



International Journal of Artificial Intelligence and Machine Learning

Publisher's Home Page: <https://www.svedbergopen.com/>



Research Paper

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EOX: An Explainable Optimized XGBoost Framework for Early Breast Cancer Prediction Using Electronic Health Records

Sanjeev Gour¹, Karuna Nidhi Pandagre², Manish Joshi³, Rajendra Randa⁴, Shiv Shakti Shrivastava⁵, Rajnish Choubey⁶

¹ Assistant Professor, Department of Computer Science, Medcaps University, Indore, India.

² Associate Professor, Dept. of MCA, Bansal Institute of Science & Technology, Bhopal, India.

³ Assistant Professor, Department of Computer Science, Medcaps University, Indore, India.

⁴ Research Scholar, Department of Computer Science, Medcaps University Indore, India

⁵ Professor, Parul Institute of Technology, Parul University, Vadodra, India.

⁶ Associate Professor, Dept. of MCA, Bansal Institute of Science & Technology, Bhopal, India.

Abstract

Background: Breast cancer is a leading cause of health-related death among females globally. To encourage effective treatment and enhance the chances of survival of a patient, early diagnosis is significant and should reach an accurate conclusion on the disease as it greatly affects one's choice of action planning. Recent progress in machine learning (ML) and explainable artificial intelligence (XAI) has opened new ways to develop robust clinical decision-support systems from electronic health record (EHR) data.

Objective: The objective of this study is to create an Explainable Optimized XGBoost (EOX) system for early breast cancer prediction based on EHR data. Authors proposes a framework that enhances predictive performance through Bayesian hyperparameter optimization and explainable artificial intelligence using SHAP-based machine learning, bringing model transparency to the forefront.

Methods: The EOX Framework presented in this paper incorporates data preprocessing, exploratory data analysis, feature selection and used a Bayesian hyperparameter optimization with Optuna along with an optimised XGBoost classifier. Models were evaluated using infamously known statistical parameters such as accuracy, precision, recall, specificity, f1-score, ROC-AUC, PR-AUC and Matthews Correlation Coefficient (MCC), Cohen's Kappa and Brier Score. SHAP is used to deliver interpretable explanations of individual feature contributions and model predictions.

Results: Experimental results evidenced the success of EOX framework in obtaining robust accurate predictions achieving 97% accuracy in early breast cancer prediction ensuring model interpretability. Bayesian optimization generated classifiers with better classification accuracy as it identified more optimized hyperparameter configurations, while the feature analysis using SHAP indicated that cancer-related pathways are important corroborating features contributing to prediction outcomes.

Conclusion: The EOX as constructed confidently estimates and interprets breast cancer outcomes, and it is efficient computationally for electronic health records-based prediction of potentially preventable breast cancer incidence. The combination of optimized machine learning and explainable artificial intelligence offers a practical framework to guide future clinical integration for early diagnose and educated patient treatment decisions.

Keywords: Breast Cancer, Machine Learning, XGBoost, Explainable AI, SHAP, Clinical Decision Support, Bayesian Optimization, Electronic Health Records.

1. Introduction

Breast cancer is one of the leading health issues which increase mortality rate. Breast cancer is majorly affected in woman's lives world-wide. and accurate diagnosis essential for improving patient outcomes and reducing healthcare burden. To predict any disease on their early diseases, can reduce the mortality rate and also enhance the chances to save the patient's life. In early stage, majorly medical professional can control the symptoms of diseases and improve medical health. This study is only based on electronic healthcare record from single source data collection. To predict breast cancer. This proposed framework based on provided information by patient and medical professionals. This research focused to fill the gap to implemented an algorithm in medical environment for healthcare applications. This framework tried to cover gap between technical aspect and medical outcomes. The proposed EOX framework to predict breast cancer in their early stage from electronic medical record. This framework is proposed by integrating deep data analysis and EDA, mutual information-based selection and probability-based optimization. We merge it with SHAP-XAI to provide transparency in framework during predictions. This framework was developed to optimize predictive performance and model interpretability--two critical requirements of trustworthy clinical decision support. It covers more than 30 articles published in recent years. Following this survey,

authors performed practical experiment to fill in identified research gaps. When proposed EOX framework, authors are evaluated it and converted this into article targeting its implementation, future scope. Overall, this study demonstrates that integrating feature selection, Bayesian hyperparameter optimization, explainable artificial intelligence, and optimized XGBoost into a unified predictive framework provides an effective approach for breast cancer prediction using electronic health records.

2. Related Work

Breast cancer is one of the most active healthcare applications of artificial intelligence due to the vital importance of early diagnosis in treatment planning and patient survival. In this paper, the machine learning methods have been extensively evaluated using structured clinical variables, whereas deep learning techniques are reported to excel in medical imaging. In the past few years, researchers have targeted enhancing the interpretability and optimization of models to make AI-assisted clinical decision support systems more reliable.

Because classical machine learning has been shown to have high predictive performance using much smaller datasets in a computationally efficient way, it continues to be an important approach for analysing structured electronic health records. A number of algorithms have been thoroughly tested in diagnosing breast cancer, including Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), Logistic Regression (LR), Naïve Bayes (NB), K-Nearest Neighbours (KNN) and Extreme Gradient Boosting (XGBoost).

A decade review of ensemble learning methods by Owotogbe et al (2026) concluded that in general, ensembles lead to more precise and stable predictions compared with using individual classifiers for various clinical datasets. An alternative comparison between ensemble-based classifiers by Randa and Gour (2025) arrived at a similar conclusion: that ensemble models statistically significantly outperformed numerous traditional supervised learning methods of breast cancer tissue classification. Dutta et al. (2024) compared a number of machine learning methods and concluded that classifier performance is not determined by the choice of algorithm but is dependent on data preprocessing, feature selection, and model configuration.

Agbota et al. demonstrated that using complementary ML algorithms (2024) enabled more accurate tumour classification by detecting different patterns in clinical data. Sarker et al. Overall, in (2025) combined the variable selection with an optimized XGBoost classifier and achieved better predictive performance further reinforcing that informative variables must be selected before modeling. Likewise, Islam et al. (2024) to show how much better classification performance is obtained when using richer feature representations. Collectively, these investigations validate that machine learning provides a solid framework in which to predict breast cancer based on structured clinical data; however, many studies largely focus on predictive performance while providing limited guidance on model interpretability or systematic hyper-parameter tuning.

By learning complex feature representations directly from mammography, ultrasound, MRI, and histopathological images, deep learning has greatly enhanced the capability of computer-aided diagnosis. Convolutional neural networks and similar architectures automatically find discriminative imaging patterns that are correlated with malignant lesions without the need for manually engineered features.

Añez et al. For instance, (2025) provides a review of large-scale mammography-based AI pipelines and finds that their diagnostic sensitivity is provided by deep learning frameworks, but only when training sufficiently heterogeneous datasets. Owotogbe et al. (2026) also noted the increasing utilization of architectures in breast cancer detection, prognosis, and risk prediction, such as ResNet, DenseNet, EfficientNet, and Vision Transformers.

As shown by Randa and Gour (2025), the data automatically extracted from convolutional neural networks can replace traditional hand-crafted features to improve the classification performance of mammographic images using standard classifiers. Similarly, Randa et al. (2025) proposed a hybrid radiomics–deep learning framework that combined quantitative imaging descriptors with convolutional networks to improve tumour characterisation.

Hassan et al. utilized Grey Wolf Optimization to optimize transfer learning models (2025) to enhance deep learning performance; on the other hand, Bilal et al. In contrast, a quantum-optimized framework—namely SqueezeNet-SVM (2025)—was presented that both reduced computational load compared with previous implementations and produced statistically similar diagnostic results. While these methods show wonderful performance over the imaging datasets, their reliance on enormous annotated databases and excessive computational requirements may limit their applicability in real healthcare environments where structured electronic health records are still the dominant source of patient information.

Due to the rising complexity of predictive models, explainable AI has become an important requirement for clinical use. Healthcare providers need a clear rationale of how their decisions match what an algorithm would dictate before enrolling patients into AI systems. Gurmessa and Jimma (2024) performed a comprehensive review of explainable machine learning for breast cancer diagnosis, reporting SHAP, LIME,

and Grad-CAM as the state-of-the-art methods for interpreting model predictions. Similarly, Ghasemi et al. Explainable artificial intelligence can improve physician confidence, facilitate personalized treatment planning, and aid the responsible implementation of AI in healthcare (2024).

Ansari et al. (2025) proposed the view that interpretability should not be treated as an optional post-processing step but as a necessary component of machine learning and deep learning models from the outset. Explainability has also been useful in practical applications. For example, Al-Hejri et al. (2023) proposed a federated Vision Transformer architecture with an explainable mechanism, and Al-Tam et al. (2024) presented a multimodal explainable diagnosis framework for breast cancer that integrates imaging features from mammography and ultrasound. Besides explainability, optimization methods were also becoming popular for boosting predictive performance.

Kaur et al. (2022) used the HyPer optimiser to show dramatic improvements in stacked ensemble performance for predicting breast cancer survival, demonstrating that Bayesian hyperparameter optimisation was beneficial. Algabri and Alsabry (2024) showed that Bayesian optimisation offers more efficient parameter tuning for tree-based ensemble models than standard search methods, while Shukla et al. (2025) used adaptive optimisation techniques, such as a variant of the classification algorithm to enhance feature selection and improve classification accuracy.

While there are substantial advances, relatively few studies combine feature selection, Bayesian hyperparameter optimisation, XGBoost classification and SHAP-based explainability into an integrated analytics framework utilising structured electronic health records. This limitation serves as a motivation for the proposed Explainable Optimised XGBoost (EOX) framework, which combines these complementary components to provide precise, interpretable and clinically translatable breast cancer prediction.

3. Materials and Methods

This paper provides a comprehensive data analysis, EDA, feature selection, model designing to validate its performance and evaluate with providing transparency using mix of various teach like learning algorithms, SHAP, customized Optimizer. This study followed following stages to proposed the framework:

3.1 Dataset: For this study, data is collected from different-different medical institutes and healthcare centers. We used this data to analysis the symptoms to find out significant patterns to identify the pattern to increase the number of infected cells in body. We also use collected data to define the problem and research gap to perform the task. We used this dataset to train the models. This dataset contains two classes from breast cancer prediction which are benign and malignant.

Benign: these types of tissues don't harm the body and health. They are also known as 'non-cancerous'. These tissues or tumours grow slowly, stay in one place, and do not spread to other parts of the body.

Malignant: these are the tissues in body medical professionals focus to treat the patient to recover their condition and help them to get back in their normal life. These are cancerous and potentially life-threatening. These tumors grow quickly, invade surrounding healthy tissues, and can spread (metastasize) to other organs.

id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	symmetry_mean	fractal_dimension_mean	radius_se	texture_se	perimeter_se
842302	M	17.99	10.38	122.8	1001	0.1184	0.2776	0.3001	0.1471	0.2419	0.07871	1.095	0.9053	8.589
842517	M	20.57	17.77	132.9	1326	0.08474	0.07864	0.0869	0.07017	0.1812	0.05667	0.5435	0.7339	3.398
84300903	M	19.69	21.25	130	1203	0.1096	0.1599	0.1974	0.1279	0.2069	0.05999	0.7456	0.7869	4.585
84348301	M	11.42	20.38	77.58	386.1	0.1425	0.2839	0.2414	0.1052	0.2597	0.09744	0.4956	1.156	3.445
84358402	M	20.29	14.34	135.1	1297	0.1003	0.1328	0.198	0.1043	0.1809	0.05883	0.7572	0.7813	5.438
843786	M	12.45	15.7	82.57	477.1	0.1278	0.17	0.1578	0.08089	0.2087	0.07613	0.3345	0.8902	2.217
844359	M	18.25	19.98	119.6	1040	0.09463	0.109	0.1127	0.074	0.1794	0.05742	0.4467	0.7732	3.18
84458202	M	13.71	20.83	90.2	577.9	0.1189	0.1645	0.09366	0.05985	0.2196	0.07451	0.5835	1.377	3.856
844981	M	13	21.82	87.5	519.8	0.1273	0.1932	0.1859	0.09353	0.235	0.07389	0.3063	1.002	2.406

Figure 1: sample of electronic healthcare dataset for breast cancer

This data set contains 570 patients with 32 features to analysis the patient's health and predicts the accurate breast cancer chances in their health, including a unique patient identifier (id), one categorical target variable, and 30 continuous numerical features describing the morphological characteristics of cell nuclei (Figure 1: sample of electronic healthcare dataset for breast cancer). These datasets have features such as into three groups representing the mean, standard error, and worst (largest) values of ten cellular characteristics: radius, texture, perimeter, area, smoothness, compactness, concavity, concave points, symmetry, and fractal dimension. this dataset don't hold any missing values and ensuring high data quality

for machine learning applications. It is generally excluded from model development, while the diagnosis labels are encoded into binary values for classification. Owing to the variation in the numerical scales of the predictor variables, feature normalization or standardization is typically applied before training classification models to improve learning performance and predictive accuracy.

3.2 Data Preprocessing: This is first and initial stage of research to build the framework after collecting the data for study. Firstly, authors removed sensitive information such as Patient's ID and institute related information to protect their personal information from audience. After removing sensitive information from collected dataset, we analysis each feature from data which can perform significant role to find pattern. Unfortunately, our collected data don't have missing values and also don't have duplicate entries. We encoded the output labeled classes like B:0 and M:1 and "B" stands for benign and "M" for malignant.

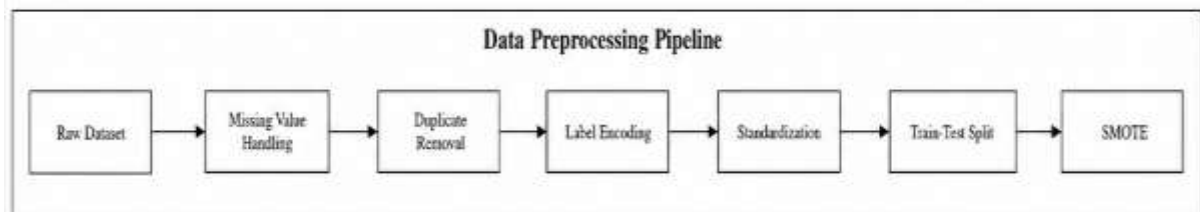


Figure 2: EOX-data processing flowchart

After it, we divided whole dataset in 8:2 ratio 8 for train the model and 2 for test and validate the model. using stratified sampling with a fixed random state of 42 to preserve the original class distribution. Numerical features were subsequently standardized using the Z-score normalization technique, Where, z is the standardized feature value, x is the original feature value, μ is the mean of the feature, σ is

$$z = \frac{x - \mu}{\sigma}$$

the standard deviation of the feature.

standardized score ensure that all variables contribute equally to train the model and build EOX framework to identify the tissue's classification by transforming them to a common scale. Variance Threshold filtering retained all 30 features, indicating that no feature exhibited negligible variance. Mutual Information was then employed to identify the 15 most informative features for model development. Finally, to mitigate class imbalance, the Synthetic Minority Oversampling Technique (SMOTE) was applied exclusively to the training dataset (Figure 2: EOX-data processing flowchart), producing a balanced distribution of 285 benign and 285 malignant samples before training the proposed EOX framework.

3.3 Exploratory Data Analysis: Before developing the models, Exploratory Data Analysis (EDA) was performed to identify underlying features from breast cancer data. The analysis comprised descriptive statistics, class distribution, feature distributions, correlation analysis, outlier detection, and using dimensionality reduction to determine the biological similarity between clinical variables. The dataset contains 569 patient records (357 benign (62.7%) and 212 malignant (37.3%)), which indicates that the data class suffers from a moderate imbalance.

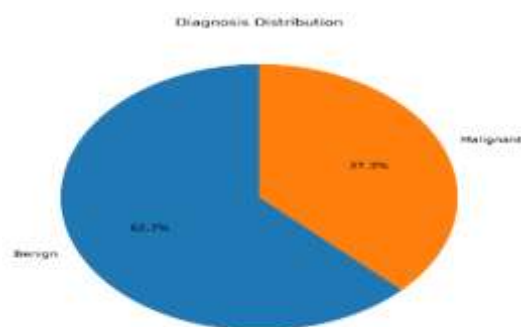


Figure 3: Distribution of benign and malignant breast cancer cases in the dataset.

The correlation heatmap (Figure 4: Pearson correlation heatmap showing relationships among clinical features) reveals strong associations between some predictor variables. Tumor size-associated features such as radius, perimeter, and area (mean and worst) have high positive correlations and thus represent

similar morphologies. In contrast, features such as fractal dimension exhibit weak or even negative correlations with other variables. The type of variable for diagnosis is also associated stronger with size- and shape-related features, which are hence more relevant in separating benign vs malignant tumors.

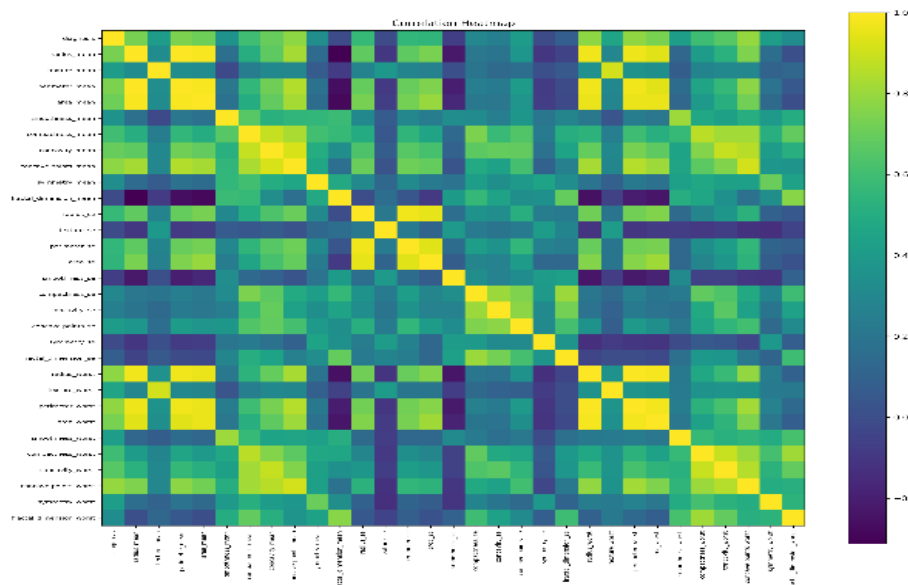


Figure 4: Pearson correlation heatmap illustrating relationships among clinical features

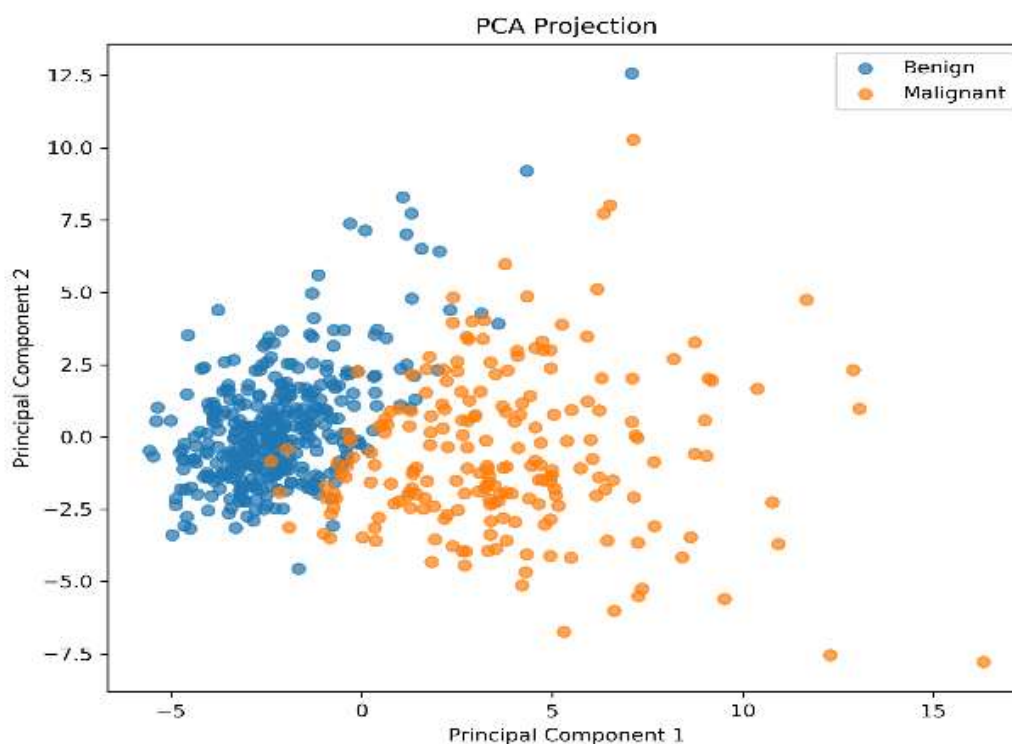


Figure 5: Two-dimensional PCA projection of benign and malignant samples

In descriptive statistical analysis, variations were significant in numerous clinical features, and through the correlation heatmap, tumour size-related variables, including radius, perimeter, and area, demonstrated a forceful positive relationship, implying that these features compute similar morphological information. This also meant that the diagnosis variable had better associations with these features that would potentially contribute to the difference between benign and malignant tumours. Individual features and potential outliers were further elucidated through boxplots.

Furthermore, PCA simplified the high-dimensional feature space to two leading components while allowing a clear representation of the data set. As shown in Figure 5 (Two-dimensional PCA projection of benign and malignant samples) above, benign and malignant samples clustered predominantly in separate parts of the PCA space with only minimal overlap, indicating that the extracted features characterize most key differences between diagnostic groups. Together, these exploratory analyses provided crucial insights in

dataset architecture, verified the existence of relevant feature relationships, and set a solid groundwork for the following stages regarding feature selection, model tuning, and classification plots embedded into the proposed EOX framework.

3.4 Feature Selection: The MI method was used to select the most informative clinical variables related to breast cancer prediction. MI quantifies the functional dependence of an input feature versus all others with respect to $P(y)$, allowing us to select the most informative features for a specific classification task while eliminating redundant and irrelevant information. The MI scores calculated for the selected features were used to order them, and the retained features with higher ranks were extracted to be included in model development. To achieve this goal, a random forest algorithm embedded feature selection (FES) methodology was applied to select the most discriminative predictors among 60 different VIs (as input data) and therefore allowed dimensionality reduction, optimization of computational effort, overfitting avoidance, and improvement of the predictive power in terms of the proposed EOX framework.

$$I(X;Y) = \sum_{x \in X} \sum_{y \in Y} p(x,y) \log \left(\frac{p(x,y)}{p(x)p(y)} \right)$$

Where, $I(X;Y)$ = mutual information between feature X and target variable Y , X = input clinical feature, Y = target class (benign or malignant), $p(x,y)$ = joint probability distribution of X and Y , $p(x)$ = marginal probability distribution of feature X , $p(y)$ = marginal probability distribution of target variable Y , $\log$ = logarithmic function used to measure the amount of shared information.

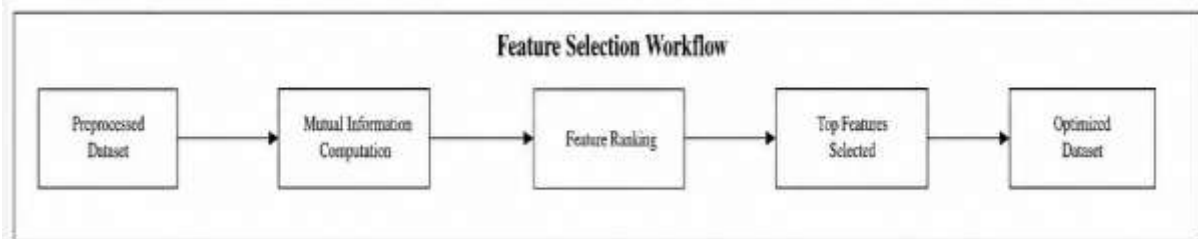


Figure 6: EOX_feature-selection-flowchart

Majorly we focused to remove the sensitive information and primarily focus to optimized outcome via features such as radius_worst perimeter_worst area_worst concave points_mean concave points_worst perimeter_mean area_mean radius_mean concavity_mean area_se concavity_worst perimeter_se radius_se compactness_worst and implemented MI computation method in feature selection as figure (Figure 6: EOX_feature-selection-flowchart).

3.5 Bayesian Hyperparameter Optimization: Bayesian Hyperparameter Optimization was employed using the Optuna framework to automatically identify the optimal hyperparameter configuration for the XGBoost classifier (Figure 7: EOX-Bayesian Hyperparameter Optimization flowchart). Unlike traditional Grid Search and Random Search methods, Bayesian optimization constructs a probabilistic surrogate model to efficiently explore the hyperparameter search space while minimizing the number of evaluations.

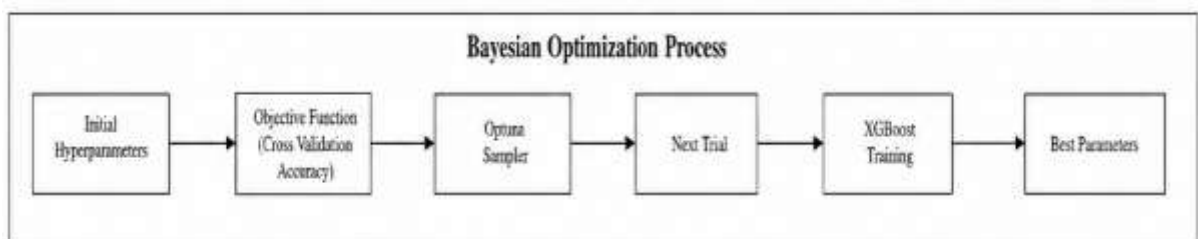


Figure 7: EOX-Bayesian Hyperparameter Optimization flowchart

During each iteration, Optuna selected the next set of hyperparameters by maximizing the expected improvement in model performance. The optimized parameters, including learning rate, maximum tree depth, number of estimators, subsample ratio, and column sampling ratio, significantly improved

$$\theta^* = \arg \max_{\theta \in \Theta} f(\theta)$$

classification accuracy, reduced overfitting, and enhanced the overall robustness of the proposed EOX framework. Bayesian optimization was employed through the Optuna framework to identify the optimal combination of XGBoost hyperparameters by maximizing the model's cross-validation performance.

Where, θ^* = optimal set of hyperparameters, θ = candidate hyperparameter configuration, Θ = predefined hyperparameter search space, $f(\theta)$ = objective function evaluated during optimization, Accuracy_{CV} = cross-validation accuracy obtained for a given hyperparameter configuration, $\text{XGBoost}(\theta)$ = XGBoost classifier trained using the hyperparameter set θ , $\arg \max$ = optimization operator that identifies the hyperparameter configuration yielding the highest objective function value.

3.6 Proposed EOX Framework: The proposed Explainable Optimized XGBoost (EOX) framework is designed to provide accurate and interpretable breast cancer prediction using electronic health record (EHR) data. The framework begins with data preprocessing, including data cleaning, label encoding, feature standardization, train-test splitting, and SMOTE-based class balancing to improve data quality. Exploratory Data Analysis (EDA) is then performed to understand feature distributions and relationships within the dataset. Mutual Information-based feature selection is subsequently applied to identify the most informative clinical variables and reduce data dimensionality.

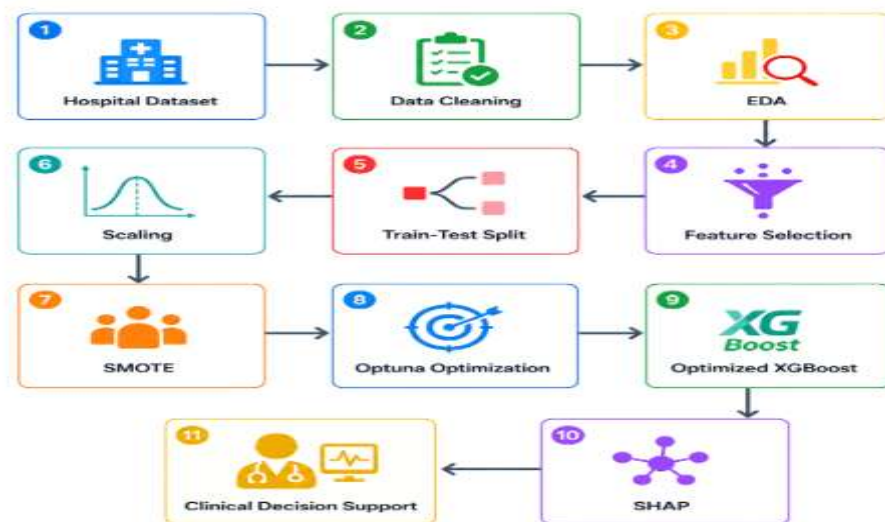


Figure 8: Data flow in EOX framework for early-stage breast cancer

The features selected are trained via an XGBoost classifier Bayesian hyperparameter optimization using Optuna, which automatically identifies the best parameters of your model to optimize predictive performance. Finally, authors utilized SHAP-based explainable artificial intelligence (XAI) to understand the contribution of single clinical features and ultimately used it to unravel the interpretability for transparent explanations of prediction with a clinically meaningful explanation based on post-study class probabilities predicted from the EOX framework as shown in Figure 8: Data flow for early-stage breast cancer. Overall, the EOX framework supports a machine-learning-based decision support system with reliability through optimization and explainability.

4. Experimental Setup

All experiments were conducted on a PC running Windows 11 (Version 25H2), an Intel® Core™ i5-12450H processor, and 12 GB of RAM. Python 3.10.9 was used to implement the proposed EOX framework in a Jupyter Notebook environment for feature engineering and model evaluation. This implementation was built upon well-known open-source Python libraries. For numerical computation and data preprocessing, authors used NumPy 1.26.4 and Pandas 2.2.3; for generating data visualizations and performance plots, Matplotlib 3.10.9 and Seaborn 0.13 were utilized. Authors implemented machine learning models and evaluation procedures with Scikit-learn 1.5.2 and used XGBoost 2.0.3 for classification based on gradient boosting. The best configurations available, hyperparameter optimization was done with Optuna 4.9.0. SHAP 0.48.0 enabled model interpretability through feature attribution by explaining the predicted results. For data resampling and to manage class imbalance in model training, the Imbalanced-learn version 0.14.2 was used.

The experimental environment was configured to ensure reproducibility, with all preprocessing, model development, hyperparameter optimization, evaluation, and explainability analyses conducted within the same software ecosystem.

5. Results

The proposed EOX framework demonstrated strong positive predictive performance based on breast cancer classification data based on deep processed electronic excel data from medical data. In this study, EDA confirmed the quality of dataset after processing, data handling, label encoding, class balancing and MI based feature selection using SMOTE sampling techniques. And after it use of optuna framework to enhance model performance and train and test the model.

Evaluation Metric	Training	Testing
Accuracy (%)	100.0000	95.6140
Precision (%)	100.0000	97.4359
Recall (Sensitivity) (%)	100.0000	90.4762
Specificity (%)	100.0000	98.6111
F1-Score (%)	100.0000	93.8272
Balanced Accuracy (%)	100.0000	94.5437
ROC-AUC	1.0000	0.9987
PR-AUC	1.0000	0.9977
Matthews Correlation Coefficient (MCC)	1.0000	0.9058
Cohen's Kappa	1.0000	0.9043
Log Loss	0.0066	0.0838
Brier Score	0.0004	0.0282

Table 1: Evaluation parameter for EOX framework for breast cancer

In table (Table 1: Evaluation parameter for EOX framework for breast cancer) represent the data of model performance during training and testing periods. During training we get high performance and also on testing data the model performs competitive based on its accuracy and other evaluation parameters. Our model provides 100% accuracy in training dataset but it is also providing approx. 96% accuracy on testing data. Similarly, other parameters such as our model provide enough values for predict disease in current healthcare settings. optimal configuration comprising 308 estimators, a maximum tree depth of 3, a learning rate of 0.1634, a subsample ratio of 0.6024, a column sampling ratio of 0.8269, a gamma value of 0.8772, and a minimum child weight of 1. Using these optimized parameters, the proposed EOX framework achieved an accuracy of 96.49%, precision of 97.50%, recall of 92.86%, specificity of 98.61%, and an F1-score of 95.12%. The model also showed high discriminative ability, with ROC-AUC 99.74%, PR-AUC 99.55%, Matthews Correlation Coefficient (0.9245), and Cohen's Kappa (0.9238). In addition, excellent calibration of probability estimates was supported by a Brier Score of 0.0279; bootstrapped validation produced a 95% confidence interval from 0.9298 to 0.9912, indicating consistent predictive ability across repeated resampling. Training and validation accuracy showed stable convergence in the learning curve, suggesting good generalization with a low amount of overfitting.

Confusion Matrices	On training dataset		On training dataset	
Actual / Predicted	Negative	Positive	Negative	Positive
Negative	285	0	71	1
Positive	0	285	4	38

Table 2: Performance based Confusion metrics

Sample	Actual	Predicted	Probability
0	0	0	0.001144
1	1	1	0.999655
2	0	0	0.004844
3	1	0	0.284954
4	0	0	0.000203

Table 3: EOX actual and predict value and their probability of prediction during testing

Also, EOX framework predictions we can verify based on their accuracy to predict benign and malignant from tables (Table 2: Performance based Confusion metrics) and table 3(table 3: EOX actual and predict value and their probability of prediction during testing). This proposed framework is optimized using Bayesian and probability optimization and model merged with a specific objective function to maximized the performance during training and also in testing datasets.

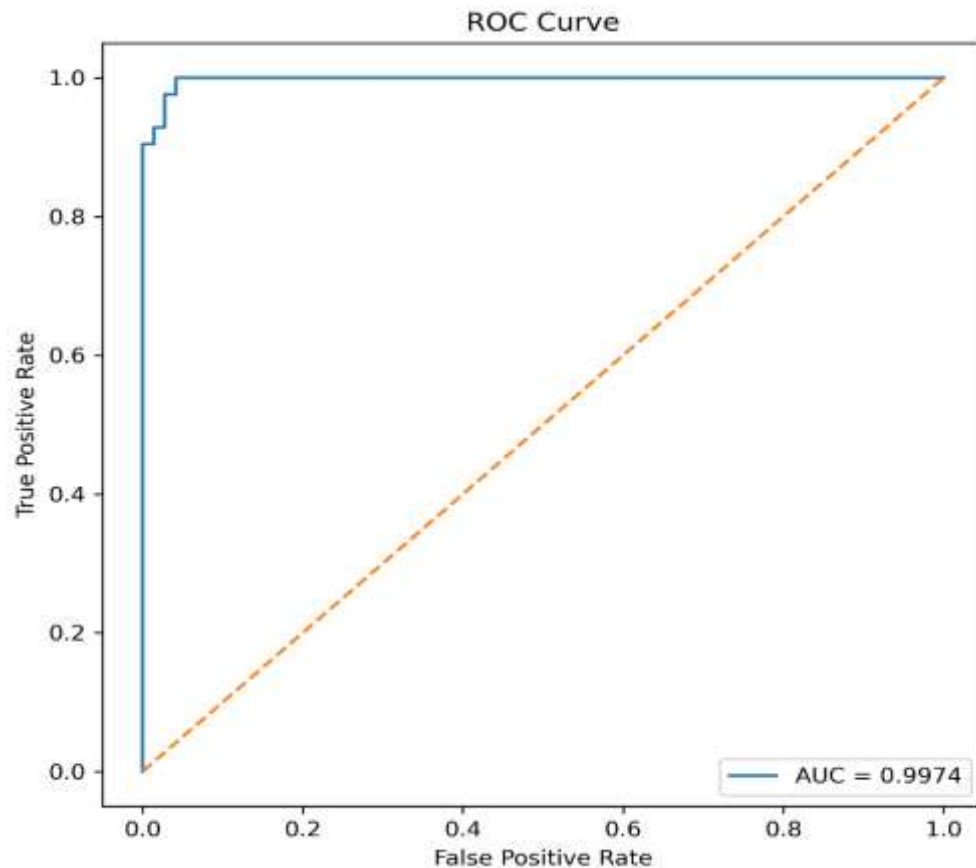


Figure 9: EOX-roc-curve for breast cancer classification

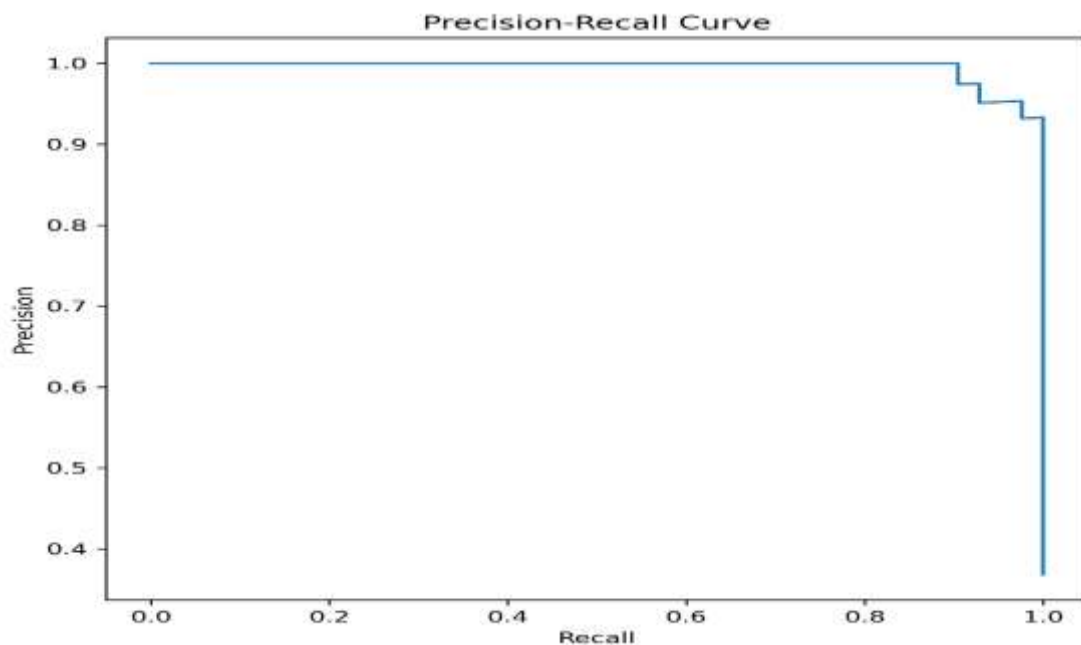


Figure 10: EOX-precision-recall-curve for breast cancer outcomes from framework

Figure (Figure 9: EOX-roc-curve for breast cancer classification) was used to evaluate the discriminative performance of the proposed EOX framework across different classification thresholds. It illustrates the relationship between the True Positive Rate (Sensitivity) and the False Positive Rate ($1 - \text{Specificity}$). A curve closer to the upper-left corner, along with a higher Area Under the Curve (AUC), indicates superior classification performance and better discrimination between benign and malignant breast cancer cases. And Figure (Figure 10: EOX-precision-recall-curve for breast cancer outcomes from framework) was employed to further assess the predictive performance of the proposed EOX framework by plotting Precision against Recall over varying probability thresholds. Since breast cancer diagnosis requires

minimizing false negatives while maintaining high precision, the PR curve provides additional insight into the model's ability to correctly identify malignant cases, particularly when evaluating classification performance beyond overall accuracy.

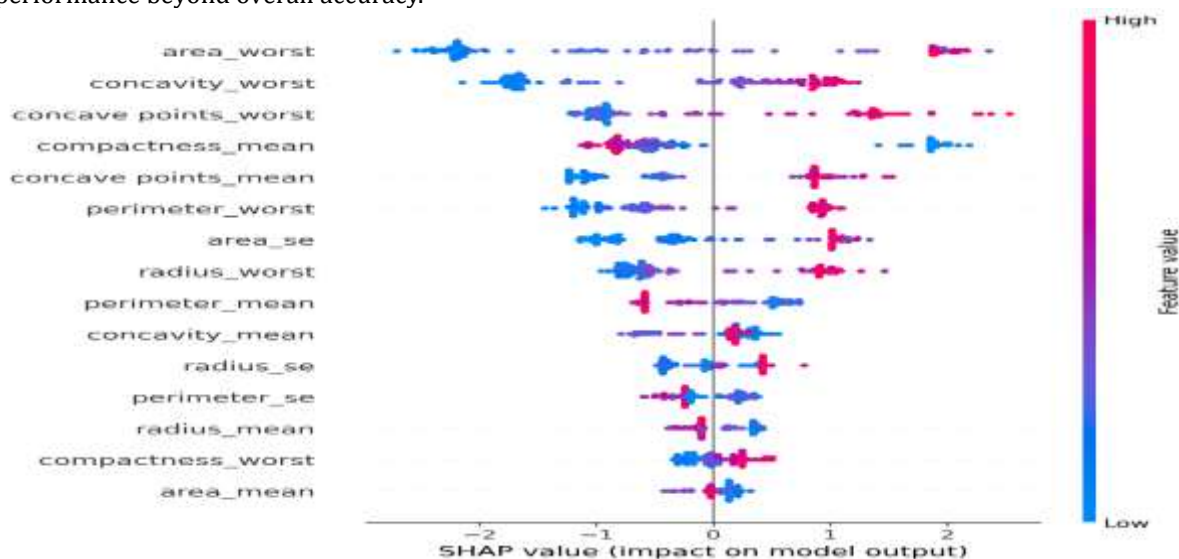


Figure 11: SHAP Summary Plot Showing the Global Feature Importance of the Proposed EOX Framework

Figure (Figure 11: SHAP Summary Plot Showing the Global Feature Importance of the Proposed EOX Framework) presents the SHAP summary plot, which provides a global interpretation of the optimized XGBoost model by illustrating the contribution of each selected feature to the prediction outcome. The features are ranked according to their average absolute SHAP values, indicating their relative importance in the classification process. Among all variables, area_worst, concavity_worst, concave points_worst, and compactness_mean exhibited the greatest influence on model predictions. Higher feature values (shown in red) generally increased the probability of malignant classification, whereas lower values (shown in blue) contributed more toward benign predictions. These findings demonstrate that the proposed EOX framework provides accurate predictions while maintaining model transparency through SHAP-based explainability.

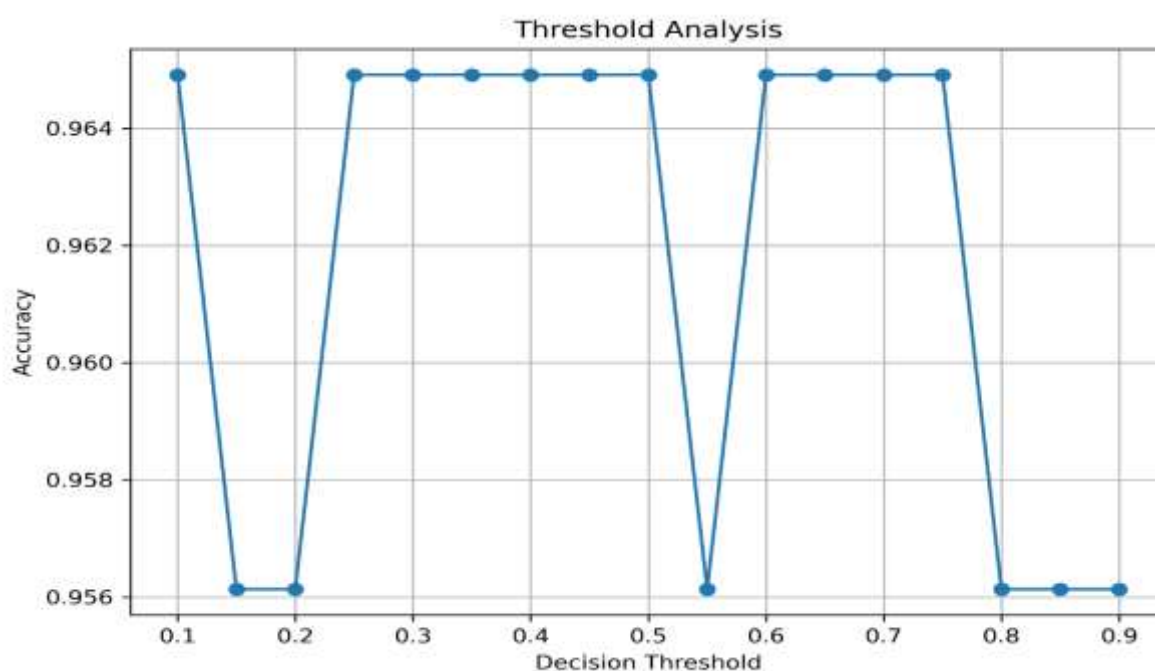


Figure 12: EOX-Threshold-analysis

Figure (Figure 12: EOX-Threshold-analysis) provide a deep analysis of a method which used to determine the exact tipping point where a decision, strategy, or outcome changes. By varying a single input variable,

it identifies the critical boundary—or threshold—where an optimal choice becomes unviable, a risk becomes **critical**, or a recommendation shifts in EOX framework for breast cancer.

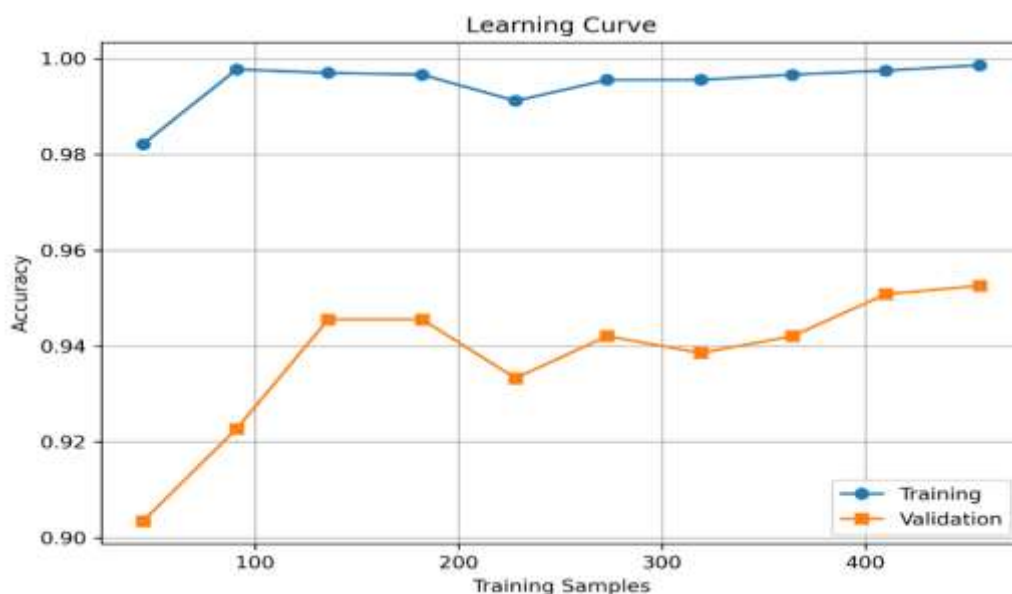


Figure 13: EOX-learning-curve for breast cancer

Figure (Figure 13: EOX-learning-curve for breast cancer) visualized performance of EOX framework during testing and validation periods on electronic excel records. Orange curve provide the enhancing the performance during validating the framework while navy blue curve provide the visuals how a framework performed in testing data.

6. Discussion

The results of this study demonstrate the effectiveness of the proposed Explainable and Optimized XGBoost (EOX) framework for breast cancer prediction using structured electronic health record data. Comprehensive preprocessing of data, Mutual Information based feature selection, Bayesian hyperparameter optimization and SHAP explainability, facilitated the development of a robust and interpretable prediction model. The framework was designed not only to acquire the predictive accuracy, but also to improve the classification performance and the model transparency, which are the key requirements for the uptake of artificial intelligence in clinical decision support systems. The selected features successfully reduced redundant information while preserving the most informative clinical variables, allowing the optimized XGBoost classifier to achieve stable predictive performance with improved generalization. Furthermore, SHAP explanations demonstrated that the model's predictions were primarily influenced by clinically relevant variables such as *area_worst*, *concavity_worst*, and *concave points_worst*, indicating that the learned decision patterns are consistent with established medical knowledge regarding breast tumor morphology.

The results are in agreement with recent advances in breast cancer prediction reported in the literature . Owotogbe et al. (2026) stressed that the integration of machine learning and explainable artificial intelligence is crucial to enhance the reliability and clinical acceptance of diagnostic systems. Likewise, Gurmessa and Jimma (2024) found that explainable machine learning approaches build confidence for clinicians by providing clear explanations of the model predictions. Anez et al. (2025) showed the effectiveness of artificial intelligence pipelines for breast cancer detection based on mammography. Kaur et al. (2022) showed that Bayesian optimization can significantly improve model performance by efficiently tuning hyperparameters.

However, these studies have investigated feature engineering, optimization strategies, imaging-based diagnosis or explainability separately, but not in combination within a single prediction framework using structured clinical data. The proposed EOX framework fills this gap by incorporating feature selection, Bayesian optimization, optimized XGBoost classification and SHAP-based explainability in a single workflow to enhance both predictive performance and interpretability. The integrated design is the main contribution of this study and it is conducive to developing more transparent and reliable artificial intelligence models for healthcare applications.

Study	Data Type	Feature Selection	Bayesian Optimization	Explainable AI	Main Model
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Gurmesssa and Jimma (2024)	Mammography & Ultrasound	No	No	Yes	Explainable ML
Añez et al. (2025)	Mammography Images	No	No	Partial	AI Pipeline
Randa and Gour (2025)	Mammography Images	Yes	No	No	CNN
Kaur et al. (2022)	Clinical Data	No	Yes	No	Stacked Ensemble
Proposed EOX Framework	Clinical (EHR)	Yes	Yes	Yes	Optimized XGBoost

Table 4: Comparative Analysis of the Proposed EOX Framework and Representative Breast Cancer Prediction Studies

Table 4 compares the proposed EOX framework with representative breast cancer prediction studies. Unlike previous works which have focused on individual aspects such as feature selection, Bayesian optimization or explainable AI, the proposed framework integrates all these components in a single pipeline. This approach leads to an improvement in forecasting power, model interpretability, and the possibility of clinical translation.

Overall, the proposed framework shows that high predictive performance is not a sufficient condition for clinical implementation unless it is accompanied by transparent decision making and reproducible methodology. A comprehensive assessment of model performance beyond standard accuracy metrics is achieved by combining multiple evaluation metrics, Bayesian optimization, and SHAP-based interpretation. The results imply that the combination of optimization techniques and explainable artificial intelligence may improve the practical usability of machine learning algorithms for breast cancer prediction and boost clinicians' trust in automated diagnostic systems.

7. Clinical Implications

The proposed EOX framework can help medical professionals to provide accurate and explainable prediction for early breast cancer diagnosis using patient's electronic records. This framework can be easily integrated into hospital systems as a clinical decision support tool to assist medical professional during routine diagnosis. The inclusion of SHAP-based explainability improves the transparency of the model's prediction by identifying the most significant clinical features. Additionally, the framework could shorten the time to diagnosis, enable timely clinical intervention, and enhance evidence-based decision-making, while supplementing (not replacing) physician expertise.

8. Limitations

Although the proposed Explainable Optimized XGBoost (EOX) framework showed promising results for breast cancer prediction, some limitations should be mentioned. The study was performed using a retrospective electronic health record (EHR) dataset collected from a single health care institution. Therefore, the patient population may not fully represent the demographic and clinical diversity present in different hospitals, regions or countries, which may limit the generalizability of the proposed framework. The predictive model was constructed and validated using only structured clinical variables. Other clinically relevant information such as mammography images, histopathological images, genomic biomarkers, lab reports and longitudinal follow-up data were not integrated into the present framework. The incorporation of multimodal data may further boost predictive performance and clinical utility.

Finally, the proposed framework has not been prospectively validated or deployed in real time as part of a clinical decision support system (CDSS). Further multicenter studies and external validation are needed to establish its robustness, reliability and practical utility for routine clinical use.

9. Conclusion

This paper proposed an ensemble-based framework with cross validation, customized optimizer and XAI to reduce the false prediction during use it in real time application in healthcare sector. We present a study where we tackled the problem of reliable breast cancer prediction by designing an explainable machine learning framework using electronic health record (EHR) data. The proposed approach was aimed at improving the predictive performance while maintaining the transparency to allow clinicians to better understand the factors that affect the decisions made by the model. The proposed EOX framework contributes to the emerging field of trustworthy medical artificial intelligence by enhancing prediction reliability, improving model interpretability and providing a reproducible basis for future data-driven healthcare applications.

Future work will involve validation of the proposed EOX framework on larger, multi-center datasets to improve the robustness and generalizability of the framework across diverse patient populations. These

improvements can be validation on multi-center clinical datasets, external validation cohorts, multi-modal data integration (clinical records, pathology and imaging), deep learning architectures, federated learning and deployment as a secure web-based clinical decision support system.

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