ORIGINAL ARTICLE

Predicting Osteoporosis with Various Machine Learning Algorithms Using Dual-Energy X-Ray Absorptiometry: A Comparative Analysis

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Abstract

Purpose: Osteoporosis is characterized by reduced bone density and increased fracture risk. Early identification using predictive models may improve screening and clinical decision-making. This study aimed to evaluate the performance of multiple Machine Learning (ML) algorithms in predicting osteoporosis using Dual-Energy X-ray Absorptiometry (DEXA) data and clinical variables.

Materials and Methods: Data from 1,000 individuals who underwent DEXA scanning at a rheumatology clinic between 2021 and 2023 were analyzed. Five classification algorithms—Artificial Neural Network (ANN), Random Forest (RF), Support Vector Machine (SVM), Decision Tree (DT), and Logistic Regression (LR)—were developed using stratified k-fold cross-validation. Model performance was evaluated using accuracy, sensitivity, specificity, and Area Under the Receiver Operating Characteristic curve (AUROC).

Results: Osteoporosis was identified in 23.5% of participants (mean age: 58.4 years). The ANN model demonstrated the best overall performance, achieving an AUROC of 0.937, accuracy of 94.6%, sensitivity of 89.0%, and specificity of 96.3%. RF showed the second-highest performance (AUROC= 0.837). Feature importance analysis identified age, body mass index, vitamin D level, and hypertension as key predictors. Model performance slightly decreased after feature selection, suggesting complementary predictive value among variables.

Conclusion: Machine learning models, particularly ANN, demonstrated strong performance in predicting osteoporosis and may support early screening and clinical decision support systems. Further external validation using multicenter datasets is required before clinical implementation.

Keywords: Osteoporosis; Machine Learning; Prediction; Dual-Energy X-Ray Absorptiometry; Bone Mineral Densitometry.

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1. Introduction

Osteoporosis is a common metabolic condition marked by a reduction in bone density and quality, which results in heightened vulnerability and risk of fractures [1, 2]. It frequently goes undetected because of the absence of symptoms and is prevalent among older individuals. With the swift aging of the global population, osteoporosis presents major medical, financial, and societal challenges [3, 4]. Fractures are often the first indication of the condition, influenced by genetic, racial, physiological, environmental, and lifestyle factors affecting bone density maintenance throughout life [5-7].

More than 200 million individuals across the globe are affected by osteoporosis, resulting in approximately 9 million fractures each year [2]. About 20% of fracture patients need long-term care, with 60% never fully recovering their previous level of independence [8]. These fractures cause pain, discomfort, long-term complications, disabilities, reduced quality of life, and increased mortality risk [9].

Early detection and prevention are key in preserving bone density and effectively managing osteoporosis [10, 11]. In this era, various imaging methods like DEXA, Quantitative Ultrasound (Q-US), Quantitative Computed Tomography (QCT), and Peripheral Quantitative Computed Tomography (PQCT) are used to measure bone density and osteoporosis early detection [12]. Among them, DEXA is viewed as the gold standard for its precision, reproducibility, and minimal radiation exposure. Bone mineral density from DEXA results estimates osteoporosis but does not fully predict individual fracture risk [13]. Clinical risk models like FRAX and the Garvan calculator use both bone density and clinical factors to predict absolute fracture risk, but they have certain limitations. FRAX is commonly used worldwide to estimate the 10-year risk of hip fracture or osteoporosis but has limitations. One key limitation is its simplistic binary approach to risk factors instead of assessing each factor individually. Factors like multiple prior fractures or increased use of glucocorticoids, tobacco, and alcohol are linked to higher fracture risk. Moreover, FRAX relies solely on the T-score from dual-energy X-ray absorptiometry of the femoral neck, restricting its use for patients with conflicting T-scores at other sites or with different technologies [14].

Therefore, healthcare providers should update their approach to osteoporosis by utilizing advanced diagnostic models and predictive algorithms to enhance treatment strategies. It is obvious that the high diagnostic accuracy of bone density can bring the desired treatment protocol and significantly help the clinician in making treatment decisions.

In this context, advancements in artificial intelligence and Machine Learning (ML) significantly influence healthcare, especially in the accurate diagnosis of diseases [15, 16]. ML, a branch of AI, generates predictive models and identifies patterns using training data [17, 18]. It encompasses algorithms such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Logistic Regression (LR) that assist in predicting diseases. Utilizing ML for osteoporosis prediction provides a non-invasive and affordable approach to enhance diagnostic precision [19, 20]. This study aims to develop ML models for osteoporosis prediction and determine influencing factors in its occurrence.

Studies utilizing ML to predict osteoporosis have mainly concentrated on restricted datasets, such as screening individuals over 50 or employing ML techniques to predict osteoporosis risk in postmenopausal women [21]. Some studies compare new models to traditional ones in specific age groups [22]. Other researchers use the LR model separately for men and women [23]. Some focus solely on women using ANN for osteoporosis. Research has been conducted on predicting osteoporosis using different ML algorithms, including K-Nearest Neighbor (KNN) [23]. Some use Strut analysis for an osteoporosis diagnostic model with panoramic radiography [24]. Others have solely focused on women in osteoporosis assessment using ANN for ML [25]. A different research study has assessed the prediction of osteoporosis through the use of various ML algorithms, including KNN [26, 27]. Some studies utilized radiography system data, while others used modalities like CT scan, MRI, ultrasound, and DEXA, with a focus on the femoral neck [23, 28-30].

Their data lack key influencing factors and remain unintegrated. The study aims to use advanced ML models to predict osteoporosis effectively by integrating key aspects from the lumbar spine and hip using DEXA imaging. The objective is to evaluate these models, offer a cost-efficient and non-invasive diagnostic method for the early identification, intervention, and enhancement of patient results in osteoporosis management.

2. Materials and Methods

Supervised ML techniques were utilized to forecast the likelihood of osteoporosis. Our approach was segmented into four stages, which comprised: 1) Gathering data; 2) Processing data; 3) Creating models; and 4) Assessing models. The data processing, model creation, and performance evaluation were carried out using the Python programming language within the Google Colab platform.

2.1. Data Collection

The study examined cases of individuals aged 31 to 86, both male and female, seen from April 2021 to March 2023. It analyzed data from 1000 people who underwent DEXA scan at the Rheumatology Clinic of Ardabil City Hospital. Excluded patients had specific conditions or factors, such as disc herniation, spondylolisthesis, fractures, malignancies, vertebral infection, prior lumbar disc surgery, hormonal treatment, bilateral femur fractures, non-cooperation, and metal implants. Procedures were carried out using the Hologic Discovery System (Hologic Inc., Bedford, MA). Accuracy and reproducibility of exposure factors were verified by the medical equipment company's quality control before the study, along with daily calibration. DEXA was conducted on the neck of the femur and lumbar spine to assess bone density. According to World Health Organization (WHO) criteria, osteoporosis was diagnosed if the T-score was below -2.5 [31].

The dataset comprises 13 features from the Hospital Information System (HIS) in an Excel file. Ten features, like gender, are nominal and binary for osteoporosis prediction models, while three (age, BMI, and vitamin D) are quantitative variables. This research was granted approval by the ethical review board at Ardabil University of Medical Sciences, under the code IR.ARUMS.MEDICINE.REC.1402.059, covering its design, protocol, and informed consent form, which were assessed and sanctioned by the Institutional Review Board for both scientific and ethical validity.

2.2. Data Preparation

Data preprocessing is a crucial phase that must be completed before utilizing data in an ML model. This step ensures that the data is clean, free from errors, and formatted correctly for the algorithm, thereby avoiding negative impacts on the model's effectiveness. In this analysis, several preprocessing techniques, including data cleaning, normalization, transformation, and scaling were employed to prepare the data. Normalization and the standard scaler function from the scikit-learn preprocessing libraries were utilized for data scaling. Binary features, such as gender, were converted into values of 0 and 1. Furthermore, the target variable for the model's predictions was binary (1, 0), with '1' signifying the osteoporosis group and '0' indicating the normal group. As osteoporosis constituted 23.5% of the dataset, indicating class imbalance, stratified k-fold cross-validation was applied to preserve class distribution across folds. Additionally, class weights were incorporated during model training to reduce bias toward the majority class and improve model performance for minority-class prediction.

To build and evaluate models, the complete dataset needs to be split into training and testing datasets. K-fold cross-validation is a resampling method employed to train and assess ML models. This technique involves a single parameter, k, which indicates the number of groups to be formed from a given sample of data. Consequently, this method is often called k-fold cross-validation. When a specific k value is selected, it can replace k in the model's reference, meaning that when k = 10, it is referred to as 10-fold cross-validation. This approach is preferred as it often provides a more reliable or less optimistic estimate of the model's performance compared to simple train-test splits. In this study, we utilized stratified k-fold cross-validation. While stratified k-fold cross-validation is similar to standard k-fold cross-validation, it employs stratified sampling rather than random sampling. The hyperparameters of all machine learning models were optimized using a grid search strategy combined with stratified k-fold cross-validation. This approach systematically evaluated predefined parameter combinations to identify the configuration yielding the best validation performance while preserving class distribution across folds.

2.3. Model Building

To predict osteoporosis, we utilized five different classification models: Decision Tree (DT), Random Forest (RF), SVM, LR, and ANN. DTs create models structured like a flowchart, where every internal node indicates a feature, each branch signifies a decision rule, and every leaf node provides the final prediction. This method iteratively trains to split the tree according to the value of each attribute [32, 33]. RF is a classification approach that combines multiple DTs during training. The output of RF is determined by the class selected by most of the trees [34]. LR is a statistical technique commonly employed for classification analysis. LR calculates the likelihood of an event happening [35, 36]. SVM is a widely used classification model. The goal of the SVM algorithm is to find the best decision boundary or line that can classify n-dimensional space. This optimal decision boundary is referred to as a hyperplane [37]. The ANN constructs a framework that mimics the biological organization of the human brain and its neural connections to learn, generalize, and make decisions. In this research, we employed a Multi-Layer Perceptron (MLP), which is a traditional form of neural network. An MLP is a type of feedforward artificial neural network that generates a set of outputs based on a set of inputs. An MLP is characterized by multiple layers of nodes interconnected as a direct graph linking the input and output layers.

The ANN model was developed using the Keras library. Keras is recognized as a prominent high-level deep learning library, providing an intuitive interface for effectively building and training neural networks. A widely utilized layer in Keras is the dense layer, which facilitates the creation of fully connected neural networks. In this research, a sequential model composed of fully connected dense layers was employed for the ANN. The other ML algorithms were implemented using the Scikit-Learn library.

Different ML algorithms require various hyperparameters that need to be fine-tuned during the training phase via iterative optimization. The optimal hyperparameters for each ML algorithm are detailed in Table 1.

Table 1. The ML models' hyperparameters

Model	Optimal hyperparameters
SVM	kernel= radial basis Sigma (rbs), C=1
LR	solver=liblinear, Penalty = l2
DT	criterion=Gini index
ANN	Number of hidden layers=1, number of neurons in each layer =16, 8 and 1, input and hidden layer activation=Selu, output layer activation = sigmoid, loss=binary cross-entropy, optimizer=Adam, lr=0.037, epochs =53, batch-size=83
RF	n_estimators=100, criterion=Gini index

2.4. Feature Selection

The strategy of feature selection was utilized to improve the models' performance. RF is a widely used algorithm for feature selection in data science processes. Consequently, we implemented the embedded method alongside the RF algorithm from the Sklearn library. According to the outcomes of the feature selection model, features deemed significant (importance > 0.5) were chosen. The ML models were developed using the selected features, and their performance was re-assessed.

2.5. Model Performance Assessment

We assessed the effectiveness of models using four different metrics: accuracy, recall (also known as sensitivity), specificity, and AUROC (area under the receiver operating characteristic curve). Additionally, we computed 95% confidence intervals for the various performance metrics obtained through the percentile method. AUROC refers to the area under the receiver operating characteristic curve (ROC curve). The ROC curve visually represents the performance of a classification model at various categorization thresholds. This curve charts two key parameters: the True Positive Rate (TPR) and the False Positive Rate (FPR). For classifiers, the AUROC is regarded as an effective performance indicator. To evaluate the performance of the ML classification models, we generated AUROC curves.

3. Results

3.1. Patient's Characteristics

From a total of 1000 patient records, 761 were female and 239 were male, with an average age of 58.42. Osteoporosis was present in 23.5% of the cases. A summary of the demographic and clinical characteristics can be found in Table 2.

3.2. Performance of ML Algorithms

The performance of the developed models is evaluated using five different metrics (see Table 3). The ANN and RF models exhibited the highest sensitivity at 89% and 78.6%, respectively. For specificity, the ANN and SVM models achieved the highest values at 96.3% and 94.2%. In terms of accuracy, the top performers were ANN and RF, with scores of 94.6% and 86.5%, respectively. According to the AUROC, the ANN model demonstrated superior performance with an index of 0.937, followed by RF at 0.837, LR at 0.832, SVM at 0.769, and DT at 0.715. The AUROC results for the developed models are illustrated in Figure 1. Moreover, detailed information regarding the AUROCs of each individual model can be found in Supplementary (Figures Supplementary 1- Supplementary 5).

4. Discussion

This research was carried out to explore the effectiveness of ML algorithms in predicting osteoporosis. We employed five widely used ML algorithms (ANN, SVM, RF, DT, and LR) to predict the occurrence of osteoporosis. To enhance the models' generalizability, the dataset was partitioned into training and testing sets through stratified k-fold cross-validation. This approach is favored for its ability to preserve the distribution of the target variable across each fold, reducing the likelihood of bias in model assessment. The AUROC values for the

Table 2. Demographic characteristics and variable features of the participants

Variables		Total N=1000	Osteoporotic N=235	Controls N=765	P-value
Age (years)		58.4 ± 11.0	63.1 ± 10.5	57±10.8	0.001
Body Mass Index (kg/m^2)		27.8 ± 4.4	26.6 ± 4.2	28.2±4.3	0.001
Serum Vitamin D (ng/ml)		28.4 ± 16.9	27.0 ± 15.2	28.8±17.4	0.150
Gender	**Female**	761 (76.1%)	212 (90.2%)	549 (72.8%)	0.001
	Male	239 (23.9%)	23 (9.8%)	216 (28.2%)	
Corticosteroids		89 (8.9%)	45 (19.1%)	44 (5.8%)	0.001
Immunosuppressive		75 (7.5%)	43 (18.3%)	32 (4.2%)	0.001
Diabetes Mellitus		199(19.9%)	70 (29.8%)	129 (16.9%)	0.001
Hypertension		348 (34.8%)	102 (43.4%)	246 (32.2%)	0.002
Hyperlipidemia		193 (19.3%)	46 (19.6%)	147 (19.2%)	0.900
Coronary Artery Disease		79 (7.9%)	23 (9.8%)	56 (7.3%)	0.220
Cardiovascular Disease		113 (11.3%)	45 (19.1%)	68 (8.9%)	0.001
Psoriasis		22 (2.2%)	11 (4.8%)	11 (1.4%)	0.003
Hypothyroidism		30 (3%)	11 (4.8%)	19 (2.5%)	0.084
Femoral T-score		-1.8 ± 0.8	-2.9 ± 0.4	-1.5 ± 0.6	0.001
Lumbar T-score		-1.9 ± 0.9	-3.2 ± 0.7	-1.53 ± 0.5	0.001

The data are presented as mean ± std or count (%).

Table 3. Performance of models in the prediction of osteoporosis

Model	AUROC (95%CI)	Accuracy (95%CI)	Sensitivity (95%CI)	Specificity (95%CI)
DT	0.72 (0.52-0.92)	0.74 (0.38-0.90)	65.3 (31.0-99.1)	76.1 (21.0-100)
RF	0.84 (0.57-0.98)	0.87 (0.41-0.98)	78.6 (53.2-100)	88.8 (24.4-100)
LR	0.83 (0.69-0.96)	0.76 (0.64-0.87)	30.4 (1.9-84.1)	90.4 (68.6-100)
SVM	0.77 (0.59-0.92)	0.77 (0.66-0.87)	21.9 (00.0-50.1)	94.2 (84.8-99.7)
ANN	0.93 (0.71-1.00)	0.95 (0.66-1.00)	89.0 (50.5-100)	96.3 (74.9-100)

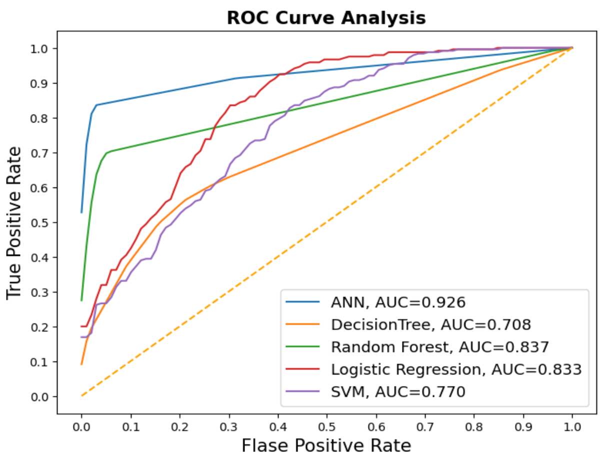

Figure 1. The AUROCs of the created models

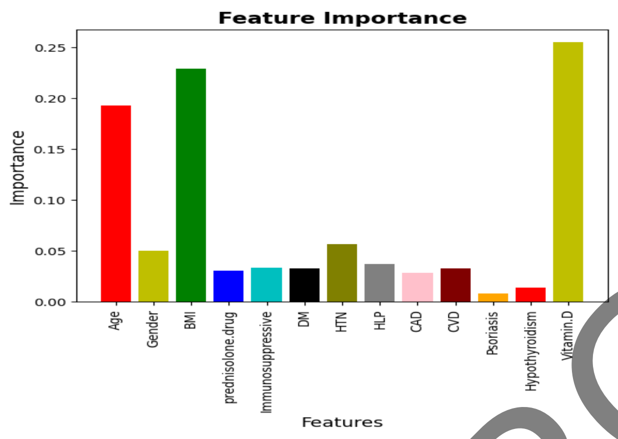

Figure 2. The importance of features

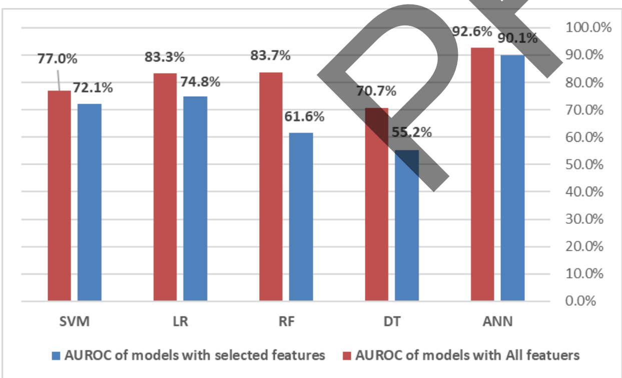

Figure 3. Comparison of ML models with all and selected features

ANN, RF, and LR models demonstrated a strong ability to predict the risk of osteoporosis, with results exceeding 0.83. In a study performed by Shim *et al.* [21], the ANN model had the best performance, with an AUROC of 0.743. In another study by Meng *et al.* [25], an ANN model was developed for osteoporosis prediction, and the AUROC value was 0.829. Bui *et al.* [38] compared RF, ANN, SVM, and LR to predict osteoporosis. The best results were obtained with the RF model, with an AUROC of 0.854. In a comparable investigation, Yang *et al.* [22] evaluated several ML algorithms. The SVM model produced the most favorable outcomes, attaining an AUROC of 0.84. In our research, the ANN surpassed other models in its ability to predict osteoporosis, reaching a 93% AUROC, which exceeds the results of earlier studies.

Feature selection in ML is crucial for output impact [39]. we identified key variables like Age, BMI, Vitamin D, and HTN. Smaller models were constructed for comparison with larger ones. Reduction in variables diminished performance, showing that removed variables effect on ML model performance in diagnosing osteoporosis. The observed reduction in model performance following feature selection suggests that variables excluded during this process may still contain complementary predictive information. Machine learning models often benefit from complex interactions among multiple features; therefore, removing certain variables may reduce the model's ability to capture underlying relationships within the data, ultimately leading to decreased predictive performance.

We applied the RF algorithm to determine the importance of features and potential predictors of osteoporosis. According to research by Bui *et al.*, age, weight, and height have been demonstrated to significantly increase the risk of osteoporosis [38]. The findings of our study indicated that, in addition to these factors, the level of vitamin D was one of the most important predictors of osteoporosis. Therefore, in our study, its importance was even greater than age and BMI. The importance of vitamin D has also been confirmed in clinical studies. For example, Lips and colleagues demonstrated that taking Vitamin D supplements is associated with a decrease in bone turnover and an enhancement in bone mineral density [40]. Also, Chou-Hou *et al.* showed that the steroid hormone in vitamin D, which can influence bone quality and quantity, is essential for skeletal health and mineral metabolism [41].

Our study has advantages over previous similar studies. Previous studies were often conducted on a specific and limited population, such as women or diabetic patients, and mostly on the data of elderly people, but this study was conducted to predict all people aged 31 to 86 years. Unlike other studies that did not include vitamin D in the model build, our study included this feature. The ANN model built in our study has a high performance compared to previous models in the prediction of osteoporosis. We create a neural network using Keras dense layers. The dense layer is the prevalent and used layer that is the deeply connected neural network layer [42].

However, it's essential to acknowledge some limitations in the study. First, the study relied on a specific dataset from a single clinic, which could introduce selection bias and limit the generalizability of the findings. Second, the dataset's relatively small size might impact the robustness of the models when applied to larger and more diverse populations. Third, our research could not forecast the onset of osteopenia and osteoporosis through a multi-classification algorithm aimed at reducing the risk of osteoporosis prior to fracture occurrence. Fourth, Factors such as patient positioning errors, measurement line placement for T-score calculation, and conditions like obesity, regional calcification, spondylosis, osteoarthritis, and osteophytes can impact osteomalacia diagnosis accuracy by reducing bone mineralization. Efforts have been made to minimize errors by selecting patients without acquisition or condition limitations, although complete avoidance of errors may not be possible in this study. Ultimately, model evaluation in this study was based solely on internal validation using stratified cross-validation. Although this approach helps reduce overfitting, the absence of external validation may limit the generalizability of the findings to other populations and clinical settings.

From a clinical perspective, the proposed model could be integrated into Hospital Information Systems (HIS) as a clinical decision support tool. Patient demographic and laboratory data routinely recorded in the HIS could be automatically analyzed by the model to identify individuals at high risk of osteoporosis. Such integration may assist clinicians in prioritizing patients for further DEXA evaluation and early preventive interventions, thereby supporting more efficient screening and decision-making in routine clinical practice.

Future research could benefit from incorporating data from multiple sources and employing larger datasets to enhance model performance and applicability. In addition to clinical factors and characteristics, other factors such as nutrition, socio-economic status, and geographic location can also be effective in osteoporosis and help in building predictive models when data related to these types of characteristics of people are not available.

5. Conclusion

In summary, this research showed that osteoporosis can be effectively predicted using supervised ML algorithms. The ANN model emerged as the strongest performer, achieving high sensitivity, specificity, and overall accuracy. The study's findings hold promise for enhancing the earlier diagnosis of osteoporosis. ML algorithms can offer a different method for recognizing and evaluating individuals who are at a greater risk for osteoporosis and can be utilized in creating clinical decision support systems for diagnosing osteoporosis. Further study is necessary to validate the models on larger and more varied datasets, allowing for their translation into clinical practice and potentially improving osteoporosis management outcomes.

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All data produced or examined during this research can be obtained from the corresponding author upon reasonable request.

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Supplements

Detailed information on the AUROCs of the machine learning models found in Supplementary.

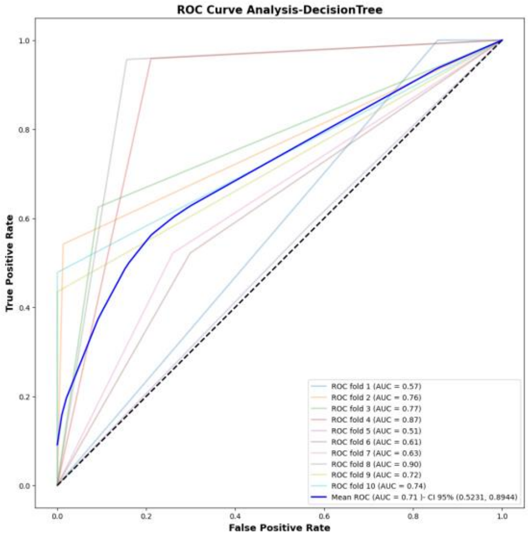

Figure Supplementary 1. AUROC for decision tree

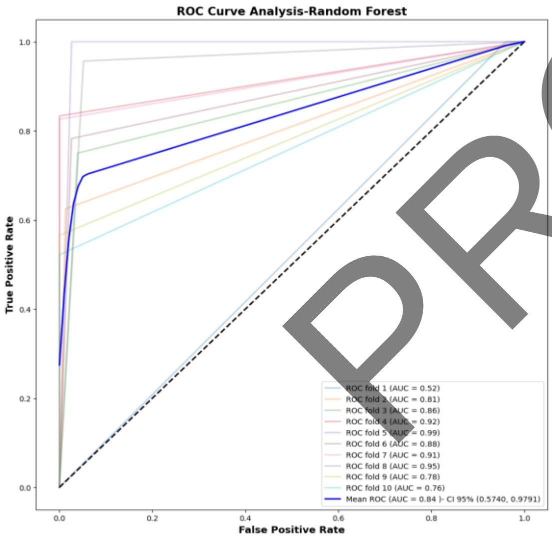

Figure Supplementary 2. AUROC for random forest

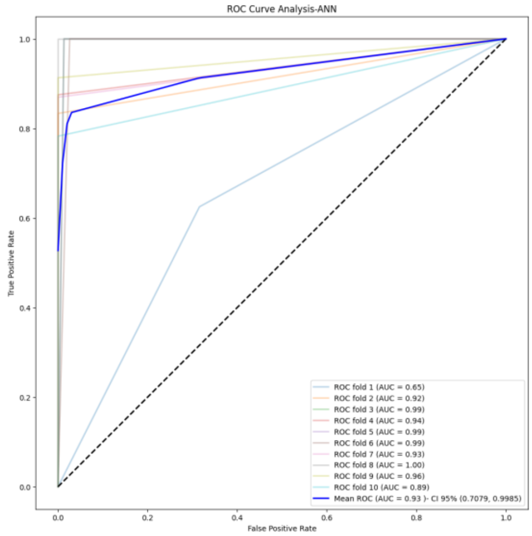

Figure Supplementary 3. AUROC for ANN

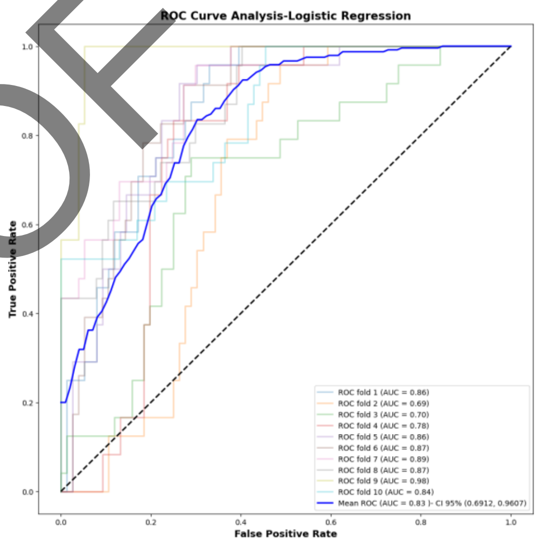

Figure Supplementary 4. AUROC for logistic

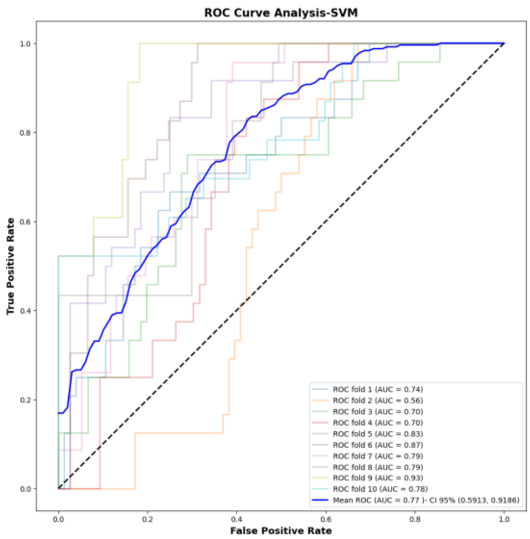

Figure Supplementary 5. AUROC for SVM

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