International Journal of Optimal Research in Science and Technology (IJORST)
Volume 12, Issue 1, August 2025

Breast Cancer Classification Using Artificial Neural Network

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***Abstract*— Breast cancer is among the most frequent cancers in women worldwide, so early detection and correct classification are vital for proper treatment and high survival rates. Traditional methods of diagnosis with mammography and biopsy examination highly rely on the skill of radiologists, which leads to inconsistency of diagnosis and human-made mistakes. To mitigate these problems, this study proposes a deep learning-based breast cancer detection and classification system through Artificial Neural Networks (ANN) and the AdaBoost algorithm. The system detects CBIS-DDSM dataset DICOM images into three categories: normal, benign, and malignant. The steps involve image preprocessing, including resizing, normalization, noise filtering, feature extraction, and model training. ANN, through hierarchical feature learning capacity, identifies intricate patterns in healthcare images, whereas AdaBoost enhances the classification performance through the combination of multiple weak classifiers to form a strong ensemble model. The system is being measured with precision, recall, F1-score, and accuracy to provide a complete performance overview. The experiments confirm that the new system significantly enhances the classification accuracy, minimizing diagnostic variation and simplifying the decision-making process for radiologists. A Graphical User Interface (GUI) is also integrated with ease of use so that medical personnel can easily upload images and receive results. This paper highlights the promise of deep learning to automate breast cancer diagnosis as an objective, scalable, and reliable tool in screening programs. The future will hold a merge of multi-modal imaging data (MRI, US) and interpretability-friendly AI methods to offer better interpretability and clinical adaptation.**

Keywords*— Breast Cancer, DICOM Images, CBIS-DDSM, Deep Learning, Artificial Neural Networks (ANN), AdaBoost, Classification.

I. Introduction

Breast cancer is among the most common causes of death among women worldwide, and therefore correct diagnosis and early detection are critical to enhance the patient's outcomes. The World Health Organization (WHO) indicates that breast cancer accounts for nearly 25% of all cancer diagnoses and 15% of cancer-related deaths among women. In an era of recent advances in the medical imaging sciences, mammography, ultrasound, and magnetic resonance imaging (MRI) are regular methods for detection of breast abnormalities. Nonetheless, conventional schemes for diagnosis are tremendously skill-dependent and therefore the diagnosis itself is time-consuming, subject to human inaccuracies, and subjective. Inaccurate diagnosis or delayed diagnosis can result in late-stage occurrence of disease and diminish the probability of successful treatment. As a reaction to these problems, machine learning (ML) and artificial intelligence (AI) methods have been suggested as effective means of automating breast cancer detection and classification.

Deep learning methods have recently demonstrated superb performance in medical image analysis, outperforming conventional approaches in various domains such as oncology, cardiology, and neurology. Of these approaches, Artificial Neural Networks (ANN) and ensemble learning methods like AdaBoost have been popular due to their very high accuracy rate of pattern recognition and classification tasks. ANNs, being imitated models of biological neurons' structure and functionality, are extremely efficient learners of sophisticated patterns within intricate data, such as medical imaging. Nevertheless, AdaBoost does improve the step of classification through aggregation of many weak classifiers in forming a strong ensemble, therefore strengthening diagnostic capability.

This research explores a method for breast cancer classification using deep learning-based ANN and AdaBoost for DICOM images on the CBIS-DDSM dataset. The system is intended to reduce diagnostic inconsistency, increase accuracy in classification, and assist radiologists to make data-driven consistent decisions. The integration of a Graphical User Interface (GUI) contributes to the system's usability in real clinical practice. Breast cancer appears as abnormal cell growth in breast tissue, usually in the form of a benign or malignant tumor. Benign tumors are not cancerous and do not metastasize, but malignant tumors can invade surrounding tissues and spread to other parts of the body. Early detection is crucial because patients diagnosed during the early stages (Stage 0 or I) have much higher survival rates than those diagnosed at later stages (Stage III or IV).

Conventional breast cancer diagnosis relies significantly on mammography, touted as the gold standard for screening. Mammograms, however, are hard to read, particularly when the breasts are dense, resulting in false positives and false negatives. Research has shown that radiologists can miss up to 20% of breast cancer because of overlapping tissues or slightly abnormal tumor features that are difficult to spot visually. In addition, reading high numbers of mammograms in high-throughput screening programs is extremely burdensome for radiologists and can lead to fatigue-related errors..

To overcome such limitations, computer-aided diagnosis (CAD) systems have been made to help radiologists detect and classify breast abnormalities. Early CAD systems involved hand-designed feature extraction algorithms, e.g., texture analysis, edge detection, and morphological filtering. While these algorithms were better at diagnostic performance, they were unable to generalize across heterogeneous datasets because of differences in imaging conditions and patient populations. The arrival of deep learning has transformed the field such that neural networks can learn hierarchical features from raw images directly, thus dispensing with feature engineering through human intervention.

II. LITERATURE SURVEY

Ahmad et al. [1] introduce an end-to-end computer-aided diagnosis (CAD) system for the detection of breast cancer, employing YOLO for effective lesion detection, Associated-ResUNets for effective segmentation, and a tailored BreastNet-SVM for overall classification. The approach performed well, with 98.5% detection accuracy and 99.16% classification accuracy on the CBIS-DDSM dataset. The system best balances detection and classification and is a viable diagnostic tool in clinical environments. Ahmad et al., however, reference the usefulness of enhancing model accuracy in the context of small lesions, especially calcifications, which have minor and irregular characteristics. Such difficulties in detecting calcifications indicate possible limitations in YOLO's feature extraction ability when working with fine-grained lesion features, indicating potential for improvement in addressing subtle abnormalities in breast imaging data. Moon et al. [2] created a CAD system for the detection of breast cancer using convolutional neural network (CNN) architectures combined with image fusion methods.

With skip connections and multi-representational images, the system is able to successfully overcome gradient vanishing, a typical issue in deep networks, at a level of accuracy of 91.1%. The method enables improved spatial information retention as well as enhanced model stability. Yet, the research identifies a deficiency in dealing with differences in tumor shapes, especially since such differences rely much on operator modification while imaging. Such a weakness indicates that consistency in segmentation by the model can be compromised by subjective imaging methods to yield varied results across datasets. Khan et al. [3] applied an integration of CNN models ResNet, VGGNet, and GoogleNet with data augmentation to perform breast cancer image classification.

Their strategy provided a level of accuracy as high as 97.525% that implies great robustness in their classifier. Their paper emphasizes the issue of establishing an even more general model with persistent performance in any dataset of variation. With every CNN design optimized for disparate feature sets, reliance on a sole dataset undermines their findings' generality. Therefore, extending the training of their model on diversified datasets may enhance the flexibility of their approach toward wider clinical utility. Masni et al. [4] used the YOLO approach for the detection of breast lesion on the DDSM dataset aimed at detecting mass and calcification lesions and with an accuracy level of 85.52%. The study puts forward limitations with the detection of small, asymmetrical calcifications because of its faint appearance. This limitation is especially critical in microcalcification cases, which are known to be indicators of early breast cancer. The research highlights the necessity for more advanced feature extraction techniques that are able to reflect the subtle shape and texture variations of such lesions, and a hybrid technique or further preprocessing being proposed as means to improve detection for difficult cases. Das et al. [5] compared deep CNN architectures (VGG19, ResNet50, and MobileNet-v2) on the DDSM and INbreast datasets. They obtained 87.8% accuracy on DDSM and 95.1% on INbreast, highlighting the effect of dataset variability on model performance. The research points to image quality and dataset diversity as factors that determine model accuracy, indicating that heterogeneity of mammogram image resolution and contrast can have a considerable impact on the detection ability of the model.

To mitigate this, the authors propose incorporating additional clinical features to further improve diagnostic accuracy and model robustness in terms of differing image qualities. Trang et al. [6] integrated clinical information into CNN models, viz., VGG16, ResNet-v2, and Xception, and reported 84.5% accuracy in breast cancer classification. By augmenting mammographic data with clinical information, the paper emphasizes the significance of employing complementary data to enhance diagnostic precision. The combination of clinical data (e.g., patient history or risk factors) and imaging data allows the contextual recognition of observed anomalies. This work shows that using more than one type of data may give a more complete and precise diagnostic system, particularly when it is tested on a varied collection of mammographic images.

Alruwaili et al. [7] applied transfer learning with ResNet50 and Nasnet-Mobile models to the MIAS dataset to differentiate between benign and malignant breast cancer cases with 89.5% accuracy using ResNet50. Data augmentation was used to avoid overfitting, which enhanced model stability. Yet, the study identifies a requirement for increased robustness via further training of datasets. This drawback indicates the difficulties of overfitting with small datasets, implying that wider training on varied datasets may make the model more versatile for clinical use in the real world. Peng et al. [8] proposed a new approach to mass detection through the integration of Faster R-CNN and multiscale feature pyramid networks.

This method obtained maximum true positive rates (0.94 and 0.96 in CBIS-DDSM and INbreast, respectively) that correctly identified masses from various densities of the breasts. The study, though, recognizes that there were difficulties in the detection of architectural distortions, which are abnormalities that do not necessarily occur in obviously well-defined structures. The authors advise making the models more sensitive to these smaller and lesser definable lesion features through other pre-processing or feature extraction mechanisms. Vedalankar et al. [9] utilized AlexNet integrated with SVM classifiers to solve the class imbalance on mammography data (CBIS-DDSM and mini-MIAS) with the highest accuracy obtained at 92%. While very effective, this study was in its limitation posed by the narrow dataset size and the potentiality of impacting generalizability to the model. The authors further recommend further verification on larger sets to enhance the robustness given that small-sized datasets can hinder the model's capacity to detect varied lesion patterns.

Saber et al. [10] used freezing and fine-tuning methods to the VGG16 model for boosting classification performance to 98.96% on the MIAS dataset. These methods allow the model to preserve useful features while paying attention to particular characteristics of lesions. Image quality constraint affected the consistency of the model, and the authors suggested that the model should be tested over varied image qualities and resolutions to evaluate the model's generality. Hekal et al. [11] developed a CAD system utilizing AlexNet and ResNet-50, with Otsu thresholding for optimized feature extraction, achieving an accuracy of 91% on the CBIS-DDSM dataset. The study identifies challenges in consistently handling different image types and resolutions, which affect model performance. The authors highlight the need for improved algorithms capable of adapting to various image characteristics, which could enhance the reliability of automated systems in diverse clinical environments. Shams et al. [12] proposed a hybrid CAD model that integrates CNN and GAN architectures to improve breast cancer classification. The model attained a maximum accuracy of 93.5% on DDSM and INbreast datasets, with GANs enhancing feature extraction from intricate breast tissue images. Although these advances are made, the study identifies a limitation in reducing false negatives, especially in fine-grained tumor features, indicating that more refinement is required to minimize misclassification rates. Tavakoli et al. [13] introduced a block-based CNN architecture tailored with binary mapping for accurate lesion segmentation, which resulted in 95% accuracy on the MIAS dataset. The performance of the model is strong on low-complexity datasets; however, it fails when dealing with more complex datasets. The authors propose that further validation against larger and more extensive datasets would be needed to evaluate the robustness and scalability of the model.

Zhang et al. [14] published a paper based on a study of a computer-aided diagnosis (CAD) system termed BIRADS-SDL to detect breast cancer using ultrasound images. BIRADS-SDL was compared to traditional stacked convolutional auto-encoder (SCAE) and semi-supervised deep learning (SDL) models with original images as inputs and an SCAE with BIRADS-oriented feature maps (BFMs) as inputs. The experimental results illustrated that BIRADS-SDL achieved the optimal performance among the four networks with classification accuracy approximately 92.00 ± 2.38% and 83.90 ± 3.81% on two databases. It would appear that the results indicate the potential for the use of BIRADS-SDL as a valuable tool to facilitate effective CAD of breast ultrasound lesions, specifically with the minimal datasets. Efficiency and effectiveness may be increased through CAD systems while minimizing inter-operator variability. False-positive or false-negative results could be provided by CAD systems, and performance also depends on input image quality. Integration of CAD systems with other imaging modalities and algorithms to compensate for variation in image quality can enhance their accuracy and reliability.

III. METHODOLOGY

The block diagram of the fuzzy logic-based lung cancer and cancer stage detection using tumor grading is shown in Fig.1.

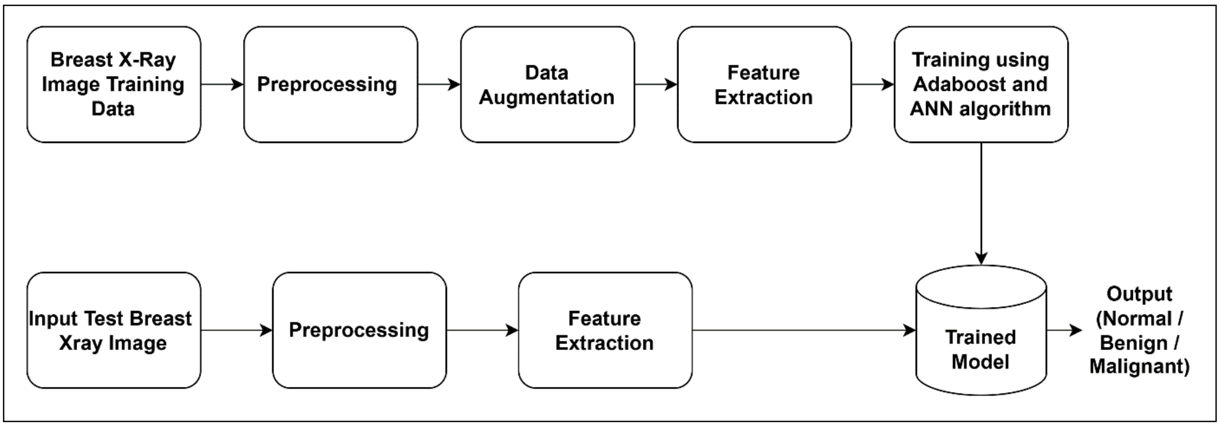

Fig. 1. Block diagram of ANN based breast cancer recognition

The block diagram of the proposed system is explained in detail below.

A. *Breast cancer image dataset*

The system begins from the CBIS-DDSM dataset, a processed subcollection of the Digital Database for Screening Mammography (DDSM) designed especially for breast cancer research. The dataset contains DICOM images of breast tissue labeled meticulously into three broad classes: normal, benign, and malignant. CBIS-DDSM is a dataset specially suited for the training of machine learning models because it includes heterogenous images that have rich metadata with both image acquisition information as well as patient information. The DICOM images are of good quality and also in a standardized format, therefore are best for machine learning scenarios where precise analysis based on the images is essential. With this dataset, the system builds a full basis for training and testing models on realistic, medically relevant data.

B. *Image Preprocessing*

Data preprocessing is a crucial step that gives machine-learning compatibility and consistency to images. Since DICOM images may have very dissimilar resolution, size, and quality, data preprocessing involves resizing all the images to a consistent size, so input sizes become consistent while training models. Normalization is also done to normalize the pixel values to a normal range, e.g., 0 to 1, so stable and faster convergence of models can be achieved. Noise reduction algorithms are also used as an attempt to remove any background noise or artifacts, thereby making the image sharper and allowing the model to focus on prominent image features. Data augmentation techniques such as rotation, flip, and scaling augment the dataset by creating many transformed of each image. This approach generalizes the model more because it trains the model on diverse orientations and all types of images.

C. ANN and Adaboost Model

In this block, two distinct ML models, ANN and AdaBoost, are chosen to differentiate images of breast tissue: . ANN is a biologically inspired kind of neural network and is very powerful in the task of learning complex hierarchies and patterns from images. The multi-layered architecture of the ANN enables fine-grained features to be extracted to distinguish normal, benign, and malignant tissues. Parallel to this, AdaBoost, an ensemble learning method, increases the classification accuracy by combining many weak classifiers—models that are slightly better than random guesses—into a robust predictive model. AdaBoost accomplishes this by repeatedly classifying images that had been misclassified by previous classifiers, thereby increasing the accuracy of the model.

D. Model training

The training stage is a crucial step where the preprocessed images are presented to the ANN and AdaBoost models so that they can learn to classify every image as benign, or malignant. Model parameters are progressively tuned during training to reduce classification errors so that the models can learn to extract significant features that correspond to every category of breast tissue. This learning process entails updating the weights and biases within the neural network and parameter tuning within the AdaBoost model. Through training over a large heterogeneous dataset, the models acquire the strength of generalization, that is, the ability to make accurate predictions on classifications on unseen images. The aim is to create a reliable model and, further, robust against variation in the image data in order to improve its potential for effective detection of cancer in real-world scenarios. Upon termination of the training process, the model retains with it the learnt parameters, the weights and the biases that transmit the patterns and relations learned from the training cases. This model, having been trained, is the system's most important predictive component, ready to classify new Xray images based on its learned patterns of normal, benign, and malignant breast tissue. The trained model actually "remembers" the characteristic features of each category so that it can predict on new data. By remembering this acquired knowledge, the model can always apply its knowledge to real-world cases, and therefore it is an extremely helpful machine in clinical diagnosis where accurate and consistent classification is of utmost importance.

E. Model evaluation

After training, the model is subjected to a strict testing process on an explicitly defined set of DICOM images not encountered during training. Such a test dataset enables the performance of the model to be assessed under an actual world-like scenario, its reaction to novel, unseen images. The performance of the model is measured against major metrics: accuracy (ratio of correctly labeled images), precision (the capability of the model to detect true positives without false labeling), recall (the capability of the model to detect all cases of interest), and the F1-score (harmonic mean of recall and precision). These measurements provide a general estimate of the model's strengths and weaknesses to ensure that it is of the needed quality for application in medicine. This process of evaluation is significant as it aims at the power and reliability of the model, ensuring that it can be applied in a clinical setting.

F. Graphical User Interface (GUI)

GUI is the system's user interface through which the clinicians or radiologists can use the classification tool in a natural manner. The DICOM images can be classified by the users and see the output along with seeing the evaluation metrics such as accuracy, precision, recall, and F1-score to estimate the model's reliability using the GUI. The GUI bridges the gap between complex backend machine learning processes and a charming front-end interface to the point where the system is made available for use as a diagnostic tool by clinicians. The interactive system not only enhances usability but also facilitates clinical processes, thereby enabling clinicians to provide more accurate, consistent, and timely diagnoses for improved patient outcomes.

IV. Results and Discussion

The results obtained from the suggested system are discussed in this section. This system used two algorithms ANN and Adaboost for classifying the breast images as cancers and non-cancerous.

A. Results of Adaboost algorithms

The results of the AdaBoost algorithm for breast cancer classification indicate a moderate level of accuracy in distinguishing between normal, benign, and malignant cases.

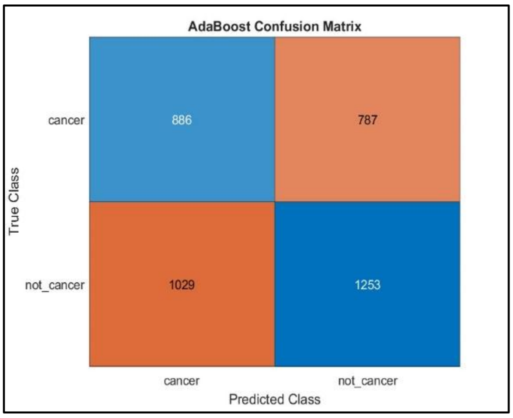

Fig. 2. Confusion matrix for breast cancer recogniton using Adaboost algorithm

The most important indicator-based performance measures indicate that AdaBoost had precision value of 0.6142, recall value of 0.5491, F1-score value of 0.5798, and accuracy value of 0.5408. The measures indicate that the model is actually doing a fair job in correctly predicting the cancer cases but its recall value indicates that a number of the malignant cases could have been misclassified, which is an acute issue in medical diagnosis. In comparison to the

ANN-based classification method, AdaBoost with a value of accuracy of 0.5818 had superior precision and F1-score, which indicated that it is more effective at minimizing false positives. . The AdaBoost confusion matrix also shows the number of correct and incorrect predictions, and indicates where the model fails, namely in distinguishing between malignant and benign cases. While AdaBoost's ensemble learning approach enhances classification via the combination of weak learners, its recall limitations ensure that optimization will be required. Future research can include optimizing feature extraction methods, hyperparameter optimization, or combining AdaBoost with deep learning methods to achieve better performance in medical image classification.

B. Results of ANN algorithms

The performance of the Artificial Neural Network (ANN) algorithm for classifying breast cancer illustrates its ability to detect normal, benign, and malignant instances from DICOM images. The confusion matrix of ANN-based breast cancer recognition is illustrated in Fig. 3.

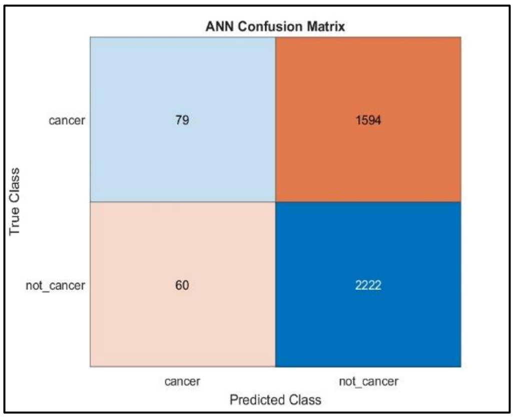

Fig. 3. Confusion matrix for breast cancer recogniton using ANN algorithm

The performance measures based on key values indicate that ANN has an accuracy of 0.568, a recall of 0.047, an F1-score of 0.087, and an overall accuracy of 0.5818. Although ANN was slightly more accurate than AdaBoost, its recall value is extremely low, indicating that the model was not able to classify malignant cases correctly, which can lead to false negatives correctly. ANN classification confusion matrix also puts an emphasis on the trends in misclassification and is requesting enhanced sensitivities against cancerous situations. Even if its deep learning, ANN can still be optimised with superior optimisation approaches, data augmantation measures, and the process of optimisation of its hyperparameters. Also, fusing ANN along with ensemble approaches or explainability methods could elevate its interpretability along with stabiltiy while dealing with medicical contexts. Subsequent research must focus on improving the model architecture and training methods to achieve more precise and clinically useful breast cancer detection.

The accuracy of the Adaboost and ANN-based breast cancer classification is tested in terms of precision, recall, F1 score, and accuracy. Comparative assessment of the evaluation matrix of adaboost and ANN is given in Table I.

TABLE I. PERFORMANCE OF ANN AND ADABOOST FOR BREAST CANCER RECOGNTION

	Precision	Recall	F-measure	Accuracy
Adaboost	0.6142	0.5491	0.5798	0.5408
ANN	0.568	0.047	0.087	0.5818

Table I summarizes comparative performance assessment of ANN and AdaBoost in the detection of breast cancer using precision, recall, F1-score, and accuracy. It is apparent that AdaBoost was more accurate in accuracy and F1-score, which indicates higher capability in classifying the positive instances accurately with fewer false positives. ANN, on the other hand, gave slightly higher overall accuracy but with much poorer recall, indicating that it failed to detect the malignant cases effectively, which indeed is of paramount importance in medical diagnosis. Comparison reveals the two models' trade-offs in the sense that AdaBoost gives more stable classification and ANN relatively better generalization. Optimization of feature selection, data balancing, or use of ensemble methods in deep learning models could improve future research towards breast cancer classification.

The graphical user interface of the system is shown in Fig.4.

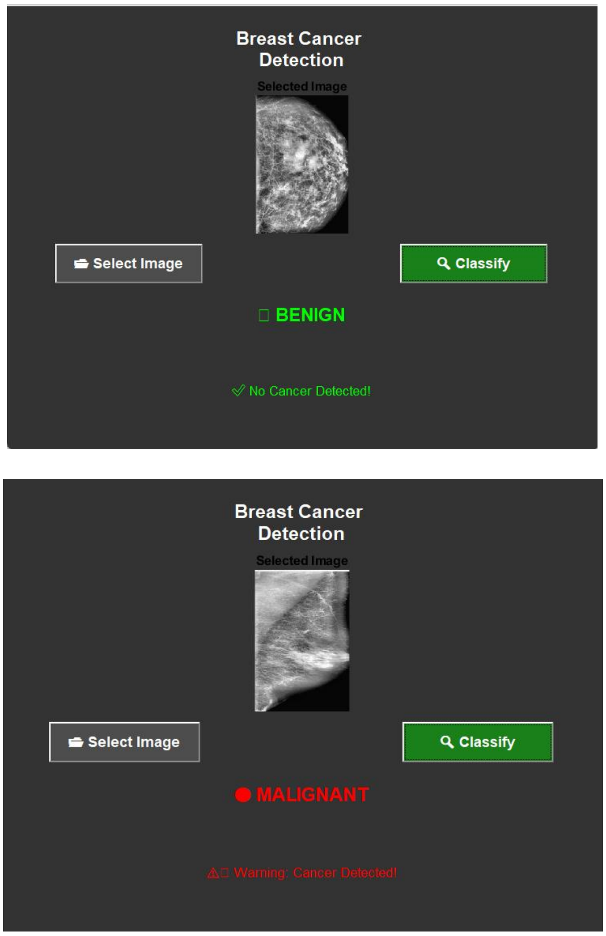

Fig. 4. Result of breast cancer recognition

Fig. 4 illustrates the result of breast cancer recognition system, which clearly indicates the results of classifying breast cancer images to normal, benign, and malignant classes using the above-discussed machine learning models (ANN and AdaBoost). This plot can represent the classification result graphically according to the true labels and predicted labels of the test set, perhaps together, or as a performance metric plot of confusion matrices, accuracy, precision, recall, or F1-score. It helps in giving a good clear perspective of the potential of the model to classify and distinguish among the various types of breast tissue abnormalities, pointing areas of correctness and possible misclassifications. From visualization of the result, Figure 4 aids in increasing the comprehensibility of the model's performance and gives details regarding how good it would be for use in real-life clinical practice.

V. Conclusion and Future Scope

The research deploys an Artificial Neural Network (ANN) and AdaBoost-based methodology for detection of breast cancer based on the DICOM images from the CBIS-DDSM dataset. Implementations of both these machine learning algorithms have reflected their capabilities towards classification of the breast tissue in normal, benign, and malignant types. Both AdaBoost resulted in higher accuracy and F1-score, though ANN resulted slightly better in absolute accuracy. Nonetheless, the poor recall value of ANN signals the necessity for enhancements in identifying malignant cases correctly, vital in medical diagnosis. The system, aided by a Graphical User Interface (GUI), facilitates smooth interaction for radiologists and medical practitioners to effectively scrutinize images of breast cancer and make informed decisions. Notwithstanding the encouraging outcomes, both models' performance indicates that there are further improvements to be made in order to enhance classification reliability and minimize false negatives to achieve enhanced clinical usability.

Future research can involve improving the accuracy of classification by employing improved deep learning methods such as Convolutional Neural Networks (CNN), Transformers, or ensemble techniques merging ANN with ensemble-based techniques. Also, use of explainable AI (XAI) techniques will improve interpretability of the model, and the model will be more transparent and trustworthy to physicians. Extended to incorporate multi-modal imaging data, i.e., MRI and ultrasound, can also improve the system's generalizability and robustness. Cloud-based systems or mobile app-based systems for real-time deployment can improve access for remote and resource-limited healthcare environments. Incorporation with automated decision support systems for risk prediction and treatment planning via AI prediction can enable early diagnosis and individualization of treatment planning. These technologies will enable the development of more scalable, efficient, and clinically viable breast cancer detection platforms for large-scale use in the healthcare sector.

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