



## ORIGINAL ARTICLE

# Design and development of deep learning algorithm with convolutional neural networks for breast cancer classification

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### Abstract

Breast cancer is one of the primary causes of cancer death among women worldwide. Mammography and ultrasound are used as radiological methods for the early detection of breast cancer in women. Generally, Breast Cancer Detection is done subjectively by expert Radiologists. Still, the radiologist has high inter-observer variability as it is challenging to detect breast cancer tumors in high-density breasts. Many Computers Aided Diagnosis (CAD) systems developed in the past, but accuracy and precision are not up to the mark and are not used in clinical practice. The histopathologist is not well-trained, so it leads to incorrect analysis. With image processing and machine learning, there is an interest in changing dependable pattern acknowledgment-based systems to improve the excellence of diagnosis. Still, there is continuous social demand to design and develop a CAD system for Breast Cancer Detection, which will assist radiologists in making accurate decisions as a second opinion. This paper will use the deep learning model to address the above-discussed issue to efficiently assist in the automatic Breast Cancer Detection for clinical practice. The objective is to analyze existing algorithms and study different pre-processing classification algorithms for mammographic breast cancer classification compared with the state-of-the-art methods reported in the literature survey section. ©2022 ijrei.com. All rights reserved

## 1. Introduction

Breast cancer is a second major disease in women death in world after lung cancer in previous few years. There are a predictable 1,898,160 new cases and around 6,08,570 deaths in 2021. There are predictable 2.4 million new cases analysed and around 523,000 deaths per year. Breast cancer growth is an open danger to women's life [1] (Fig. 1 indicates breast cancer start in different parts but three main parts: a) lobules are the glands that produce milk, b) ducts are tubes that carry milk to the nipple, and c) connective tissue surrounds and holds all together) [1]. By A breast cancer multi-classification method using a recently proposed deep learning model. Breast cancer multi-

classification from histopathological images faces challenges of classification of binary classes (benign and malignant), and the broad variability of high-resolution image appearances, high coherency of cancerous cells, and extensive inhomogeneity of colour distribution. Accurate detection and classification of breast cancer is a critical task in medical imaging. The breast cancer image dataset is taken from cancer imaging archives. In the pre-processing step of classification, the breast cancer image is filtered with the support of a wiener filter for classification [2]. The convolutional neural network has set the powerful data of an image and is used to eliminate the structures. After performing the removal process, the reduction process is executed to speed up the train and test data handing out.

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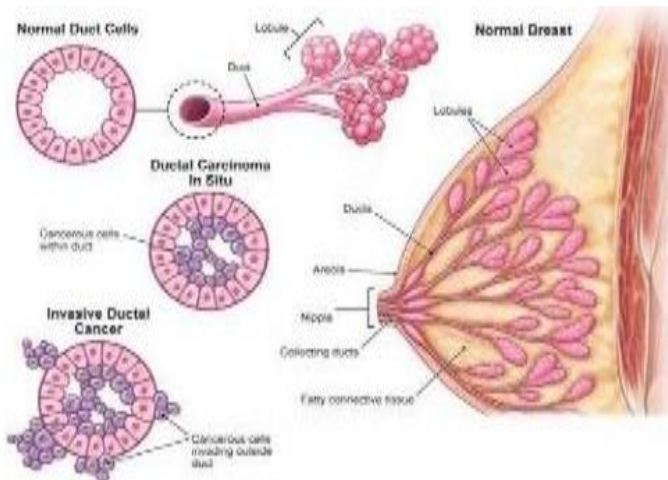


Figure 1: Breast Cancer Start in Different parts of breast a) Duct b) Lobules c) connective tissue and types of breast cancer a) normal b) Ductal carcinoma in situ c) Invasive Ductal Cancer

According to the World Health Organization (WHO), early cancer detection significantly increases the chances of making the right decision on a successful treatment plan. Cancer persistence becomes more complex in higher stages of its growth, and more than 50% of Indian women have breast cancer. About 85% of breast cancers happen in women who have no family past of breast cancer. Mammography and ultrasound are the most widely used radiological methods for early detection of breast cancer in women Proposed project title is intended to address the above-discussed issue to efficiently assist automatic Breast Cancer classification for clinical practice [4]. Fig.1 Indicates different types of breast cancer classification (normal Duct Cells, normal Breast, Invasive Ductal Cancer, Ductal Carcinoma in Situ) [1] proposed the accurate detection and Classification of breast cancer is a life-threatening task in medical imaging due to the complexity of breast tissues. The support vector machine learning, extreme learning machine, RBNN, DNN, and other classifiers performed the Classification [3]. Breast cancer classification divides breast cancer into types giving to different systems principles and helping a different purpose. The primary Classification is the histopathological type, the grade of the tumor, and the expression of proteins and genes. In deep learning breast cancer analytics, “cancer detection” consists of different tasks, including Classification, which is Identifying the probability of the perfect image as “benign” or “malignant.” Benign, also called Fibroadenomas, are solid, noncancerous breast lumps in women between 15 and 35. The Computer-Aided Diagnosis (CAD) systems are applied for detection and Deep Learning to classify breast cancer histopathological images into benign and malignant classes M. Amrane [3].

### 1.1 Related Work

Accurate classification of the digital image is an understood infuriating and inspiring work in front of researchers due to its change in size, shape, grade, receptor status and gens in each image [5]. For the last few years, many researchers have proposed different classification techniques developed for a breast cancer diagnosis; the accuracy of many of them was evaluated using the datasets [20]. The primary objectives behind the proposed work:

- To build an algorithm to automatically identify whether a patient has breast cancer or not by looking at histopathological images.
- To remove noise and pictorial tissues from the image background area.
- Study and analyze different preprocessing classification algorithms for histopathological breast cancer classification.
- To propose a Deep Learning Algorithm (CNN-Convolutional Neural Network) for Breast Cancer Classification and Python Language with for large dataset on the Environment Google Collab.
- The purpose of classification is to select the effectiveness of a specific treatment having the best accuracy.

### 1.2 Literature review

Detect breast cancer through the neural network by several image pre-processing methods, including image enhancements, noise removal, and difference development. Breast biopsies based on mammography and ultrasound results have been diagnosed as benign at approximately 40-60 % [7]. In deep learning, using Convolutional Neural Networks (CNN) to classify abnormalities as benign or malignant in dataset images. The training folder has 277,524 images in each category. In contrast, the validation folder has 47765 ideas in each CNN is a particular type of deep learning that achieves many activities in speech recognition, image recognition and classification by [8]. The advantages of deep CNNs to overcome the drawbacks of conventional mass detection models [3]. Breast cancer classification divides breast cancer into types giving to different systems principles and helping another purpose. Accurate detection and classification of breast cancer is a life-threatening task in medical imaging due to the complexity of breast tissues [7]. So, increasing worldwide demand for direct detection of breast cancer and classification at many hospitals. This has two purposes:

- To examine the various deep learning models in classifying breast cancer histopathology images.
- To examine the latest models that have not been done in previous studies like Dense-net, CNN, Res-Net, Dual Path Net, Senet, and NAS Net had been identified, if these are used to give to their proposed model with CNN.

Sr.No	Author	Model	Dataset	Accuracy
1	Lizhang Xie a et. al[6]	CNN	Mini – Mias and BCDR	65% - 85%
2	Dalal Bardou et.al [1]	CNN	BIRADS	95%
3	Mohamad Mahmoud Al Rahhal et.al[4]	CNN	Break-His	73.68%
4	Majid Nawaz et. al [2]	CNN	Break-His	95.34%
5	Jiang Y et.al [10]	CNN	SE-ResNet	93.81%
6	Fung Fung Ting et.al.[14]	CNN	Break-His	89.6%

CNN uses to solve the significant number of restrictions in the neural network while working with the image interpretation tasks such as breast cancer detection and classification. A three-class variety is normal, malignant, and benign [11]. After a thorough analysis of algorithms and techniques studied from the review papers we decided (Fig.2 Indicates the analysis of all Review papers with their CNN model and dataset with their Accuracy.) to go with Convolutional Neural Networks (CNN) with Breaks this Datasets.

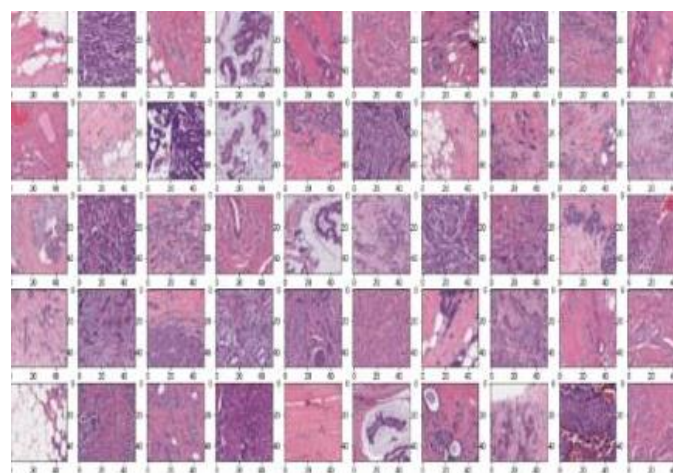
## 2. Implementation

### 2.1 Proposed Methodology

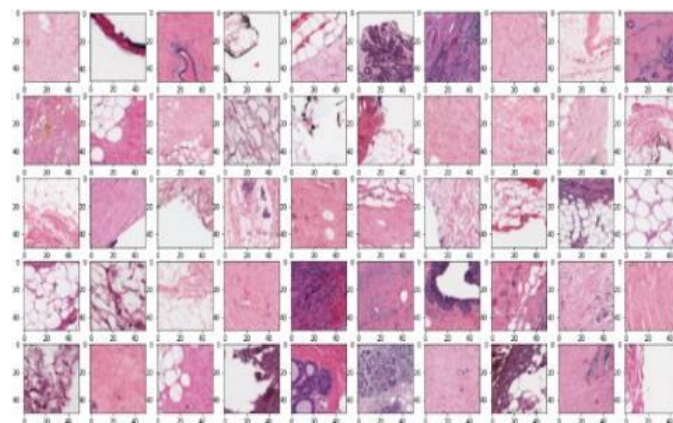
A set of local features were extracted, and a feature coding method was employed in order to combine the local elements into an image representation [10]. Three-dimensional pyramid matching was used to capture the 3-D structure of the images. Support vector machine used to categorize photos. The dataset has been randomly split into 80% training and 20% testing for each magnification factor [19]. Twenty-five percent of the training data is retained and used to select the best model’s parameters for cross-validation. After choosing the best parameters, it was added to the training data [8]. A similar testing dataset is used in Project. The dataset augmentation techniques are only applied to the CNN approach, where each image is flipped and rotated. Our proposed methodology consists.

#### 2.1.1 Input Dataset

In this Project, we take a validated dataset of Histopathological images from the Break -His data set as an input image. We can see 279 files for each patient named with id, and each file contains x-ray images of an individual patient. We have 277,524 images in the dataset, but we get 46246 ideas into the breast-histopathology images. Fig.2 indicates the validated dataset with their health and cancer patches with 277524 images. Most mammograms are light pink, but some dark ones, too [9]. To put images in a data frame for easy access, we find two types of images that indicate malignantly (0) for the 30060 images and benign (1) for the 16186 images with data types int 64. It appears that the number of healthy rays is more than the number of diseased rays



(a)



(b)

Figure 2: Indicates the validated dataset, (a) Healthy patches, (b) Cancer patches.

	image_id	target	patient_id
0	12892_idx5_x2001_y501_class1.png	1	12892
1	8975_idx5_x1251_y1551_class1.png	1	8975
2	13694_idx5_x1851_y1051_class1.png	1	13694
3	9037_idx5_x251_y801_class0.png	0	9037
4	9290_idx5_x2001_y201_class0.png	0	9290

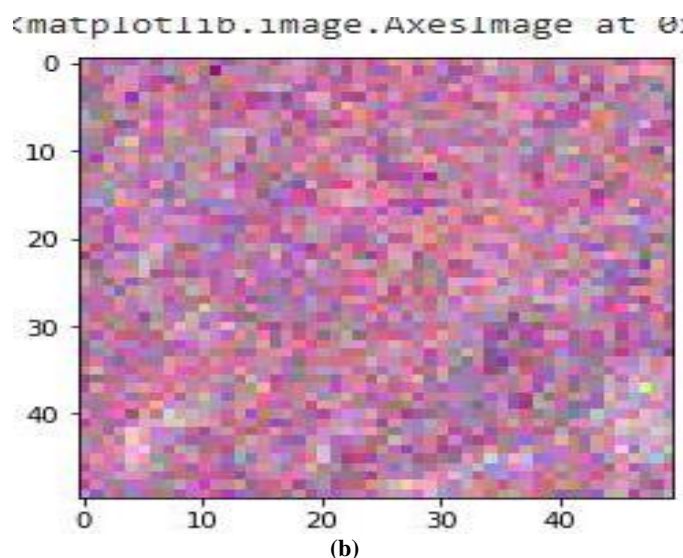
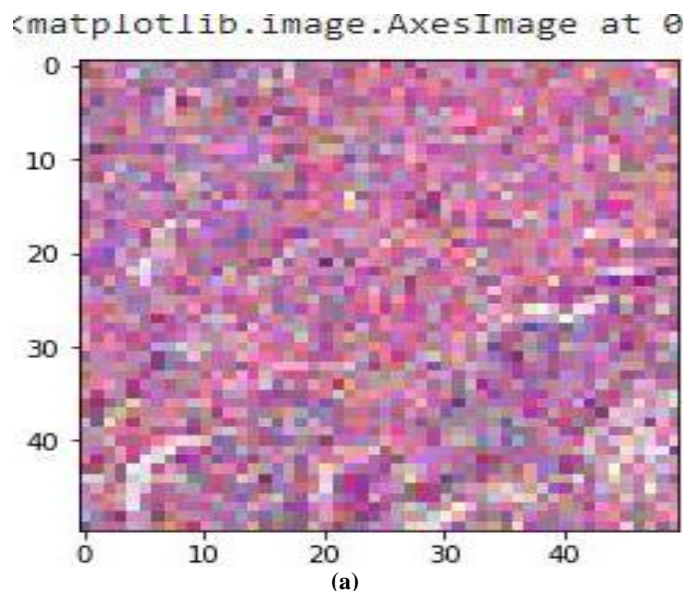


Figure 3: Image processing, (a) Histological image before pre-processing, (b) Histological image after pre processing

### 2.1.2 Pre-Processing

All histological images consist of noise, artifact labels, and pectoral muscles; this should be removed for further processing. The overlapping patches, removing edges, improving the visual quality by removing the noise, resizing, and filtering are performed in this process indicated in fig.3. Here, the normal benign and malignant images are filtered using the wiener filter [10].

### 2.2 Classification using deep learning

Deep learning uses Convolutional Neural Networks (CNN) in classifying abnormalities as benign(noncancerous) or malignant(cancerous) using Break-His databases [13]

proposed a deep learning-based scheme to analyze breast cancer datasets. A computer model learns to perform classification tasks directly from images, text, or sound by Majid Nawaz et. [2]. With a huge quantity of data and classy hardware, deep learning models are easily applied due to the difference and difficulty of image data in the medicinal field, achieving state-of-the-art accuracy and exceptional human-level performance. Kui Liu et al. [14] proposed that the structured deep learning model has achieved outstanding performance (average 95% accuracy) on a large-scale dataset, which determines the method's strength in providing an efficient tool for breast cancer multi-classification in clinical.

### 2.3 CNN (Convolutional Neural Network)

CNN is an efficient recognition algorithm used in pattern recognition and image processing with a simple structure, fewer training parameters and adaptability. Usually, we start with a low number of filters for low-level feature detection by Mohamad Mahmoud Al Rahhal [4]. In CNN, we use the additional filters to sense high-level features based on 'scanning' t the input with the filter of a size and matrix calculations to derive a feature. A convolutional neural network (CNN) method boosts the automatic identification of breast cancer by analyzing hostile ductal carcinoma tissue zones in whole-slide images (WSIs). A Convolutional Neural Network (CNN) is a type of deep learning architecture presented to achieve the correct classification of breast cancer. MURTAZA K. ELBASHIR et al. [15] proposed that Automated classification of cancers using histopathological images is a challenging task for accurate detection of cancer sub-type. Majid Nawaz et al. [2] applied a deep learning approach based on a Convolutional Neural Network (CNN) model for multi-class breast cancer classification. Already training the model, it is suitable to describe many call-backs.

- Convolutional layer (Convolution 2D) is the input layer. It has 32 feature maps with a size of  $5 \times 5$  and a rectifier function.
- The pooling layer that takes the maximum value is MaxPooling2D, with a pool size of  $2 \times 2$ .
- Dropout layer it is set to randomly exclude 20% of the neurons in the layer to avoid overfitting.
- flattened layer that converts the 2D matrix data into a Flatten vector. It agrees that the connected layer process the output. The fully connected layer with 128 neurons and rectifier activation function are used. Finally, the output layer has ten neurons for the ten classes and a SoftMax activation function to output probability-like predictions for each class by Fung Ting et al. [14].

The various convolutional neural network (CNN) architectures are automatically used to detect breast cancer [19], and they proposed that Automated classification of cancers using histopathological images is a challenging task for accurate detection of cancer sub-types. Convolutional

Neural Networks specialize in applications in photo & video recognition. CNN is mainly used in image analysis tasks like Image recognition, Object detection & Segmentation. The

output shape and the parameters involved in each layer indicate in Fig.5.

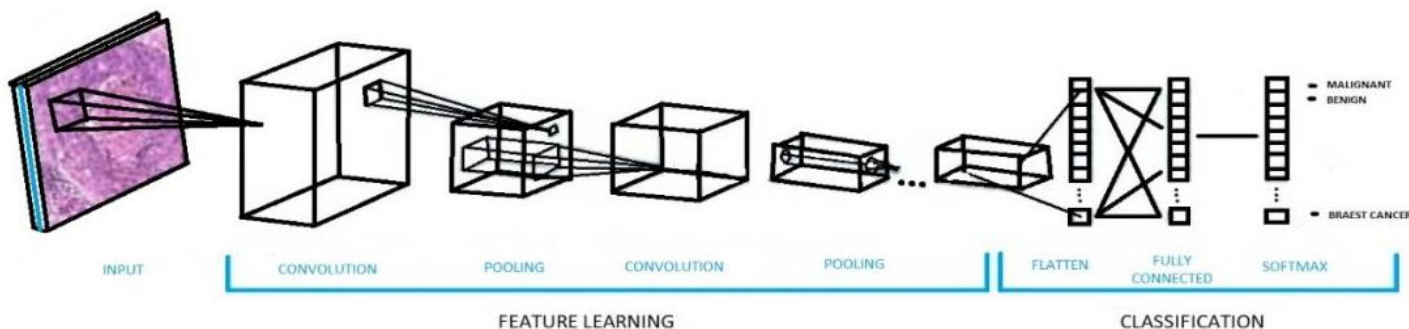


Figure 4: CNN Model

```
Model: "sequential_2"
```

Layer (type)	Output Shape	Param #
conv2d_2 (Conv2D)	(None, 22, 22, 32)	1568
conv2d_3 (Conv2D)	(None, 19, 19, 32)	16416
max_pooling2d_2 (MaxPooling 2D)	(None, 9, 9, 32)	0
dropout (Dropout)	(None, 9, 9, 32)	0
flatten_2 (Flatten)	(None, 2592)	0
dense_4 (Dense)	(None, 256)	663808
dense_5 (Dense)	(None, 2)	514

```
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Total params: 682,306
Trainable params: 682,306
Non-trainable params: 0
```

Figure 5: Sequential Model Summary

```
Epoch 1/60
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1: UserWarning: `Model.fit_generator` is deprecated and will be removed in
  """Entry point for launching an IPython kernel.
4163/4163 [=====] - 43s 10ms/step - loss: 0.5187 - accuracy: 0.7548 - val_loss: 0.4836 - val_accuracy: 0.7741
Epoch 2/60
4163/4163 [=====] - 41s 10ms/step - loss: 0.4774 - accuracy: 0.7873 - val_loss: 0.5496 - val_accuracy: 0.7583
Epoch 3/60
4163/4163 [=====] - 40s 10ms/step - loss: 0.4446 - accuracy: 0.8040 - val_loss: 0.4406 - val_accuracy: 0.8097
Epoch 4/60
4163/4163 [=====] - 41s 10ms/step - loss: 0.4350 - accuracy: 0.8094 - val_loss: 0.4211 - val_accuracy: 0.8141
Epoch 5/60
4163/4163 [=====] - 40s 10ms/step - loss: 0.4252 - accuracy: 0.8162 - val_loss: 0.4169 - val_accuracy: 0.8154
Epoch 6/60
4163/4163 [=====] - 40s 10ms/step - loss: 0.4165 - accuracy: 0.8171 - val_loss: 0.4109 - val_accuracy: 0.8166
Epoch 7/60
4163/4163 [=====] - 41s 10ms/step - loss: 0.4116 - accuracy: 0.8191 - val_loss: 0.4218 - val_accuracy: 0.8065
Epoch 8/60
4163/4163 [=====] - 41s 10ms/step - loss: 0.4078 - accuracy: 0.8220 - val_loss: 0.4061 - val_accuracy: 0.8249
Epoch 9/60
4163/4163 [=====] - 41s 10ms/step - loss: 0.4002 - accuracy: 0.8274 - val_loss: 0.3941 - val_accuracy: 0.8216
Epoch 10/60
4163/4163 [=====] - 40s 10ms/step - loss: 0.3957 - accuracy: 0.8293 - val_loss: 0.4694 - val_accuracy: 0.7859
Epoch 11/60
4163/4163 [=====] - 41s 10ms/step - loss: 0.3879 - accuracy: 0.8324 - val_loss: 0.3946 - val_accuracy: 0.8227
<keras.callbacks.History at 0x7f57bbc20550>
```

Figure 6: The perform analysis basis on the loss and accuracy with respect to the epoch

### 2.4 Model Checkpoint

When training requires a lot of time to achieve a good result, often many iterations are needed. It is better to save a copy of

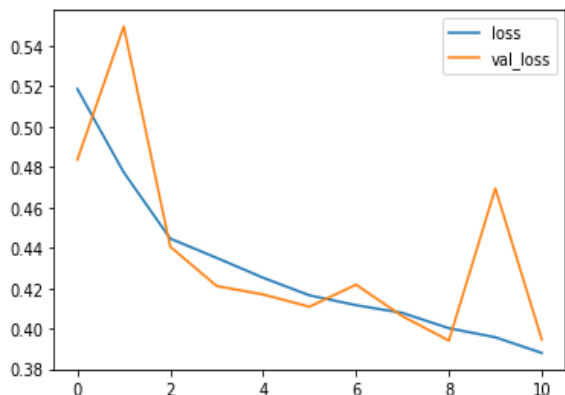
the best-performing model only when an epoch that improves the metrics ends [17]. Before training the model, we will do a Model Checkpoint. Then CNN model by using a global average pooling layer followed by 50% dropouts to reduce

over-fitting and batch normalization and a dense layer with two neurons for two output classes, i.e., benign and malignant [7].

### 2.5 Performance Metrics

The most common metric for evaluating model performance is accuracy. However, misclassification scores don't make sense when only 20% of your dataset is of one class (malignant) and 80% of other types (benign). You can be 80% accurate and still catch none of the malignant cases, which could make a terrible classifier [11] and indicates for analyzing misclassification; it's essential to check the precision, recall, F1-score, ROC/AUC Curves and confusion matrix.

<matplotlib.axes.\_subplots.AxesSubplot at 0x7f57bbd9a150>



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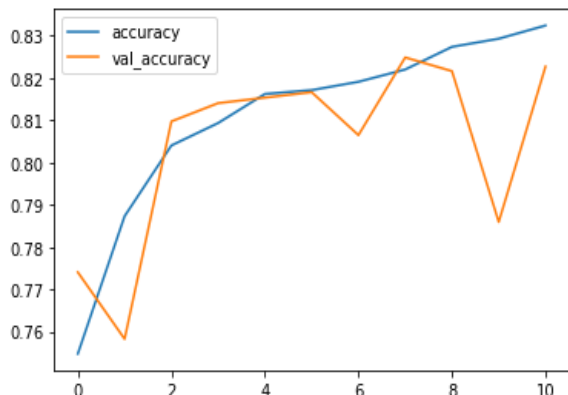
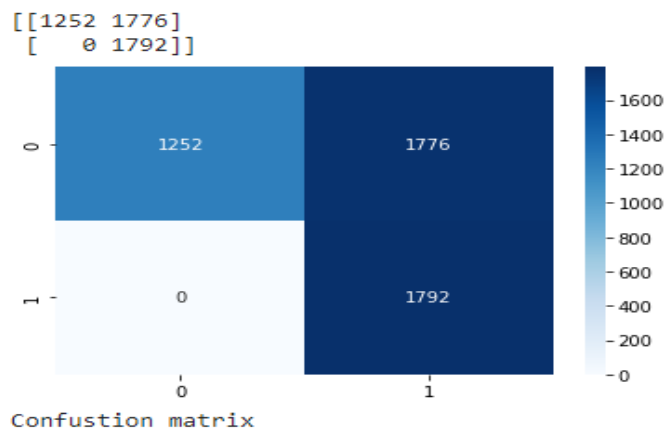


Figure 7: Plot the graph of Loss and accuracy with respect to the epoch

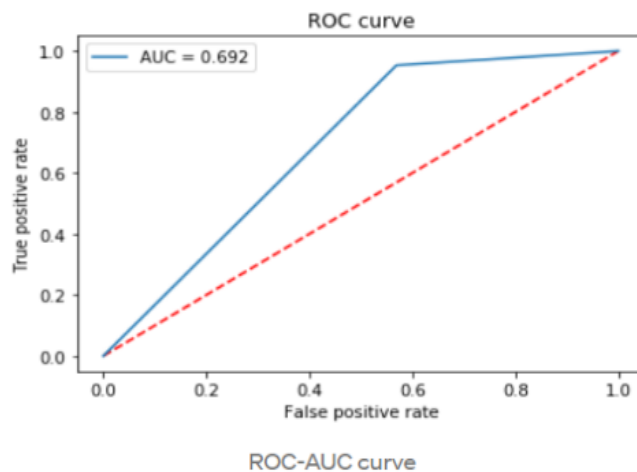
### 3. Conclusion Matrix

Confusion Matrix analyzing misclassification. The matrix row denotes a predicted class, and the column indicates an actual type. The diagonals represent the classes that have been correctly classified. This helps as we not only know which classes are being misclassified but also what they are being misclassified as [6].



### 3.1 ROC curves

The 45° line, where the Area Under the Curve is 0.5. The highest a model can get is an AUC of 1, where the curve forms a right-angled triangle [20]. The ROC curve help corrects a model. For example, if the bottom left corner of the curve is closer to the random line, it implies that the model is misclassifying at Y=0. If it is accidental on the top right, it indicates the errors Y=1.



### 3.2 Image Classification

We prefer to use a larger batch size to train my models as it allows computational speedups from GPUs' parallelism, but it is known that too large of a batch size will lead to poor generalization [20]. Therefore, it is often advised to start at a small batch size reaping the benefits of faster training dynamics and steadily growing the batch size through training [3]. Then split, the data set into two sets, train and test sets, with 80% and 20% images, respectively.

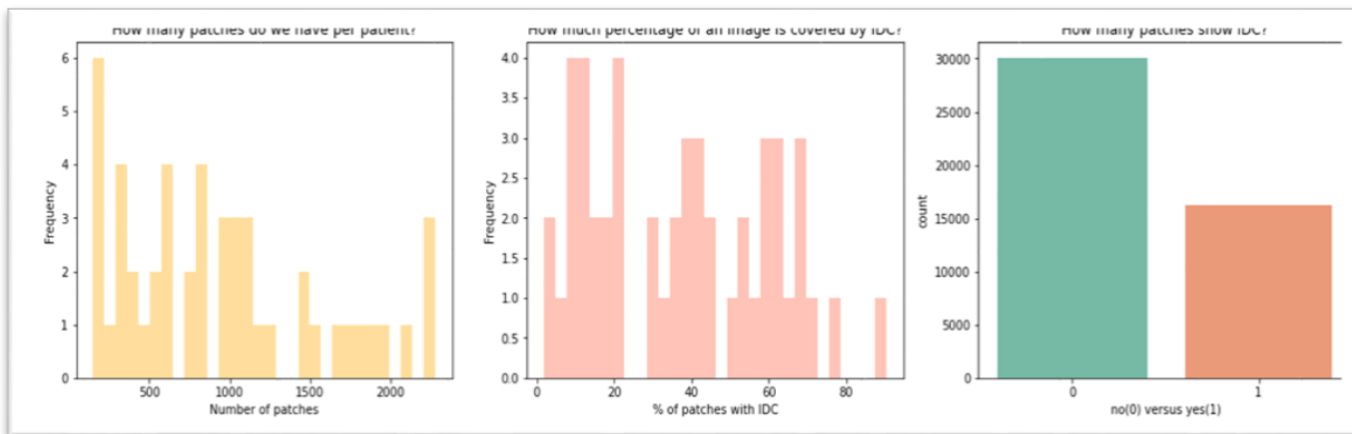


Figure 8: Plot Chart regarding no for malignant (0) and yes for Benign (1) (how many patches per patient, how many patches show IDC as well as percentage of an image covered by IDC)

The complete image classification is as follows: Our input is a training dataset that consists of 277524 images, each labeled with one of 2 different classes. Then, we use this training set to train a classifier to learn what every one of the classes looks like; train 0 for 27054 datasets and train 1 for 14567 datasets as well as 3006 images for test 0 and 1619 images for test 1, where 0 indicates benign and 1 indicates cancer. We assess the classifier's quality by requesting it to predict labels for a new established of images that it has not seen previously. We will

then compare the trustworthy brands of these images to the ones predicted by the classifier [18]. The next to build the model. Before training the model, we will do a Model Checkpoint. Then we'll go with the Dense-Net model using a global average pooling layer followed by 50% dropouts to reduce over-fitting and batch normalization and a dense layer with two neurons for two output classes, i.e., benign and malignant [18].

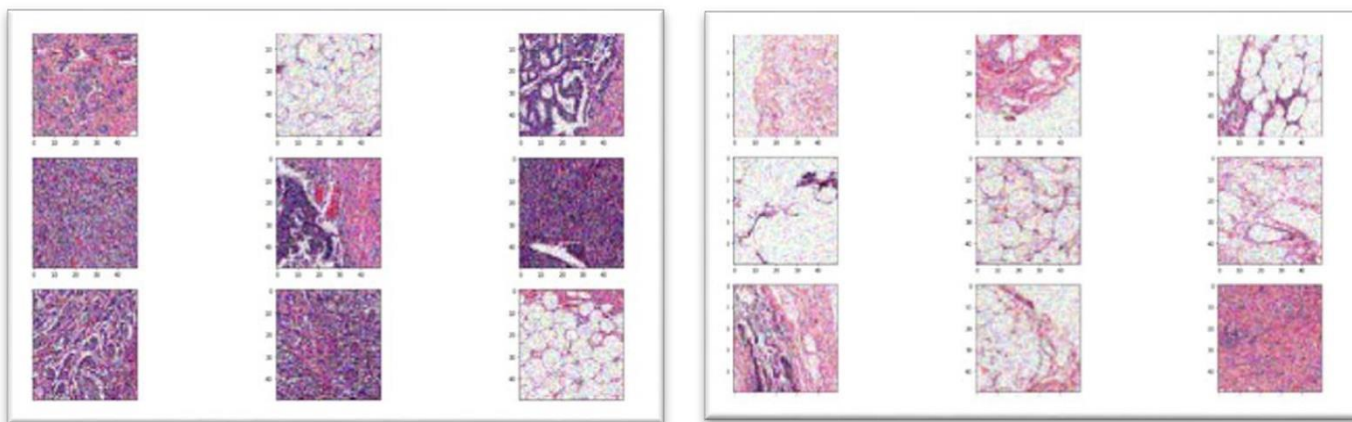


Figure 9: Indicates after Testing and Training the model with output of malignant and benign samples

### 3.2.1 Single Image classification

For the Single image, get on any source available loaded on disk that's input is predicated image indicates the accuracy and the loaded image is less than equal to 0.5, meaning the Yes otherwise indicates No using TensorFlow Framework. Fig.10 indicates the given image is malignant by showing the yes with accuracy.

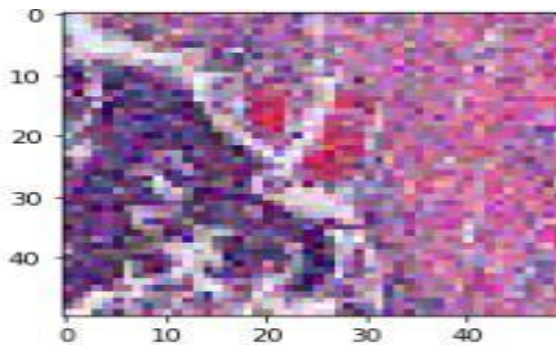


Figure 10: Image – Malignant (yes)

#### 4. Discussions

In topology (which consists of two convolutional layers and three fully connected layers) to classify breast cancer images into benign and malignant. However, they only reported accuracy of 829.50%. Thus, they decided to use a complex topology, a variant of Break-His [18] networks. This topology consists of three convolutional layers with a filter

size of  $5 \times 5$  and two fully-connected layers. The images were divided into small patches using a sliding window and random strategy with different sizes to train the network. The patches results are combined for the whole image to get the final classification result. The authors reported an accuracy ranging from 84.80% where they used sum fusion rules on the different trained models with varying patch sizes by [24].

Table 1: Accuracy Table with dataset and classes.

References	Dataset	Classes	Accuracy	Precision	Recall	F-1 Score
F. A. Spanhol et al[15]	Break- His	Benign/malignant	89.50			92.90
T. Araújo et al[16]	Break-His	Carcinoma/Non-carcinoma	90.00			
F. A. Spanhol et al [17]	Break- His	Benign/malignant	84.80			88.80
N. Bayramoglu et al[18]	Break- His	Benign/malignant	84.60			
A.-A. Nahid et al[19]	Break- His	Benign/malignant	97.19	98.00	98.20	98.00
Z. Han et al[20]	Break- His	Multi-class	96.90			

The average accuracy (based on patient score) was 96.90%, while for the multi-task, the average accuracy was 97.19% for the benign/malignant classification task. In raw images [20], handcrafted features, and frequency-domain information were fed into a CNN to classify the breast histology images into benign and malignant. The reported performance was between 94.40% and 97.19%. We find that our topology outperforms the proposed approaches in [22] in terms of accuracy, where we achieved state-of-the-art accuracy between 84.80%. In this work, we compared the performance of convolutional neural networks with various configurations for classifying breast cancer histology images into benign and malignant and into benign and malignant subclasses [22]. The intended CNN worked on binary and multi-class classification. The multi-class classification performance was lower than the binary variety due to the number of handled classes and the comparisons among the sub-classes. The performance of the handcrafted features-based approach, where we used coding models to encode the local descriptors to build image representation, was too low compared to the CNN [17]. Convolutional neural networks are also used to replace traditional classifiers with fully connected layers to train the handcrafted features (DSIFT and SURF), which helped increase the performance of the handcrafted features. Convolutional neural networks have become state-of-the-art, demonstrating an ability to solve challenging classification tasks. Our proposed CNN topology has beaten the previous ones for the binary classification task, where we reached a performance of between 85.30% and 95.50%.

#### 5. Conclusions

After, the CNN algorithm with the Break-His dataset leads to the development of prediction systems. We are done with dataset work, i.e., splitting it into benign and malignant by labeling it as 0's and 1's, respectively and studied the CNN Model structure for classification. This Convolutional Neural

Network technique will provide a better type than some other existing models. In the end, our Breast Cancer Classification using Deep learning project will be concluded with the best accuracy, which will help researchers to go with the best appropriate treatment for clinical practice

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