Measurement 180 (2021) 109543

Contents lists available at ScienceDirect

Measurement

journal homepage: www.elsevier.com/locate/measurement

4*x*-expert systems for early prediction of osteoporosis using multi-model algorithms

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ARTICLE INFO

Keywords:
Deep learning
Multi-model
Decision tree
Random forest
Logistic regression

ABSTRACT

Osteoporosis occurs due to micro-architectural deterioration of the bone tissues with an increased risk of bone fragility, which can cause fractures in the bone without much pressure applied to it. The T-score of a person's bone density report can be used to calculate the difference between BMD to that of healthy bones. Currently, osteoporosis is detected using conventional methods like DXA scans or high computational power requiring FEA tests. Considering individual approaches and mono-prediction techniques leads to omission of micro-fractional prediction parameters. In this paper, we have proposed a 4*x*-expert system for suspected osteoporosis patients, which is designed using multi model machine learning algorithms for improving prediction and accuracy through the various computational process. The experiment results shows, that the 4*x*-expert system covers the extensive prediction and accuracy of any suspected bone disorder patients, ranging from 75% to 97%.

1. Introduction

Osteoporosis, also referred to as "porous bone" in Greek, is a chronic disease where the bones of individuals become weaker, thereby increasing the risk of fractures [1]. It is a complex, multifactorial, and slow emerging health complication [2]. Though being a widespread malady, it is generally overlooked. This disease is underrated and is clinically silent because the repercussions are only experienced when one is manifested with a fracture. This asymptomatic disease is a complex health problem persistent in women worldwide, 80% of which are postmenopausal cases, if not treated or prevented, costs quality of life to older women [3]. One common method through which osteoporosis is detected is by the calculation of Bone Mineral Density (BMD) [4]. BMD estimates the thickness of bones via X-rays. Through X-ray images, one can get an approximate amount of calcium and minerals are present in that particular part of the bone. If this amount is substantially more, the bones are tough, denser, and have a less probability of breakage [5–7]. The earlier osteoporosis is diagnosed, the less are chances of fracture. A person affected with osteoporosis is prone to fractures and severe bone damage while performing daily activities or when a very small amount of pressure is applied on the bone, which does not affect a healthy bone [8]. Thus, can also shorten life expectancy. BMD test is used to measure or calculate the T-score. The T-score of a person's bone density report can be used to calculate the difference between his/her BMD to that of a healthy 30-year-old [9]. A T-score is calculated from standard deviation, which is a mathematical term that calculates the variation from the standard or the mean. The score obtained for a bone test (BMD or DXA) is rated as the standard deviation of the definition. The conventional method of using a Dual-Absorptiometry Energy (DXA) scan is less available and costly to use. Using Finite Element Analysis (FEA) is an alternative approach but requires a very high computational power for its process, is a widely used system in material sciences [10]. Some researches states that other alternatives that are more easily available and require less computational power. A WHO report states that over 100 million people die every year with unaccounted and untreated diseases. Some researchers has estimated that among 230 million Indians, with age more than 50 years, about 46 million nearly ~ 20% of the whole were women affected with Osteoporosis [11]. There are enormous techniques are used in the research community to predict bone disorder and osteoporosis [12–15]. It is a chronic health problem depleting the

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https://doi.org/10.1016/j.measurement.2021.109543
Received 4 January 2021; Received in revised form 20 April 2021; Accepted 1 May 2021
Available online 12 May 2021
0263-2241/

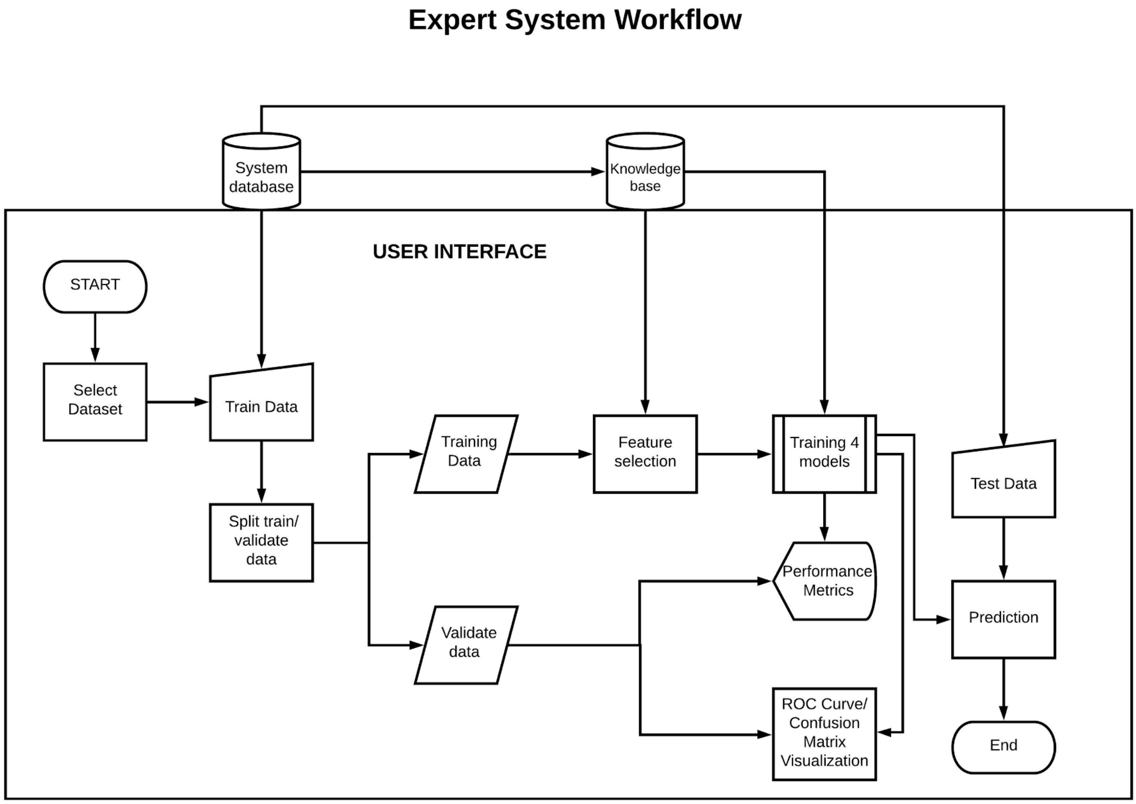

Fig. 1. The workflow of expert system.

health index in women worldwide accused of low mineral content in bones, not be a symptom of aging [16]. This research aims to explore a method with a combination of models and algorithms and create an expert system with the same to detect osteoporosis as early as possible.

2. Related works

Hartley et al. [17] proposed the use of X-ray scans for osteoporosis detection to exploit its advantages, such as regular availability and low cost, and use it to make diagnosis more accessible for the patients. The BMD was also calculated using DXA scan to juxtapose the results, which shows the brighter the image, the more likely it is a healthy bone. As the calcium content in a bone is responsible for absorbing the X-rays, but the fact that the difference can be seen in the X-ray after 30–60% of the damage is already done, i.e. the disease is already in an advanced stage. Barkaoui et al. [18] used femur bone scan to create the 3D model and then apply load for using tools and software, and the results could determine the extent of healthy bone in the subject. They used the FEA approach and created a 3-D model using MIMICS software and ANSYS was used to calculate its finite element analysis. The high-computational power required by this approach limited its use to clinical adoption. Ciusdel et al. [19] used a deep learning model based on the convolutional neural network, to predict the average strain. FEA was used to calculate the target values. The prediction of the deep learning CNN model used was juxtaposed with the physics-based FEA results calculated. Liu, et al. [20] investigated the importance of deep learning for the discovery of high potential anti-osteoporosis. Which leads to know about several kinds of research for identifying the features and parameters for bone characterization.

Iliou et al. [21] worked with 1083 pathological cases and 2343 normal subjects with a diagnosis based on an analysis of laboratory bone densitometry. Four diagnostic parameters for the prediction of osteoporosis risk, notably age, sex, height, and weight, were obtained with the selected classifiers for later evaluation. 20 classifier algorithms and methods were accessed for this research. Delen [22] worked on modelling relationships between osteoporosis and its potential risk factors. Cruz et al. [23] systematically compiled and summarized the key strategies used to classify osteoporosis-related risk groups, identifying their problems and patterns. Techniques that applied principles of AI for categorizing risk groups were highlighted in conjunction with previously performed examinations like QUS and DEXA, which concludes that building a model using AI to predict risk groups are often proved to be very helpful for the patients in their treatment.

The fuzzy logic algorithms were executed in three steps, Fuzzification, Fuzzy inference, and Defuzzification [24–27]. The current research studies involve a deep neural network for osteoporosis detection [28]. Throughout the literature surveys, we found that using a single algorithm or model for detection and prediction of osteoporosis would not yield a better result, instead, we went for a combination of models and algorithms. Hence, we came up with our expert system that uses multiple algorithms.

3. 4*x* multi-model deep learning algorithms

The objective of this research paper is to have a better method and efficiency in the prediction of osteoporosis. We have used the expert system for better prediction. Expert systems are smart decision-making systems that can simulate decision-making ability, ranging from business solutions to health care domains [29–31]. Expert systems have been used in the field of artificial intelligence for a long time, which can be used to design and train to solve complex problems with less computational power required [32]. There are mainly two components in an expert system i.e. Knowledge base and a rules/inference engine. A third component can be added to the user interface. The work flow of an expert system is given in Fig. 1. In our proposed system we have created an expert system that uses multiple machine learning algorithms for the prediction of osteoporosis on the dataset. We have a hybrid model of 4*x* (Four Expert System Algorithms), namely logistic regression, decision

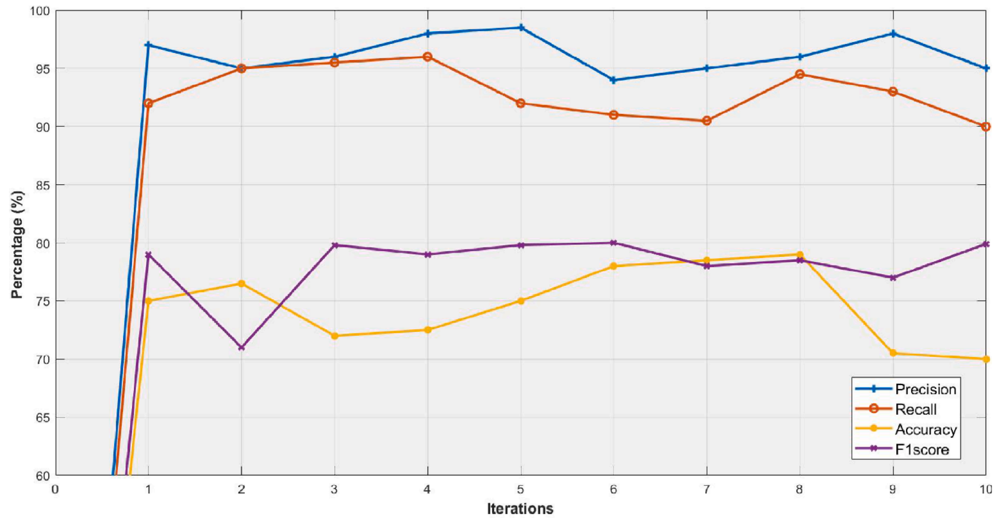

Fig. 2. Predicted through Decision Tree.

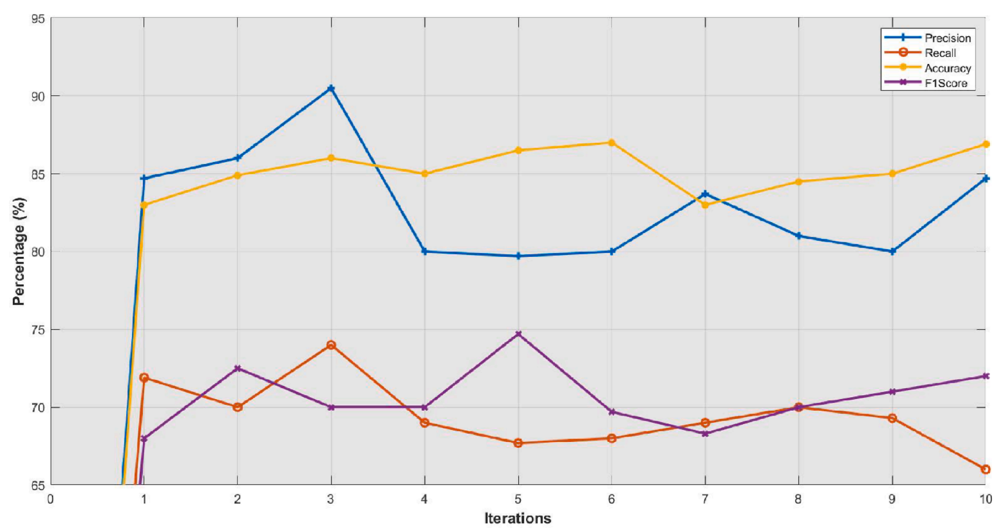

Fig. 3. Predicted through Random Forest.

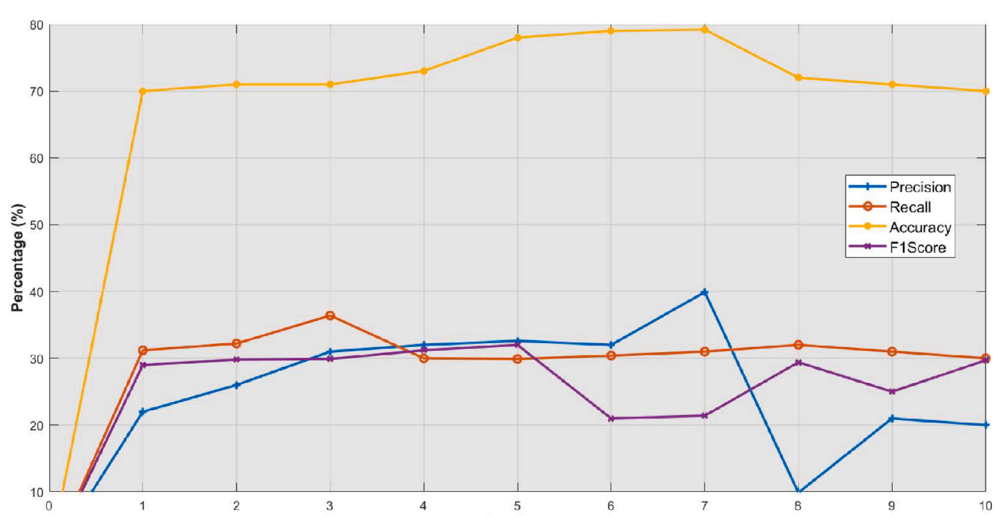

Fig. 4. Predicted through Logistic Regression.

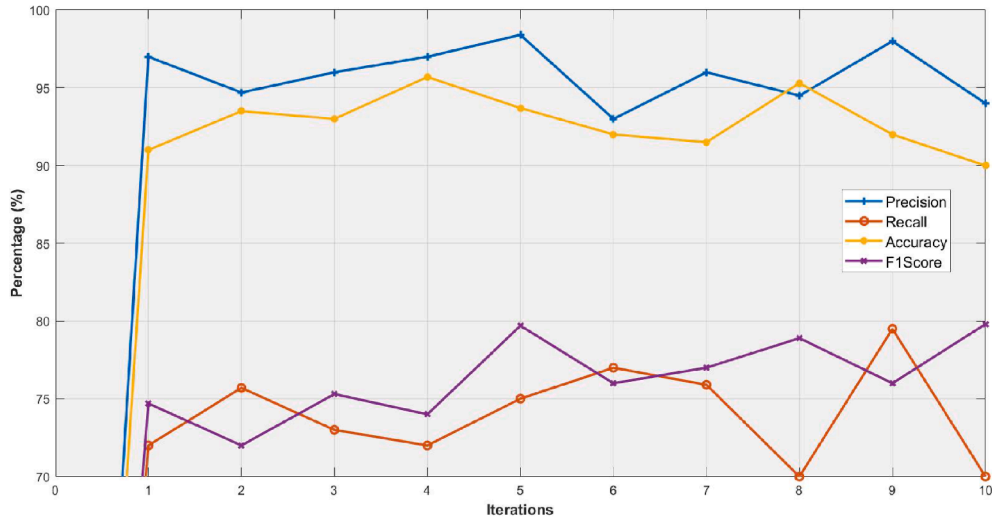

Fig. 5. Predicted through XGBoost.

Table 1
Comparison of confusion matrix results.

Model	True Positives	True Negatives	False Positives	False Negatives
Logistic Regression	5	86	13	24
Decision Tree	33	84	20	5
Random Forest	38	77	27	0
XGBoost	33	84	20	5

tree, random forest, and XG Boost. Our proposed expert system will train the models for all the mentioned algorithms and then compare the results for these algorithms. The dataset used contains records of 40 postmenopausal women of different ages. The dataset is stored in .CSV format for training and another dataset for testing and validation is used which has the same attributes. The source of data is "E-GEOD-13850 [33], which has been used for the entire predication model, various ANN approaches are also used for different medical diagnostic predictions [34–36]. In a deeper sense, to predict osteoporosis in the patient using the characteristics provided in the dataset which includes age, spine z-score, hip z-score, smoking habits, and BMD level. The complete design for extracting the accurate results is hidden behind the clean user interface. The user interface has been designed using ipython widgets on top of jupyter notebook. The interface supports the user by selecting to view the predictions for the test data for every model. The result (osteoporosis, osteopenia, normal) is displayed for all the entries present in the test data.

4. Feature and target variable selection by the user

Feature variables are defined as the individual independent variables that are provided as input to the system. In simple terms, we can consider one column of the dataset to be one feature which is the case in our system. These features can also be called attributes. We have provided the option of feature selection to the user based on the preferences. It is important to understand that feature selection is an important step for training the model as it can hugely affect the performance of the predictive model. The target variable is the attribute for which we want the output or prediction to be performed. In our 4x-system, we have classified into three criteria namely normal, osteopenia and osteoporosis. The two target variables which can be used for our system are hip z-score or spine z-score as we use the a-score-based method for the classification of osteoporosis.

5. Training the four classification models

Logistic regression: It is a classification type algorithm and we use logistic regression when our target variable is divided. The basic concept used in linear regression is to find and define a relationship between the various columns or characteristics and an outcome or target variable. The proposed model uses multi-class logistic regression. The basic idea or logic used in a multi-class logistic regression model and a binary/normal logistic regression is almost same. For an instance, to find out whether the patient is suffering from osteoporosis, osteopenia, or normal. This is called a multi-class problem. Which is projected as 3 binary classification problems, i.e. whether it is osteoporosis or not, whether it is osteopenia or not, and whether it is normal or not. In such a way, it's like 3 binary logistic regression with only yes and no as the possible values for each of them. We will run all three classification models independently on our input dataset. Our required solution is the classification where the probability of yes is the highest or the strongest probability among the 3 binary models. In our logistic regression model, we have three possible classes namely normal, osteopenia and osteoporosis. Our logistic regression model is trained on the selected features and then classification is done based on another unique feature. The proposed system takes the three values like 0 for normal cases, 1 for osteopenia cases, and 2 for osteoporosis cases.

Decision tree: A decision tree has a flow-chart-like structure where every test on any feature variable is represented by internal nodes. Our model being a predictive model, having multiple discrete classes for the target variable. Thus the proposed model is also using a similar kind of classification tree. Our model uses the user-selected custom features for creating branches of the tree and any of the features can be removed or added to make the prediction more accurate and improve the performance. The decision tree uses a hyperparameter named information gain for creating the model, that is the case decision tree can use any area in the nodes to split the overall training sessions into a smaller version. Acquisition of data is one of the modifications of this algorithm.

Random forest: It is a prediction model developed by integrating numerous decision trees. The decision tree is the basis for the construction of any random forest model and is an accurate model. There is an immediate relationship between the count of trees present within the forest and hence the results that can be obtained: the more we train the number of trees, the more accurate we get the result. Random Forest

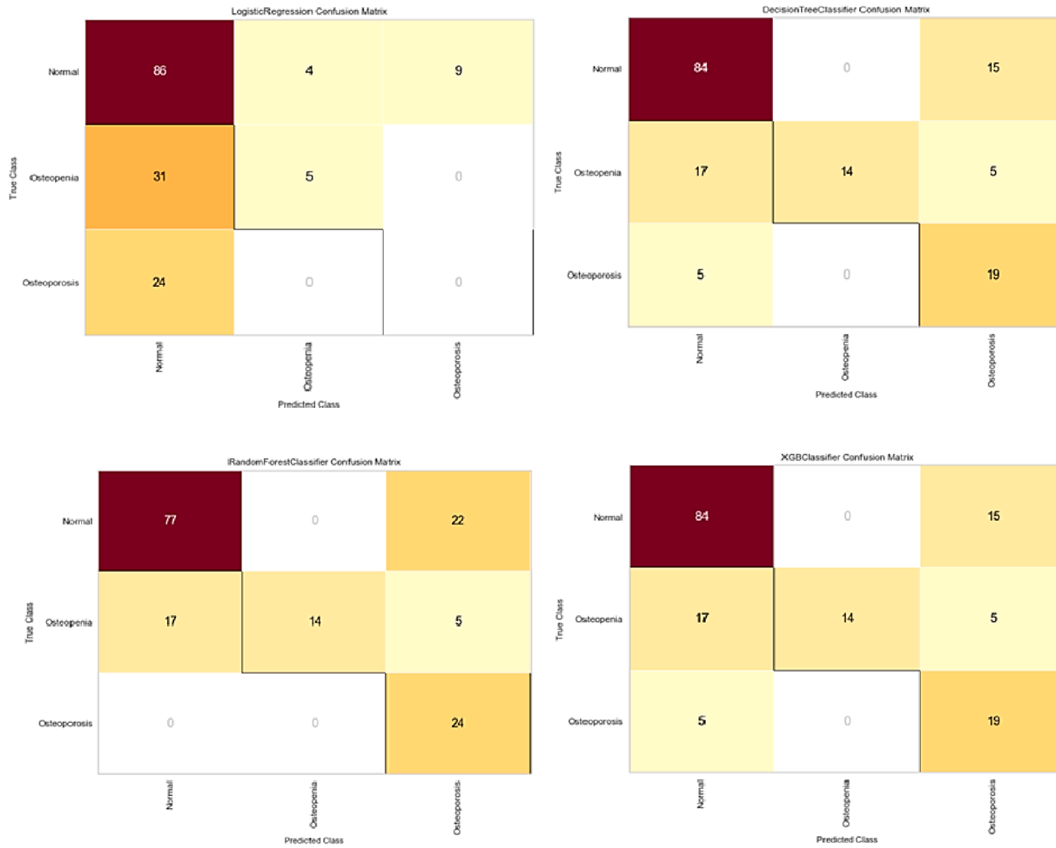

Fig. 6. Confusion Matrix of 4x-Expert System.

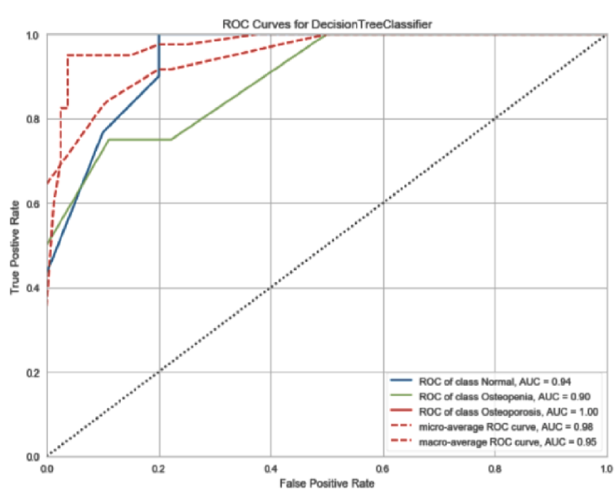

Fig. 7. Random forest-ROC.

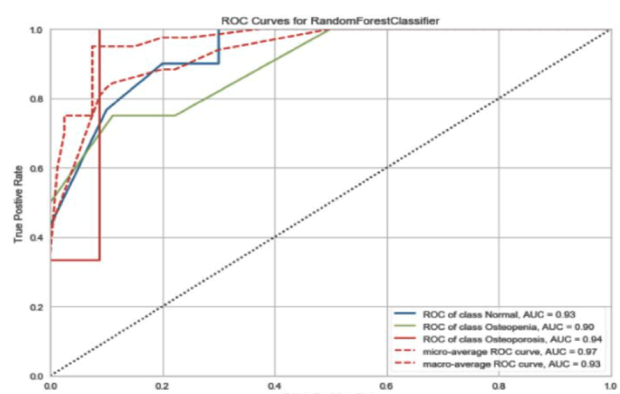

Fig. 8. Decision Tree-ROC.

decides the class after applying voting to the predicted classes by the individual trees for classification, or by calculating the mean prediction for regression. Random forests address the overfitting tendency of the decision trees and have shown robustness concerning noise.

XGBoost: "eXtreme Gradient Boosting commonly known as XGBoost", is a decision tree-based ensemble algorithm. It's the result of gradient boosting equipment designed by Tianqi Chen's power-boosting machines, now with contributions from many engineers. It represents an extensive group of specialized techniques from a combined group of the "Distributed Machine Learning Community or DMLC". Often, we cannot depend upon the results we get from a specific single machine learning model. Here we use the collective learning principle which can offer a remedy scientifically for mixing the predictive power of several learners altogether and get the best result. The result would be a single model that offers integrations of various models.

6. Metrics and definition

6.1. Confusion matrix

We have used a confusion matrix to describe the performance of our models. It enables us to create a visualization of the actual performance

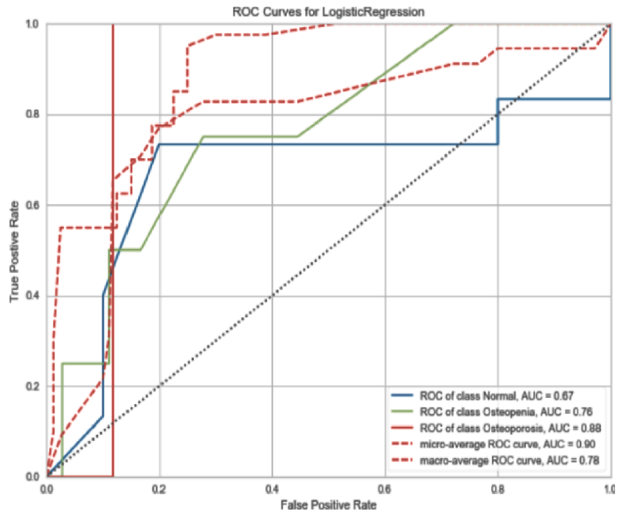

Fig. 9. Logistic Regression –ROC.

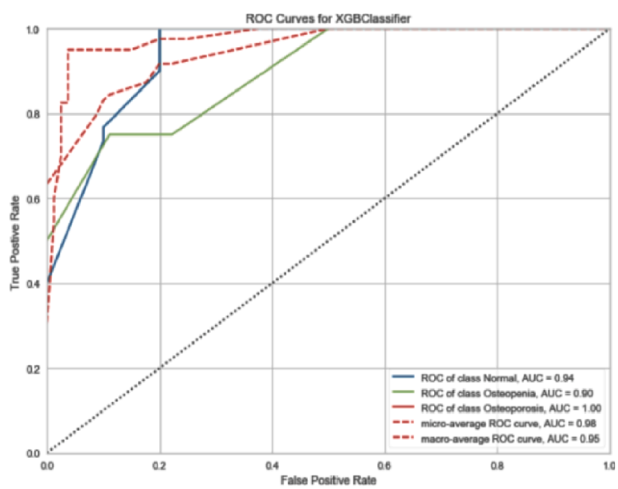

Fig. 10. XGBClassifier-ROC.

of the model. The confusion matrix can be used to visualize how confused or accurate our model is in predicting the results. It can specify the type of error our model is making. It is an utmost useful matrix which is used for calculating or measuring "Recall, Precision, Accuracy and most importantly plotting the AUC-ROC Curve". To be able to completely evaluate any prediction model we must calculate both precision and recall. For an instance, false positives can be costly in e-mail spam detection algorithm but false negatives can be costly in our osteoporosis prediction model. We plotted numerous curves for each of the classes using the 1 vs all method. Therefore, in our case, we have three classes named Osteoporosis (0), Osteopenia (1), and Normal (2), we plotted ROC for osteoporosis vs osteopenia and normal, the next one for osteopenia vs osteoporosis and normal, lastly normal vs osteopenia and osteoporosis.

6.2. Multi-Class or Multivariate-classification model

In our case of a multivariate classification model, the target or resultant column has three or more possible values. We have used this type of prediction model as specified previously.

6.3. Accuracy

The metric calculated by taking a "ratio of number of correct prediction to the total number of samples" in the input data is known as accuracy. The number of correct predictions includes true positives, as well as true negatives from the confusion matrix, and the total number of predictions includes all the predictions made including "true positives, false positives, true negatives and false negatives". Therefore, it cannot be used in cases where a slight error in classification or misclassification can have serious costs associated with it. When dealing with a fatal disease like osteoporosis, the cost of diagnosing a person as normal or negative for osteoporosis who is having osteoporosis is much higher as compared to falsely diagnosing someone positive for osteoporosis and then conducting further tests to confirm.

6.4. Precision

Precision aims to give a proportion of how much identification was correct. The ratio of "true positives" to the combined "sum of true positives and false positives" or the number of positive predictions made by the model to the number of predictions where output class is positive. It can also be called as a "positive predictive value" or PPV. It can be used to identify the measure of exactness of a classifier, a low precision indicates a large number of false positives. If a person suffering from low bone density or osteoporosis is not classified incorrectly, any such mistake can be very costly for the person. Hence, we need to reduce the false positive rate to a negligible level in the model.

7. Performance analysis and results

A total of 200 patients was classified and analyzed by 4 classifying models, namely decision tree, random forest, logistic regression, and XG Boost. Predictions from the uploaded testing dataset were divided into 'Normal', 'Osteoporosis', and 'Osteopenia'. Following predictions were retrieved for every model. In the resulting Figures, Fig. 2, Fig. 3, Fig. 4, and Fig. 5, it is evident that XGBoost and Decision Tree models are performing exceptionally well in separating different classes and classifying them correctly with much higher accuracy than other models.

From the above output Figures (Figs. 2–5), It is observed clearly that logistic regression is not performing as well as the other three models. The assessment parameters of the decision tree produce 70–95% of performance (Fig. 2). Whereas the logistic regression produces 20–40% for precision, F1Score, accuracy, and up to 80% for recall. Except for accuracy all other metrics for logistic regression are extremely low, and as specified and studied earlier accuracy may not be able to give a correct performance for a model. Considering other metrics, it is observed that random forest performs better than logistic regression. Also, we can observe that the Decision tree and XGBoost models perform similarly in this case. Both the models are having a high percentage of precision, recall, accuracy, and f1 score. So, we can conclude from these

Table 2
Consolidated ROC_AUC values for 4*x* Models.

Model	ROC_AUC of Normal	ROC_AUC of Osteopenia	ROC_AUC of Osteoporosis	Micro-average ROC_AUC	Macro-average ROC_AUC
Decision Tree	0.94	0.90	1.00	0.98	0.95
Random Forest	0.93	0.90	0.94	0.97	0.93
Logistic Regression	0.67	0.76	0.88	0.90	0.78
XGBoost	0.67	0.76	0.88	0.90	0.78

Table 3
4*x* Similarity Index of Certain Patients (Ages Ranging from 40 to 65).

S. No	Age	BMD Level	Logistic Regression Prediction	Decision Tree Prediction	Random Forest Prediction	XGBoost Prediction
1	40	1	Normal	Normal	Normal	Normal
2	41	1	Normal	Normal	Normal	Normal
3	42	1	Normal	Normal	Normal	Normal
4	43	1	Normal	Normal	Normal	Normal
5	44	1	Normal	Osteopenia	Osteopenia	Osteopenia
6	45	1	Normal	Normal	Normal	Normal
7	46	1	Normal	Osteopenia	Osteopenia	Osteopenia
8	47	1	Normal	Normal	Normal	Normal
9	48	0	Normal	Osteopenia	Osteopenia	Osteopenia
10	49	0	Normal	Normal	Osteopenia	Osteopenia
11	50	0	Osteopenia	Osteopenia	Osteopenia	Osteopenia
12	50	1	Normal	Normal	Normal	Normal
13	51	1	Normal	Normal	Normal	Normal
14	52	1	Normal	Normal	Normal	Normal
15	53	1	Normal	Normal	Normal	Normal
16	54	1	Normal	Osteopenia	Osteopenia	Osteopenia
17	55	1	Normal	Normal	Normal	Normal
18	56	0	Normal	Osteopenia	Osteopenia	Osteopenia
19	57	0	Normal	Normal	Normal	Normal
20	58	1	Normal	Normal	Normal	Normal
21	59	0	Normal	Osteoporosis	Osteoporosis	Osteoporosis
22	60	1	Normal	Osteoporosis	Osteoporosis	Osteoporosis
23	61	1	Normal	Normal	Normal	Normal
24	62	1	Osteoporosis	Osteoporosis	Osteoporosis	Osteoporosis
25	63	1	Osteoporosis	Osteoporosis	Osteoporosis	Osteoporosis

metrics that the decision tree and XGBoost algorithms are performing best on this dataset.

7.1. Confusion matrix

Looking at the confusion metrics table below concluded from confusion matrix visual plots, we can derive some logical observations.

It is found from Table.1 and Fig. 6 the above metrics comparison, logistic regression is showing a high value of false negatives, which is a costly result for us as it is a question of life or death for the patient. Furthermore, we can observe that decision tree and boost models are also showing some false negatives but the random forest is showing no false negatives and that's more important for us. It is successfully able to predict 24 out of 24 osteoporosis cases. So, from this important result, we should prefer the random forest model. For osteopenia, these three models are performing similarly. Hence, we can conclude that random forest is performing best for this use case as it will not leave any osteoporosis case. As expected from the Logistic regression with lower metrics scores, it has the highest number of False negatives, which is a high-value cost function, the model should not be considered ideal in this case. Random Forest would be our best bet for choosing a model for the data as it has 0 false negatives. Also, Random Forest can correctly identify all Osteoporosis cases.

Looking at ROC_AUC visual plots of Fig. 7, Fig. 8, Fig. 9, Fig. 10 and a consolidated index from Table.2 ROC_AUC metrics observations have been concluded. The inference from Table.2 and figures (Fig. 7-Fig. 10), that the higher the AUC value, the better the model is in forecasting. From the above table, we can analyze the performance of our model in identifying the separate classes accurately. The micro average ROC curve can be treated here as the ideal line as it is the closest to 1 in every case, according to which we can compare the performance of our model in predicting the correct classes. We can interpret in our case decision tree is the best model for correctly classifying the patient's condition as normal with an AUC of 0.94 which represents that the classifier has a 94% chance of patient's condition as normal, followed by Random Forest with a 93% chance. The prediction of the 4x similarity index in Table.3 represents the various prediction of patients aging between 40 and 65.

The sample space results for age groups between 40 and 63 has been projected in Table.3 and the assessment for every algorithm has been given. The extreme coverage of confirming the cases is been represented and it shows that in some algorithm it is normal and some it represents osteopenia or osteoporosis, by applying this mixed model it leverages the coverage of prediction.

8. Conclusion

The proposed 4*x-Expert systems* concludes that the Decision tree and XGBoost models achieves the best results for accuracy (92.5%), precision (97%), recall (75%), and from visualizations of the confusion matrix and ROC_AUC curve. The proposed *4x* model uses multiple machine learning algorithms to cover the extensive fractional coverage on predicting osteoporosis. The model is also flexible in concerning the features that the user wants to focus on. If the user is concerned with minimizing the false negative, as it can wrongly tell a patient that they are not affected by osteoporosis and thus delay their treatment. With a user-friendly interface, this expert system is easy to be used by health care professionals for analysis. Patients diagnosed as not normal can be focused more on further medical tests, in such a way it directs the physician for recommending diagnosis for the affected patients.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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