**CHAPTER TWO**

**2.1 Definition of Terms**

**Bioinformatics:** An interdisciplinary field that combines biology, computer science, andstatistics to analyze and interpret biological data, often leveraging machine learning for disease diagnosis and treatment.

**Breast Cancer:** A common and potentially fatal disease characterized by the uncontrolledgrowth of abnormal cells in the breast tissue**.**

**Classification Algorithms:** Machine learning models used for categorizing data into predefinedclasses, such as determining whether a tumor is benign or malignant.

**Explainable AI (XAI):** A branch of AI that focuses on making machine learning models transparent and interpretable, ensuring that medical professionals can understand how predictions are made.

**Feature Selection:** The process of selecting the most relevant features from a dataset toimprove the efficiency and accuracy of a machine learning model**.**

**Machine Learning (ML):** A subset of artificial intelligence (AI) that enables computer systemsto learn patterns from data and make predictions or decisions without being explicitly programmed.

**SHAP:** is a method based on game theory that explains the output of machine learning models by assigning **feature importance scores**. It helps us understand **how much each feature contributes** to a model's prediction.

**Oncology:** is the branch of medicine that deals with the prevention, diagnosis, and treatment of cancer.

**Fuzzy Logic:** A mathematical framework used to model reasoning that is approximate rather than fixed and exact. It is particularly effective in dealing with uncertain or imprecise data.

**Prognostic Models:** Models used to predict the likely progression or recurrence of a disease based on various clinical, pathological, or genetic factors.

**hyperparameter tuning:**Hyperparameters are settings or configurations that are not learned from the data but are set before the training process begins. They can significantly affect the model's behavior.

**Random search:** is a hyperparameter optimization technique used to find the best combination of hyperparameters for machine learning models

**classification algorithms:** are a subset of supervised learning techniques used to predict categorical labels for a given set of input features

**Local Interpretable Model-Agnostic Explanations (LIME)**: It provides insights into the predictions made by complex models by approximating them with simpler, more interpretable models in the vicinity of the instance being explained.

**Surveillance:** Monitoring cancer incidence and survival over time**.**

**Epidemiology:** Studying patterns, causes, and effects of cancer in specific populations.

**End Results:** Reporting long-term outcomes like survival rates and mortality.

**2.2 Literature Review**

The integration of machine learning into bioinformatics has significantly enhanced disease diagnosis, offering greater accuracy and efficiency compared to traditional diagnostic methods. Numerous studies highlight the effectiveness of machine learning models in detecting and classifying diseases, particularly breast cancer, which remains a leading cause of mortality worldwide.

Several research works emphasize the limitations of conventional diagnostic techniques. Mammography, a widely used breast cancer detection method, has an accuracy rate of approximately 70%, often leading to misdiagnoses. Biopsies, although more reliable, are subject to human error and conflicting specialist opinions, sometimes necessitating multiple procedures. The shortage of skilled pathologists further exacerbates these challenges, delaying accurate diagnoses and timely treatment.

To address these issues, researchers have employed various machine learning classifiers for breast cancer prediction.

**A** studycarriedout **by** (Yavuz*et**al*., 2023) review others work (Amrane*et**al***.,** 2018**)** applied KNN and NB with 97.51% accuracy on KNN​, (Bayrak **et** al**.** 2019**)** achieved 97.36% accuracy using NB​, (Yadav*et**al***.,** 2019**)** reported SVM and RF had highest accuracy of 97.2%​, and (Muhtadi2022**)** applied KNN, RF, and SVM with SMOTE-Tomek, reaching 93.01% accuracy. The study by (Yavuz*et**al*., 2023) evaluated four popular machine learning algorithms—Naive Bayes (NB), K-Nearest Neighbor (KNN),DecisionTree (DT), and Random **Forest (RF)** on **three types of datasets**: Original dataset, Unbalanced dataset, and SMOTE-balanced datasets

The overall performance across dataset is Random Forest (RF) on the SMOTE-balanced **dataset**, RF achieved: Accuracy: 98%, F1 Score: 0.99 for both benign and malignant classes on the test dataset (real sample of 60 records): All 60 predictions were correct 100% accuracy.

Another study carried out by (**Zhou *et al.,* 2024)** visualizing the data, the develop and train 6 different machine learning algorithms decision tree, stochastic gradient descent (SGD), random forest, K-NN, SVM, logistic regression, and AdaBoost logistic in this study. The final evaluation results demonstrate that the AdaBoost-Logistic model achieves a remarkably high classification accuracy of 99.21%, effectively facilitating the classification and diagnosis of breast cancer. A study by (La Moglia & Almustafa 2025) analyzing an 11-feature breast cancer dataset applied eight machine learning classifiers, finding that Logistic Regression achieved the highest testing accuracy of 91.67% without feature selection. Feature selection improved the performance of other models, such as LightGBM (LGBM), which attained a notable 90.74% accuracy.

Another study by (Islam *et al*., 2024). focused on breast cancer classification among Bangladeshi patients using Explainable AI techniques. The study compared Decision Tree, Random Forest, Logistic Regression, Naïve Bayes, and XGBoost classifiers, finding that XGBoost achieved the highest accuracy of 97%. SHAP analysis was utilized to provide interpretability by assessing the impact of individual features on model predictions (*Scientific Reports, 2024*).

(Islam *et al*., 2024) conducted another study titled Predictive modeling for breast cancerclassification in the context of Bangladeshi patients by use of machine learning approach with *explainable AI*, which examined five machine learning methods for classifying breast cancer using a primary dataset of 500 patients from Dhaka Medical College Hospital. XGBoost was identified as the best-performing model with an accuracy of 97%. The study also employedSHAP analysis to interpret model predictions and understand the impact of each feature on classification results.

A study by(Ahmed *et al*, 2024). evaluated five supervised machine learning techniques—Decision Tree, Random Forest, Logistic Regression, Naïve Bayes, and XGBoost—on a dataset of 500 patients from Dhaka Medical College Hospital. XGBoost emerged as the most effective classifier, achieving an accuracy of 97%. Additionally, SHAP analysis was applied to interpret the XGBoost model’s predictions and assess the impact of individual features on classification outcomes.

Further comparative analyses of machine learning models have shown that Support Vector Machines (SVM) consistently outperform other classifiers in breast cancer diagnosis. Studies utilizing datasets such as the Wisconsin Breast Cancer Dataset and Surveillance, Epidemiology, and End Results (SEER) database have demonstrated SVM’s effectiveness, with accuracy rates reaching up to 97.9%. Additionally, models incorporating deep learning approaches, such as Multilayer Perceptron (MLP) and Neural Decision Forest, have shown superior classification performance, with MLP achieving an accuracy of 96.49% and an AUC-ROC score of 0.9959.

The application of Explainable AI (XAI) in breast cancer diagnosis has further enhanced the transparency and trustworthiness of machine learning models. SHAP analysis, for example, has been used to determine the influence of specific features on model predictions, enabling medical professionals to make informed decisions based on AI-generated insights.

A study by (Zhang *et al.,* 2023) explored AI and machine learning applications in cancer diagnosis. The research highlighted the role of ML in improving the accuracy of disease detection, particularly in oncology. The study found that AI-driven models outperformed human clinicians in predicting various cancers, including breast cancer, lung cancer, and prostate cancer. The research underscored the potential of AI in treatment selection and patient prognosis estimation

A study by (Devi *et al*, 2024) compared traditional machine learning classification methods with deep learning techniques. The evaluation, carried out using the UCI Wisconsin Diagnostic Data Set, revealed that deep learning models such as MLP outperformed conventional ML classifiers, achieving the highest accuracy and sensitivity scores.

The reviewed paper by (Manalı *et al*., 2024) introduces a novel three-channel AI-based system, leveraging decision fusion to integrate results from multiple classifiers: SVM with Local Binary Patterns (LBP): Classifies tumor types based on texture features. Pre-trained CNN (ResNet50): Extracts features and classifies potential tumors using SVM. Custom CNN Model: Directly classifies mammogram images after training.

Using a combination of classifiers through decision fusion (applying rules like the product rule), the proposed method attained an exceptional accuracy of **99.1%**, outperforming many existing methods.

The Breast Cancer Prediction and Diagnosis Model (BCPM), developed by (Almarri *et al*. 2024), represents a significant advancement. This model utilizes a combination of ML algorithms—including logistic regression, random forests, decision trees, support vector machines, and neural networks—to improve the precision of breast cancer diagnosis and prognosis.

The BCPM model integrates diverse data sources, including electronic health records, clinical trials, and public datasets. It applies data cleaning, feature scaling, and feature selection to enhance model training. Using metrics such as AUC, sensitivity, and specificity, the model is evaluated for performance. The incorporation of **K-Fold cross-validation** further ensures the reliability of the findings. Notably, BCPM's strength lies in its capability to personalize treatment strategies by assessing age, tumor type, genetic anomalies, and other features—demonstrating ML's transformative potential in clinical decision-making.

In this paper develop by (Goel *et al.* 2024) we have applied several ML algorithms like DT (Decision tree), RF (Random Forest) Classifier, NB (Naïve Bayes) classifier, KNN, ADABOOST, GBDT, SVM (Support Vector Machine), SGD, RF (Random Forest) Classifier. And we have applied feature selection to extract best attributes so that ML classifier can provide better accuracy to our model and helps in saving life of many peoples. The accuracy of GDBT is 97%, SVM classifier is 96.4%, ADABOOST is 96%, SGD is 94%, RF classifier is 92%, KNN is 90% DT classifier 90% and NB classifier 90%. Out of all GBDT provides best accuracy which is 97%. The article by (Jagetiya & Dadhech 2024) presents a comparison of the performance of various machine learning (ML) algorithms on the **Wisconsin Breast Cancer Dataset (WBCD)**. These models were employed to classify breast cancer tumors as **malignant** or **benign**, with varying levels of accuracy. Some key findings regarding the accuracy of the models include:

K-Nearest Neighbors (KNN): KNN is a distance-based classifier that showed **high accuracy** in detecting both malignant and benign tumors. However, it can be sensitive to noisy data and may suffer from performance degradation with large datasets. Multilayer Perceptron (MLP): The MLP performed well in the classification task, achieving competitive accuracy levels, but it can be prone to overfitting if not properly regularized. Random Forest: This ensemble learning algorithm performed **very well**, providing **high accuracy** by aggregating predictions from multiple decision trees. Its ability to handle complex datasets with many features made it an effective choice for breast cancer classification. Support Vector Machines (SVM): SVM was highlighted as one of the most accurate classifiers in the study, with **outstanding performance** in distinguishing between malignant and benign tumors. It achieved lower misclassification errors compared to other models.

Additionally, the paper refers to the use of feature selection techniques like PrincipalComponent Analysis (PCA) and LinearDiscriminant Analysis (LDA), which helped improve the accuracy of these models by reducing dimensionality and focusing on the most relevant features.

Deep Learning Models (CNNs): The article also compares traditional ML methods with deep learning approaches, particularly Convolutional Neural Networks (CNNs). The use of CNNs for image-based classification of histopathological data has shown **great promise**, with some models outperforming traditional machine learning algorithms in terms of classification accuracy. However, CNNs require large amounts of training data and computational power, which can be a limitation in clinical settings.

The paper presented by (Jakkaladiki & Filip2023). comparison of the proposed model against several other models, highlighting the accuracy, precision, recall, and F1 score:

The TLBCM model outperforms the other models with an accuracy of 98.3%, which is significantly higher than CNN + LSTM (82.5%) and ResNet + LSTM (90.1%). DenseNet, a transfer learning method, achieved 97% accuracy, showing its strength in breast cancer classification, closely followed by ResNet (93%). SVM achieved 87% accuracy, with high precision and recall, making it one of the top traditional machine learning models for breast cancer classification. Decision Tree performed the worst among these models with an accuracy of 82**%**.

The paper by (Amarendra K., & Bhaskar Marapelli 2024). evaluates the Breast Histopathologydataset using various machine learning and deep learning classifiers. It compares the performance of these models before and after hyperparameter tuning using random search:

KNN performed well with an accuracy of 77% before tuning and 78% after tuning, showing a slight improvement. It outperformed the logistic regression in terms of accuracy and recall. CNN model significantly improved after hyperparameter tuning, increasing its accuracy from 84% to 88%, with a high recall of 92% and AUC of 88%. This made the CNN the top-performing deep learning model in the study. DNN model, on the other hand, showed a large improvement after tuning, with its accuracy rising from 64% to 80%. Logistic regression and Gaussian Naive Bayes saw moderate improvements, with logistic regression going from 73% to 76%, and Gaussian Naive Bayes from 74% to 75%.

A comparison study conducted by (Kumar ***et al.* 2024).** outlines that SVM classifier achieved 97% accuracy when applied without quick correlation-based streamlines. This indicates that SVM can be highly effective for breast cancer classification, especially when optimized and used with the right features, Logistic regression performed with 95% accuracy and included classification based on maximumperimeter and texturefeatures, further enhancing its ability to categorize breast cancer effectively, CNNs have shown remarkable performance in early-stage diagnosis of non**-**communicablediseases **(**NCDs**)**, including breast cancer. These models have demonstrated great potential for extracting morphological and texturalfeatures to enhance diagnosticaccuracy. The authors also pointed out that CNNs required heavy computationalresources, particularly for image preprocessing, though these networks proved resilient in noisy and irrelevant feature environments

A study conducted by (Madeswaran *et al*., 2023). Show that Naive Bayesian classifier is highly effective for breast cancer prediction due to its simplicity, quick execution, and the ability to handle high-dimensional datasets. It also performs well in scenarios with missing or incomplete data, which is common in medical datasets. The classifier can be utilized in large-scale breast cancer screening programs and has been shown to provide accurate predictions, leading to earlier diagnoses and better resource allocation for healthcare providers, Linear regression helps identify important predictors of breast cancer risk. It can be used to develop risk assessment tools for healthcare professionals, enabling early detection and improved outcomes for individuals at high risk. Linear regression is also useful for evaluating the effectiveness of screening programs and identifying the most significant factors affecting breast cancer development. SVM is particularly effective for non-linear data patterns, which are common in medical datasets. It can handle large, complex datasets and is capable of selecting the most relevant features, which helps reduce overfitting and improve prediction accuracy. SVM is versatile, allowing for both binary and multi-class classification, making it suitable for a wide range of breast cancer classification tasks. SVM's ability to maximize the margin between classes results in high classification accuracy, making it one of the most widely used algorithms for breast cancer prediction, Deep learning models excel at handling high-dimensional, complex medical data, such as imaging data and other clinical information. These models can provide highly accurate predictions and reduce the possibility of human error by automating the diagnostic process. Deep learning has revolutionized breast cancer detection by enabling earlier identification of the disease, ultimately improving patient outcomes. By integrating deep learning with technologies like computer vision and artificial intelligence, more comprehensive and accurate predictions can be made, contributing to more precise early-stage diagnosis and treatment decisions. After an accurate comparison by (**Naji *et al.*** 2021). between our models, we found that Support Vector Machine achieved a higher efficiency of 97.2%, Precision of 97.5%, AUC of 96.6% and outperforms all other algorithms. In conclusion, Support Vector Machine has demonstrated its efficiency in Breast Cancer prediction and diagnosis and achieves the best performance in terms of accuracy and precision. It should be noted that all the results obtained are related just to the WBCD database, it can be considered as a limitation of our work, it is therefore necessary to reflect for future works to apply these same algorithms and methods on other databases to confirm the results obtained via this database. A study conducted by (Nazari*et**al***.** 2023). Compared to other methods random forest (RF) has higher performance (accuracy 99.26%, precision 99%, and area under the curve (AUC) 99%). The results of assessing the impact and correlation of variables using the RF method based on PCA indicated that pathology, biomarker, biochemistry, gene, and demographic factors with a coefficient of 0.35, 0.23, 0.15, 0.14, and 0.13 respectively, affected the risk of BC (*r*2 = 0.54). In this study by (Raha *et al.* 2024) we experimented with various machine learning models to predict breast cancer using the WBCD. We applied Random Forest, XGBoost, SVM, MLP, and Gradient Boosting classifiers, with the Random Forest model outperforming the others by achieving an impressive accuracy of 99.46%. Due to its strong performance, we employed SHAP for global interpretability and LIME for local explanations, ensuring that the model’s decisions are transparent and understandable

A study by (Okebule *et al.* 2023), in their comprehensive review published in the **ABUAD** International Journal of Natural and Applied Sciences, compared several machine learning algorithms. The following are some of the models discussed along with their reported accuracy percentages:

Vector Machine (SVM): Achieved a classification accuracy of 97.13%, making it one of the most reliable models for breast cancer diagnosis. Decision Tree: Recorded an accuracy of 92.72%, offering a good balance between accuracy and interpretability. Naïve Bayes: Had a predictive accuracy of 96.50%, particularly effective due to its simplicity and speed. K-Nearest Neighbors (k-NN): Reached an accuracy of 95.90%, performing well when optimized with the right value of ‘k’. Artificial Neural Network (ANN): Reported an accuracy of 97.08%, very close to that of SVM, indicating its potential in handling non-linear data patterns.

These results indicate that multiple models are capable of achieving high prediction accuracy. However, (Okebule *et al*. 2023) emphasized that **SVM and ANN stood out as the most effective**, both achieving over 97% accuracy on the dataset used. For instance, (Song *et al*. 2024) developed machine learning models that utilized data from 6,477 patients to accurately predict breast cancer prognosis. Their study specifically highlighted the performance of the Extreme Gradient Boosting (XGBoost) algorithm, which achieved an AUC score of 0.813 in predicting the five-year overall survival rate for breast cancer patients. The key predictive features identified in this study included age, tumor size, hormone receptor status, and lymph node involvement. The XGBoost model outperformed traditional statistical models, demonstrating greater accuracy and the ability to manage complex interactions between variables in breast cancer prognosis. (Sultana 2024) conducted a review on ML methodologies used for breast cancer prediction, noting that different classifiers, such as Support Vector Machines (SVM), Decision Trees (DT), and K-Nearest Neighbors (KNN), have been employed with varying success rates. with (Sultana J., 2024) reporting that Logistic Regression reached up to 97.18% accuracy in classifying benign and malignant tumors, showcasing the efficacy of machine learning over standard clinical practices. (Wang 2024) designed a machine learning-based breast cancer prediction system utilizing several models, including Logistic Regression, Random Forest (RF), Support Vector Machine (SVM), and eXtreme Gradient Boosting (XGBoost). The performance of each model was evaluated in terms of accuracy, area under the curve (AUC), sensitivity, and specificity. XGBoost: AUC of 0.99 in the training set and 0.89 in the validation set. Random Forest: AUC of 0.93 in the training set and 0.80 in the validation set. Support Vector Machine (SVM): AUC of 0.93 in the training set and 0.79 in the validation set. Logistic Regression: AUC of 0.55 in the training set and 0.78 in the validation set. (Yang *et al*. 2023) emphasized the potential of machine learning models to predict breast cancer-related lymphedema using eXtreme Gradient Boosting, achieving an AUC of 0.99 in training and 0.89 in validation sets, suggesting strong predictive capabilities.

A study by (Minnoor, M., & Baths, V. 2023). Five models are selected for a preliminary comparison- Random Forest (RF), Support Vector Machine (SVM), Decision Tree (DT), Multilayer Perceptron (MLP), and K-Nearest Neighbors (KNN). The Random Forest model performs the best with a cross-validation recall score of 0.9896.

The Random Forest model outperforms all other models by achieving a perfect score on all the measured metrics. The Support Vector Machine model performs the second best.

A study by (Kawina**, I., K., A., &** Marapelli**, B.** 2024). used both machine learning like (Logistic regression, KNN, Gaussian Naïve Bayes) and Deep learning (CNN, DNN) on two secondary datasets that are freely available on the Kaggle, the Breast Histopathology image dataset and the BreakHis\_400X dataset. The breakHis\_400x dataset results show that the CNN Model is the highest in terms of performance when it comes to classifying breast cancer with an accuracy of 87.5% seconded by deep neural network (DNN) 84.6%. Amongst the machine learning classifiers, it has been observed that the gaussian naïve bayes performs quite good when random search hyperparameter tuning has been performed although the K-nearest neighbors is better than the other machine learning classifiers. The CNN model performed exceptionally well in terms of performance and accuracy than the DNN model in predicting between the two classes of breast cancer. This shows that CNN is better at classification than DNN.

A study by (**Mahmood, D. A., & Aminfar, S. A.** 2024). presents a comprehensive analysis of the application of machine learning (ML) and deep learning (DL) techniques in the diagnosis of breast cancer, underscoring their significant potential in enhancing breast cancer detection methods. The findings indicate that both ML and DL approaches hold substantial promise for supporting the diagnosis and treatment of cancerous tumors. Nevertheless, several challenges remain that must be addressed to fully realize their benefits in clinical settings. Various models—such as ShuffleNet, ResNet, VGG16, ResNet18, InceptionV3Net, and Xception—have been employed by researchers to analyze medical images extracted from established databases, demonstrating their effectiveness in identifying malignant and benign breast tumors.

A study by (**Naji *et al.*** 2021). used Wisconsin Breast Cancer Diagnostic dataset (WBCD) we applied five main algorithms which are: SVM, Random Forests, Logistic Regression, Decision Tree, K-NN, calculate, compare and evaluate different results obtained based on confusion matrix, accuracy, sensitivity, precision, AUC to identify the best machine learning algorithm that are precise, reliable and find the higher accuracy. All algorithms have been programmed in Python using scikit-learn library in Anaconda environment. After an accurate comparison between our models, we found that Support Vector Machine achieved a higher efficiency of 97.2%, Precision of 97.5%, AUC of 96.6% and outperforms all other algorithms.

A study by (**Rahman *et al*. 2025).** Five supervised machine learning algorithms were implemented: Logistic Regression, Support Vector Classification (SVC) with linear and radial basis function (RBF) kernels, Decision Tree, and Random Forest. The study demonstrates the efficacy of machine learning techniques in the early detection and differential diagnosis of benign and malignant breast lesions, with the Support Vector Classifier using a Radial Basis Function (SVC-RBF) kernel emerging as the most accurate model. Achieving a remarkable accuracy of 99% on the Wisconsin Breast Cancer Diagnostic dataset, the SVC-RBF model exhibited superior precision (99% for benign and 98% for malignant cases), sensitivity (99% and 98% for benign and malignant cases, respectively), and specificity, with robust F1 scores for both classes. These results underscore its robustness and reliability in minimizing diagnostic errors, making it highly suited for clinical applications.

A study by (Raza*et**al****.*** 2024) On WDBC dataset was analyzed using a different machine learning classifiers such as K-NN, SVM, Random Forest (RF), Decision Tree (DT), and NB diagnose breast cancer using a variety of Machine learning models. learning technique. The Logistic Regression machine learning classifier shows effectiveness with high accuracy (96%) as compared to others.

This paper by (**Selvaraj *et al.* 2024).**  provides a new technique using a convolutional neural network (CNN) approach to analyze the WSI IDC- IICA-SVM-KNN tissue areas for automatic IDC- IICA-SVM-KNN detection. This research effectively analyses three different KNN architectures by detailing each in detail. IICA-SVM-KNN Model 3 is used to achieve an accuracy of 98.4% in the suggested system. While both Model 1 and Model 2 use three-layer CNNs, the superior five-layer CNN for this task is found in Model 3. All the plans were based on a massive dataset of over 284,000 48-by-48-pixel RGB image patches. As evidenced, the suggested model outperformed the ML algorithm and provided accurate findings, which could reduce the requirement for human involvement and the associated cost of cancer detection. Using a secondary database like Kaggle is a significant drawback of this work; future research into breast cancer identification should instead be based on original data.

A study by (Sun *et al*. 2024). used Logistic regression, Random decision forest, Support vector machine, eXtreme gradient boost. Among the four models, the XGBoost model showed the best predictive performance, with an area under the curve (AUC)of0.99inthe training set and 0.89 in the validation set. The XGBoost model demonstrated good calibration in both the training and validation sets, showing good consistency consistency with the ideal model.

The study by (Clift*et al***.** 2023**).** compared four models—Cox regression (85.8%), competing risks regression (84.9%), neural network (84.7%), and XGBoost (82.1%)—and found that statistical methods, particularly the Cox model, demonstrated superior performance in predicting 10-year breast cancer mortality

**2.3 Summary of Review and Gaps to Fill**

The reviewed literature underscores the significant impact of machine learning in breast cancer diagnosis, improving accuracy and reducing diagnostic time compared to traditional methods. Studies have demonstrated the effectiveness of various classifiers, with XGBoost and SVM consistently achieving high accuracy rates. Additionally, the integration of feature selection and Explainable AI techniques has enhanced model performance and interpretability.

Despite these advancements, several gaps remain in the existing research:

1. Limited Real-World Implementation: Most studies rely on publicly available datasets, which may not fully represent the diversity of real-world patient populations.
2. Lack of Standardized Feature Selection Methods: Different studies employ varying feature selection techniques, leading to inconsistencies in reported model performances.
3. Need for More Robust Deep Learning Models: While deep learning approaches such as MLP and Neural Decision Forest have shown promise, further research is needed to optimize these models for real-time clinical applications.
4. **Dataset Limitations**: Most current research relies on limited datasets, often from single institutions, which can hinder model generalizability. Expanding the dataset variety to include diverse populations can enhance model robustness and efficacy
5. **Data Diversity**: Most studies focus on single-institution data, potentially limiting generalizability across diverse populations
6. Using a secondary database like Kaggle is a significant drawback of this work; future research into breast cancer identification should instead be based on original data.

Future research should focus on addressing these gaps by conducting large-scale, real-world studies, standardizing feature selection techniques, optimizing deep learning architectures, and ensuring compliance with medical regulations. By overcoming these challenges, machine learning can further revolutionize disease classification and contribute to more accurate, efficient, and accessible healthcare solutions.