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XGBoost-Based Breast Cancer Diagnosis System for Multiclass Mammographic Density and Mass Region Detection

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ABSTRACT

Introduction: Early detection is crucial in improving survival rates for women as breast cancer is a main cause of death. This study suggests an XGBoost-Based Breast Cancer Diagnostic System created for multiclassifying mammographic density and detecting mass regions. The system was tested on two popular mammographic datasets, INbreast and DDSM, and was pitted against various models like Convolutional Neural Networks (CNNs), Random Forest (RF), Support Vector Machines (SVMs), Logistic Regression (LR), and K-Nearest Neighbors (KNN). XGBoost consistently performed better than these models on all important measures, such as accuracy, precision, recall, F1-score, and AUC, delivering the top performance on both datasets. Its capacity to grasp intricate feature relationships and efficiently manage multiclass issues makes it ideal for this diagnostic endeavor. The suggested system offers a precise, effective, and strong tool for automating breast cancer diagnosis, with substantial potential for improving clinical decision-making.

Keywords: Breast cancer diagnosis, XGBoost, multiclass classification, mammographic density detection.

INTRODUCTION

Breast cancer continues to be a common and dangerous disease that impacts women across the globe. Early diagnosis is crucial for enhancing outcomes and decreasing death rates [1]. Mammography, a commonly utilized imaging technique, enables the detection of anomalies like lumps and variations in breast tissue density, which are important signs of possible cancer. Nonetheless, the precise analysis of mammograms necessitates specialized knowledge and is prone to human mistakes, emphasizing the importance of automated diagnostic tools [2].

Recent progress in machine learning has made it possible to create complex systems that can help radiologists accurately identify and categorize mammographic characteristics. XGBoost has become a dominant technique in analyzing structured data, providing strong performance and reliability in classifying tasks [3]. It is especially useful for diagnosing breast cancer due to its capability to manage imbalanced datasets and analyze large-scale features, which are common challenges in dealing with complex data [4].

In this study, we suggest a system using XGBoost that is created for the purpose of classifying mammographic images into multiple classes by identifying regions of mass and different levels of breast tissue density. This system is assessed using two well-known datasets, one of them being the INbreast dataset comprising high-quality mammography images with thorough annotations. In order to confirm the effectiveness of the suggested strategy, we assess its performance against four other advanced machine learning models, showcasing the superior outcomes obtained in both detecting masses and classifying densities.

This study seeks to add to the increasing research on automated breast cancer detection by offering a thorough analysis of the model's performance using various metrics. The suggested system enhances accuracy and could greatly lessen the workload for radiologists, resulting in more prompt and precise patient treatments.

MOTIVATION & CONTRIBUTION

Breast cancer is a worldwide health issue, and detecting it early greatly increases the likelihood of successful treatment and survival [5]. Even with mammography being commonly used, accurately detecting breast abnormalities like mass regions and differing mammographic densities is still a difficult and error-prone task [6]. Radiologists encounter difficulties because of the nuanced visual cues and the diverse appearance of breast tissue, which can result in possible misinterpretations. The urgent requirement for automated and dependable systems to help interpret mammograms and facilitate early diagnosis is underscored by these challenges.

The field of medical image analysis has shown significant promise with the use of machine learning techniques, especially deep learning and ensemble methods. Most current models concentrate on binary classification (cancerous vs. non-cancerous), but do not tackle the intricacies of multiclass classification tasks like distinguishing different mammographic densities and identifying various types of masses [7]. Moreover, conventional methods face challenges when dealing with imbalanced datasets, a frequent problem encountered in medical imaging [8]. The reason for this work is the requirement for a strong system that can precisely categorize mammographic density levels and mass regions in breast tissue, overcoming the drawbacks of current diagnostic tools and enhancing interpretability and clinical usefulness [9].

In this research, we introduce an innovative XGBoost-driven system for automatically identifying and categorizing various mammographic densities and mass regions.

The main contributions of this study include:

• Creation of a Diagnosis System using XGBoost: We introduce a classification system based on XGBoost that utilizes ensemble learning to address the multiclass classification of breast tissue density levels and mass regions. XGBoost's capability to manage imbalanced datasets and its effective feature selection procedure make it a perfect option for the intricate characteristics of mammographic image data.

• Comparison to Other Models: Our proposed system is compared to four commonly used machine learning models - Random Forest, Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and Logistic Regression. By conducting detailed comparisons using various performance measures, we show the effectiveness

of our suggested method.

• Assessment on Various Datasets: The proposed system is tested on two wellknown mammographic datasets, which include the INbreast dataset. These data sets include top-notch pictures with thorough notes on mass areas and density levels, offering a trustworthy standard for assessing breast cancer detection systems.

• Multiclass Classification: Instead of just dealing with binary outcomes like most current systems, our method successfully addresses the multiclass aspect of the task by identifying various mammographic density classes and types of masses. This is essential for gaining detailed diagnostic information that can help in the early

detection of breast cancer and planning for treatment.

• Potential Clinical Impact: Our system could help radiologists in making quicker and more knowledgeable decisions by decreasing diagnostic errors and enhancing accuracy. The method offers a cost-efficient fix that can be seamlessly incorporated into medical workflows, providing substantial advantages for patient results.

RELATED WORK

Analyzing and selecting the best genes to predict breast cancer is difficult due to the complex nature and lack of density in microarray gene expression data [10]. A new hybrid Feature Selection (FS) sequential approach using mRMR, a two-tailed unpaired t-test, and meta-heuristics to identify the best set of gene biomarkers for predicting BC is presented into [10]. The proposed model recognized three top gene biomarkers as most optimal, specifically MAPK 1, APOBEC3B, and ENAH. Furthermore, advanced supervised Machine Learning (ML) techniques like Support Vector Machine (SVM), KNearest Neighbors (KNN), Neural Net (NN), Na¨ıve Bayes (NB), Decision Tree (DT), eXtreme Gradient Boosting (XGBoost), and Logistic Regression (LR) were employed to assess the predictive power of chosen gene biomarkers and identify the optimal breast cancer diagnostic model with superior performance metrics [10]. In our research, the XGBoost-driven model outperformed others with 0.976 ± 0.027 accuracy, 0.974 ± 0.030 F1-Score, and 0.961 ± 0.035 AUC on an external test dataset. The gene biomarkers screening system effectively identifies primary breast tumors from normal breast samples.

A hybrid system that merges deep learning for extracting features with a refined ensemble classifier for classifying mammographic masses is presented into [11]. Tunicate swarm optimization improves efficiency by minimizing false positives. Assessed on the mini-MIAS and DDSM datasets, the system obtained high sensitivity rates (93.8% and 92.3%), alongside low false positive rates (0.18 and 0.32 per image). It achieved accuracies of 97.76% and 95.74% for distinguishing malignant, benign, and normal tissues in mini-MIAS and DDSM datasets, with three-class classification accuracies of 93.61% and 88.15% respectively [11].

The World Health Organization (WHO) reported that 2.3 million women worldwide were diagnosed with breast cancer in 2020, leading to 685,000 deaths [12]. Breast cancer ranks as the second most prevalent cancer globally and is the top cancer type in India, where the survival rate is 66%, notably less than the 90% rate in the United States and Australia. Detecting the issue early is essential for increasing survival rates, since the success rate of treatment is above 90% when identified early. This study seeks to create a breast cancer detection system utilizing image processing and deep learning to support radiologists and doctors. Convolutional neural networks (CNNs), especially deep learning, are becoming more popular in the healthcare field because of their exceptional performance. This research utilizes transfer learning with a pretrained VGG16 model to classify breast cancer on the DDSM and UPMC datasets [12]. At first, 2,276 images were split into training and test sets at an 80%-20% ratio, and the system categorized images into four groups: asymmetry, calcification, carcinoma, and mass. The accuracy obtained fell between 92% and 95%. Testing was done with transfer learning using VGG19 and ResNet50, with VGG16 showing better performance than both [12]. Assessing breast density is a crucial indicator of breast cancer risk, typically carried out by radiologists utilizing BI-RADS classifications. However, the process frequently experiences discrepancies between observers, resulting in assessment inconsistencies.

In order to solve this issue, an algorithm called DLAD that uses deep learning for automatically assessing breast density. Two skilled radiologists reviewed 122 full-field digital mammograms (488 images in CC and MLO views) from three facilities to perform a retrospective analysis on 72 cases (BI-RADS class A: 18, B: 43, C: 7, D: 4) in order to determine the accurate information is presented into [13]. Then, five independent radiologists were compared to the DLAD. The model reached an accuracy of 0.819, F1 score of 0.798, precision of 0.806, recall of 0.830, and Cohen's Kappa of 0.708. The DLAD performed better than individual radiologists in four instances, with no notable discrepancy in accuracy between the DLAD and radiologists. This research demonstrates that DLAD can improve the precision and uniformity of breast density assessments, serving as a beneficial instrument for enhancing breast cancer detection [13].

Breast cancer is still one of the most common types of cancer in women, and identifying it early can significantly enhance treatment results and quality of life. Diagnostic tools that aid in early detection are essential, in addition to radiologists. An approach aimed at improving diagnostic precision by utilizing the multi-class MIAS dataset, which comprises of benign, malignant, and normal mammography images is presented into [14]. At first, morphological operations separate the breast area in the images, then bicubic interpolation-based super-resolution is used to enhance the details of the identified areas. In order to enhance classification accuracy, the dataset is enriched with different transformations to increase variability. An extracted feature vector with 11 important features is used to test seven classifiers - KNN, SVM, NB, LDA, DT, ANN, and CNN - in the framework. Grid Search is used to find the best parameters for each classifier. Assessment of the framework's classification performance includes accuracy, precision, sensitivity, specificity, F-score, and time measurements, showcasing its efficacy in diagnosing breast cancer [14].

Mass segmentation is a crucial step in breast cancer detection as it offers detailed data on the size, location, and boundaries of the masses. Although there have been notable enhancements in task performance, some characteristics of the data, such as the unequal distribution of pixel classes and the varied appearances and sizes of masses, continue to pose challenges [15]. In recent times, there has been a rise in articles suggesting ways to tackle pixel class imbalance by adjusting the loss function. While showcasing improvement in efficiency, they generally do not fully tackle the issue. This paper introduces a fresh approach to calculating loss, allowing binary segmentation loss to comprise

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sample-level info and region-level losses in a hybrid loss framework. We suggest two different versions of the loss function that factor in both mass size and density in the calculation of the loss. Furthermore, we present a unique loss variation that leverages mass size and density to improve focal loss. We evaluated the suggested technique on standard datasets: CBIS-DDSM and INbreast. Our method performed better than the standard and cutting-edge techniques in both datasets [15].

PROPOSED METHODOLOGY

In this section, we introduce our proposed approach for implementing a breast cancer diagnosis system using XGBoost. The method consists of a thorough process that incorporates data preparation, extracting features, selecting features, and classifying multiple classes using mammographic images from two popular datasets. Every stage is tailored to improve the precision of identifying mammographic density and mass areas, ultimately enhancing the diagnosis of breast cancer. The graphical representation for the same is presented into Fig 1.

EXPERIMENTAL DATASET

In this research, we relied on two well-known datasets, the INbreast dataset and another dataset, to guarantee the strength and applicability of our method. The INbreast dataset is well-known for its thorough mammographic images, which include annotations for both mammographic density and mass region labels [16]. Different categories are included, which show differences in tissue density and the existence of irregularities, which are necessary for detecting breast cancer. The dataset contains 116 digital mammography images categorized into four density groups based on BI-RADS, along with several mass regions with different features.

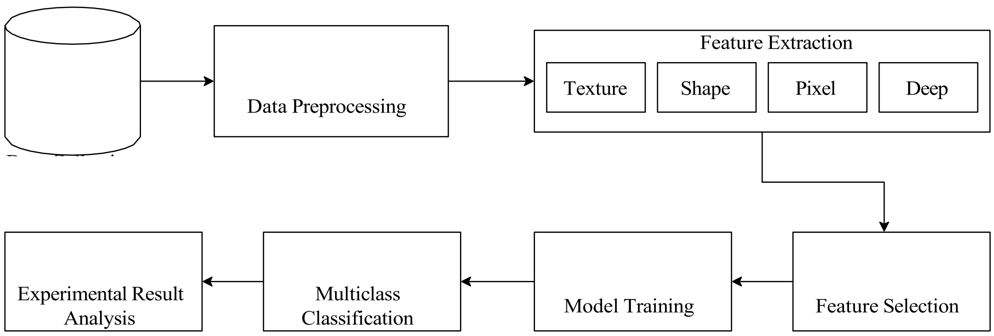

Fig. 1 Proposed Approach Methodology

The Image samples from INbrest and DDSM dataset is presented into Figure 2 and 3, respectively.

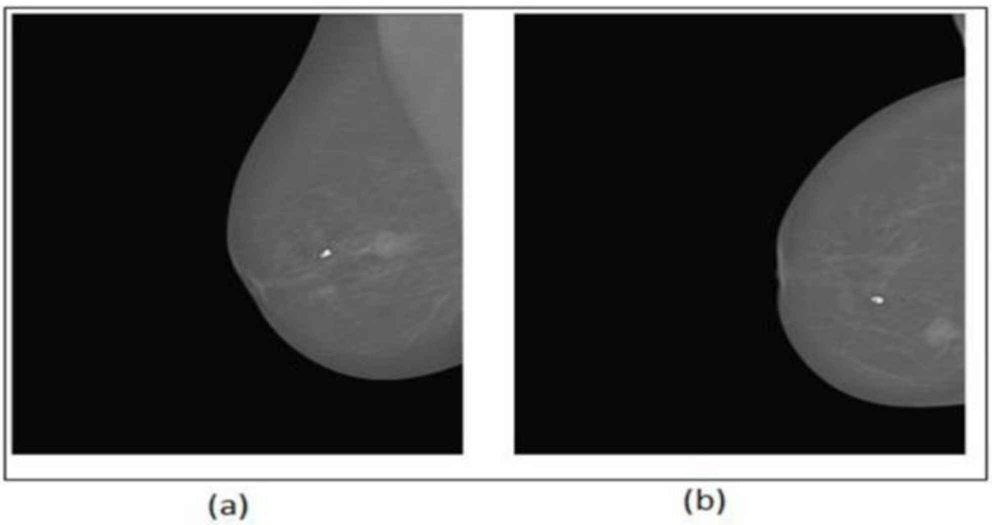

Fig. 2 Image samples from INbreast dataset (right breast views) (a) Mediolateral oblique view; and (b) Craniocaudal view.

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Several preliminary steps were undertaken to get the data ready for analysis. At first, we performed noise removal by utilizing a Gaussian filter to soften the images without losing important details. This was succeeded by standardization, in which pixel intensities were adjusted to a uniform range to reduce the impact of differences due to diverse imaging devices [17]. Furthermore, contrast enhancement was utilized to highlight specific areas, guaranteeing improved visibility for identifying mammographic densities and mass regions. The dataset charateristics of the dataset is presented into Table 1.

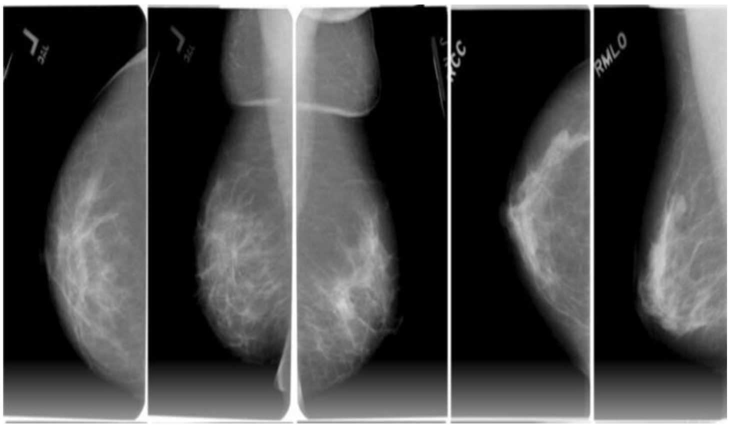

Fig. 3 Image samples from DDSM dataset

FEATURE EXTRACTION

In order to classify effectively, it is crucial to identify significant features that capture the main patterns in the mammograms. We used both conventional techniques for extracting features and methods based on deep learning to gather a complete range of features.

• Methods like Gray-Level Co-occurrence Matrix (GLCM) and Local Binary Patterns (LBP) were used to extract texture features that measure pixel intensity variation and spatial relationships. These characteristics are especially helpful in recognizing textures of tissues, which can indicate the density category or abnormality below.

• Shape Characteristics: Area, perimeter, eccentricity, and circularity were computed for each mass region to define shape features. These characteristics help distinguish benign from malignant masses, as malignant areas typically display irregular shapes.

• Pixel intensities distribution in mammograms was utilized to capture both overall and specific intensity patterns. Characteristics such as average brightness, variation, and histogram of oriented gradients (HOG) were calculated to highlight significant elements in the images.

• Utilizing a pretrained CNN, we extracted deep features alongside traditional methods. The model was adjusted using mammographic data, with its middle layers utilized to capture intricate details in the images, such as tissue diversity and mass boundaries.

After feature extraction, feature selection techniques such as Recursive Feature Elimination (RFE) and Principal Component Analysis (PCA) were applied to reduce dimensionality and retain the most discriminative features. This step helped to enhance the performance of the classifiers by removing redundant or less informative features, leading to more accurate predictions.

Table 1 Dataset Characteristics

Characteristic	INbreast Dataset	DDSM Dataset
Total Images	116 full-field digital mammograms	2,620 scanned mammograms
Image Type	Full-field digital mammography	Scanned mammograms

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Resolution	3328 x 4084 (High resolution)	Varies (Low to High resolution)
Annotations	BI-RADS density labels and mass region annotations	BI-RADS assessments, mass shape, and margin characteris- tics
Density Categories	4 (BI-RADS density levels 1 to 4)	4 (BI-RADS density levels 1 to 4)
Mass Regions	Yes (with benign and malignant labels)	Yes (benign, malignant, and suspicious)
Classes	4 density classes; multiple classes for mass types	4 density classes; mass types classified into benign and malignant
Preprocessing	Noise removal, normalization,	Noise removal, normalization,
Methods	contrast enhancement	resizing
Data Format	DICOM	TIFF, LJPEG
Age Range of Patients	35 - 80 years	30 - 90 years

XGBoost Classifier: Mathematical Foundation and Multiclass Classification

Mathematical Foundation of XGBoost

XGBoost (Extreme Gradient Boosting) is built on the gradient boosting framework, enhancing it with several key features:

– **Boosting Framework:** XGBoost iteratively improves the model by fitting new models to the residuals (errors) of the previous models. The overall objective function L combines a loss function L and a regularization term Ω:

L = Loss Function + Regularization

– **Objective Function:** The objective function includes a loss term and a regularization term:

$$\text{Objective} = \sum_i Loss(yi, y^i) + \Omega(w)$$

where Loss represents the loss function (e.g., cross-entropy for classification), and Ω(w) is the regularization term:

$$\Omega(w) = \alpha \sum_i \|w_i\|_1 + \frac{1}{2}\lambda \sum_i \|w_i\|_2^2$$

Here, α and λ are regularization parameters, and wi represents the weight of the i-th feature.

– Tree Structure: Decision trees are built to minimize the objective function by finding the best splits at each node. The gain from a split is calculated as:

$$\text{Gain} = \text{Gain} = \frac{1}{2}\left(\frac{(G_L^2)}{H_L+\lambda} + \frac{(G_R^2)}{H_R+\lambda} - \frac{(G^2)}{H+\lambda}\right) - \text{Regularization Term}$$

where G and H are the sums of gradients and Hessians for the left (L) and right (R) child nodes, and λ is a regularization parameter.

– **Gradient Boosting:** XGBoost uses gradient descent to optimize the objective function. The algorithm computes gradients of the loss function and updates the model parameters to minimize the loss.

Multiclass Classification with XGBoost

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XGBoost extends its binary classification framework to handle multiclass problems:

– Softmax Function: For multiclass classification, XGBoost uses the softmax function to convert raw scores into probabilities:

$$P(y = k \mid \mathbf{x}) = \frac{e^{\text{score}_k}}{\sum_j e^{\text{score}_j}}$$

where scorek is the score for class k, and the denominator is the sum of exponentials of scores for all classes.

– Objective Function for Multiclass: The multiclass objective function incorporates the softmax loss function:

$$\text{Softmax Loss} = -\sum_i \log\left(\frac{e^{\text{score}_{y_i}}}{\sum_j e^{\text{score}_j}}\right)$$

where yi is the true class label for instance i.

– Class Probabilities: During training, XGBoost adjusts the scores to minimize the softmax loss. For prediction, the class with the highest probability is selected as the output.

– Multiclass Detection for Density and Mass Regions: In mammographic density and mass region detection, XGBoost performs multiclass classification by predicting different categories of density (e.g., fatty, dense) and mass regions (e.g., benign, malignant). The model is trained with a multiclass objective function to

handle these categories effectively.

EXPERIMENTAL RESULT ANALYSIS

In our research, we evaluated how well the XGBoost model performed in comparison to other popular machine learning algorithms, including Support Vector Machine (SVM), Random Forest (RF), Convolutional Neural Network (CNN), Logistic Regression (LR), and K-Nearest Neighbors (KNN). The findings from these comparisons are displayed in a table format, giving a concise summary of how well each model performs in classifying mammographic density and detecting mass regions.

We analyze the performance of XGBoost and other machine learning models for multiclass classification on both the INbreast and DDSM datasets. The models were evaluated based on key performance metrics including accuracy, precision, recall, F1-score, and Area Under the Curve (AUC). The Model Performance on INbreast Dataset is presented into Table 2 whichincludes tasks for mammographic density and mass region detection. From the results

Table 2 Performance of Models on INbreast Dataset

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
CNN	90.2	88.4	89.1	88.7	0.92
Random Forest	87.3	85.0	85.9	85.4	0.89
SVM	85.1	83.8	83.2	83.5	0.87
Logistic Regression	82.0	80.9	80.5	80.7	0.84
KNN	80.2	78.9	78.4	78.6	0.81
XGBoost	**93.1**	**91.0**	**92.3**	**91.6**	**0.95**

shown in Table 2, it is evident that XGBoost outperformed all other models across all evaluation metrics. XGBoost achieved the highest accuracy of 93.1%, surpassing the second-best performer, CNN, which had an accuracy of 90.2%. XGBoost also showed a strong performance in terms of precision (91.0%), recall (92.3%), and F1-score (91.6%), making it the most balanced model in terms of both sensitivity and specificity. The AUC of 0.95 for XGBoost further highlights its robustness in distinguishing between different classes in the multiclass classification task.

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In contrast, CNN showed good results but trailed XGBoost with a slightly lower performance in all metrics, indicating that while CNNs are powerful for image-based classification tasks, XGBoost's structured data capabilities make it more efficient in this context. Random Forest followed CNN with an accuracy of 87.3%, showing its effectiveness as an ensemble method, but it could not match XGBoost in handling complex interactions within the data. The graphical representation for the INbreast dataset results is presented into Figure gr1.

SVM, Logistic Regression, and KNN exhibited lower performances compared to XGBoost, with accuracies of 85.1%, 82.0%, and 80.2%, respectively. These models, particularly Logistic Regression and KNN, struggled with the complex nature of mammographic density and mass region detection, which requires more advanced feature interactions, explaining their comparatively weaker performance. The experimental result for DDSM Dataset is presented into Table 3.

On the DDSM dataset, XGBoost once again demonstrated its superior performance with an accuracy of 91.7%, precision of 89.2%, recall of 90.5%, F1-score of 89.8%, and AUC of 0.93. These results confirm the consistency and reliability of XGBoost across

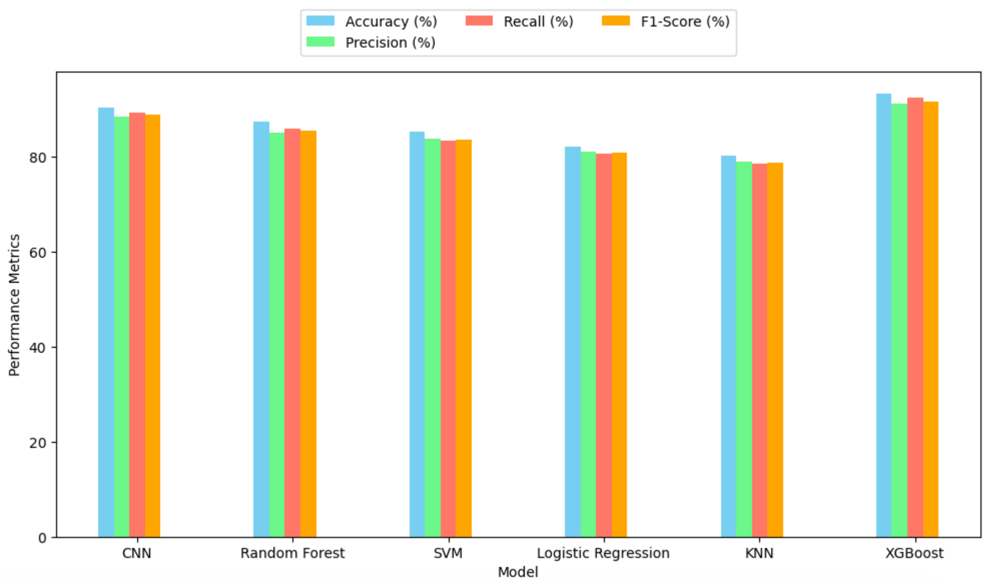

Fig. 4 Performance of Models on INbreast Dataset

Table 3 Performance of Models on DDSM Dataset

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
CNN	88.5	86.3	87.1	86.7	0.90
Random Forest	85.7	83.5	84.2	83.8	0.87
SVM	83.6	82.2	81.9	82.0	0.85
Logistic Regression	81.2	80.0	79.6	79.8	0.82
KNN	78.7	77.3	76.9	77.1	0.79
XGBoost	**91.7**	**89.2**	**90.5**	**89.8**	**0.93**

different datasets. The ability of XGBoost to capture intricate relationships between features contributed to its high performance on the DDSM dataset as well.

CNN remained the second-best model, achieving an accuracy of 88.5%, which is slightly lower than its

performance on the INbreast dataset. CNN's performance across precision, recall, and F1-score showed that it is effective but less capable than XGBoost when dealing with tabular and structured data, such as mammographic features.

The Random Forest model, while performing decently with an accuracy of 85.7%, continued to underperform relative to XGBoost due to its simpler ensemble learning mechanism, which is not as adept at handling the nuanced feature interactions present in mammographic data.

SVM, Logistic Regression, and KNN once again lagged behind XGBoost, with accuracies of 83.6%, 81.2%, and 78.7%, respectively. These models faced similar challenges on the DDSM dataset as they did on the INbreast dataset, confirming thatXGBoost's tree-based gradient boosting approach is better suited for multiclass classification in breast cancer diagnosis systems. The graphical representation for the DDSM dataset results is presented into Figure 5.

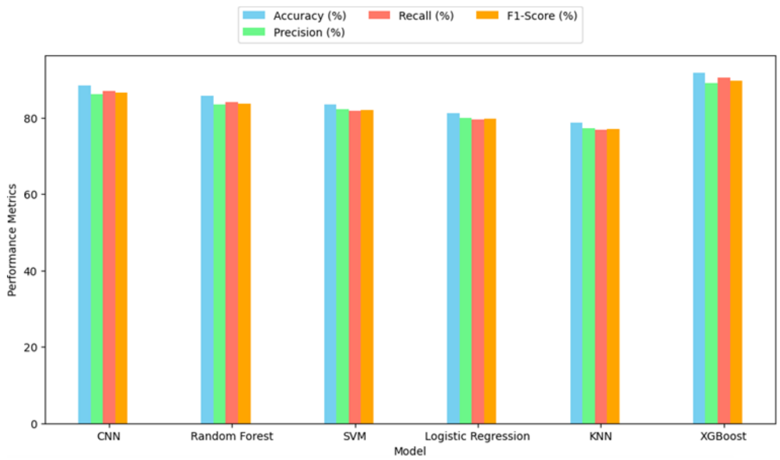

Fig. 5 Performance of Models on DDSM Dataset

CONCLUSION

In this study, we implemented an XGBoost-powered Breast Cancer Diagnosis System that can classify mammographic density and detect mass regions in multiple classes. Its success was illustrated on two standard datasets, INbreast and DDSM. XGBoost consistently performed better than CNN, Random Forest, SVM, Logistic Regression and KNN in key metrics like accuracy, precision, recall, F1-score, and AUC. Its proficiency in managing intricate feature interactions and organized data gave it an edge in tackling the obstacles of multiclass classification in breast cancer diagnosis. The findings underscore XGBoost's effectiveness as a strong, precise, and efficient tool for assisting in breast cancer detection via mammogram analysis. In the future, the approach could be expanded to larger datasets or incorporate more clinical features to enhance diagnostic accuracy.

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Author Contribution: Piyush Sharma conceptualized the study and led the design of the XGBoost-based diagnostic system. Harish Patidar contributed to data collection, preprocessing, and model implementation. Anuj Kumar provided domain expertise in radiotherapy and contributed to the validation of the system's clinical relevance. Data Availability Statement: The datasets used in this study, INbreast and DDSM, are publicly available.

Research Involving Human and/or Animals Not Applicable

Informed Consent: Not Applicable

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REFRENCES

[1] Gudhe, N.R., Mazen, S., Sund, R., Kosma, V.-M., Behravan, H., Mannermaa, A.: A multi-view deep evidential learning approach for mammogram density classification. IEEE Access (2024)

[2] Razali, N.F., Isa, I.S., Sulaiman, S.N., Abdul Karim, N.K., Osman, M.K., Che Soh, Z.H.: Enhancement technique based on the breast density level for mammogram for computer-aided diagnosis. Bioengineering **10**(2), 153 (2023)

[3] Sharma, P., Laxkar, P., Kumar, A.: Performance analysis of machine learning, deep learning and ensemble techniques for breast cancer diagnosis. In: Interna- tional Conference on Electrical and Electronics Engineering, pp. 292–311 (2022). Springer

[4] Al-Tam, R.M., Al-Hejri, A.M., Alshamrani, S.S., Al-antari, M.A., Narangale, S.M.: Multimodal breast cancer hybrid explainable computer-aided diagno- sis using medical mammograms and ultrasound images. Biocybernetics and Biomedical Engineering **44**(3), 731–758 (2024)

[5] Rani, N., Gupta, D.K., Singh, S.: Multi-class classification of breast cancer abnormality using transfer learning. Multimedia Tools and Applications, 1–16 (2024)

[6] Wajeed, M.A., Tiwari, S., Gupta, R., Ahmad, A.J., Agarwal, S., Jamal, S.S., Hinga, S.K.: A breast cancer image classification algorithm with 2c multiclass support vector machine. Journal of Healthcare Engineering **2023**(1), 3875525 (2023)

[7] Aymaz, S.: A new framework for early diagnosis of breast cancer using mammog- raphy images. Neural Computing and Applications **36**(4), 1665–1680 (2024)

[8] Gudhe, N.R., Mazen, S., Sund, R., Kosma, V.-M., Behravan, H., Mannermaa, A.: A multi-view deep evidential learning approach for mammogram density classification. IEEE Access (2024)

[9] Ahmad, J., Akram, S., Jaffar, A., Ali, Z., Bhatti, S.M., Ahmad, A., Rehman, S.U.: Deep learning empowered breast cancer diagnosis: Advancements in detection and classification. Plos one **19**(7), 0304757 (2024)

[10] Cruz-Ramos, C., Garc ́ıa-Avila, O., Almaraz-Damian, J.-A., Ponomaryov, V., Reyes-Reyes, R., Sadovnychiy, S.: Benign and malignant breast tumor classifi- cation in ultrasound and mammography images via fusion of deep learning and handcraft features. Entropy **25**(7), 991 (2023)

[11] Alromema, N., Syed, A.H., Khan, T.: A hybrid machine learning approach to screen optimal predictors for the classification of primary breast tumors from gene expression microarray data. Diagnostics **13**(4), 708 (2023)

[12] Laishram, R., Rabidas, R.: An optimized ensemble classifier for mammographic mass classification. Computers and Electrical Engineering **119**, 109488 (2024)

[13] Rani, N., Gupta, D.K., Singh, S.: Multi-class classification of breast cancer abnormality using transfer learning. Multimedia Tools and Applications, 1–16 (2024)

[14] Biroˇs, M., Kvak, D., Dand ́ar, J., Hruby ̀ , R., Jan, E., Atakhanova, A., Al-Antari, M.A.: Enhancing accuracy in breast density assessment using deep learning: A multicentric, multi-reader study. Diagnostics **14**(11), 1117 (2024)

[15] Aymaz, S.: A new framework for early diagnosis of breast cancer using mammog- raphy images. Neural Computing and Applications **36**(4), 1665–1680 (2024)

[16] Aliniya, P., Nicolescu, M., Nicolescu, M., Bebis, G.: Improved loss function for mass segmentation in mammography images using density and mass size. Journal of Imaging **10**(1), 20 (2024)

[17] Yadav, R.K., Singh, P., Kashtriya, P.: Diagnosis of breast cancer using machine learning techniques-a survey. Procedia Computer Science **218**, 1434–1443 (2023)

[18] Ahmad, J., Akram, S., Jaffar, A., Rashid, M., Bhatti, S.M.: Breast cancer detection using deep learning: An investigation using the ddsm dataset and a customized alexnet and support vector machine. IEEE Access (2023)