Comparative Analysis of the Performance of XGBoost and LightGBM Algorithms on Breast Cancer Classification

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ABSTRACT

Breast cancer is one of the most prevalent types of cancer in women worldwide. Regarding deaths caused by cancer, breast cancer is the second leading cause of cancer-related mortality. Fine-needle aspiration (FNA) is a method for detecting breast cancer at an early stage; however, it has limitations. These limitations include a small number of samples, which could be one of the factors for diagnostic errors, and the level of experience of the person performing the procedure. The application of machine learning to solve some problems in the healthcare sector includes cancer detection using machine learning algorithms such as XGBoost and LightGBM. The two learning algorithms, XGBoost and LightGBM, are efficient machine learning algorithms that differ in terms of how they learn:level-wise learning for XGBoost and leaf-wise learning for LightGBM. We compared both XGBoost and LightGBM in terms of accuracy, sensitivity, and specificity to determine which would perform best in classification. From the results obtained in the experiments, XGBoost performed better, with an average accuracy, sensitivity, and specificity of 97.03 %, 97.40%, and 96.81 %, respectively. The average accuracy, sensitivity, and specificity of LightGBM were 95.59%, 94.70%, and 96.10%, respectively.

General Terms

Cancer Detection, Machine Learning, Prediction Model, Level-wise Learning, Leaf-wise Learning, Diagnostic Errors

Keywords

XGBoost, LightGBM, classification, breast cancer, comparison, fine-needle aspiration

1. INTRODUCTION

1.1 Importance of Breast Cancer Worldwide

Breast cancer is a neoplasm of the breast and is the most commonly diagnosed cancer worldwide, accounting for 2.3 million new cases among women in 2022, which is approximately one in four cases of cancer diagnosed in women. It is the most common cancer among women in 157 of the 185 countries [1,5]. It causes nearly 760,000 deaths annually (approximately 15% of all cancer deaths worldwide [3]). The majority of deaths resulting from breast cancer occur in LMCs because these countries lack appropriate facilities for disease detection and management. The incidence of breast cancer is expected to reach 3.5 million cases by 2050, with a major increase in mortality rates observed in Africa and Asia [1,6]. An exceptional subgroup is women in the reproductive age group (15–49 years), as women in this age group are at the highest risk of reproductive activities, which can pose significant risks to the physical, reproductive, psychoemotional, and economic stability of women in this age group owing to breast cancer diagnosis [2]. Although it is estimated that only 0.5–1% of the total incidence occurs in men [5], the incidence of breast cancer increases with age; this means that 71% and 79% of all cases and deaths recorded are in people aged > 50 years, respectively [5]. Approximately 80% of all cases occur in women without a family history, and modifiable factors (obesity, represented by an increase in BMI, high consumption of alcohol, and a sedentary lifestyle) have been found to be strongly related to the incidence of breast cancer [5].

1.2 Incidence and Mortality Trends

The International Agency for Research on Cancer has released an online tool called "Cancer Over Time." This resource is an authoritative, up-to-date international compilation of trends in age-standardized rates of cancer-specific incidence and mortality, compiled from robust population-based cancer registry records collected at the sub-national and national levels [4]. In 2022 and 2023, 2.3 million new cases were reported, making breast cancer the leading cancer in women worldwide [5].

Furthermore, the prediction for an increase in new cases by 2040 is >3 million, and the increase in deaths per year is >1 million owing to the aging and increasing overall populations [6]. Hence, affordable and effective methods for detection and therapy are urgently needed on a large scale.

1.3 Importance of Early Detection

Early detection is unequivocally the most important determinant of breast cancer outcome. In the early and localized stages of breast cancer, the 5-year survival rate is approximately 99%[7]. Early stage cancers have fewer invasive surgical requirements and can be managed with less intensive chemotherapy than advanced-stage cancers. Hormone therapy can be used alone or in combination with targeted radiation therapy as part of the overall cancer therapy. The financial health-economic argument for the early detection of cancer is clear, as treating an early stage of cancer is far less expensive than treating a later stage [7, 27].

However, these hopes are tempered by several systemic factors that have made the early detection of cancer somewhat elusive in the developing world. Cancer remains a taboo subject in some settings, and shame and cultural factors can make it difficult for women to seek medical attention for early lesions [8]. However, the lack of screening tools, such as mammography, is a cause for late-stage presentations, particularly in the developing world.

1.4 Problem Statement: Limitations of Current Diagnostic Modalities

Several diagnostic techniques, including imaging, biosensors, and molecular biotechnology, are available for the early detection of breast cancer. Various detection methods have been described in detail, with an emphasis on sensitivity, patient comfort, economic viability, and the promising use of wearable devices, such as smart bras and real-time detection systems, to establish a new paradigm for detection [9].

Despite technological advancements, current detection techniques have significant limitations. The present gold standard for screening, mammography, is limited by dense breast tissue, which makes tumor identification exceedingly difficult. These limitations can lead to false-positive results (causing additional patient distress, tests, and expenses) or false-negative results, particularly in young women with denser breasts[10]. Although it excels at evaluating dense breast tissue, it can miss some microcalcifications characteristic of the earliest cancers. Although exceedingly sensitive, MRI lacks specificity, is expensive, and has non-uniform protocols, restricting its use as a widespread screening technique [10]..

1.5 Key Limitations of Fine Needle Aspiration (FNA)

Fine-needle aspiration (FNA) is a minimally invasive cytology technique that involves removing tissue and fluid from a questionable lesion using a fine needle attached to a syringe.. [11] Fine-needle aspiration (FNA) is a minimally invasive cytological technique in which tissue and fluid are removed from a questionable lesion using a fine needle attached to a syringe.[11] However, FNA has limitations that are relevant to invasive and in situ breast diseases.

Most critically, FNA cannot reliably differentiate between in situ and invasive carcinomas, which is vital when considering immediate sentinel lymph node biopsy [12]. FNA samples can be very hypocellular or contain blood, resulting in inadequate specimens (4–13% for palpable lumps and up to 36% for non-palpable lumps)[12]. The diagnostic accuracy decreases for tumors < 10 mm, non-palpable tumors that require image guidance, lobular carcinoma (which has naturally lower cellularity), and tubular carcinoma, and is highly dependent on operator skill [13]. Mimicking lesions, such as fibroadenomas, papillary lesions, and sclerosing adenosis, may be misinterpreted, resulting in false-positive and false-negative diagnoses.

1.6 Human Dependency, Error, Time, and Cost

Given that breast cancer detection relies heavily on human observers (manual mammography interpretation), significant issues are presented that are inherent to errors in diagnosis, time consumption and costs. Errors are fundamental to the manual observation of images, and even at present, 10%–30% of breast cancers are missed by radiologists owing to perceptual and interpretive errors [14,15].

This has serious ramifications; for example, 26.6% of breast cancers cause diagnostic delays, and in these cases, mastectomies occur 42.6% of the time compared with 20.1% in patients without delayed diagnoses [17]. In addition to being time-consuming and costly for healthcare providers, a single false-positive mammogram costs $527 compared with a true-negative mammogram at $3, representing a difference of $503. Economic and emotional factors may also prolong the diagnostic period..

1.7 The Role of Machine Learning in Breast Cancer Diagnosis

This deficiency in traditional diagnostic techniques has led to a surge in interest in the use of artificial intelligence (AI) and machine learning (ML) as game-changers for breast cancer detection and classification. Studies have reported the creation of AI models using combined clinical blood markers, ultrasound, and breast biopsy pathological information to detect and predict distant metastasis (LR- and lightGBM-based algorithms for internal and external validation) [19].

ML classification models, such as support vector machines (SVM), random forests, k-nearest neighbors (kNN), decision trees, and artificial neural networks, have been reported to possess very high diagnostic accuracy in classifying malignant and benign breast lesions, some of which have an accuracy of over 97% [21, 22]. A systematic review of AI applications in breast cancer diagnosis (2024–2025) demonstrated the increased use of deep learning and hybrid transfer learning models in clinical practice, particularly for histopathological image classification and non-invasive subtype identification [20].

This advancement in diagnostics reduces costs, increases access, and opens new avenues for the early detection of breast cancer metastasis. The fusion of technological advances with human intelligence can also be a key step forward in lowering diagnostic errors in mammography [16], and the application of AI in breast cancer prediction is highly encouraging and can be one of the most prominent trends in this field [23].

Hence, there is a need for cost-effective, user-friendly techniques to increase patient comfort and access, particularly in developing countries. Innovation, comprehensiveness, and computational-driven techniques required to enhance breast cancer detection have emerged as a major area in contemporary oncology research to address research gaps [26].

1.8 Objective of Study

A comparative analysis was performed to assess XGBoost and LightGBM for classifying breast cancer data with cytological features from fine-needle aspirations (FNA). These algorithms will be benchmarked for accuracy, sensitivity, and specificity to determine which performs better and is suitable for clinical use.

1.9 Research Questions

1. *How effectively do XGBoost and LightGBM classify the breast cancer data?*

This question aimed to evaluate the general classification ability of each model in the Wisconsin Breast Cancer Diagnostic (WBCD) dataset to determine whether they are sufficiently efficient for use in a clinical context.

2. *Which algorithm achieved the highest sensitivity, specificity, and accuracy?*

Sensitivity and specificity (i.e., correct classification of malignant and benign cells, respectively) are considered to be of similar importance in clinical diagnosis as the accuracy of breast cancer data classification. This question was posed to determine which of the two classification models produced the highest values for sensitivity, specificity, and accuracy of the WBCD data, while also considering accuracy.

3. *How do level-wise (XGBoost) and leaf-wise (LightGBM) approaches affect the classification performance?*

XGBoost employs a level-wise (depth-first) approach that attempts to balance tree construction and prevent overfitting by considering all nodes in a level for expansion before moving to the next level of the tree. LightGBM employs a leaf-wise (best-first) tree construction approach that preferentially expands the leaves that generate the highest reduction in loss. Although it produces a lower loss, it can result in overfitting on small datasets [28]. This question evaluates which learning approach is more applicable and performs better for breast cancer data.

4. Which algorithm offers the best suitability for breast cancer diagnosis using machine learning?
In the clinical context, a model's suitability goes beyond simple indices in terms of being computationally efficient, interpretable, and not overly biased on imbalanced data; this question attempts to weigh all results to determine which model is more suitable.

2. RELATED WORK

Recent advances in machine learning, deep learning, and ensemble methods have considerably enhanced the accuracy, robustness, and clinical relevance of breast cancer classification and diagnostic techniques. Current research focuses on hybrid, ensemble, and explainable AI methods to overcome the limitations of existing ML models.

Anitha et al. (2025) indicated that Extreme Gradient Boosting (XGBoost) achieved 97.1% of accuracy compared to SVM when used to classify breast cancer. Kanimozhi et al. (2025) demonstrated that by using a hybrid of Random Forest (RF) and XGBoost, the accuracy further increases to 97.8% with improved performance in the balance between precision and recall. This clearly demonstrates the strength of ensemble learning in the field of medical diagnosis [29].

In addition, more recent papers on higher-impact studies have confirmed this tendency. The Scientific Reports publication highlights a double machine learning (DML) framework with hybrid learning models (ML + DL) to improve the accuracy of early breast cancer detection by implementing efficient feature selection and dimensionality reduction techniques.

Ensemble learning methods with optimization techniques also perform well in terms of classification. Khan et al. (2024) demonstrated that, in combination with a genetic algorithm for feature selection, ensemble methods achieved an accuracy of up to 99.42%, outperforming conventional ML methods for breast cancer diagnosis [30].

The combination of deep learning and stacked ensemble architecture also provided good accuracy. In 2024, Karamti et al. In 2024, Karamti et al. proposed a stacked ensemble model in which convolutional neural networks were integrated, resulting in a significant improvement in breast cancer classification in histopathological images by analyzing the image-based features. Recent comparative studies in this direction have achieved over 99% accuracy for breast cancer detection using an ensemble of CNN models [31].

Gradient boosting is another powerful algorithm used for breast cancer prediction. Interpretability and transparency are important areas of recent research in this field. Studies incorporating interpretability methods, such as SHAP and LIME, have shown that gradient boosting models (XGBoost, LightGBM, and AdaBoost) achieve an AUC of over 99% but remain interpretable, which is crucial for clinical applications.

LightGBM is known for its fast and accurate performance. Recent research on breast cancer prediction has demonstrated its efficiency and accuracy, with training that is faster than that of other models. This performance, together with the ability to extract clinically relevant features previously demonstrated by Permana and Romdendine (2024), makes LightGBM a promising tool.

However, ensemble learning is not the only model type that performs well. In a comparative study by Ghosh and Chatterjee (2024), the SVM classifier performed better than the aforementioned models on some datasets, achieving 98.24% accuracy, thus suggesting that performance varies depending on the data.

Although significant progress has been made in these areas, several issues need to be addressed, such as generalization to diverse populations and the real-time applicability of models within the clinical environment (efficiency and safety). Furthermore, ethical concerns, such as fairness and explainability, are important research areas that are not always adequately addressed when developing AI solutions. Finally, the ease of integration into real clinical settings is a key development area that requires interpretability, trustworthiness, and regulations [21].

In summary, Q1 studies consistently highlight the excellent performance of ensemble, hybrid, and deep learning models in breast cancer diagnosis and prediction. Future studies should focus on incorporating the explainability, scalability, fairness, and clinical integration of these models for real-world healthcare applications.

3. RESEARCH METHODOLOGY

In this study, XGBoost and LightGBM algorithms were applied to the breast cancer dataset. The research comprised several major stages aimed at producing the expected outputs. The overall research process is illustrated in the flowchart shown in Figure 1.

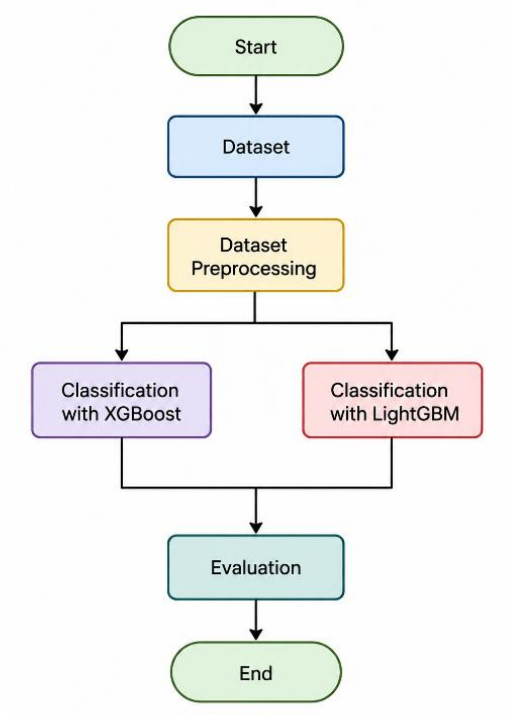

Figure 1. Research Stages

• Breast Cancer Dataset

The data used in this study were obtained from a public dataset available on Kaggle (https://www.kaggle.com/datasets/uciml/breast-cancer-wisconsin-data). The dataset consists of 569 rows and 31 columns and has been used in previous studies [8]. The data represent the results of digital image computations of breast masses conducted using fine-needle aspiration (FNA).

Table 1. Breast Cancer Dataset Attributes

No	Attribute	Type
1	diagnosis	String
2	radius_mean	Float
3	texture_mean	Float
4	perimeter_mean	Float
5	area_mean	Float
6	smoothness_mean	Float
7	compactness_mean	Float
8	concavity_mean	Float
9	concave points_mean	Float
10	symmetry_mean	Float
11	fractal_dimension_mean	Float
12	radius_se	Float
13	texture_se	Float
14	perimeter_se	Float
15	area_se	Float
16	smoothness_se	Float
17	compactness_se	Float
18	concavity_se	Float
19	concave points_se	Float
20	symmetry_se	Float
21	fractal_dimension_se	Float
22	radius_worst	Float
23	texture_worst	Float
24	perimeter_worst	Float
25	area_worst	Float
26	smoothness_worst	Float
27	compactness_worst	Float
28	concavity_worst	Float
29	concave points_worst	Float
30	symmetry_worst	Float
31	fractal_dimension_worst	Float

- **Dataset Preprocessing**

Furthermore, several steps were performed in the preprocessing stage to process the data that would be used in the model. The purpose of this preprocessing stage was to improve the accuracy of the machine learning models in learning the data used. Figure 2 shows a flowchart of the preprocessing stage.

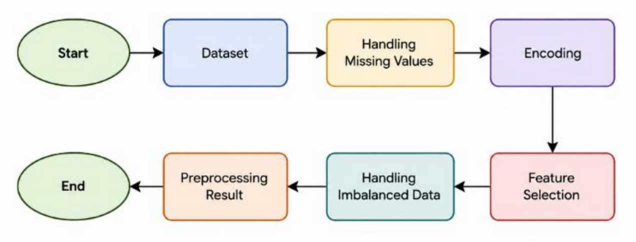

Figure 2. Preprocessing Stages

3.1. Handling Missing Values

The handling of missing values was performed to address empty values in each column. Missing values may occur because of errors during data entry [9]. The algorithm does not function properly when there are missing values in one of the columns [24].

3.2. Encoding

Encoding was performed to transform the attributes that contained non-numeric data. At the model development stage, all data types in the dataset were numerical.

3.3. Feature Selection

To optimize the performance of the algorithms used and achieve better results, feature selection must be performed to reduce the model complexity and computation time [10]. Features with low correlation values were eliminated from the dataset.

3.4. Handling Imbalanced Data

When the range of data values is not evenly distributed, the trained model may be biased towards the minority class. Thus, handling imbalanced data is required to achieve an equal balance between majority and minority classes. In this study, the SMOTE technique was used because it provides balanced and accurate performance [11].

- **XGBoost**

XGBoost is an implementation of gradient boosting that works by combining a collection of decision trees that are obtained gradually. Each decision tree subsequently corrects the predictions of the previous model until the most optimal result is achieved. The algorithm uses K additional functions to predict the output value (Yi) for each (Xi) in Equation (1) and measures the prediction error generated by the model against the target value in Equation (2) [12].

$$\hat{y}_i = \varphi(x_i) = \Sigma_{k=1}^{K} f_{k(x_i)} \qquad \dots\dots\dots (i)$$

$$\mathscr{L}(\varphi) = \Sigma\_i\ l(\hat{y}\_i, y\_i) + \Sigma\_k\ \Omega(f\_k) \qquad \dots\dots\dots (ii)$$

- **LightGBM**

LightGBM is an algorithm in the gradient boosting family that applies a leaf-wise approach. In each step, it selects the leaf with the largest gain for splitting and continues to divide it to reduce errors and achieve better accuracy [13].

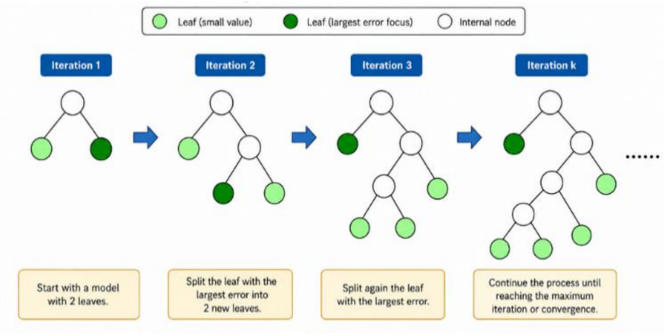

Figure 3. LightGBM Illustration

- **Evaluation**

In the final stage, an evaluation was conducted to assess the performance of each model that implemented XGBoost and LightGBM algorithms. A confusion matrix was used as an evaluation tool. The confusion matrix is presented in the form of a table used to compare the classification results of the system with the actual outcomes [14]. Based on the confusion matrix results, the evaluation metrics used were accuracy, sensitivity, and specificity.

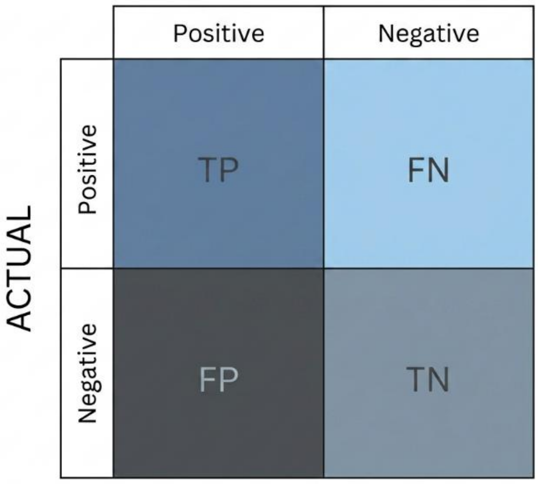

Figure 4. Confusion Matrix

$$Accuracy = = (TP + TN) / (TP + TN + FP + FN) \quad \ldots (iii)$$

$$Sensitivity = TP / (TP + FN) \quad \ldots\ldots\ldots\ldots\ldots(iv)$$

$$Specificity = TN / (FP + TN) \quad \ldots\ldots\ldots\ldots\ldots(v)$$

4. RESULTS AND DISCUSSION

4.1. Data Preprocessing

As explained previously, data preprocessing was performed to improve the quality of the dataset when training the model using this algorithm. This process consists of several stages.

4.1.1 Handling Missing Values

There are null values in the breast cancer dataset, as seen in Table 2.

Table 2: Breast Cancer Dataset Description

Column Name	Data Type	Missing/Null Values Count
area_mean	float64	0
area_se	float64	0
area_worst	float64	0
compactness_mean	float64	0
compactness_se	float64	0
compactness_worst	float64	0
concave points_mean	float64	0
concave points_se	float64	0
concave points_worst	float64	0
concavity_mean	float64	0
concavity_se	float64	0
concavity_worst	float64	0
diagnosis	object	0
fractal_dimension_mean	float64	0
fractal_dimension_se	float64	0
fractal_dimension_worst	float64	0
id	int64	0
perimeter_mean	float64	0
perimeter_se	float64	0
perimeter_worst	float64	0
radius_mean	float64	0
radius_se	float64	0
radius_worst	float64	0
smoothness_mean	float64	0
smoothness_se	float64	0
smoothness_worst	float64	0
symmetry_mean	float64	0
symmetry_se	float64	0
symmetry_worst	float64	0
texture_mean	float64	0
texture_se	float64	0
texture_worst	float64	0
Unnamed: 32	float64	569

4.1.2. Encoding

Encoding is performed on the diagnostic attribute, which is still an object type, and is converted into a numeric data type.

Table 3: Column Data Type Before and After Encoding

Column Name	Data Type Before Encoding	Data Type After Encoding	Total Rows
diagnosis	object	float64	569

4.1.3. Feature Selection

Feature selection was applied to reduce the dataset complexity and dimensionality. Figure 8 shows the correlation matrix of the attributes. Attributes with a correlation value of < 0.2 with the dependent variable (diagnosis) were removed from the dataset. Consequently, there were five attributes with a correlation value of < 0.2, reducing the total number of attributes from 31 to 26.

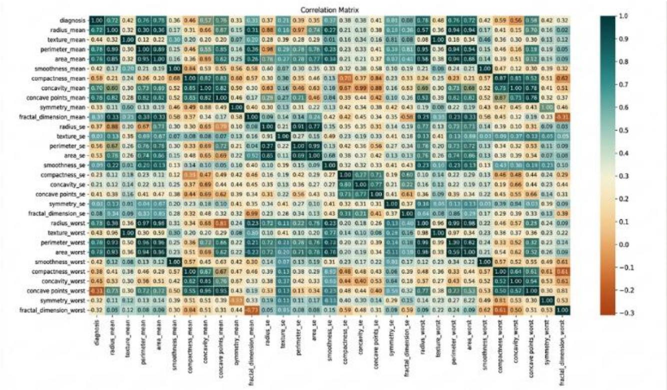

Figure 5. Correlation Matrix

4.1.4. Handling Imbalanced

Data, the SMOTE technique, will be used in the imbalanced data handling stage to address imbalanced values in the training data. In Figure 6, the synthetic minority over-sampling technique (SMOTE) method was implemented over the training set has been performed to balance the distribution of the classes. The code employed for this is as follows:

```
smote = SMOTE()
X_resampled, y_resampled = smote.fit_resample(X_train, y_train)
```

Figure 6. Application of SMOTE Technique on Training Data

4.2. Model Classification Using XGBoost and LightGBM

After preprocessing, the data were divided into training and testing datasets at a ratio of 70%: 30% before model training. SMOTE was applied to the training data to improve the model training accuracy, as explained previously [25]. This study conducted 30 training trials on each XGBoost or LightGBM model to obtain an average value from the evaluation results and provide more realistic results.

Table 4: Model Calculation Results with LightGBM Algorithm

Experiment	Accuracy	Sensitivity	Specificity
1	95.90%	93.65%	97.22%
2	94.73%	95.23%	94.44%
3	95.32%	95.23%	95.37%
4	96.49%	95.23%	97.22%
5	95.90%	93.65%	97.22%
.....	.....	.....	.....
30	95.32%	93.65%	96.29%
Average	**95.59%**	**94.70%**	**96.10%**

Table 4 presents the results of 30 model experiments using the LightGBM algorithm, which achieved an average accuracy, sensitivity, and specificity of 95.59 %, 94.70%, and 96.10 %, respectively.

Table 5: Model Calculation Results with XGBoost Algorithm

Experiment	Accuracy	Sensitivity	Specificity
1	97.66%	96.82%	98.14%
2	97.07%	98.41%	96.29%
3	97.07%	98.41%	96.29%
4	97.66%	98.41%	97.22%
5	97.66%	96.82%	98.14%
.....	.....	.....	.....
30	97.66%	98.41%	97.22%
Average	**97.03%**	**97.40%**	**96.81%**

Table 5 shows the outcomes of the model experiment conducted 30 times using the XGBoost algorithm, where the mean accuracy, sensitivity, and specificity were 97.03 %, 97.40%, and 96.81 %, respectively.

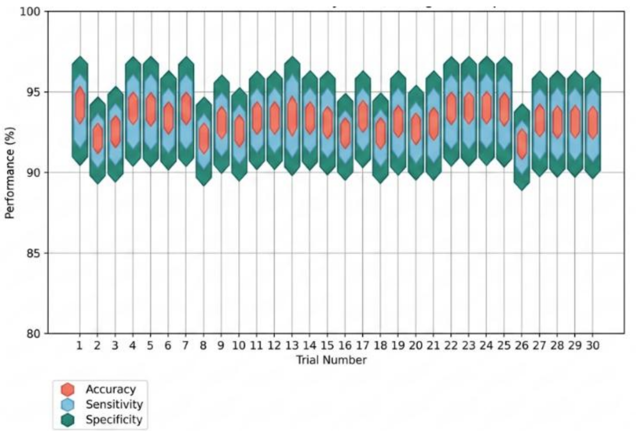

Figure 7. Model Performance Matrics Visulaized with Stacked Hexagonal Elements

Figure 6 shows the results of 30 model runs using LightGBM with the accuracy, sensitivity, and specificity. The accuracy remained above 95%, although it decreased during the model training. Although the sensitivity tended to hover between 90 and 95%, it increased several times. The specificity remained approximately the same, with an accuracy of greater than 95%.

5. CONCLUSION

From the experiments conducted by applying the LightGBM and XGBoost algorithms 30 times each in the training process using breast cancer datasets that contained 569 rows and 26 attributes, a clear question arises: which algorithm performs better? The performance metrics, such as accuracy, sensitivity, and specificity of XGBoost, were found to be the highest, with average values of 97.03%, 97.40%, and 96.81%, respectively. Although LightGBM had lower accuracy than XGBoost, the performance of LightGBM also achieved a satisfactory result, with a slight average margin of difference in accuracy of 1.44%, a sensitivity of 2.7%, and a specificity of 0.71% with respect to XGBoost.

6. REFERENCES

[1] World Health Organization (WHO). Global Breast Cancer Initiative (GBCC). Available at: https://www.who.int/initiatives/global-breast-cancer-initiative

[2] Hu, K. et al. Global patterns and trends in breast cancer incidence and mortality according to sociodemographic indices: an observational study based on the global burden of disease. BMJ Open, 9, e028461 (2019).

[3] LIV Hospital. 12 Essential Facts About Breast Cancer: Global Statistics, Risks, and Outcomes. Available at: https://int.livhospital.com/12-essential-facts-about-boob-cancer-global-statistics-risks-and-outcomes/

[4] International Agency for Research on Cancer (IARC). Cancer Over Time. Available at: https://gco.iarc.who.int/overtime/en/about

[5] World Cancer Research Fund International (WCRFI). Breast cancer statistics. Available at: https://www.wcrf.org/preventing-cancer/cancer-statistics/breast-cancer-statistics/

[6] Arnold, M. et al. Current and future burdens of breast cancer: Global statistics for 2020 and 2040. The Breast, 66, 15–23 (2022). PMC9465273.

[7] Painless mammogram. Early Detection of Breast Cancer. Available at: https://thepainlessmammogram.com/early-detection-in-breast-cancer/

[8] Unger-Saldaña K. Challenges to the early diagnosis and treatment of breast cancer in developing countries. World Journal of Clinical Oncology, 5(3), 465–477 (2014). PMC3437146.

[9] Frontiers in Oncology. Advanced Diagnostic Techniques and Wearable Technologies for Breast Cancer Detection. Front. Oncol. (2025). doi: 10.3389/fonc.2025.1587517.

[10] Ibid. [Same as Ref. 9].

[11] Cleveland Clinic. Fine-needle aspiration (FNA). Available at: https://my.clevelandclinic.org/health/diagnostics/17872-fine-needle-aspiration-fna

[12] Willems, S.M. et al. Diagnostic cytopathology of fine-needle aspiration biopsies of breast lesions. Journal of Clinical Pathology (2016). PMC5019018.

[13] Moschetta, M. et al. Role of fine-needle aspiration in breast lesions. Diagnostic and Interventional Radiology, 20(4), 300–306 (2014). PMC4063267.

[14] Computers Biol. Medicine Human Error in Manual Breast Cancer Analysis. Comput Biol Med (2025). doi: 10.1016/j.compbiomed.2025.01.015.

[15] Hoff, S.R. et al. Missed and true intervals and screen-detected breast cancers in a population-based screening

program. Academic Radiology (2018). PMC5980911.

[16] Ibid. [Same as Ref. 15].

[17] Richards MA et al. Influence of delay in the presentation and treatment of symptomatic breast cancer on survival. British Journal of Cancer, 85(4), 478–480. (1999). PMC3332709.

[18] Ong, M.S. & Mandl, K.D. National expenditure for false-positive mammograms and overdiagnosis of breast cancer. Ann Intern Medicine (2015). PMC3079487.

[19] Li Y et al. Machine learning models for predicting distant metastasis in breast cancer using clinical blood markers and pathological data. BMC Cancer (2024). PMC11211559.

[20] Darbandi, N. et al. Advancements in AI for Breast Cancer Diagnosis: A 2024–2025 Systematic Review Update. In: AI Revolution: Research, Ethics and Society, pp. 157–165 (2026). doi: 10.1007/978-3-032-13056-3_13.

[21] Yilmaz, A. et al. Comparison of classification success rates of different machine learning methods for breast cancer diagnosis. Diagnostics, 13(4), 651 (2023). PMC9924317.

[22] Nahid, A.A. & Kong, Y. Classification Prediction of Breast Cancer Using Machine Learning. Neural Comput Appl (2023). PMC9848804.

[23] Anitha, P., Surya, V., Geetha, R., Loganathan, E., Singaravel, G., & Prakash, N. (2025). High-accuracy breast cancer classification utilizing XGBoost and support vector machine. Https://doi.org/10.1109/icdici66477.2025.11135150

[24] Kanimozhi, J. K., Bavya, G., Kalyanasundaram, P., Anitha, P., Geetha, R., & Loganathan, E. (2025). Evaluating the effectiveness of Random Forest + XGBoost versus support vector machines in achieving high accuracy and precision for breast cancer classification. Https://doi.org/10.1109/icscsa66339.2025.11170741

[25] Permana, A., & Romdendine, M. F. (2024). The ensemble learning approach revealed significant clinical attributes in real-world breast cancer cases. G-Tech. Https://doi.org/10.33379/gtech.v8i2.4044

[26] Athisayamani, S., Tamilazhagan, S., Singh, A. R., Hwang, J.-Y., & Joshi, G. P. (2025). A novel double machine learning approach for the early detection of breast cancer. Scientific Reports 15, 22971.

[27] Khan, M. Z., Srivastava, P., Aljubayri, I., Pattanaik, P., Ahmad, J., & Chelabi, K. (2024). Optimized breast cancer detection using genetic algorithms and ensemble machine learning models. Journal Electrical Systems.

[28] Karamti, H., Alharthi, R., Umer, M., Shaiba, H., Ishaq, A., Abuzinadah, N., Alsubai, S., & Ashraf, I. (2024). Breast cancer detection employing a stacked ensemble model with convolutional features. Computational Biology and Medicine.

[29] Pinheiro, J. M. H., & Becker, M. (2024). Breast cancer classification using gradient boosting algorithms with explainability. ArXiv preprint.

[30] Sait, A. R. W., & Nagaraj, R. (2024). Enhanced LightGBM-based breast cancer detection using mammographic images. Diagnostics, 14(2), 227.

[31] Ghosh, P., & Chatterjee, D. (2024). Comparative analysis of machine learning algorithms for breast cancer classification. BioRxiv.