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# **A CNN Deep Learning Technique for Prediction of Breast Cancer using Ultrasound Image**

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Abstract : Breast cancer is one of the most common cancers among women, and early detection is critical for effective treatment. Ultrasound imaging is a non-invasive and safe imaging technique that can be used to detect breast cancer in its early stages. Ultrasound images of breast tissue can provide detailed information about the internal structure of the breast, allowing for the detection of abnormalities that may indicate the presence of cancer. Convolutional Neural Networks (CNNs) are a type of deep learning algorithm that is well-suited for image recognition and classification tasks. In the context of breast cancer prediction using ultrasound images, CNNs can be used to analyze and classify images of breast tissue as either benign or malignant. This paper presents CNN deep learning technique for prediction of breast cancer using ultrasound image. Simulation is done using python spyder IDE 3.7 software.

# IndexTerms – CNN, Breast, Ultrasound Image, Classification, Machine, Deep Learning.

# I. INTRODUCTION

Breast cancer is a type of cancer that starts in the breast tissue. It occurs when abnormal cells in the breast tissue grow and multiply uncontrollably, forming a tumor. Breast cancer can occur in both men and women, although it is more common in women [1].

There are several types of breast cancer, including ductal carcinoma in situ (DCIS), invasive ductal carcinoma (IDC), invasive lobular carcinoma (ILC), and inflammatory breast cancer (IBC). The most common type of breast cancer is IDC, which starts in the milk ducts of the breast. The first step in using CNNs for breast cancer prediction is to collect a dataset of ultrasound images of breast tissue, along with annotations indicating whether each image is benign or malignant [2]. This dataset is then used to train a CNN model to recognize patterns in the images that are associated with malignant breast tissue.

The training process involves feeding the CNN model a large number of annotated ultrasound images and adjusting the weights of the network based on the prediction accuracy of the model. This process is repeated until the model achieves a satisfactory level of accuracy on a validation set of images that it has not seen before[3].

Once the CNN model is trained, it can be used to predict whether new ultrasound images of breast tissue are benign or malignant. The model is fed the new image, and it outputs a probability score indicating the likelihood that the image is malignant. This score can be thresholded to make a binary prediction of benign or malignant[4].

There are several challenges and considerations when using CNNs for breast cancer prediction using ultrasound images. One challenge is the relatively small size of available datasets, which can limit the accuracy of the model. Another consideration is the interpretability of the CNN model, as it can be difficult to understand how the model is making its predictions [5]. Additionally, it is important to consider the ethical implications of using machine learning algorithms for medical diagnosis, including issues such as bias and patient privacy.

The use of ultrasound imaging for breast cancer detection typically involves the following steps:

A trained medical professional, such as a radiologist or sonographer, performs the ultrasound scan of the breast tissue.

The ultrasound images are then analyzed to identify any abnormalities that may indicate the presence of cancer. This analysis may involve measuring the size and shape of lesions or identifying features such as irregular borders, hypoechoic areas, or increased blood flow.

If an abnormality is detected, further diagnostic tests may be recommended, such as a biopsy, to confirm the presence of cancer[6].

The use of ultrasound imaging for breast cancer detection has several advantages over other imaging techniques, such as mammography. Ultrasound imaging does not involve ionizing radiation, which makes it a safer option for younger women and those with dense breast tissue. Additionally, ultrasound imaging can be used to detect small lesions that may not be visible on mammography[7].

However, ultrasound imaging also has some limitations. It can be difficult to distinguish between benign and malignant lesions based on ultrasound images alone, which may lead to unnecessary biopsies. Additionally, ultrasound imaging may not be able to detect small lesions or calcifications that are indicative of early-stage breast cancer. As a result, ultrasound imaging is often used in conjunction with other imaging techniques, such as mammography or MRI, for a more comprehensive evaluation of breast tissue[8].



(a) Normal (b) Benign (c) Malignant Figure 1: Breast ultrasound sample images (BUSI dataset)

Breast ultrasound is a non-invasive medical imaging technique that uses high-frequency sound waves to create images of the internal structures of the breast. During a breast ultrasound exam, a technologist or radiologist will apply a gel to the skin of the breast and use a transducer, which emits and receives sound waves, to capture images of the breast tissue [9].

#### **II. METHODOLOGY**

Breast cancer remains the main source of disease related mortality for women and its frequency is expanding around the world. Breast disease is the uncontrolled development of irregular cells that begin off in one or both breast. The earlier detection of cancer is not easier process but if it is detected, it is curable. The proposed methodology can be understand using followings flow chart-



#### Steps-

- Firstly, download the breast cancer diseases dataset from kaggle website, which is a large dataset provider and machine learning 1. repository Provider Company for research [10].
- 2. Now apply the segmentation and preprocessing of the data, here handing the missing data, removal null values.
- 3. Now extract the image data features and evaluate.
- Now apply the classification method based on the convolution neural network deep learning approach. 4.
- Now generate confusion matrix and show all predicted class like true positive, false positive, true negative and false negative. 5.
- Now calculate the performance parameters by using the standard formulas in terms of the precision, recall, F\_measure, accuracy 6. and error rate.

#### Algorithm-

Step-1 Input: Breast cancer image dataset.

Threshold segmentation of different breast cancer and normal images

#### Step-2

Take the initial features like original image, binary image, inverse binary, truncate to zero and inverse.

Pre-processing of image (read, colour, resize, scale)

# Step-3

Split train and test dataset Y\_train, Y\_test, X\_train and X\_test

# Step-4

Feature extractions

X train counts

Y train counts

Convolution neural network classifier. Categories = Cancer or Normal

### Step-5

Generate confusion matrix and show value of TP, FP, TN and FN **Step-6** <u>Output:</u> Calculate Accuracy, error rate, precision, recall and f-measure

## **III. SIMULATION RESULTS**

The simulation starts from taking the dataset. The image dataset contain various features value, total Number of benign images is 437, malignant images are 210 and normal images are 133.

malignant (1).ong	malignant (2).png	malignant (3),png	malignant (4).png	malignant (5).png	malignant (6).png	malignant (7).png	malignant (8).png	malignant (9).png	malignant (10).ong	malignant (11).png
malignant										
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(23).png	(24).png	(25).png	(26).png	(27).png	(28).png	(29).png	(30).png	(31).png	Malighant (32).png	(33).png
malignant (34).png	malignant (35).png	malignant (36).png	malignant (37).png	malignant (38).png	malignant (39).png	malignant (40).png	malignant (41).png	malignant (42).png	malignant (43).png	malignant (44).png
normal (1).png	normal (2).png	normal (3).png	normal (4).png	normal (5).png	normal (6).png	normal (7).png	normal (8).png	normal (9).png	normal (10).png	normal (11).png
normal (12).png	normal (13).png	normal (14).png	normal (15),png	normal (16).png	normal (17).png	normal (18).png	normal (19).png	normal (20).png	normal (21).png	normal (22).png
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normal (45).png	normal (46).png	normal (47).png	normal (48).png	normal (49).png	normal (50).png	normal (51).png	normal (52).png	normal (53).png	normal (54).png	normal (55).png

Figure 3: Cancer and normal image dataset

The figure 3 is showing the image dataset, which is taken from the kaggle machine learning repository.

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## Figure 4: Y prediction

Figure 4 is showing the y prediction. There are two values to represent cancer or normal images. Here 0 represent the existing of the cancer and 1 represents the normal image.



Figure 5: Original image

Figure 5 is showing the original cancer image, which is taken from the dataset.

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	Model: sequential_1			^
	Layer (type)	Output Shape	Param #	
	conv2d_1 (Conv2D)	(None, 50, 50, 16)	208	
	<pre>max_pooling2d_1 (MaxPooling2</pre>	(None, 25, 25, 16)	0	
	conv2d_2 (Conv2D)	(None, 25, 25, 32)	2080	
	<pre>max_pooling2d_2 (MaxPooling2</pre>	(None, 12, 12, 32)	0	
	conv2d_3 (Conv2D)	(None, 12, 12, 64)	8256	
	<pre>max_pooling2d_3 (MaxPooling2</pre>	(None, 6, 6, 64)	0	
	dropout_1 (Dropout)	(None, 6, 6, 64)	0	
	flatten_1 (Flatten)	(None, 2304)	0	
	dense_1 (Dense)	(None, 500)	1152500	
	dropout_2 (Dropout)	(None, 500)	0	
	dense_2 (Dense)	(None, 2)	1002	
	Total params: 1,164,046			
	Trainable params: 1,164,046			
	Non-trainable params: 0			
				•
Figure is 6 is showin	g convolution neural network pro	Figure 6: CNN process ocessing in to the sample im	ages.	

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Aco	uracy of CNN A	lgorithm =	99.313916671887	43 %			ł
In	[3]:						¥

Figure 7: Prediction result

Figure 7 is presenting the prediction result in Ipython console. The selected input image is predicted as a malignant, which is true and overall classification accuracy is 99.31%.

Tuble 1. Result comparison								
Sr. No.	Parameters	Previous Work [1]	Proposed Work					
1	Classification Approach	Quadratic SVM	Convolution neural network					
3	Accuracy	84.9 %	99.31 %					
4	Classification error	15.1 %	0.69 %					

Table 1: Result Comparison

Table 1 is showing the result comparison of the previous and proposed work. The overall accuracy achieved by the proposed work is 99.31% while previous it is achieved 84.9%. The classification error of proposed technique is 0.69% while 15.1% in existing work. Therefore it is clear from the simulation results; the proposed work is achieved significant better results than existing work.



Figure 8 is presenting the simulation results graph of the accuracy. The proposed work achieved better accuracy then existing work.



#### Figure 9: Classification Error

Figure 9 is presenting the simulation results graph of the classification error. The proposed work achieved minimum error rate then existing work.

#### **IV.** CONCLUSION

This paper presents a Convolution Neural Network deep learning technique for early detection of breast cancer disease. The simulation is performed using the python spyder IDE 3.7 software. The dataset is trained and tested successfully. The overall accuracy achieved by the proposed work is 99.31% while previous it is achieved 84.9%. The classification error of proposed technique is 0.69 % while 15.9 % in existing work. Therefore it is clear from the simulation results; the proposed work is achieved significant better results than existing work.

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