment of different models based on their relative merit in osteoporosis disease prediction. Figure *1* illustrates the overall system architecture of the proposed osteoporosis prediction framework.

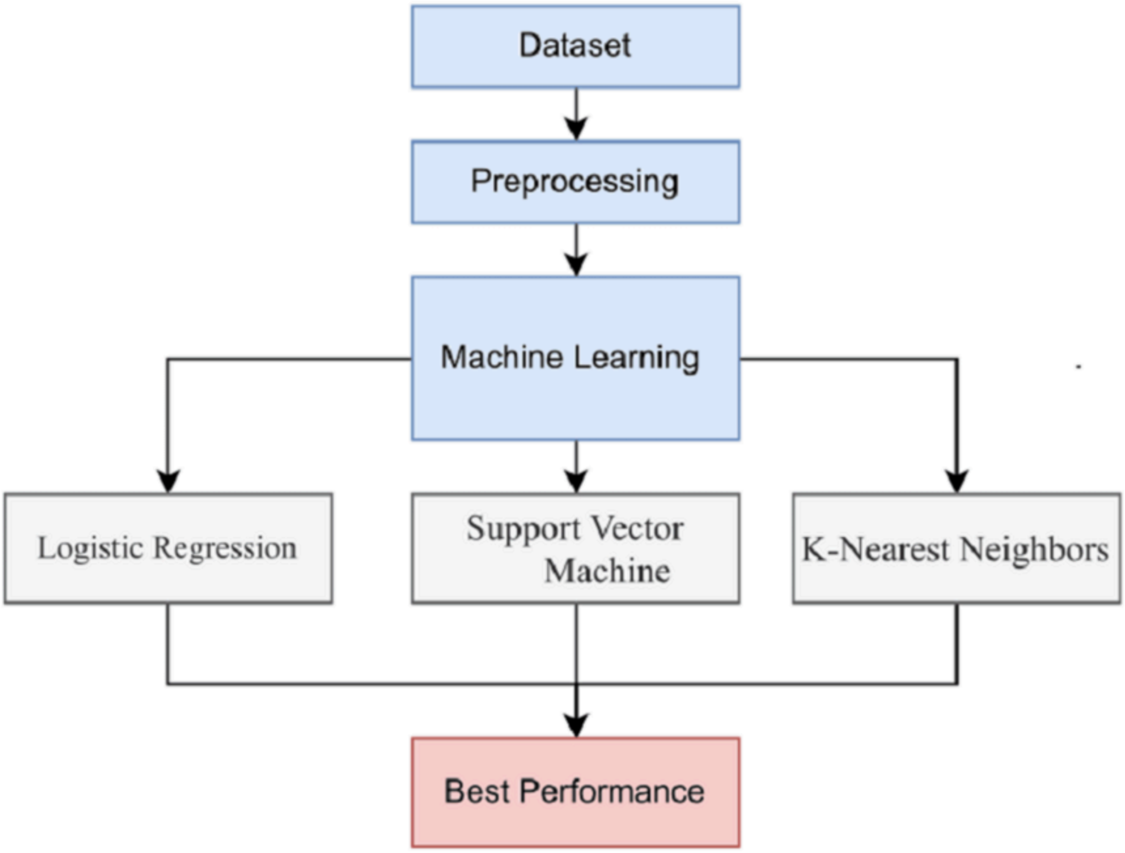

FIGURE 1: Overall System Architecture

Machine learning models

In this section, the machine learning models used in the prediction of osteoporosis disease are described. The three non-tree-based classifiers that are most widely used, including LR, SVM, and KNN, were chosen for their paradigms of learning.

Logistic Regression

In this study, LR is employed as a baseline classifier because of its simplicity and ability to provide interpretable probability-based predictions for osteoporosis risk assessment. It generates class probability through the application of the logistic function to the linear combination of input features. Because of its probabilistic approach, LR has results that are very interpretable in medical decision-support applications. This particular research uses LR as its baseline classifier in predicting osteoporosis. Its strengths are its quick training time, simplicity in calculation, and interpretability. Although LR is very straightforward in approach, it has the chance to perform competitively in case the features are related to class labels in a more or less linear fashion. Nonetheless, its effectiveness may be questionable in complex nonlinear relations among features in medical applications [13]. Algorithm 1 illustrates the pseudocode of the LR algorithm.

Algorithm 1. Pseudocode for LR

Input: Training dataset D, learning rate α, number of iterations T

Output: Trained LR model parameters w, b

Step 1: Initialize weight vector w and bias b with small random values.

Step 2: Repeat the following steps for T iterations:

Step 3: Compute the linear combination: $z = w^T x + b$

Step 4: Apply the sigmoid activation function to obtain predicted probability: $\hat{y} = \frac{1}{1+e^{-z}}$

Step 5: Calculate the cross-entropy loss function.

Step 6: Update the parameters w and b using gradient descent.

Step 7: End the training loop.

Support Vector Machine

The SVM model is applied in this work to improve class separation by constructing an optimal decision boundary for accurate osteoporosis classification. SVM has been very prominent in the literature in terms of generalization performance in high-dimensional spaces. SVM employs kernels for the nonlinear patterns present commonly in healthcare data, projecting the features into another space of a possibly much larger dimensionality. This turns the learning process capable of nonlinear boundaries. Kernel parameters are one crucial point in the performance, as well as complexity computation, for the models based on the SVM algorithm used in predicting osteoporotic diseases [14]. Algorithm 2 represents the pseudocode of the SVM algorithm.

Algorithm 2. Pseudocode for SVM

Input: Training dataset D, regularization parameter C, kernel function K

Output: Trained SVM classifier

Step 1: Transform input samples into higher-dimensional space using kernel function K.

Step 2: Formulate the margin maximization optimization problem.

Step 3: Solve the quadratic optimization problem to determine support vectors.

Step 4: Construct the optimal separating hyperplane.

Step 5: Store the model parameters and support vectors.

Step 6: Use the trained model to classify test samples.

K-Nearest Neighbors

The KNN algorithm is adopted in this study to perform instance-based classification using distance similarity among patient records. It classifies a given data instance by determining the majority class of its nearest neighbors in the feature space. Rather than undergoing model training like parametric models, the KNN algorithm makes predictions using stored training instances. The closeness of different instances in the data is usually determined by distance measures such as the Euclidean distance. The current study utilizes the KNN algorithm to determine the effectiveness of the instance-based learning approach in classifying patients suffering from osteoporosis. The KNN algorithm is very suitable for identifying the local characteristics of the data; in addition, it does not require any optimization of parameters in the prediction approach. Its results are dependent on the value of the number of neighbors and the scaling of instances in the analysis [15,16]. Algorithm 3 illustrates the pseudocode of the KNN algorithm.

Algorithm 3. Pseudocode for KNN

Input: Training dataset D, test sample x, number of neighbors k

Output: Predicted class label

Step 1: Compute the distance between the test sample and all training samples.

Step 2: Sort the distances in ascending order.

Step 3: Select the top k nearest neighbors.

Step 4: Perform majority voting among the selected neighbors.

Step 5: Assign the class label with the highest votes as the prediction result.

Results And Discussion

Experimental results and discussion

In this section, an experimental evaluation of the proposed machine learning models for predicting osteoporosis disease will be carried out. For this purpose, the results of the LR, SVM, and KNN models are evaluated using standard metrics. By comparing the results, the best model among them will be identified.

Performance Metrics

To get a holistic assessment, various performance measures have been used. Accuracy rate measures the overall goodness of the results of the classifications achieved. Precision and recall were analyzed to evaluate the reliability of positive osteoporosis predictions and minimize false clinical alarms. Recall shows the goodness of the model in identifying true instances of positives, and it is highly required in medical settings for reducing the cases of missing people's diseases. The F1 score shows the overall goodness of the model in averaging precision and recall. Secondly, another performance measure ROC-AUC has been used. In order for the evaluation of the models to be thorough, it involved the use of various metrics of classification accuracy. This is the accuracy of the classification performed by the various models. Precision is a measure of accuracy in terms of the proportion of truly predicted positive values from all values that have been predicted as positive by the various models in the classification carried out among patients with osteoporosis in order to avoid bias in the diagnosis of the disease for lack of proper prediction by the models. F1 is the mean of precision and recall in terms of classification accuracy of the various models. ROC-AUC is yet another measure of accuracy used in the classification carried out by the various models for new patients.

Comparative Performance Analysis

Table *1* highlights the models that were chosen for the comparison of performance. It is clear that there are large gaps between the classifiers. First, the LR model scored very high on all evaluation measures, thereby confirming the effectiveness of this type of model as a standard or benchmark model. The SVM model that followed performed effectively with consistent classification performance. In contrast, the KNN model scored relatively low since this model relies heavily on computational processes.

Models	Accuracy	Precision	Recall	F1-Score
Logistic Regression	98.56%	98.59%	98.56%	98.48%
Support Vector Machine	98.12%	98.11%	98.12%	98.04%
K-Nearest Neighbors	94.13%	94.03%	94.13%	93.92%

TABLE 1: Comparative Performance of Machine Learning Models

The experimental results show that the accuracy and F1-score values for LR were the highest among the evaluated classifiers, at 98.56% and 98.48%, respectively. SVM also performed reasonably well, and its generalization performance was very high, with an accuracy of 98.12%. In the case of KNN, the accuracy was moderate, at 94.13%. It can be clearly noted that the KNN classifier is sensitive to the data. In general, LR achieved the best baseline classification performance for the prediction of osteoporosis among the non-tree classifiers.

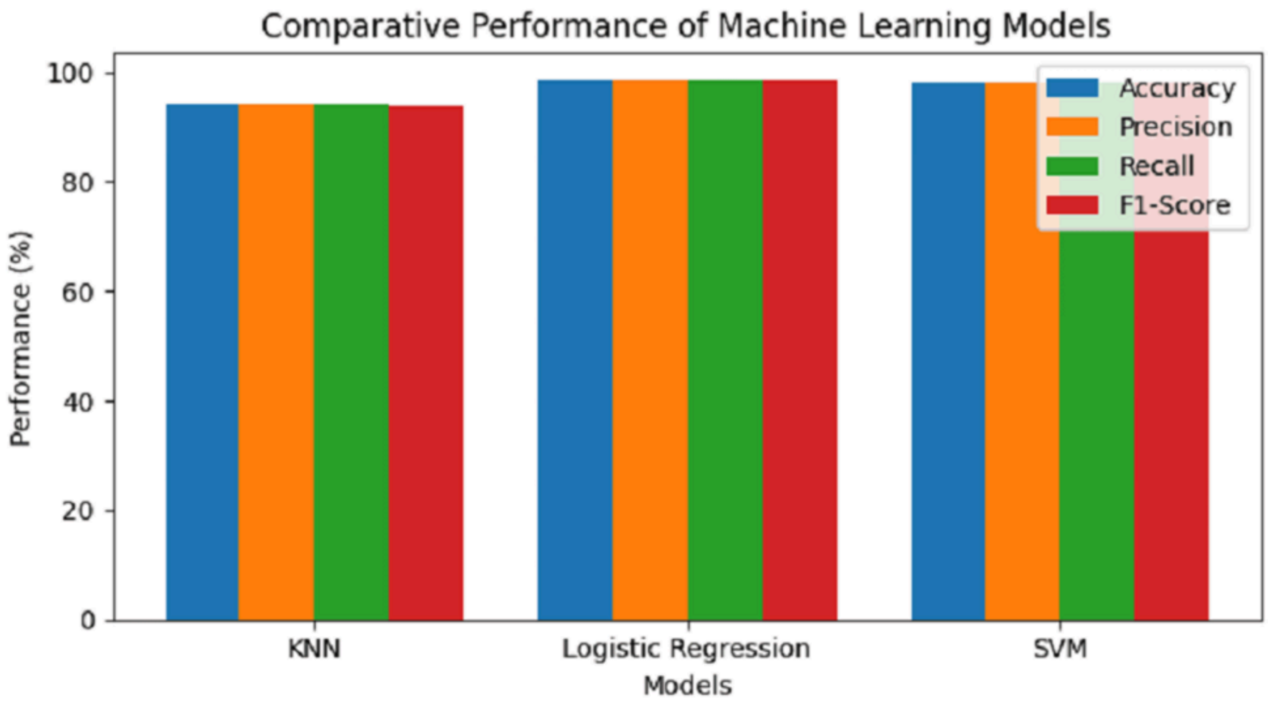

FIGURE 2: Comparative Performance Analysis

KNN, K-Nearest Neighbors; SVM, Support Vector Machine

Figure *2* illustrates that the comparative analysis has made clear that the highest performance across all evaluation criteria was achieved by LR, followed by SVM. KNN performed relatively poorly because of its vulnerability to distance-based classification and feature distributions.

Testing Time

The data illustrated in Figure *3* shows a comparison of how long each of the three algorithms took to execute. LR consumed less overall time compared to SVM, while KNN used more time due to distance-based computations.

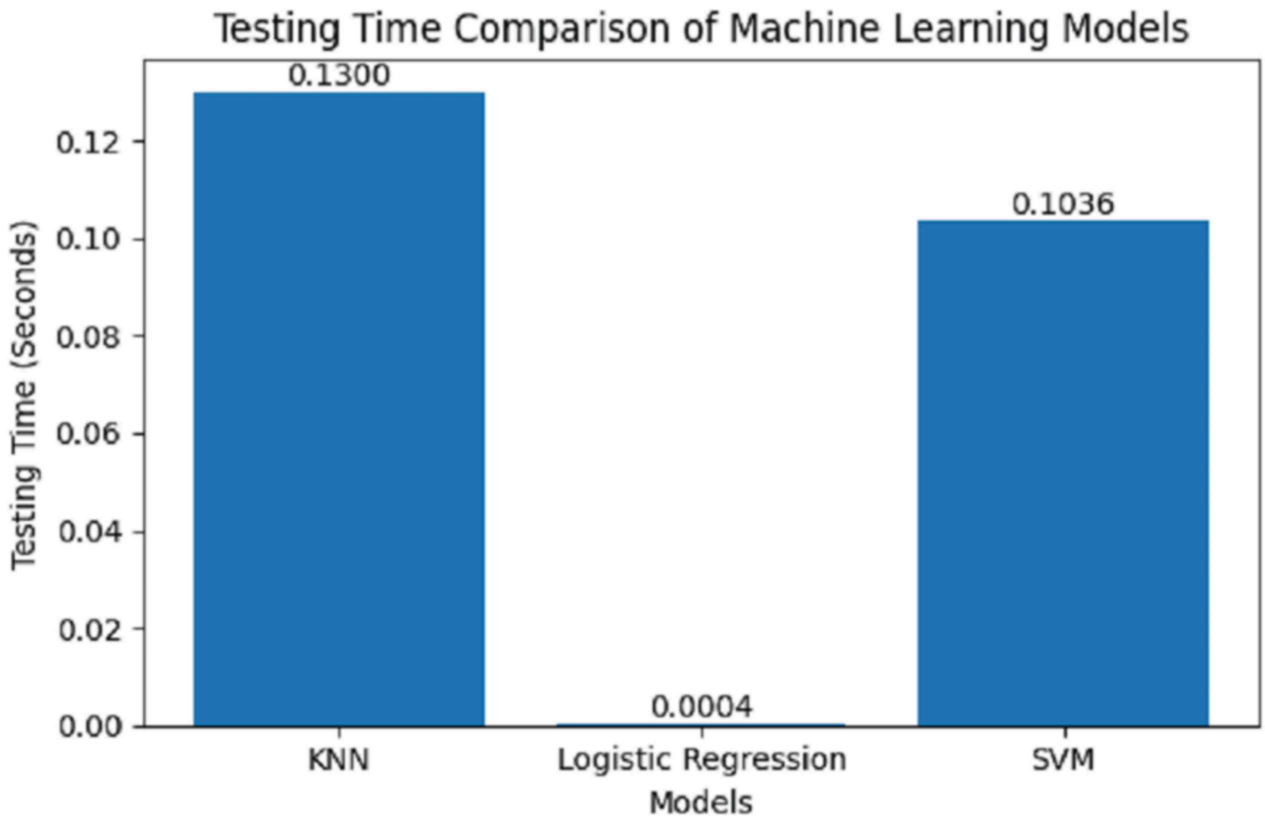

FIGURE 3: Testing Time Comparison

KNN, K-Nearest Neighbors; SVM, Support Vector Machine

ROC-AUC

Figure 4 shows that the ROC-AUC score analysis reveals that the accuracy of the SVM algorithm is highest, with a value of 0.9993, followed by LR at 0.9981. The lowest ROC-AUC score is observed in the KNN model at 0.9832.

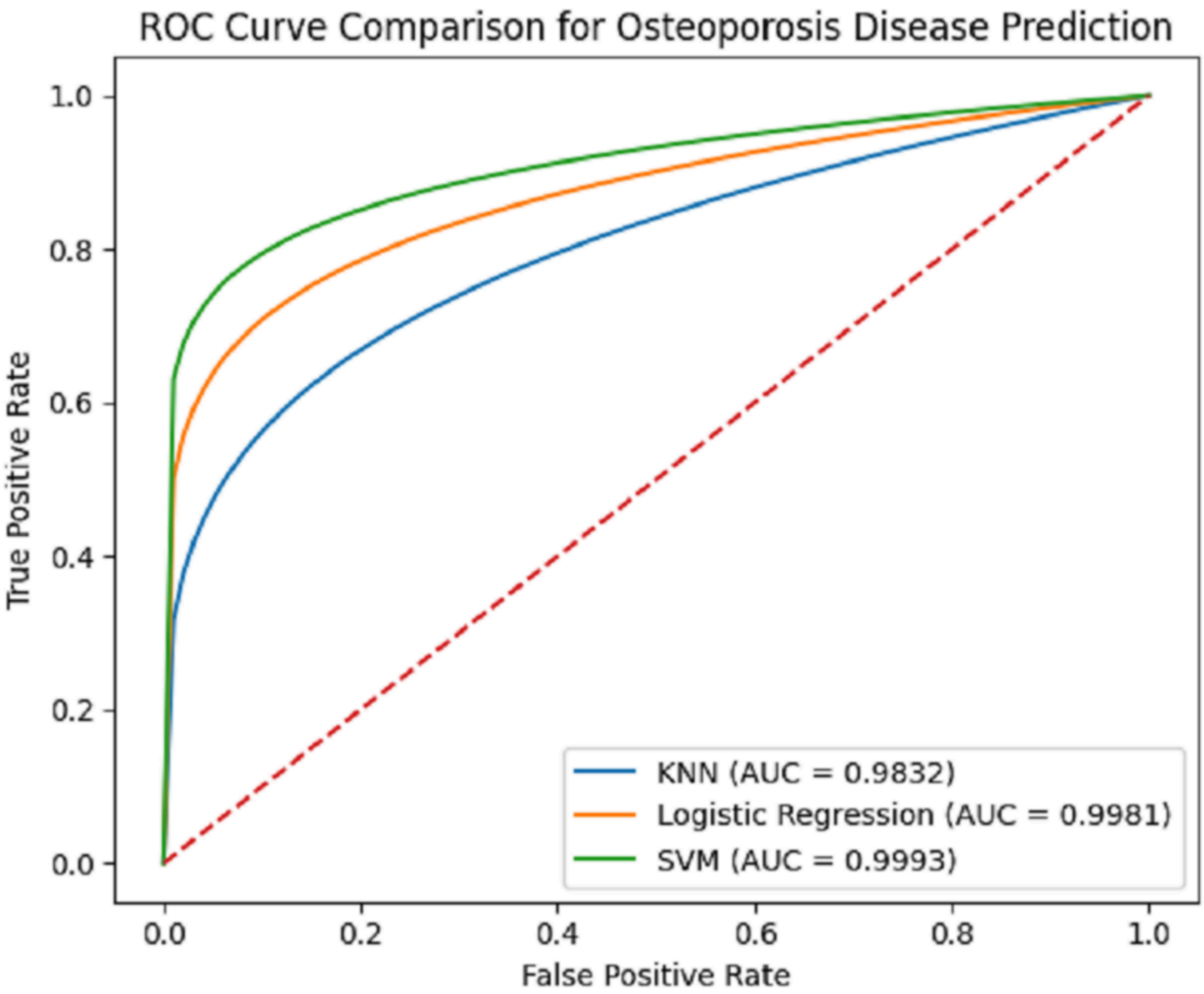

FIGURE 4: ROC–AUC Performance Comparison

KNN, K-Nearest Neighbors; ROC–AUC, Receiver Operating Characteristic–Area Under the Curve; SVM, Support Vector Machine

Confusion Matrix

The confusion matrix in Figure *5* is a representation within the accuracy of the LR model graph concerning the classification among the classes Normal, Osteopenia, and Osteoporosis, in order to guarantee the correctness of the predictions and the diagnoses obtained.

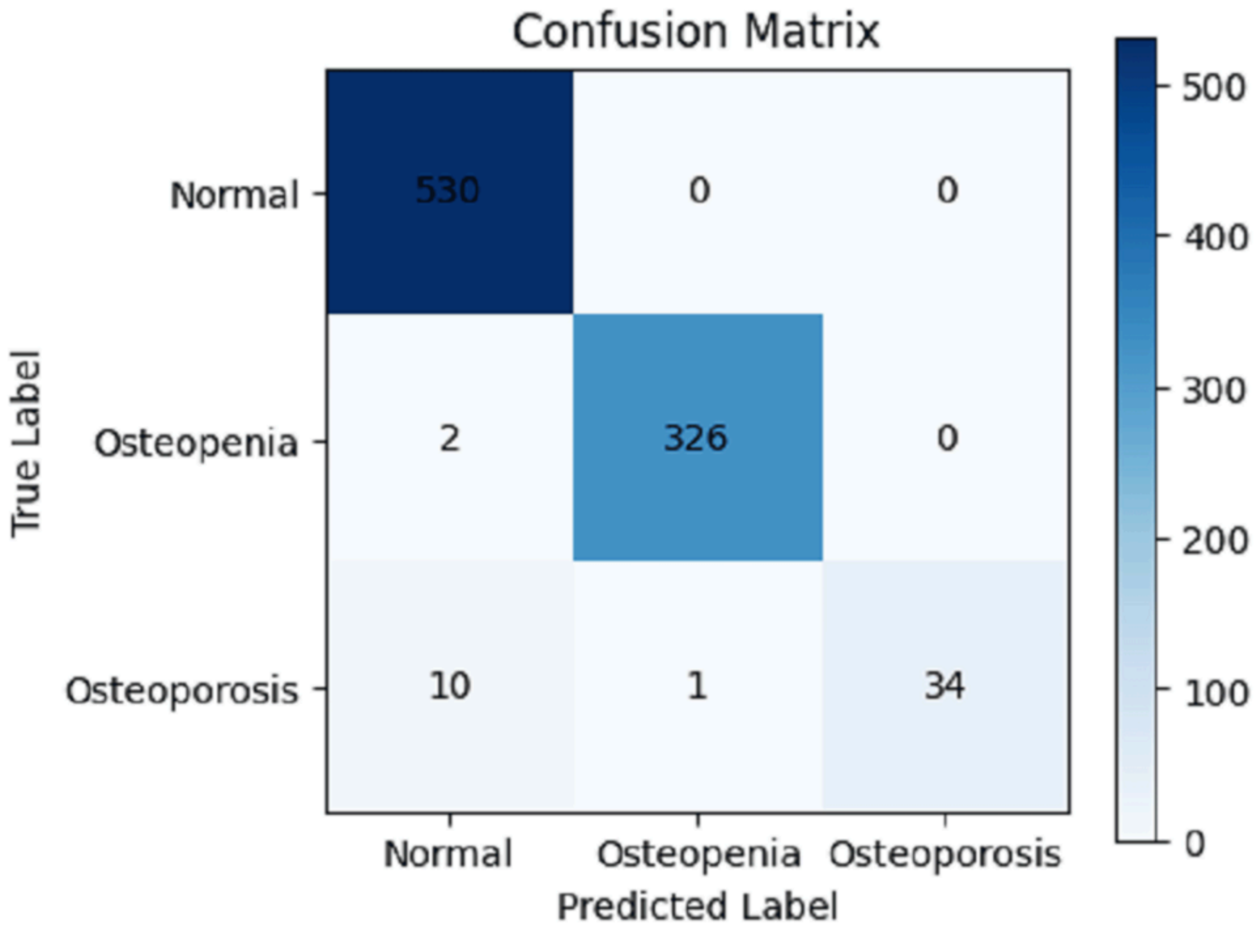

FIGURE 5: Confusion Matrix

Discussion

The success of the KNN technique may be credited to its approach to instance-based learning. Even though the technique has only managed moderate results in comparison to the other models, it was successful in detecting the relations in the vicinity [9,14]. The SVM has been very successful in the task of generalizing because it tries to maximize the gap between different classes. The approach of the LR technique has been very straightforward. Even though it is successful in generating competitive results, it has been very time-efficient. The experimental results confirm the success of non-tree machine learning approaches in the task of predicting the osteoporosis disease [7,13].

Comparison With Tree-Based Models

For the validation of non-tree-based machine learning algorithms, Random Forest and Extreme Gradient Boosting (XGBoost) have also been tested on the same osteoporosis dataset after following the same data preparation process. The maximum accuracy has been obtained for LR with 98.56%, whereas, in descending order of accuracy, other models include SVM with 98.12%, KNN with 94.13%, XGBoost with 93.69%, and Random Forest with 93.58%. Despite the comparable performance of Random Forest and XGBoost algorithms, both could not perform better than the proposed non-tree-based machine learning algorithms. This result shows that LR and SVM are more accurate when predicting osteoporosis disease.

Cross-Validation Analysis

In order to evaluate the robustness of the generated classifiers and their generalization capability, stratified 10-fold cross-validation was conducted. The highest mean accuracy obtained amongst all the five models used was LR model with accuracy of 99.63% ± 0.35%, followed by SVM with accuracy of 98.50% ± 0.70%. Other algorithms that were considered are as follows: Random Forest (97.71% ± 1.39%), XGBoost (97.04% ± 0.60%), and KNN (93.98% ± 0.84%). Low standard deviations obtained during each fold indicate uniform classification results and thus validate the robustness of the developed osteoporosis prediction system.

Conclusions

This work experimentally evaluates three non-tree-based classifiers to identify a computationally efficient and clinically interpretable osteoporosis prediction framework. Therefore, the goal is to assess their performance regarding osteoporosis identification using clinically relevant data while maintaining computational efficiency and interpretability. The obtained experimental outcomes demonstrate that all evaluated models achieved reliable predictive performance. This confirms the applicability of machine learning approaches for automatic osteoporosis prediction. In this category, the model with the highest accuracy of 98.56% was LR; this is because all aspects considered had equal results. The next model with similarly good results is SVM, boasting an accuracy of 98.12%; this shows that it has a strong generalization capability. The KNN model performs moderately in this category, with an accuracy of 94.13%; this shows that it operates based on distances between examples. Other comparative studies have also been carried out using Random Forest and XGBoost, which indicated that the models developed in this study performed much better than their tree-based counterparts for the considered dataset. Moreover, the stratified 10-fold cross-validation analysis proved the robustness and generalizability of the constructed prediction framework.

Future studies will be directed at the extension of the proposed framework using learning techniques as well as multimodal data sources, for example, medical images and biochemical components, hyperparameter tuning, and application of explainable artificial intelligence methods such as Lcoal Interpretable Model-agnostic Explanations and SHapley Additive exPlanations. Furthermore, external validation using bigger sets of data will be implemented in an effort to further determine the general applicability of the learning-based methods proposed within the context of osteoporosis prediction systems.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Mathankumar T, Vijayarani S

Acquisition, analysis, or interpretation of data: Mathankumar T

Drafting of the manuscript: Mathankumar T

Critical review of the manuscript for important intellectual content: Vijayarani S

Supervision: Vijayarani S

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial**

relationships: All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Data Availability Statements

The datasets (and/or code) supporting this study are available from the corresponding author upon reasonable request.

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