



Investigation of Convolutional Neural Networks for the Identification of Breast Cancer

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KEYWORDS Breast Cancer Detection, Convolutional Neural Networks (CNNs), Machine Learning Ultrasound Imaging, Automated Diagnosis	ABSTRACT: Early diagnosis is crucial for the identification of breast cancer, and this research investigates the use of convolutional neural networks (CNNs) to analyze ultrasound pictures and distinguish between benign, malignant, and normal breast tissue. The process starts with ultrasound image capture, then moves on to segmentation to identify areas of interest and image enhancing methods to increase quality. Using a pre-trained ResNet101 architecture, the Convolutional Neural Network (CNN) model is optimized for feature extraction and classification. 1578 tagged ultrasound pictures classified into benign, malignant, and normal classifications make up the Breast Ultrasound Pictures Dataset (BUSI), which is used to train and assess the model. The model demonstrated its capacity to reliably categorize breast tissue types with a validation accuracy of 99%, indicating exceptional performance. Precision, recall, F1-score, and confusion matrix are important assessment metrics that demonstrate the model's ability to distinguish between benign, malignant, and normal instances with little misclassification. The findings also show that the model can generalize well to fresh data, which qualifies it for use in clinical settings.
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1. Introduction

Cancer is a set of diseases that induce abnormal cell proliferation and may spread to other parts of the body, making it a major medical concern and the top cause of death worldwide. Breast cancer is the most often diagnosed cancer in women and a leading cause of morbidity and death in women, and it is fast becoming a substantial source of morbidity and mortality in developing countries. Breast cancer cells expand uncontrollably, and the cells lose shape as the disease progresses [1].

Breast cancer is a worldwide health issue that has a substantial impact on individuals. It has a significant effect on the global rates of morbidity and mortality. In 2020, breast cancer led to the fatalities of 685,000 individuals worldwide, as 2.3 million women received the dreadful diagnosis. This is one of the most prevalent types of cancer, primarily affecting women and shedding a severe light on the healthcare system. The significance

of early detection and precise categorization of breast cancer in this intricate environment cannot be emphasized, as they are essential for the development of effective treatment programs and, in the end, the enhancement of patient outcomes [2].

There are two categories into which breast cancer is classified: normal and aberrant. These categories are further divided into benign (non-cancerous) as well as malignant (cancerous) categories. Benign tumors are an unnatural growth that rarely results in a patient's mortality. However, certain types of benign tumors can also increase the likelihood of developing cancer. Conversely, malignant tumors are more severe and their timely diagnosis is essential for successful treatment. The treatment of this condition is contingent upon the cancer's stage. This may involve surgery, radiation, chemotherapy, and hormone therapy [3]. Early detection of breast cancer is essential for improving survival rates, as it was one of the most prevalent malignancies world-



wide. Timely treatment is facilitated by early detection, which can substantially enhance the likelihood of recovery. Traditional diagnostic methods, including biopsies and mammography, are frequently implemented; however, they possess constraints. Especially in the field of medical imaging, artificial intelligence (AI) has demonstrated significant potential in recent years to enhance medical diagnosis. Convolutional Neural Networks (CNNs) are a deep learning algorithm that is one of the most effective AI techniques. Image analysis is particularly well-suited to CNNs, as they can autonomously acquire critical features from the images, thereby reducing the necessity-ty for manual labour and enhancing the precision of the results. CNNs can be trained to recognize patterns in mammography or other medical images that suggest the presence of malignant cells in the context of breast cancer detection [4]. In recent years, machine learning techniques have demonstrated potential as instruments for enhancing the accuracy and efficacy of breast cancer diagnosis as well as detection. Convolutional neural networks have garnered attention as a result of their potential applications in the processing of ultrasound imaging [5].

This paper explores how CNNs can be used for automatic breast cancer detection. It aims to show how CNNs can help doctors make more accurate diagnoses by quickly and reliably identifying signs of cancer in medical images. By using CNNs, we hope to improve the overall accuracy of breast cancer detection, reduce human error, and make the process faster and more accessible for patients, especially in areas where there is a shortage of skilled medical professionals [6].

1.1 Breast Cancer Detection

Breast cancer is one of the most common tumors worldwide, and early identification is critical to increasing survival rates. Traditional diagnostic procedures, such as mammography and biopsy, are limited in their accuracy and accessibility. Convolutional Neural Networks, a deep learning technology, have showed great potential in overcoming these restrictions by automating the processing of medical pictures. CNNs can effectively recognize patterns in medical imagery, such as ultrasound scans, and help identify anomalies that indicate breast cancer[7]. This study investigates how CNNs may be used to diagnose breast cancer

accurately and automatically using ultrasound pictures, with the goal of improving diagnostic accuracy. To diagnose the breast cancer various medical imaging methodologies are processed like Ultrasound, Magnetic resonance imaging, X-ray mammography are used for detecting the early stage breast cancer[8].

1.2 Application of CNNs in Breast Cancer Detection

Convolutional Neural Networks have become an effective tool for breast cancer detection, especially when using ultrasound images. Ultrasound imaging is widely used in the diagnosis of breast cancer because it gives detailed images of breast tissue without using radiation. However, the interpretation of ultrasound images requires considerable expertise, and mistakes can occur. This is where CNNs come into play. CNNs are engineered to automatically learn features from ultrasound images so that they could recognize patterns associated with malignancies, such as tumors or abnormalities in tissue structure[9]. Large datasets of labeled ultrasound images allow CNN models to learn the distinction between benign and malignant tumors with great accuracy. The advantage of applying CNNs for ultrasound image analysis is the fact that it processes images faster than the human radiologists, resulting in quicker outputs for the patients. Studies have found that CNN-based models could help improve the accuracy in diagnostics by reducing human errors and inconsistencies in the interpretation of images. These models learn to identify features not necessarily visible to the human eye in ultrasound images that would otherwise be missed, allowing for early detection. Secondly, CNNs are scalable and can be used easily in various healthcare settings since there is a possibility that most of these settings would lack skilled professionals[10].

2. Literature Review

2.1 Overview of Breast Cancer Detection

Breast cancer is a significant cause of mortality among women worldwide, particularly in developing countries, where early detection and treatment are essential for successful outcomes. Arslan Khalidet al. (2023) emphasize the advancements in artificial intelligence and machine learning (ML) techniques, which have enabled the development of accurate models for diagnosing and classifying breast cancer. This study proposes an



efficient deep learning model that leverages mammograms of varying densities to classify breast cancer subtypes, including invasive ductal carcinoma (IDC) and ductal carcinoma in situ (DCIS). Using a dataset of 3002 mammogram images, the research compares six ML models, highlighting the Random Forest's superior accuracy and versatility. This study underscores AI's transformative potential in breast cancer detection and treatment[11]. **Nehmat Houssami et.al (2012)**, reviewed evidence on DBT accuracy, noting consistent findings despite limited studies. Two-view DBT showed equal or superior accuracy to standard DM, while its integration with DM improved cancer detection and reduced false positives. Preliminary screening trials suggest combining DBT with DM enhances breast cancer detection, though further evaluation is needed for logistical and cost implications. The review emphasizes the potential of synthetic 2D+3D mammography to address radiation concerns and highlights the need for large-scale trials to assess DBT's effectiveness in population screening, ultimately guiding clinicians and researchers in advancing breast imaging[12]. Breast cancer, the most common malignancy in women, often lacks early symptoms, leading to late detection and more challenging treatment. **Basem S Abunasser et al. (2023)** emphasize the need for improved screening processes to enhance early detection rates and reduce the population not covered by screening programs. Proposed improvements include efficient identification of women requiring preventive exams based on risk factors, integrating thermal imaging in the pre-screening phase, and leveraging software to assist in mammographic tumor detection. Their study highlights the role of medical information systems like MEDIS.NET in creating screening lists and utilizing computer-aided detection for mammography and thermography. These advancements promise to optimize breast cancer screening and support timely, accurate diagnosis[5]. **Syed Jamal Safdar Gardezi et.al (2019)**, highlighted how advancements in ML, particularly deep learning (DL), have significantly improved the diagnostic capabilities of computer-aided diagnosis (CAD) systems. This review examines traditional ML and DL methods in breast cancer diagnosis, focusing on recent studies using multiview mammogram datasets. Traditional ML techniques show limited applicability to specific datasets or breast density types, whereas DL

methods demonstrate remarkable potential for clinical implementation. Despite challenges like data scarcity and computational costs, these issues have been mitigated through data augmentation and advanced DL algorithms, offering improved diagnostic capabilities for breast cancer[13].

A comprehensive examination of the classification of breast cancer through the use of histology images and CNNs is presented by **Bardou et al. (2018)**. Their research delves into the intricate characteristics of histopathology specimens, utilizing the built-in capabilities of CNNs to identify patterns that are both significant and indicative of malignant tumors. By meticulously training and optimizing their neural network design, the researchers demonstrate remarkable success in the precise classification of breast cancer subtypes. This discovery offers a glimpse into the potential of deep learning approaches to revolutionize histopathology diagnosis[14]. As a related effort, **Chaudhari (2018)** In order to ascertain the optimal architecture for enhanced diagnostic performance, this study compares CNN models for breast cancer diagnosis. By conducting a meticulous evaluation of various CNN configurations, the author elucidates the benefits and drawbacks of each model, providing valuable insights for academicians and professionals who strive to implement deep learning techniques in medical settings. Chaudhari underscores the importance of optimizing performance and reliability by customizing deep learning frameworks to specific diagnostic tasks. This is achieved by testing multiple CNN architectures against pre-established diagnostic criteria[15]. **Ms. Sharon et.al (2024)**, Utilizing Django, a web application was created to facilitate the management and analysis of breast cancer histopathological images. The application employs a CNN (Convolutional Neural Network) model and histogram normalization to accurately classify benign and malignant lesions. In order to accommodate the CNN input, histopathological images endure pre-processing, which includes resizing and normalization. By fine-tuning pre-trained models, transfer learning improves prediction accuracy. The system generates downloadable reports, classifies images, and provides secure access. Future enhancements may involve the incorporation of sophisticated search algorithms, broader medical image support, as well as enhanced machine learning[16].

**Table 1.** Related work on breast cancer classification

Author(s)	Model(s)	Year	Results
Gour et al. [17]	ResHist is a 152-layer CNN that is based on residual learning.	2020	Without data augmentation, an F1-score of 90.49% and an accuracy of 84.34% were achieved for the classification of breast cancer histopathological images. The model obtained an F1-score of 93.45% and an accuracy of 92.52% through data augmentation.
Gupta and Chawla [18]	AlexNet, VGG16, VGG19, GoogleNet, Inception-v3, ResNet50, ResNet152	2019	The breast cancer classification obtained the maximum accuracy of 93.27%.
Dabeer et al. [19]	CNN	2019	Achieved an impressive prediction accuracy of up to 99.86% in the automated detection of breast cancer.
Kassani et al. [20]	CNN	2019	For the BreakHis, ICIAR, PatchCamelyon, and Biomiang datasets, the ensemble method achieved remarkable accuracies of 98.13%, 95.00%, 94.64%, and 93.10%, respectively.
Adeshina et al. [21]	DCNN	2018	When assessed on the BreakHis dataset, achieved an outstanding internal classification accuracy of 91.5%.
Han et al. [22]	Multi-classification of histopathological images	2017	Obtained an average accuracy of 93.24% in the multi-classification of breast cancer from histopathological images.

2.2 Machine Learning Approaches in Breast Cancer Detection

Despite the fact that machine learning has successfully addressed highly intricate medical issues, there are still gaps in the early detection of cancer. Consequently, data scientists are endeavoring to create novel research methodologies that are both straightforward to implement and capable of generating highly accurate results for the early detection of cancer. In 2019, **Kadam et al.**, Feature Ensemble Learning was employed to demonstrate a method for Breast Cancer Classification (BCC). Stacked Sparse Autoencoder and Softmax Regression were created to differentiate between benign and malignant cells. They achieved 98.6% accuracy for the Wisconsin Breast Cancer Dataset (BCD)[23].

The work of predicting breast cancer using machine learning techniques is on-going. Research has demonstrated that numerous machine learning techniques, including KNN, NB, DT, SVM, and LR, have been devised for the purpose of diagnosing breast cancer. **Kabiraj et al.** proposed an Random Forest as well as XGBoost system for predicting breast cancer risk, and achieved 74.73% and 73.63%, respectively[24]. **Liu et al.** has developed EXSA, a gradient boosting algorithm also devised to forecast the progression of

breast cancer, thereby increasing the survival rate[25]. **Nanglia et al.** has described the ensemble model using KNN, SVM, and DT with 78% [26]. **Islam et al.** has applied Wisconsin dataset was subjected to a variety of supervised learning techniques, with the ANN achieving the highest accuracy at 98.57%[27]. **Amrane et al.** proposed breast cancer classification using KNN and NB using cross validation with accuracy 97.51% and 96.17% respectively [28]. **Dhahri et al.** proposed method that used genetic programming techniques for selection of best features and parameter for ML classifier[29]. **Qinghua Huang et al.** demonstrated that the maximum accuracy was obtained by SVM with a quadratic kernel function. There are both linear and nonlinear methods for data reduction, and the selection of one will be contingent upon the correlations between the dataset's features. On the other hand, the Euclidean distance between any two data points that are provided will be calculated by the overwhelming majority of ML algorithms. It is imperative to reduce the magnitude of all characteristics to the same level. Scaling is a technique that can be employed to achieve this objective [30]. **Ara et al.** employed SVM and RF to achieve 96.5% accuracy in the classification of breast cancer data into benign and malignant by performing feature selection and applying ML[31]. **Jabbar et al.** An Ensemble model



has been developed in this study to classify breast cancer data. This model is a combination of Bayesian networks as well as Radial Basis Function, which results in accurate classifications. The optimal accuracy of the model is 97.42%[32]. **varsha et al.** employed a variety of machine learning techniques as well as also combined ensemble learning to predict breast cancer, resulting in an accuracy of 98.14%[8]. **V. Chaurasia and T. Pal** Utilized their model to identify the most effective machine learning algorithms for breast cancer prediction. In their research, they implemented SVM, Naïve Bayes, RBF NN, DT, as well as rudimentary CART. The model that was implemented successfully obtained the highest AUC of 96.84 % on SVM in the Wisconsin Breast Cancer (original) datasets[33].

2.3 Convolutional neural network for breast cancer diagnosis and classification

The CNN architecture has been implemented in the diagnosis and classification of breast cancer due to its capacity to derive features that can be utilized to improve the visibility of malignancy in breast masses. Therefore, facilitating the early detection of breast cancer to enable its treatment at a nascent stage, prior to its further dissemination. **Wang et al.** Developed a convolution neural network that is based on Max-pooling to identify mitosis in breast images. The investigation was conducted on a limited dataset. They employed a CNN with a sequence of convolution and pooling layers to analyze a data set of 50 images. A rectangular filter was employed to accomplish 2D convolution. This network was trained to classify each pixel in the image and pixelate it. The image is classified into either mitosis (mitotic nuclei) or non-mitosis (non-mitotic nuclei) by an entirely connected layer[34]. **Rakhlin et al** employed data augmentation in a deep neural network to classify breast masses in order to diagnose breast cancer. The implementation of this trial was based on haematological and eosin (H&E) stained images. The images were 2048*1536 pixels in size. The image was to be categorized into four categories: normal, benign, in situ carcinoma, and invasive carcinoma. a deep convolution feature representation network is implemented to generate a more accurate output prediction from a substantial image dataset. After that, data preprocessing and augmentation are implemented. In order to facilitate enhanced quantitative analysis of microscopic images,

50 random color augmentations are implemented on each image. The image is subsequently cropped and downscaled following staining normalization. In order to integrate images of varying sizes, the completely connected layer is eliminated from the CNN. Additionally, feature extraction is implemented. Ten gradient boosting models are trained per repeat. The predicted class is subsequently extracted by the maximal probability score, after the average of predictions over all augmentations as well as models is computed. This is the 10-fold cross validation procedure. The network achieves an accuracy of $93.8 \pm 2.3\%$ for the classification of two classes (non-carcinomas and carcinomas). The accuracy was determined to be 87.2 ± 2.6 for a four-class system (normal, benign, in situ carcinoma, and invasive carcinoma)[35].

Ciresan et al. recommended the use of a deep neural network to detect mitosis in breast cancer. The objective is to categorize each pixel into two categories: mitosis and non-mitosis. A feed forward DNN is implemented. The input consists of 50 pixelated images. A square image window is employed in each pixel, with RGB values that predict the pixel's class. The DNN is constructed using a sequence of convolution as well as max pooling layers. The convolution layer is equipped with a rectangular filter as well as is responsible for 2D convolution. The design also includes fully connected layers that combine the output into a feature vector. This vector is subsequently employed to extract features from the input in order to classify it. The predicted output was subsequently categorized as either mitosis or non-mitosis[36]. **Ragab et al.** AlexNet, a deep convolution neural network, was employed to categorize breast mammography images into two groups. This network consisted of 5 convolution layers, 3 pooling layers, and 2 fully connected layers. In order to achieve high accuracy, a large input data set must be utilized to train a NN. However, due to the limited availability of datasets, data augmentation is employed to increase the size of the input. The rotation technique of augmentation was implemented in this instance. Initially, the threshold technique was employed to convert the input image to greyscale, and subsequently to binary. Then, the largest binary object is designated as tumorous, and the number of pixels is enumerated. Indicated by 1, the pixels with the maximum area are tumorous, while the remaining pixels are nontumorous and indicated by 0. The ultimate



output image is obtained by multiplying the input image and the binary image. The accuracy of this algorithm is 71.01%, and the accuracy was increased to 87.2% by utilizing SVM[37]. **Huynhet et al.** Additionally, they developed a CNN that employs the AlexNet architecture. AlexNet eliminates the necessity for segmentation. The 5-fold-cross validation method was implemented to extract features directly from the input image, and 219 breast lesions were considered. The gentle voting method was also selected for a more straightforward approach. Despite the fact that a small dataset of images is utilized, transfer learning methods are implemented to enhance efficiency and accuracy. The breast masses were classified into both benign and malignant cases using a CNN that included a convolutional layer, a pooling layer, and fully connected layers. Consequently, the investigation determined that the usage of CNN with AlexNet can simplify the computer-based diagnosis of breast masses[38]. **Mehdy et al.** A comparable comparative study was conducted to diagnose as well as classify breast cancer using a variety of Artificial Neural Networks. Mammogram, ultrasound, thermal, and MRI imaging are the four medical applications of ANN that are thoroughly analysed using a variety of methodologies, including SOM, CNN, and MLP. These diagnostic methods for breast cancer are reviewed and

summarized. By examining this table, it is evident that CNN outperforms MLP. CNN has a higher level of accuracy in diagnosing and classifying breast malignancy than MLP, as evidenced by the tabulated accuracy[39]. **Tello-Mijares et al.** compared performance of CNN was evaluated in comparison to that of the Bayes network (BN), multilayer perception (MLP), and tree random forest (TRF). The feature extraction process is performed stage-by-stage for each thermographic breast image from the dataset of 63 thermographic images, of which 35 are normal and 28 are abnormal. The images are in RGB color format and in JPEG image format, with a size of 680 480 3. The process includes image pre-processing, RGB and grey input, image denoising, and a curvature function for initial elliptical points for the GVF and classification. RGB images with dimensions of 277*277*3 are implemented in CNN. CNN's precision was 100%, surpassing that of TRF and BN, while MLP's accuracy was 88.88%. Consequently, CNN demonstrated superiority over the other ANN algorithms in terms of the accuracy of breast cancer diagnosis and classification. Additionally, they asserted that CNN is both efficient and robust when used in conjunction with GVF for the purpose of breast cancer detection[40].

Table 2. Comparison of accuracy of breast cancer detection from researches that used CNN or MLP architecture for breast cancer diagnosis and classification

Reference s	Archite cture	Sample Size	Approach	Accuracy	Specificity and Sensitivity
Dabeer et al.[19]	CNN	7009 images from Break His dataset	7009 images from BreakHis database is used. Images captured are distributed into 4 magnification levels	99.86%	Not specified
Guan and Loew [41]	CNN	2620 images from MIAS and DDSM	Combined 2620 images from MIAS and DDSM databases using CNN with transfer learning and additional layers.	90.5 ± 3.2	Not specified
Tan et al. [42]	BDCNN	322 mammograms from Mini-MIAS (various versions for dataset)	Used 322 mammograms with 2904 parameters. Tested using different versions.	Best accuracy: 82.71%	Sensitivity: 82.68%, Specificity: 62.73%
Iesmantas and Alzbutas et.al [43]	CNN	400 Hematoxylin and Eosin (H&E) stained breast histology microscopy images	Used a CNN with each image labeled into 4 classes: normal tissue, benign lesion, in situ carcinoma, and invasive carcinoma.	Cross-validation accuracy of 87%	Not discussed



			Convolutional Capsule Network used.		
Kathiji et al. [44]	MLP	WBCD, WDBC and WPGC datasets (training: testing ratio: 90:10)	Used WBCD, WDBC, and WPGC datasets. 10-fold cross-validation technique.	WBCD dataset: 98.99%, WDBC dataset: 100%, WPGC dataset: 100%	Sensitivity and specificity for WBCD dataset: 0.9844 and 1. WPGC/WDBC sensitivity and specificity = 1.

3. Methodology

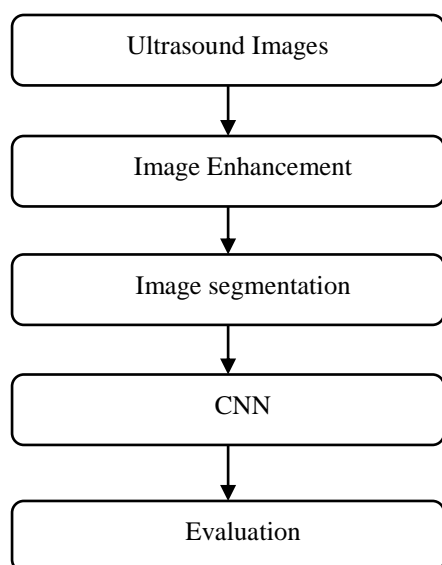


Fig 1. Flowchart

Ultrasound Images: Obtaining ultrasound images, which are the input data, is the first step in the procedure. Because ultrasound imaging is non-invasive and can capture soft tissue features, it is frequently employed in medical diagnosis. The following steps of the process are heavily influenced by the format and quality of these photos.

Images Enhancement: To increase their quality, the ultrasound images are subjected to image enhancement procedures once they are obtained. In order to improve visualization and accuracy in subsequent analysis, this phase seeks to minimize noise, improve contrast, and emphasize significant features. Adaptive Thresholding,

filtering, and histogram equalization are common improvement techniques.

Images Segmentation: Regions of interest (ROIs) are isolated from the images by segmenting them after augmentation. Partitioning the image into relevant pieces, like organs, tissues, or lesions, is known as segmentation. This stage is essential for accurate analysis since it helps concentrate on the particular regions needed for research or diagnosis. Techniques like edge detection, Thresholding, or sophisticated machine learning-based approaches (like U-Net) could be used.

Convolutional Neural Network (CNN): Using a Convolutional Neural Network (CNN), the segmented images are analyzed. One kind of deep learning model created especially for image data is CNN. They use layers of convolution and pooling to automatically extract features from the input photos. In this step, the CNN is trained to identify, categorize, or forecast patterns in the pictures, like the existence of anomalies or disease indicators.

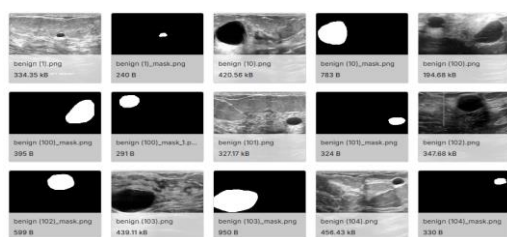
Assessment: The assessment of the model's performance is the last phase. The CNN's performance in processing the ultrasound pictures is evaluated using metrics including accuracy, precision, recall, F1-score, and area under the receiver operating characteristic (ROC) curve. This stage guarantees the created methodology's dependability and efficacy in practical implementations.

3.1 Dataset

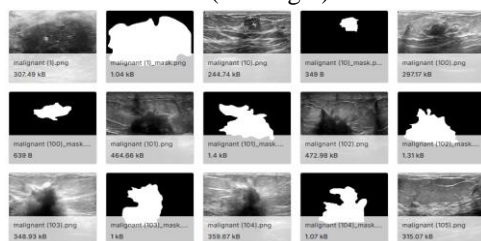
Breast Ultrasound Images Dataset: A comprehensive dataset created to support studies on breast cancer diagnosis is the Breast Ultrasound Images Dataset (BUSI). It includes 1578 ultrasound pictures that have been divided into three files according to their condition:



benign, malignant, and normal. Ultrasound images and matching segmentation masks, which accurately define the regions of interest, are included in each folder. These segmentation masks are essential for teaching machine learning algorithms to accurately detect and categorize anomalies in breast tissue. With a total size of about 245 MB, this dataset is very accessible for applications involving deep learning and machine learning. It is perfect for creating convolutional neural networks (CNNs) and other image analysis models because of its organized classification and incorporation of precise masks. Researchers can concentrate on particular tasks like binary classification (healthy vs. unhealthy) or multi-class classification and segmentation with the aid of the three separate folders.



(A. Benign)



(B. Malignant)

Fig 2. Dataset Image

3.2 Model Training

Convolutional Neural Networks (CNNs) and transfer learning with a pre-trained model such as ResNet101 can be used to identify breast cancer efficiently. ResNet101 has a great ability to extract complicated characteristics from photos because it was trained on huge datasets like ImageNet. First, the ResNet101 model is loaded, and its pre-trained weights are used as a basis. All parameters are set up to compute gradients in order to facilitate fine-tuning, which allows the model to modify its weights during backpropagation and adjust to the dataset. A bespoke layer that corresponds to the number of target classes—such as Normal, Benign, and Malignant—replaces the completely connected layer,

which was initially intended for 1000 classes. This modification guarantees precise picture classification. For effective training, the optimized model is subsequently sent to the proper device (CPU or GPU). The model is refined using methods like the Adam optimizer and cross-entropy loss. In addition to increasing the model's accuracy and capacity to generalize to new data, transfer learning boosts efficiency by lowering training time and processing needs. CNNs can efficiently evaluate medical pictures thanks to this methodology, which also offers a dependable framework for detecting tasks.

3.2.1 CNN

Deep learning models called Convolutional Neural Networks (CNNs) are made to interpret grid-like input, including pictures. Convolutional layers, which apply tiny filters to input images in order to identify local patterns like edges and textures, are the first of several essential parts that make them up. These filters pick up increasingly intricate features as the network gets deeper. To enable the model to learn more intricate patterns, non-linearity is introduced after each convolution using an activation function, usually ReLU. In order to simplify computation and increase the model's resilience to slight translations or distortions, pooling layers are utilized to shrink the spatial dimensions of the feature maps. The learned features are then flattened and utilized to carry out the final classification after the feature maps have gone through completely connected layers. The output layer generates predictions using methods like sigmoid and softmax. CNNs are trained by backpropagation, frequently using optimization techniques such as stochastic gradient descent (SGD), which involves modifying weights to minimize a loss function. CNNs are particularly useful for applications like picture identification and classification because of their capacity to automatically learn features from raw data, doing away with the requirement for manual feature extraction. They are effective for computer vision applications because of their hierarchical nature, which records patterns at several levels of abstraction.

4. Results & Discussion

Using a ResNet fine-tuning technique, the CNN model's findings demonstrate remarkable performance throughout three epochs with a step size of 5. The model's training accuracy in the first epoch was 92.01%



with a loss of 0.2904, while its validation accuracy was 95.00% with a loss of 0.1738. The model demonstrated significant progress by the second epoch, with a training accuracy of 94.14% and a loss of 0.1700. With a further decrease in validation loss to 0.1160, the validation accuracy rose to 96.00%. The model showed remarkable performance in the last epoch, with a loss of 0.1316 and a training accuracy of 95.74%. The validation loss drastically decreased to 0.0741, while the validation accuracy peaked at 99.00%. These out-comes demonstrate how well the ResNet fine-tuning model enhances training and validation results. Overall accuracy reached 99%, and the model's precision, recall, and F1-scores were almost flawless, especially for malignant cases (1.00 for precision and recall). The model correctly identified the majority of examples, with only slight misclassifications, especially in the typical category, according to the confusion ma-trix. These results show how effective the ResNet fine-tuning model with CNN is at detecting breast cancer.

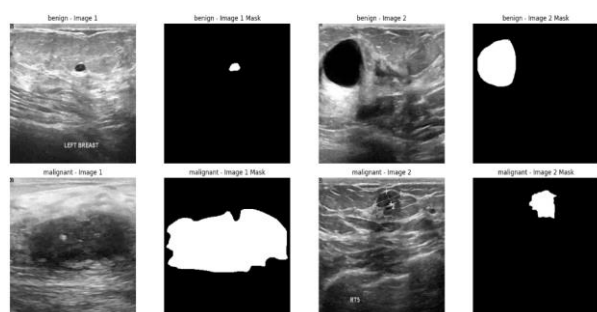


Fig 3. Sample Ultrasound Images

The three primary types of ultrasound images in the Breast Ultrasound Images Da-taset are benign, malignant, and normal. Non-cancerous growths with clearly defined edges, like cysts or fibro adenomas, are depicted in benign pictures. Although these photos show clear masses, they do not have the abnormalities associated with can-cerous tumors. Cancerous tumors with irregular shapes, poorly defined borders, and characteristics like micro calcifications and increased blood flow that suggest potential invasiveness are depicted in malignant pictures. These pictures are essential for identifying cancers that have the potential to spread to nearby tissues. Healthy breast tissue is represented by normal pictures, which have homogeneous, uniform patterns devoid of any obvious lumps or abnormalities. Normal breast tissue has a

smooth, well-defined appearance and shows no indications of benign growths or cancer. Based on the ultrasound images, each class in the dataset aids in training machine learning models—in particular, CNNs—to differentiate between various forms of breast tissue and correctly identify benign, malignant, or normal situations.

4.1 Confusion Matrix

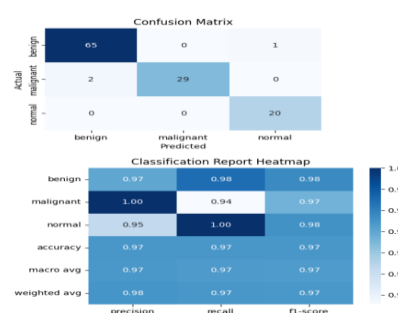


Fig 4. Confusion Matrix

The classification report heatmap and confusion matrix demonstrate the breast cancer detection model's excellent performance. Only one benign image was incorrectly classified as normal in the confusion matrix, whereas 65 benign photos were accurately identified as benign by the model. Two photos were incorrectly labeled as benign, whereas 29 images were accurately diagnosed as malignant. Additionally, the model properly classified all 20 normal photos as such. The model's high precision, recall, and F1-scores are further demonstrated by the classification report heatmap. While the recall for normal photos is 1.00, suggesting no misclassification of normal images, the precision for malignant images is 1.00, indicating all anticipated malignant images were properly categorized. All three classes have total F1-scores above 0.95, indicating a solid trade-off between recall and precision. With a 97% accuracy rate, the model demonstrates a strong capacity to distinguish between benign, malignant, and normal pictures. This indicates that the model has a low rate of misclassifications and is very successful in detecting breast cancer.

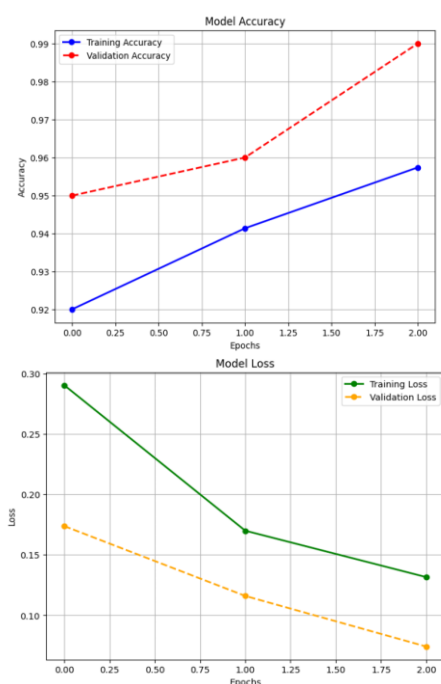


Fig 5. Model Accuracy and Model Loss

Two distinct graphs are produced by the above code: one for model accuracy and one for model loss. These graphs are essential for assessing a machine learning model's performance during training. Following each epoch, the accuracy graph shows the model's performance on the training data (shown by the blue line) and the validation data (shown by the red line). In order to prevent overfitting, both lines should ideally grow, showing that the model is learning and getting better. Conversely, the error rate for the validation data (orange line) and training data (green line) is displayed on the loss graph. While a decreasing validation loss indicates strong generalization, a decreasing training loss indicates the model is learning from the training set. Overfitting may be indicated if the validation loss begins to rise while the training loss falls. When combined, these graphs offer insightful information about the model's training process, assisting in determining whether the model is doing better, under fitting, or overfitting.

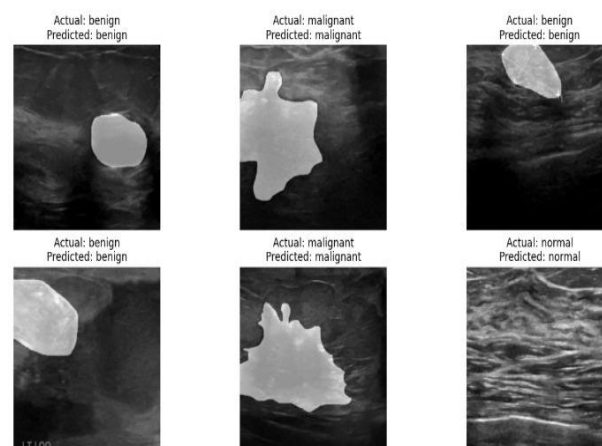


Fig 6. Breast cancer detection

The above figure illustrates the performance of a breast cancer detection model using ultrasound images, showcasing actual conditions (benign, malignant, or normal) alongside the model's predictions. The model accurately classifies benign, malignant, and normal cases, demonstrating its reliability across diverse scenarios. For instance, it correctly identifies both benign and malignant cases, as well as normal tissue, without misclassifications. This highlights the model's robustness in distinguishing between different breast tissue conditions, which is crucial for effective diagnosis and treatment planning.

5. Conclusion

During the development and assessment phases, the Convolutional Neural Networks (CNNs)-based breast cancer detection model showed very encouraging outcomes. The model successfully distinguished between benign, malignant, and normal breast tissue by using ultrasound pictures. The methodology's main steps—image enhancement, segmentation, CNN-based feature extraction, and performance evaluation—were carried out methodically, which added to the model's excellent accuracy and resilience. The CNN's capacity to identify intricate patterns in medical pictures was greatly enhanced by the use of a pre-trained ResNet101 model for transfer learning. By optimizing the ResNet101 model, it was possible to effectively adjust it to the particular dataset, increasing the accuracy of both training and validation. With an overall accuracy rate of 99%, the model's performance metrics were outstanding, indicating its remarkable ability to discern between



benign and malignant instances as well as normal breast tissue. A confusion matrix and classification report were used to further verify the findings, confirming that the model's accuracy, recall, and F1-score were consistently high—particularly for malignant patients. This suggests that the model was effective in reducing misclassifications and accurately and minimally identifying breast cancer. The model's performance over many epochs demonstrates its capacity to generalize to unknown data, underscoring its promise for practical clinical applications. CNNs and transfer learning together provide a powerful way to increase the identification of breast cancer, leading to more precise diagnoses and maybe higher rates of early detection.

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