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# Harnessing Deep Learning Techniques for Identification of Breast Tumors

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***Abstract:-*** Breast tumor is the main disease in women around the world, 25% of all cancer cases. Traditional detection methods such as mammography, ultrasound, and MRI, have interference with time-consuming to determination and potential mistakes. To address the challenges, analysts introduce intelligent learning model methods as a dependable arrangement for breast tumor location. These strategies include the utilization of artificial neural network systems that can able to learn the data patterns and recognize them in datasets. One such dataset is the MINI-DDSM (Mini-Mammography) Dataset for Breast Cancer Screening, which contains digitized mammography pictures of kinds and dangerous tumors, utilizing the learning calculations to recognize breast cancer from mammography pictures. The information was preprocessed, and the models were assessed utilizing different convolutional neural network structures. These methods may lead radiologists to analyze breast cancer rapidly and effectively to drive earlier to identify and progress the treatment. Intelligent learning model methods have a good preference, counting learning and adjusting to correct spaces, and identifying covered-up patterns and connections not mistakable to the human eye. With information on the properties of the tumor, such as estimate, shape, and surface, a radiologist can make a more educated choice approximately the best treatment arranged for a persistent. Here the mini datasets were preprocessed, data augmented, optimized, and passed on to the CNN models and some pre-trained models such as xception, and ResNet50. Profound learning methods have illustrated better results in the recognizable proof of breast tumors, moving forward in breast cancer determination and treatment. The integration of personalized pharmaceuticals and the utilization of standardized datasets such as the Mini-DDSM altogether improve the general adequacy of breast cancer treatment plans.

***Keywords***: *Breast tumor, Convolution neural network, Xception, Restnet50*.

## 1. Introduction

A breast tumor is a malignant tumor in the cells of the breast tissue. This is the most prevalent cancer in women, with a percentage of 25% of all the cancers in the world. A breast tumor is an abnormal growth of the breast and uncontrollable growth of a lump or mass. Lifestyle, age, genetic mutations, and environmental factors are the major contributors to breast tumors. All these significant aspects of reduction of breast cancer mortality and saving of lives are early detection and good, accurate detection.

Traditional means of breast cancer detection, such as mammography, ultrasound, and MRI, are relatively time-consuming, have a high rate of errors, and are cost-intensive. So researchers are trying to build models of deep learning neural networks to come up with reliable and efficient solutions for breast tumor detection and identification. Such methods of detection generally provide higher accuracy in the detection of tumors, hence improving the accuracy of diagnosis as well as the available treatment options that are probably not observable to the human eye.

The digitized mammography of the MINI-DDSM (Mini-Mammography) dataset, which contains images of benign and malignant tumors, is one of the datasets being utilized by researchers in the field. Preprocessing techniques for segmentation in the image dataset and optimization have been applied to work with the dataset. Data augmentation has been applied to generalize the model for additional images. Pre-trained models like

Xception, ResNet50, and more identify patterns and features of the images. In the final step, convolutional neural network (CNN) models are applied for high precision-based breast tumor classification and identification. There are so many benefits of intelligent learning methods over traditional methods of detection, including flexibility to study and make amendments with various spaces and identification of hidden patterns and connections. This information is based on the detection of a tumor's size, shape, and surface properties, and then this information is utilized to develop the models.

The derived results of the model will assist the doctor in deciding on the medication.

Breast cancer is one of the critical public health problems, so its continued research using reliable methods of detection and diagnosis is essential for early detection and better treatment results. Breast tumor detection deep learning techniques give more accuracy in the diagnoses and lead the doctor to make a personalized treatment plan.

This paper contributes to that effort through intelligent learning in the identification of breast tumors and their causes. The introduction of the MINI-DDSM datasets with deep learning techniques has enabled improvement in the accuracy and efficiency of diagnosis and detection of breast cancer. With that in mind, better knowledge of the behavior of breast tumors leads to better-tailored treatments and increased effectiveness.

## 2. Literature Review

Breast tumor detection in MRI images is quite a big challenge in the medical field. Most of the related work in the field of Breast tumors involves data preprocessing, feature extraction, and detection of tumors. The existing models were built in deep learning and Convolutional Neural Networks (CNN).

**Hurtado et al** (2022) the author proposed a system for breast tumor classification with the help of artificial intelligence. In this paper, the model consists of feature extraction, segmentation, image acquisition, classification, and diagnosis. The images were preprocessed and resize the images in the dataset to the same size. The Fourier transform and the wavelet transform have been employed to extract the features from the MRI images. The support vector machine in the model ensures the classification of the benign and malignant tumors. A convolution neural network model is included to train and identify the tumor cell in the image. Autoencoders were included to minimize the loss between the original and resconstructed data. By employing this model the author attained an accuracy of 95%.

**ZHENG et al** (2020) propose the deep learning technique with the Adaboost algorithm to detect breast cancer. The author suggests the supervised learning algorithm for training purposes and the unsupervised algorithm for feature extraction. The model used here is the ensemble learning which consists of CNN and Adaboost, one acts as a supervised classifier learning, and the other acts as an unsupervised feature extraction. This combination increases the accuracy of the model to 97.2%.

**Sha et al** (2019) authors implemented the deep learning model and used an optimization algorithm to automatically detect breast cancer. This paper proposed the preprocessing of the dataset, feature extraction, and segmentation. Grasshopper optimization is employed to optimize the optimal solution to the model. Convolution neural network with grasshopper optimization is included in the model to extract the feature and classify the breast tumor with more accuracy. The accuracy of a model is 92%.

**Bai et al** (2021) proposed the digital breast tomosynthesis for automatic breast cancer detection by applying deep learning techniques. The authors proposed the Digital Breast Tomosynthesis (DBT) in three steps such as classification, object detection, segmentation. Classification of the image into normal, benign or malignant by using the CNN model. The CNN model will try to classify the images into three classes by applying several filters and pooling layers. Object detection is done by the model Faster RCNN. The Faster RCNN comprises of ConvNet, region proposed network, and multitask branches. The object detection is executed by creating the bounding boxes in the detected areas. Segmentation is done by the UNet model, which is of two steps downsampling and upsampling. For analyzing the image, the authors used the Generative Adversarial network (GAN).

**Ragab et al** (2019) the author proposed a method of deep learning and Support vector machine for breast cancer detection. Here the author used the CBIS-DDSM dataset where the dataset includes the mammography images of both benign and malignant tumors. The data augmentation technique is used to train the model to decide a generalization, But the testing images are passed the original images to the model. In this paper author used the pre-trained Alex-net CNN model with the cut down of the last layer and appended the SVM model to classify the breast tumors. This architecture produces the accuracy of AUC, sensitivity, specificity, precision, and F1 score achieved 80.5%, 0.88 (88%), 0.774 (77.4%), 0.842 (84.2%), 0.86 (86%), and 0.815 (81.5%), respectively.

**Acharya et al** (2012) the author introduces the Thermography Based Breast Cancer Detection

Using Texture Features and Support Vector Machine. The author uses the infrared image dataset to process the Image acquisition, and preprocessing,  to extract the image texture feature to pass the SVM machine learning model. The SVM model is a supervised learning method inside to uses a cross-fold technique and the feature can transform the higher dimension space to classify using hyperplane to improve breast cancer detection accuracy. This proposed model's accuracy is 88.10%.

**Shen et al** (2019) the author's proposed the Deep Learning model utilized to Improve Breast Cancer Detection through Screening Mammography. For this research purpose, the author used the CBIS-DDSM and INbreast datasets. The author used pre-trained models using Resnet50 and VGG16. VGG16 pretrained model is used with the stack of several 3 X 3 convolutional layers with the same depth followed by the 2 X 2 max pooling layer. ResNet model is introduced with the stride of 2 to extract the feature map, then the model was designed in the format of Bottleneck format with the three convolutional filters of 1 X 1, 3 X 3, 1 X 1 so that the patch of the tumor is detected with more accuracy. The extracted patches were represented in the heatmap. The model produces an accuracy of 95%.

**ROSLIDAR et al** (2020) The author reviews the process of thermal imaging and deep learning approaches for breast cancer detection. This paper suggests the thermal imaging dataset used to detect breast cancer. The thermal imaging dataset is a form of temperature, the temperature distribution changes are a symptom of abnormality in body tissues. The proposed methodology consists of pre-processing aimed to suppressing unwanted data and enhancing important image features, the CNN model. The thermography dataset-based proposed system increased the binary classes of normal and abnormal classification accuracy.

**Sadoughi et al** (2018) The author has reviewed the artificial intelligence method through diagnosis of breast cancer. This paper's main focus is to detect breast cancer earlier using an artificial intelligence algorithm. The researcher has taken different types of datasets like ultrasound, mammography, and thermography.  The author demonstrated different algorithms like SVM, KNN, Naïve Bayes, and Genetic algorithm for optimization among these SVM has given accuracy for the given dataset with ultrasound =95.85%, mammography =93.069%, and thermography =100%.

## 3. Dataset

The Mini-Mammogram Digital Database for Screening Mammography (Mini-DDSM) is one of the most important databases in breast cancer research and includes a set of mammographic images. It constitutes a very critical dataset, since it comprises benign, normal, and malignant cases, thereby allowing for an extensive analysis of a wide variety of breast health conditions. Therefore, The Mini-DDSM provides the focus for early detection and diagnosis in the development and assessment of deep learning algorithms that are intended to enhance the accuracy and efficiency of detecting breast cancer. Hence, such a diverse composition would enable researchers to investigate a large number of abnormalities and significantly contribute to the advancement of medical imaging technology.

The dataset is taken from Mini DDSM, where there is careful design and annotation to cover a wide spectrum of different breast pathologies. It includes both benign, normal, and malignant instances to ensure an equal proportion of various breast statuses in the dataset. This gives way to the ability to analyze and interpret the images with a high degree of pixel information, which, in turn, serves in the creation of highly accurate algorithms for diagnosis.

My research, using this dataset, will work towards pushing the state-of-the-art in breast cancer detection by engaging with cutting-edge machine learning techniques.

By using the pixel-level information 221 x 358 in size of the Mini DDSM breast cancer dataset, this paper targets to give appreciable contributions toward the field of medical imaging and diagnosis. The application of such advanced deep learning models integrated with detailed image pixel data avails a promising alternative in enhancing the accuracy and efficiency of these breast cancer detection systems.

| Label | #images | μ (age) | σ (age) |
|---|---|---|---|
| Normal | 2728 | 57.8284 | 11.6651 |
| Cancer | 3596 | 61.3971 | 12.7968 |
| Benign | 3360 | 53.1036 | 12.0260 |
| Total | 9684 | 57.5143 | 12.7149 |

Table: Mini-DDSM dataset

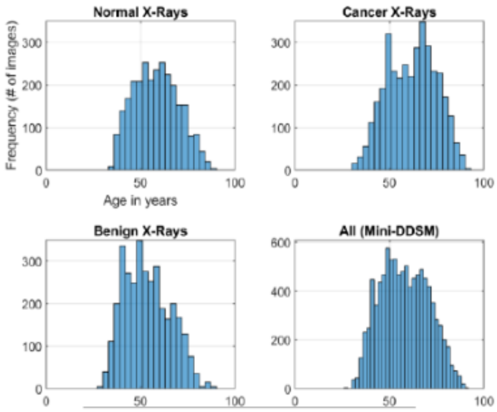



**Figure 2: The Mini-DDSM dataset Age distribution of Normal, cancer benign, and overall.**

**Data visualization**

Visualization is a process that can be used to gain a deeper understanding of data distribution, model training, model prediction, etc. A graphical or pictorial representation of a data structure facilitates complex problems and helps in the decision-making process. Visualization model training helps in the optimization phase. It is easier to determine which part of the model is valuable and important. So that the optimizer is designed with valuable parts and helps to exclude some layers so that the performance of the models does not decrease. Data visualization also helps to understand the performance of the model during training by visualizing it in a graph. It shows the accuracy and loss during each iteration. This will help determine if the epochs can be adjusted accordingly. Data visualization is more useful for visualizing the prediction made by the model. The model segments the tumor cells after several training sessions.

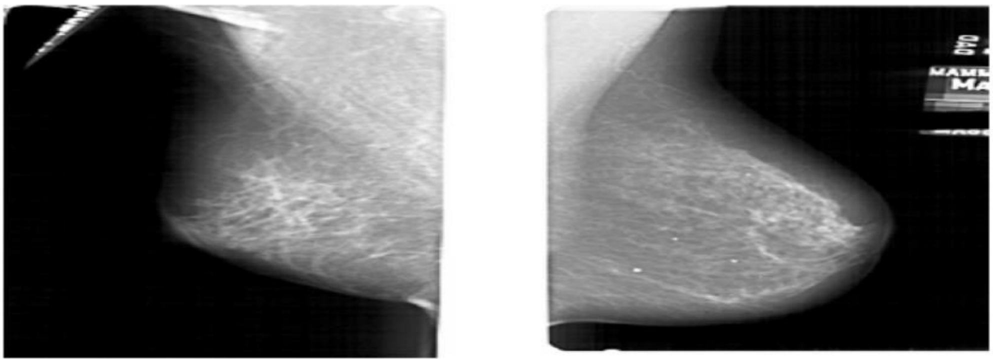
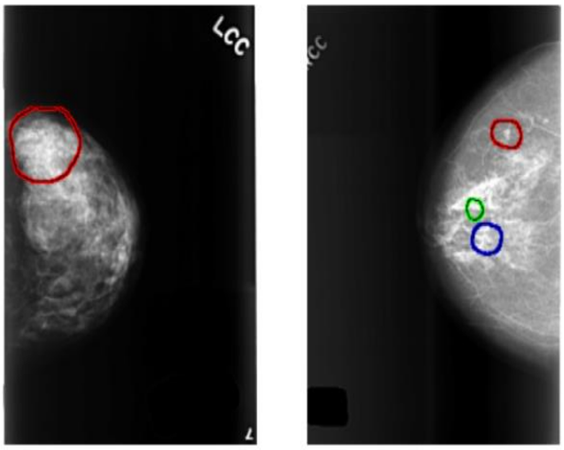


**Figure 3: The Mini-DDSM dataset Normal image.**



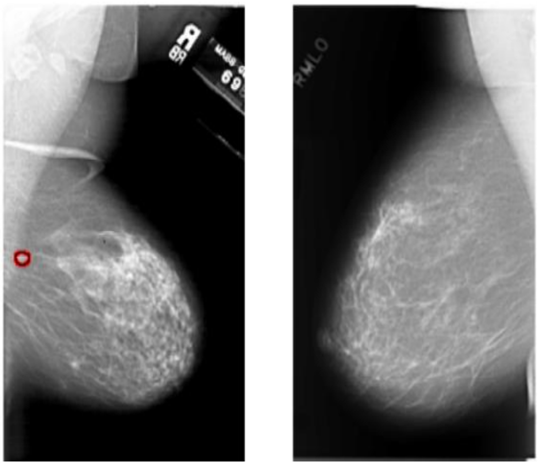


**Figure 4: The Mini-DDSM dataset Benign image** **Figure 5: The Mini-DDSM dataset Malignant image.**

## 4. Methods

### Preprocessing

The pre-processing stage is very important to increase the accuracy of breast cancer detection using high-resolution mammography images from the MINI-DDSM dataset by the deep learning models. Pre-processing of images is done in the following steps.

Image resizing is one of the important concepts of image preprocessing for mammography images. This process resizes the images into a standard size or the same size in order to pass the dataset for training the model correctly. It's easy to visualize and analyze the data.

Contrast adjustment is the operation whereby the contrasts of the image are modified to bring out the visibility of, especially, breast tumors. This technique improves the quality of the image and will be helpful for the segmentation of the breast tumor from the normal breast tissue.

Image noise removal is the pre-processing of MRI images, which eventually results in improving the quality of the image. There are a lot of noises that may occur in the images, for example: Gaussian noise, Rayleigh noise, Salt, pepper noise, etc. The filtering process that comes to the rescue of restoration from these noises includes periodic filter, mean filter, and Gaussian filter.

Data normalization refers to the process of standardizing basic information in mammography images so that it can fit the model. This method will scale the image under the range of 0 to 1.

Resampling datasets will reduce the huge size of data with an assurance that all of the vital image features will be present, and the vital characteristic for the model is that it will help the model to get over data redundancy.

**Segmentation**

In examining and interpreting medical images that involve computed tomography, X-rays, and magnetic resonance imaging, segmentation is crucial. It will be easier for the pharmacist to recommend the medication if the tumor cells are separated from the photos. The MINI DDSM dataset includes MRI pictures with great resolution. The MINI DDSM dataset is segmented using a highly specialized approach that provides accurate breast tumor detection. Because each patient has a different breast mass and tumor features, these photos are distinct. The classification techniques use deep learning techniques to try and tackle this issue. These pictures were designated as "ground truth data" so that a machine could be trained to precisely identify tumor regions. Subsequently, the tumor cells have been separated into multiple layers inside of the model and pre-trained models. The tumor region that the algorithm was trained to predict is then divided into discrete segments.

**Feature extraction**

In an image, feature extraction is this process that changes raw input data into numerical features which are processed with a view of maintaining the original dataset. For that reason, because the model can not learn from raw data, raw data is changed into numerical features, hence a poor result due to a lot of information redundancy that is contained in raw data. Convolutional Layers are just simply the feature extractors within the model. In the layer, there exist filters, also named kernels, which detect features such as edges and colors throughout an image. If an image passed to the convolution layer, then it will decrease the size of the image, and it will bring all the information in the field together in the single pixel. In the Sequential manner, the group of convolution layers, the feature of the image was extracted and converted in a smaller size. There are many convolutional layers, for example,. 2D Convolution, 3D Convolution. In 2D Convolution, it deals with the 2-dimensional image where the filters in the convolution slide over the whole image, performing an element-wise mathematical operation. Now there can be a variety of mathematical operations like multiplication, average, nearest neighbor, etc. which may be applied. So after this operation, it will have compiled the results in the single pixel based on the pixel location. This is then done over the entire image, such that 2D images or 2D matrices of certain features are transformed into another 2D image or 2D matrix of features.

**Convolutional neural network**

Convolutional neural network (CNN) is an important architecture in the deep learning, which is used to study about the features in images, audio, videos, and texts. Most popularly the CNN architecture is used to the extraction of feature information form the images. The convolutional neural network (CNN) is the model that comprises of multiple layers of convolutional layers, pooling layers, flatten layer, and fully connected layer or Dense layer. Those layers are connected sequentially, so that the extracted features are passed on to the following layers without any interventions.

Convolutional layer in the CNN architecture is the main part of the model as it is the responsible for the extraction of the features from the input dataset. Those features are passed on to the consecutive layers of convolutional layers. The convolution layer works based on combining two matrices with some mathematical formulas to get the third matrix. This is possible by sliding over the entire image with filter of certain size and stride value. Stride is nothing but the number saying the layer how much to move further on the matrix. Filter is a matrix which is used to get the features of the particular area which it was used. While applying the filters and strides in the image it will ensure that the maximum of the features where executed form the data. In some cases there is a chance that corner information of the dataset where missed or not calculated because fo the stride value and filter size. To overcome the situation Padding was included to the data. Padding means framing the original data with the 0's. So that the every corner and the nook of the image was examined. For eg, the image with the size of 4X4 and the filter size of 2X2 and stride is applied, then the filter starts form 1$^{st}$ pixel and it moves to the corresponding pixels and it extracts the features. Every convolution layer was connected with the activation functions. Those activation functions is added to ensure the non-linearity in the model and to handle and learn more complex data. The activation function used here is Rectified Linear unit (ReLU), which says that it will allow if it is more than 0 otherwise it will give 0. In this architecture, the conv2D model is used which includes the input image of **(250,250,3)** dimension which is 3-channel image.

The pooling layer is the second connected layer and it is responsible to the allow and correcting the dimension while training the model. The main responsibility of the pooling layer is to reduce the dimensionality in the input features. So that the model can train efficiently, with less computation cost and less time-consuming. There are many types of pooling layers such as the Maximum Pooling layer and the average Pooling layer which is commonly used. The working of the maximum pooling layer is that it will do the summation of all pixels in the region it is applied and replace the center of that region with that value. Likewise in the average pooling layer, the average of the region is replaced. There are some global pooling layers are there like global maximum and global average pooling.

The last layer of the convolutional layer is the fully connected layer. Which is responsible for the classification of the data by identifying the contribution of the features over the classes. The fully connected layer is also called the Dense layer. Many neurons are connected in a parallel manner and perform some mathematical operation. Each layer in the dense layer is well connected and takes input from the previous layer and passes the output to the next layer or it will pass the output after doing the mathematical operations. Every neuron in the dense layers is connected with the activation function. This activation function is responsible for the non-linearity of the data. The last layer of the dense layer is connected with the SoftMax activation function which is used for classification.

```
Model: "model"
__________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
==================================================================================================
 input_1 (InputLayer)           [(None, 250, 250, 3)]  0          []

 conv2d (Conv2D)                (None, 250, 250, 32)  128         ['input_1[0][0]']

 max_pooling2d (MaxPooling2     (None, 125, 125, 32)  0           ['conv2d[0][0]']
 D)

 conv2d_1 (Conv2D)              (None, 125, 125, 64)  2112        ['max_pooling2d[0][0]']

 max_pooling2d_1 (MaxPoolin     (None, 62, 63, 64)   0           ['conv2d_1[0][0]']
 g2D)

 conv2d_2 (Conv2D)              (None, 62, 63, 128)  8320        ['max_pooling2d_1[0][0]']

 max_pooling2d_2 (MaxPoolin     (None, 21, 21, 128)  0           ['conv2d_2[0][0]']
 g2D)

 flatten_2 (Flatten)            (None, 56448)        0           ['max_pooling2d_2[0][0]']

 dense_5 (Dense)                (None, 512)          2890188     ['flatten_2[0][0]']
                                                     8

 flatten (Flatten)              (None, 500000)       0           ['max_pooling2d[0][0]']

 flatten_1 (Flatten)            (None, 249984)       0           ['max_pooling2d_1[0][0]']

 dense_6 (Dense)                (None, 128)          65664       ['dense_5[0][0]']

 dense (Dense)                  (None, 128)          6400012     ['flatten[0][0]']
                                                     8

 dense_3 (Dense)                (None, 256)          6399616     ['flatten_1[0][0]']
                                                     0

 dense_7 (Dense)                (None, 64)           8256        ['dense_6[0][0]']

 dense_1 (Dense)                (None, 64)           8256        ['dense[0][0]']

 dense_4 (Dense)                (None, 128)          32896       ['dense_3[0][0]']
```

```
dense_8 (Dense)              (None, 32)            2080      ['dense_7[0][0]']
dense_2 (Dense)              (None, 32)            2080      ['dense_1[0][0]']
dropout (Dropout)            (None, 128)           0         ['dense_4[0][0]']
dropout_1 (Dropout)          (None, 32)            0         ['dense_8[0][0]']
concatenate (Concatenate)    (None, 192)           0         ['dense_2[0][0]',
                                                              'dropout[0][0]',
                                                              'dropout_1[0][0]']
dense_9 (Dense)              (None, 1256)          242408    ['concatenate[0][0]']
dropout_2 (Dropout)          (None, 1256)          0         ['dense_9[0][0]']
dense_10 (Dense)             (None, 512)           643584    ['dropout_2[0][0]']
dropout_3 (Dropout)          (None, 512)           0         ['dense_10[0][0]']
dense_11 (Dense)             (None, 64)            32832     ['dropout_3[0][0]']
dense_12 (Dense)             (None, 32)            2080      ['dense_11[0][0]']
dense_13 (Dense)             (None, 3)             99        ['dense_12[0][0]']
==================================================================================================
otal params: 157948971 (602.53 MB)
rainable params: 157948971 (602.53 MB)
on-trainable params: 0 (0.00 Byte)
```

**Figure 5: The CNN Model Architecture.**

**Restnet50**

ResNet50 is brief for Leftover Organize 50 and is one kind of Convolutional Neural Arrange (CNN). ResNet50 may be a 50-layer combination of the Convolutional Neural Arrange related within the remaining square course of action. It comprises 48 pieces of Convolutional layers, one piece of Max Pooling layer, and one piece of Typical Pooling layer. Such leftover arrangements are fundamentally a kind of counterfeit neural organize (ANN), forming frameworks by heaping remaining organize pieces. ResNet50 is exceptionally supportive in an picture classification show that can be compelling, connected in preparing to work with thousands of information sets and getting the finest comes about. ResNet50 is an ability that engages the demonstrate to organize, learn, and prepare the remaining capacities that characterize the input to the desired surrender. The ResNet50 demonstrate would be more vigorous on the issue of vanishing slope since the rest of the organize models in a Convolutional Neural Organize (CNN) are built with the unused approach utilizing the idea called "Easy route associations".

The ResNet50 demonstrate is based on the thought of four steps such as the Convolutional layers, the Identity square, the Convolutional square, and the Totally related piece. The ResNet50 convolutional layer is additionally the include extraction in a few layers. The convolutional layers within the ResNet50 make up the different convolutional layers after the clump normalization and ReLU enactment work. Each layer of the convolutional layer has the ReLU actuation work to ensure the non-linearity within the dataset. The Convolutional layers takes after the bunch normalization, clump normalization can offer help the appear by lessen the affectability of the illustrate to the starting weights and changing over those weights to less complex way to get ready the demonstrate.

Normal clump normalization will work like normalizing the surrender of the past actuation layer by subtracting the brutal of the bunch and confining it with the standard deviation of the clump. Progressively, to these convolutional layers are added the max-pooling layers, which decrease the spatial dimension of highlight maps with the confirmation of the foremost critical features of the pictures. The character square and the convolution piece within the remaining organize organize make beyond any doubt that the estimations of the information, which are passed to the illustrate, are given. Character piece is utilized when there's no refinement between the input and the surrender estimations of the highlights. This implies that there's no issue when the input enactment dataset is passed to the show.

The estimation of the both input and surrender actuation is same. The convolution piece is utilized when there's differentiate within the estimations of the input actuation and the yield actuation. When there's differentiate inside the input and the target the illustrate won't plan precisely to overcome this issue convolutional square will alter the estimation of the dataset. These two pieces exchange the datasets into the diverse squares. The extreme classification is done by the completely associated portion interior the ResNet50 appear. The completely associated layer is the layer that comprises of a few neurons that are associated totally to the input layer or the going before layer and the yield layers. The fully connected portion will distinguish the connection and classify it based on the extricated highlights. The proposed design is planned for a ResNet50 display that has an input dataset measurement of (250, 250, 3).

It is built with different conv_blocks including convolutional layer, bunch normalization, and Sanctioning, which are set one after the other. Each piece can take the input, and at the conclusion, all are summed up and classified by the fully associated layer. The layers in this building are within the shape of 3 layers in which 2 layers are within the shape of (None, 250) and the ultimate layer is (None, 3) with a Softmax incitation work. The whole parameters that are passed to this building are 25751426, out of which the trainable parameters are 25698306 and the testing parameters are 53120.

**Xception**

The Xception could be a brief shape of "Extreme Inception" which makes a insurgency within the profound learning and computer vision engineering. Xception makes a revolution by greatly decreasing the computational cost, input parameters, and it'll decrease the time. Xception features a higher exactness rate over other pre-trained models since xception is lesss vulnerable to overfitting.

Customary models utilize the convolutional layers to extricate the highlights. In case the dataset has tall spatial channels, at that point the computational fetched, preparing time of the demonstrate will be expanded relatively. As this show will attempt to extricate the data in all three channels parallel, the parameters check is expanding definitely. To overcome this issue Xception model is presented. This Xception show will be prepared with the depthwise convolution layers. This Depthwise convolution layers will work like in case there's tall spatial channel dataset is passed, at that point rather than doing all at once it'll independently work on each channel and concatenate the channels with 1X1 convolution.

For illustration, let's take in case the input of the primary convolution is 12 and the yield mapped to that convolution is 24, the 3X3 channels were passed. The computational parameters of the ordinary convolutional layer are calculated as 12X24X3X3 which has 2592 parameters. In case the same highlights and dimensions were passed on to the depthwise seperable convolution layer the computational parameters were calculated by (12X3X3 + 12X24X1X1) which has 396 parameters.

Depthwise convolution layers is frame of convolutional layer which performs isolated convolutions on each channel independently of the input highlights. In detail, that the show will apply the bit to each channel of the picture independently which comes about within the yield channels with the same number of input channels. The design of the Xception demonstrate contains Section stream, Center stream and Exit stream. The section stream of the Xception square is of input layer, starting convolutional piece, depthwise seperable convolutions (which has depthwise convolutional, pointwise convolutional), remaining association. Each square has the ReLU actuation work and pooling layers to guarantee the non-linearity and diminishing spatial measurements.

Then the over highlights are passed to the middle stream which is additionally of the divisible convolutional layer. Rectified linear unit is associated in each layers. This layers were rehashed to certain times were it was predefined. At that point it was passed to the yield stream or the Exit stream. Here the features are passed through ReLU enactment, Distinct convolutional layer, and at last global normal pooling is connected some time recently passing to the completely associated layer. At that point, the pictures were classified with the Soft-max classification. Xception demonstrates may be a convolutional neural arrangement is 71 layers profound. The proposed Xception demonstrates the input highlight maps in the (250,250,3) measurement dataset. The show comprises of convolution layer, actuation layer, and batch normalization layer connected in parallel for numerous layers. The whole parameters that are passed to the engineering are 20861480. Out of these the trainable parameters are 20806952 and the testing parameters are 54528.

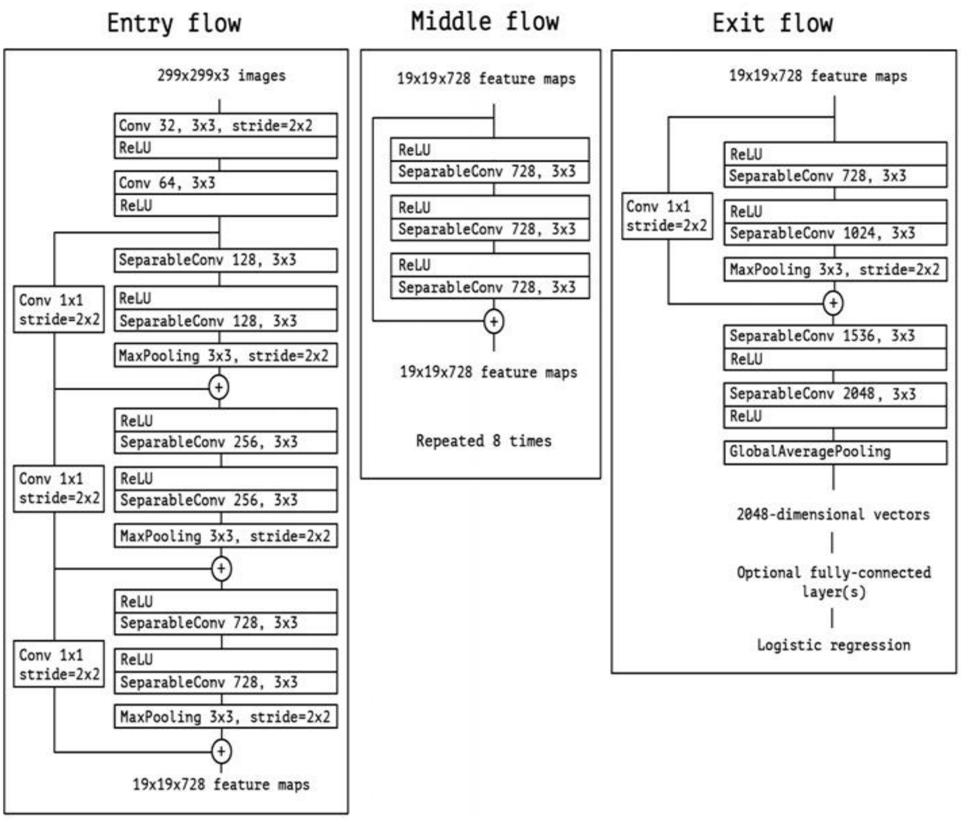
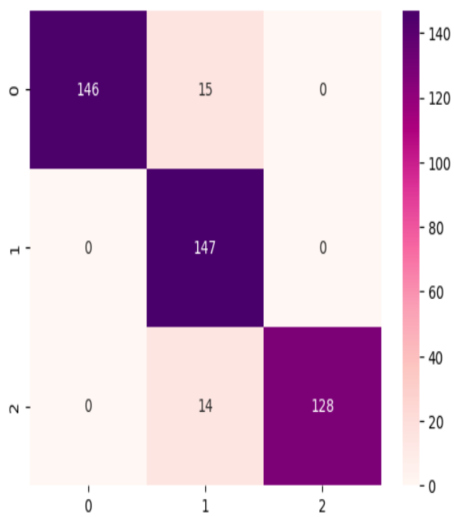
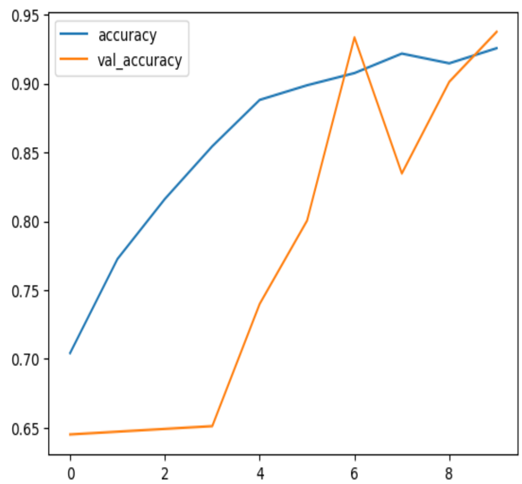



Figure 6:- The above diagram explain the architecture of xception model

## 5. Results

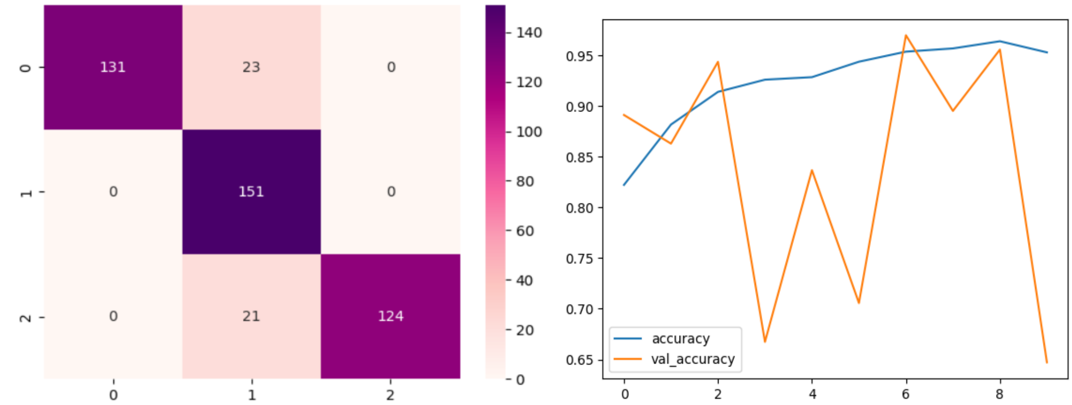
The deep learning models were inserted after the breast tumor dataset had been pre-processed, segmented, and extracted. We introduced and successfully used those deep-learning datasets. Accuracy of 98.3%, 92.2%, and 90.2% were obtained using the deep learning method CNN and the pre-trained models ResNet50, and Xception. A graph displays the accuracy and validation accuracy. The F1 score, precision, and recall are used to calculate the confusion matrix. It can be seen from the photos below that the model is well-trained and does well on the dataset.



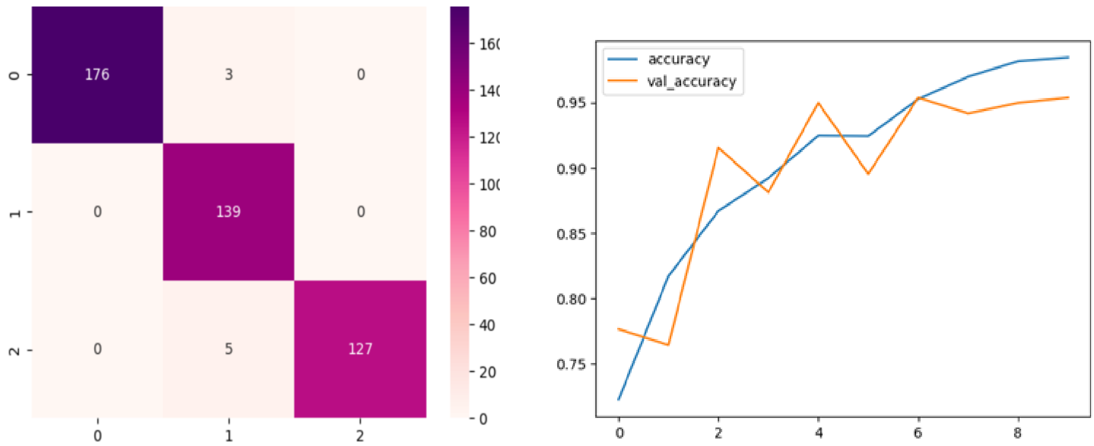
| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 1.00 | 0.91 | 0.95 | 161 |
| 1 | 0.84 | 1.00 | 0.91 | 147 |
| 2 | 1.00 | 0.90 | 0.95 | 142 |
| accuracy | | | 0.94 | 450 |
| macro avg | 0.95 | 0.94 | 0.94 | 450 |
| weighted avg | 0.95 | 0.94 | 0.94 | 450 |

**Figure 7. Chart, confusion_matix, classification_report of ResNet50.**




| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 1.00 | 0.85 | 0.92 | 154 |
| 1 | 0.77 | 1.00 | 0.87 | 151 |
| 2 | 1.00 | 0.86 | 0.92 | 145 |
| accuracy | | | 0.90 | 450 |
| macro avg | 0.92 | 0.90 | 0.90 | 450 |
| weighted avg | 0.92 | 0.90 | 0.90 | 450 |

**Figure 8. Chart, confusion_matix, classification_report of Xception.**



| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 1.00 | 0.98 | 0.99 | 179 |
| 1 | 0.95 | 1.00 | 0.97 | 139 |
| 2 | 1.00 | 0.96 | 0.98 | 132 |
| accuracy | | | 0.98 | 450 |
| macro avg | 0.98 | 0.98 | 0.98 | 450 |
| weighted avg | 0.98 | 0.98 | 0.98 | 450 |

**Figure 9. Chart, confusion_matix, classification_report of CNN.**

## 6. Conclusion

We proposed the efficacy of deep learning architectures toward the classification of breast cancer in the current work. The state-of-the-art pre-trained ResNet-50 and Xception models have reached accuracies of 93% and 90%, respectively. However, we further surpass this work by developing a novel CNN architecture designed particularly for this task.

Our proposed architecture includes three convolutional layers followed by a dedicated dense layer for each. The output from these individual dense layers is then concatenated into one and forwarded into a final classification layer. It gave an accuracy of 98%, which was quite surprising, as it outperformed pre-trained models in showing the potential of tailored architectures in breast cancer classification.

These results critically point out the fact that custom designs of CNNs have to be looked into for every medical image classification task. Pre-trained models are convenient and may be considered for initial investigations, but these are not suited to the specification of any particular dataset. Our proposed architecture, focusing on targeted feature extraction and classification through dedicated dense layers for each of the convolutional layers, proved this approach to be effective in achieving superior accuracy.

This type of research is paving the way for the study of custom CNN architectures, not only in the particular problem of breast cancer classification but in diverse medical image analysis tasks. Future work should be aimed at studying the effect of diverse hyperparameters, moving to even deeper and more complex structures in the networks while maintaining interpretability and computational efficiency. Through further improvement of these models, we will proceed with still more accurate and trustworthy tools for early detection and diagnostics of breast cancer.

### Future scope

In the future, the models can also be further extended with, for example, fuzzy systems, to rule-based cancer staging for identification of the staging of cancer in order to increase the accuracy of the diagnosis. Use expert knowledge, and in so doing, fuzzy logic and linguistic variables, in staging and classifying the stages of cancer with imaging data. With the application of advanced imaging and deep learning algorithms, the method could further help achieve diagnostic precisions.

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