Deep Learning based Breast Cancer Diagnostic System using Medical Images

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Abstract

A common and lethal kind of cancer, breast cancer, affects women worldwide. In the year 2020, around 2.26 million breast cancer cases were reported worldwide. In 2020, breast cancer will become the most common cancer globally with a projected 11.7% of all cancer cases or 2.3 million new cases. It is ranked as 7th cancer cause globally with 685,000 deaths. Diagnosis plays an essential role in cancer, since early diagnosis of the condition can help in better planning for treatment and prevent further complications. This research develops an integrated system to aid oncologists and clinicians in the diagnosis, confirmation and follow-up analysis for breast cancer using principles of artificial intelligence and medical imaging modalities. The decision making is made by deep learning models trained on thousands of images of several medical imaging modalities. On the whole, the proposed system can help the clinicians in their medical decisions and provide better service for patients with breast cancer.

Keywords: breast cancer, diagnosis, deep learning, radiology, image processing, medical imaging.

DOI: https://doi.org/10.36548/jiip.2023.2.003
Received: 04.04.2023, received in revised form: 04.05.2023, accepted: 19.05.2023, published: 29.05.2023

1. Introduction

The condition in which the breast cells proliferate uncontrollably is referred to as breast cancer. In most of the cases, the origin of cancer is the ducts or lobules. The spread of breast cancer outside of the breast is through blood arteries and lymphatic systems. In 2020, more than half of breast cancer diagnosis and two-thirds of fatalities occurred in less developed countries [1]. According to World Health Organization, caner is 3rd or 4th death cause for ages more than 70, as of in 23 countries [2].

To develop effective treatment methods for the condition, breast cancer must be diagnosed as early and accurately as possible [3]. Breast imaging is a specialization of diagnostic radiology that deals with imaging breasts for medical purposes such as screening or diagnosis. Following a physical examination, the doctor may advise a specific breast imaging modality to determine whether breast cancer is present or not [4]. Digital Infrared Thermal Imaging (DITI), Ultrasound, Mammography, Digital Breast Tomosynthesis, MRI and histopathology are the standard imaging modalities used for the diagnosis of breast cancer, worldwide.

DITI is a non-intrusive, non-contact technique that can pick up the greater temperature gradients caused by the tumor cells [5]. The most common reason for performing a breast ultrasound is to ascertain whether an abnormality found during a mammogram or physical examination of the breast is likely to be a solid tumor or a fluid-filled cyst. Mammography which is a low-energy X-ray imaging technique is used to diagnose breast cancer. It holds the breast stationary while lowering the quantity of dispersed radiation and reducing the required radiation dose [6].

Breast MRI, a mammography substitute, has significantly improved breast cancer diagnosis. Breast density has no impact on the ability of MRI to detect breast cancer, which is more sensitive than mammography [7]. Dynamic Contrast-Enhanced (DCE)-MRI is a technique that uses a power injector to gather data prior to, during, and following the intravenous delivery of a contrast agent to obtain functional data. The DCE-MRI technology is based on the quick diffusion of a low-molecular-mass contrast agent via the openings seen in these abnormal micro-vessels [8]. Histopathology is the examination of a biopsy sample under a microscope by a pathologist utilizing invasive or less invasive techniques to look at the growth of cancer, tumors, etc. [9].

With artificial intelligence, healthcare providers can create quick and precise diagnostic tools like Computer-Aided Diagnosis (CAD). Medical datasets are used to train CAD algorithms, which are based on image processing, machine learning, or deep learning. AI-based techniques, such as image processing, contrast enhancement, clustering, and contour identification, can automate the diagnosis of breast cancer. Deep learning is more effective than machine learning because the feature extraction is carried out automatically.

Hiroki et al. [10], using Deep Learning created a computer-aided breast cancer diagnosis system using ultrasonography. The VGG19 and the ResNet152 convolutional neural network ensemble were trained using ultrasound data from a clinical trial run. Singh et al. [11] developed an easy-to-use technique for detecting breast cancer in mammography images. The tumor region is removed using thresholding, and the image is smoothed using an average filter. Then, tumors in the area are discovered using the maximum mean and least variance. By using morphological closing and image gradient approaches, the tumor's border is determined.

Hameed et al [12] integrated deep learning models for breast cancer diagnosis utilizing histopathology images using ensemble approaches. The ensemble method was used to integrate four models: fully trained and fine-tuned VGG16 and VGG19. Liu et al [13] developed a weakly supervised ResNet-101 for breast cancer classification using MRI images. To determine if the lesion is benign or malignant, the ResNet model was trained with the Adam optimizer and a SoftMax function. Ravichandran et al. [14] investigated how to predict the outcome of neoadjuvant chemotherapy using DCE-MRI images. Using DCE-MRI images from before treatment, a CNN was created to forecast a pathological full response. The CNN was trained over 30 epochs and consisted of 6 convolutional blocks. Mishra et al. [15] created a CNN for the categorization of breast cancer using thermography images. Before providing the region of interest as input to the CNN, the thermal pictures underwent pre-processing.

Based on the above literature, it is evident that deep learning algorithms are providing significant results in automation of breast cancer diagnosis. The proposed effort aims to create a deep learning-based diagnostic system to assist oncologists and clinicians in the detection, management, and follow-up analysis of breast cancer.

2. Materials and Methods

A. Overview of the System

The proposed system comprises of three sections, namely, diagnosis, confirmation and follow-up analysis. Each module comprises of deep learning models trained on different imaging modalities used for diagnosis of breast cancer. Figure 1 represents the proposed system in a diagrammatic fashion.

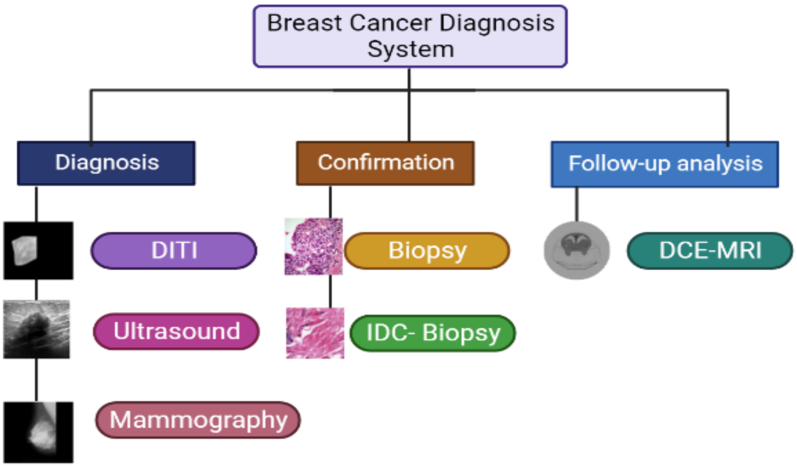

Figure 1. Diagrammatic Representation of the Proposed Diagnostic System for Breast Cancer Identification

B. Material Description

Open-source imaging databases are used for training the deep learning models. Table 1 depicts the datasets used for the image-based diagnosis.

Table 1. Overview of the image-based datasets used in the diagnostic system

Sl. No.	Name/Imaging Modality	No. of samples	Output classes
1	Ultrasound	655	Benign and Malignant
2	DMR-IR (thermal)	940	Benign and Malignant
3	MIAS-mammography	325	Benign and Malignant
4	QIN- DCE MRI	20,000	(Neoadjuvant chemotherapy)

			NAC +ve and NAC -ve
5	BreakHis-histopathology	9,109	Benign and Malignant
6	Invasive Ductal Carcinoma (IDC)-Histopathology	2,77,524	IDC -ve and IDC +ve

C. Overall Workflow

There are four different phases in the development of the proposed diagnostic system. The first is the curation of training datasets. The second phase is the pre-processing of the imaging datasets, the third phase is the development of diagnostic algorithms, and the last phase is the integration of all modules into the proposed system.

D. Diagnosis Module

The diagnosis module of the proposed system comprises of deep learning models related to initial level diagnosis of breast cancer. This includes the Digital Thermal Infrared Imaging, Ultrasound and Digital Mammography.

E. Confirmation Module

The confirmation module of the proposed system comprises of deep learning models related to confirmation of breast cancer. This includes histological examination of the biopsy sample for both invasive ductal carcinoma and low-grade breast cancer confirmation.

F. Followup Analysis Module

The follow up analysis module of the proposed system comprises of deep learning models related to analysis of the current images with previous images to predict the response of treatment. In order to construct a deep learning model that can predict how chemotherapy will affect a patient, the QIN database, which contains DCE-MRI images, was used. NAC +ve means that the treatment is going properly whereas NAC -ve means that the treatment is not going properly.

G. Classification Architecture

Deep learning neural networks are the backbone algorithm used in the diagnostic toolkit. The deep learning algorithm utilized for imaging data is called Convolutional Neural Networks (CNN). The CNN architecture comprises of a pre-trained backbone which is then appended to additional layers. MobileNetV2, EfficientNetB3, InceptionV3, EfficientNetB4 and Xception were the various backbones used for the CNNs for imaging modalities. In addition to the standard architecture, some layers were added as enhancement. In order to improve convergence, the backbone is added to a gaussian noise layer with a standard deviation of 0.25. This is then followed by a dense layer with 256 neurons, with relu activation, dropout of 0.25, a layer of batch normalization and ending with a sigmoid neuron, since all tasks are binary classification. The dropout, gaussian noise and batch normalization layers are generalization layers that prevent overfitting of the model during training process. The deep learning models employed in the suggested system's generalized architecture diagram are shown in Figure 2.

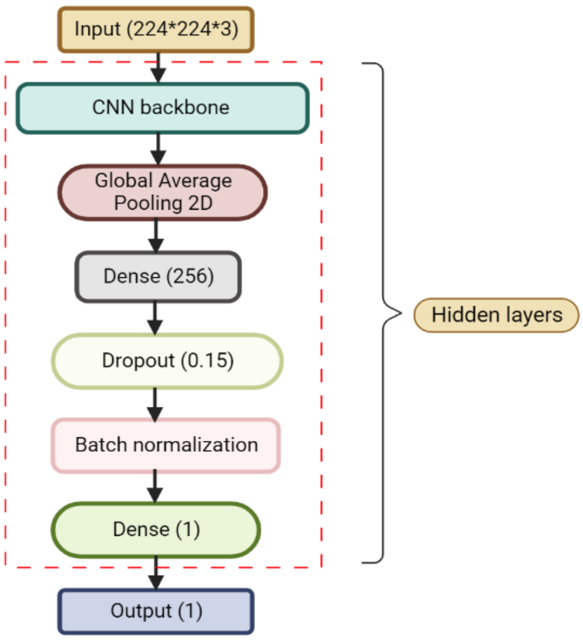

Figure 2. Representation of the proposed system's deep learning model's architectural layout

The pre-trained CNN backbone was frozen and not taking part in the training. For training the models, the binary cross entropy loss function and Adam optimizer were employed. All datasets have a batch size of 8 set. The initial training of the models involved 30 epochs of steps that varied according to the training set of data. The best trained model was obtained using callbacks like Early stopping and Model Checkpoint.

H. Evaluation Metrics

Loss, AUC, precision, accuracy, and recall are some of the metrics for classification that are frequently employed. The False Positives (FP), True Positives (TP), False Negatives (FN), and False Positives (FP) are the sources for these measures (FP).

The proportion of accurate predictions to all predictions is known as accuracy. It is symbolized by (1**).**

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \qquad \mathbf{1}$$

The ratio of accurately predicted negatives to all predicted negatives is known as precision (sometimes termed specificity). It is portrayed by (2).

$$Precision = \frac{TN}{TN+FP} \qquad \mathbf{2}$$

Recall, which is often referred to as sensitivity, is calculated as the proportion of accurately predicted positives to all positive predictions. This is represented by (3)**.**

$$Recall = \frac{TP}{TP+FN} \qquad \mathbf{3}$$

AUC stands for the area under the curve. In this case, the curve is the P-R curve (Precision-Recall). This curve results from plotting the true positive rate and false positive rate.

I. User Interface Development

One of the important components of a diagnostic system is the user-interface. The user interface is used to get the inputs from the user and also to display the output condition to them. A website is developed as a software for the proposed diagnostic system, due to its universal availability. The website is built using streamlit, a python-based web development framework. The frontend design of the proposed system comprises of the above discussed three sections, namely, diagnosis, confirmation and follow-up analysis. The neural network models that are trained on the above-mentioned public datasets are used for predictions. In the frontend, the image input is obtained from the user and is sent to the trained model that is in the backend. Once the model has predicted the output, it is displayed to the user on their command.

3. Results

The training for the models on the datasets were done using google collab. The datasets were divided into training and testing sets in an 80:20 ratio. The validation outcomes for the models developed using the datasets for medical imaging are shown in Table 2.

Table 2. Validation results for the models trained on image datasets

Modality	**Backbone**	**V. acc.**	**V. loss**	**V. prc.**	**V. recall**	**V. AUC**
DITI	MobilenetV2	95.24	0.2266	92.9	94.41	0.9856
Ultrasound	EfficientNetB2	97.24	0.08	91.6	96.6	0.9995
DM	InceptionV3	95.86	0.1469	96.52	94.49	0.9889
DCE-MRI	MobileNet	96.82	0.1668	97.23	93.99	0.9899
Biopsy	EfficientNetB3	95.57	0.1881	94.48	93.79	0.9782
IDC- Biopsy	Xception	95.48	0.2120	88.45	92.91	0.9761

The figures below represent the output screens of the developed website for all the imaging modalities present in the diagnosis, confirmation, and follow-up section of the proposed system.

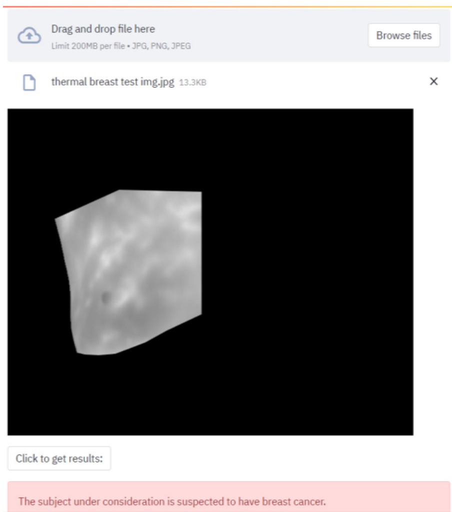

Figure 3. Output screen for thermal imaging-based diagnosis

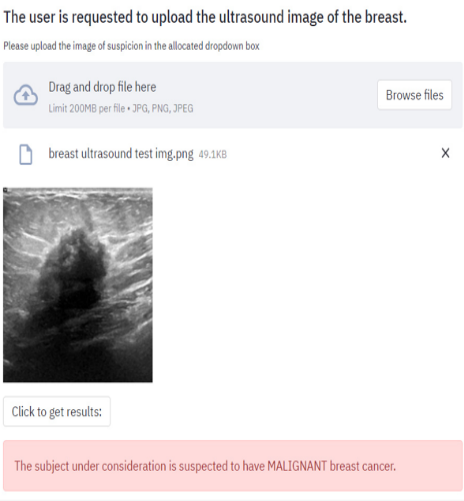

Figure 4. Output screen for ultrasound imaging-based diagnosis

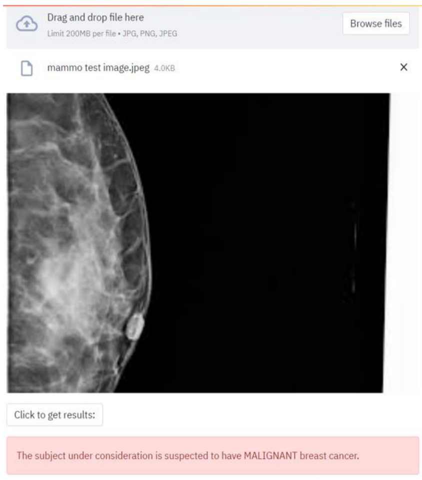

Figure 5. Output screen for mammography-based diagnosis

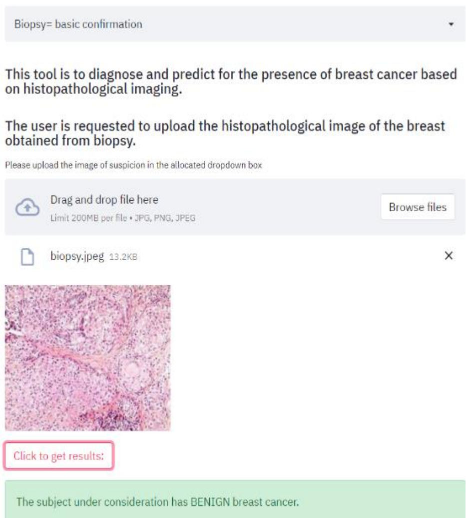

Figure 6. Output screen for histopathology-based breast cancer confirmation

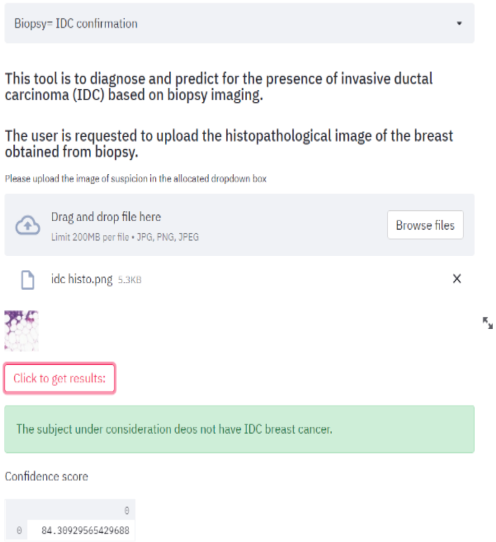

Figure 7. Output screen for Invasive Ductal Carcinoma confirmation using histopathology

Figure 8. Output screen for follow-up analysis using DCE-MRI images

4. Discussion

Hiroki et al., worked on breast cancer diagnosis using ultrasound images. The trained neural network produced an AUC value of 0.951, 90.9% sensitivity, and 87% specificity. However, the precision, recall and AUC of this proposed ultrasound model, are 96.6, 91.6 and 0.995 respectively which are higher than that of the work.

Hameed et al., worked on developing ensemble models for histopathological analysis of breast cancer. 95.2% accuracy, 95.29% F1 score, and 97.73% sensitivity were produced by the ensemble. However, this proposed model produced 95.57% accuracy and 93.97% sensitivity which are in comparison to that of the work.

Ravichandran et al., worked on the prediction of chemotherapy response using DCE-MRI images. The deep learning model produced AUC of 0.77 and an accuracy of 82%. However, this proposed model produced 96.82% accuracy and AUC of 0.9899 which surpassed the work.

Mishra et al., worked on developing CNN for breast cancer classification using The CNN produced 95.8% accuracy after training on 680 thermograms. However, this proposed model produced 95.24% accuracy which is comparable to that of the work.

Furthermore, all the literature focused on the development of deep learning models for a particular imaging modality. This work focusses on integration of all imaging modalities and diagnostic features into a diagnostic system to assist oncologists/radiologists and improve the diagnostic decisions taken by them.

However, this work has some limitations. The first one is that the models are trained on PNG/JPG/JPEG images. Also, the slice data were taken in cases of DCE-MRI, hence the entire work is being done in 2D data only. Another limitation is that the models have been trained on data obtained from different patients. It would be better if the models are trained on imaging modality data obtained from a single patient. The model present in follow-up analysis module predicts the response using a single image only, and does not compare the current image with that of the previous image.

5. Conclusion

This research has developed deep learning models for image-based diagnosis of breast cancer with satisfactory results. Moreover, a website has been developed with an interface, integrating all proposed modules into a single system. The developed system can be of significant use for oncologists and radiologists in strengthening their clinical decisions. Further works can involve the incorporation of survey forms, feature based datasets for breast cancer diagnosis. Image segmentation and comparison algorithms can be included in the follow-up analysis module for better functionality.

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