Breast Cancer Prediction Utilizing Deep Learning Methods

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Abstract:- Due to the highest mortality rate in the globe, cancer still poses a severe threat to individuals today. It is because there is insufficient early cancer detection. One of the most deadly diseases for women worldwide and the most frequently detected non-skin cancer in women is breast cancer carcinoma. The probability of a successful treatment is significantly increased by diagnostic testing of this life-threatening disease. The traditional method of diagnosing cancer highly depends on the technician's or doctor's ability in spotting anomalies in the human body. Oncethe breast's cell tissue starts to divide irregularly and aggressively, breast cancer develops. Bosom malignant tumor can be classified into five stages (0–IV), each of which reflects the severity of the disease within the patient's body. Mammary gland illness is complicated and has many varieties of clinical effects, which makes it difficult to predict and treat. Additionally, the ability to more accurately predict the onset of a malignant infection will benefit breast cancer patients in planning their future course of treatment under their doctor's directions. It is particularly challenging to predict breast cancer because of its great heterogeneity and complicated features. This projectexamines the accuracy of multiple CNN models and focuses on the prediction of Breast disease using mammography images. Therefore in the study, we explore various CNN models to identify malignancy in mammography scans, including ResNet- 50, VGG-16, Alex Net, and Google Net. Additionally, we are going to build a special Xception model with 70% accuracy to diagnose breast cancer and compare each model.

Keywords:- *Alex Net, Breast Cancer, Carcinoma, CNN-Convolutional Neural Network, Deep Learning, Diagnose, Google Net, Mammogram, Malignant infection, Machine learning, ResNet-50, VGG-16.*

I. INTRODUCTION

Malignancy has been recognized as a collection of associated infections, abnormal cell formation, and the potential for uncontrolled cell division and tissue dissemination. The GLOBOCAN project estimates that worldwide, 14.1 million new cases of malignant growth occurred in 2012 alone (excluding skin diseases other than melanoma), accounting for 14.6% of mortality. Malignant development must be identified and diagnosed in its earliest stages if it is to be eliminated. The ongoing inquiry into the development of malignancy has been carried out during the preceding years One of the most important and crucial tasks for the expert is the accurate prediction of sickness.

Images from mammograms allow us to detect cancer in its early stages. Traditionally, professionals have done this by physically examining mammography images, but now, with the use of patient information from the past, we can build a machine learning (ML) model to learn from it and predict whether a patient is malignant or benign and has cancer or not in the future. Cancer that has been caught early can be treated effectively.

In this research, we focus on a Computer-Aided Diagnosis and Detection (CAD) framework to classify safe and unsafe mass sores from mammography image tests with the use of several Deep Learning (DL) design models, and to estimate their performance. Residual Networks, also known as Res Net, VGG, Google Net/Inception, and Alex Net, will be used in this case. In addition to all these models, we'll create one that uses Xception to predict malignancy.

- *Problem Statement:*

When the breast's cell tissues divide irregularly and abnormally, mammary gland illness results. Examining mammographydatasets can assist doctors in spotting disease instances at a much earlier stage. By doing this, we can improve the patient' treatment plans and assist them in beating the disease. Because of the high variety and complexity of cancer, it is still challenging to calculate the prognosis ofa patient. For patient's to receive therapy on time, an accurate cancer prognosis is essential. Over the years,prediction models have been developed that offer a valuable contribution to risk assessment and forecasting by identifying people who are high risk, assisting in the design and planning of therapeutic trials, and facilitating healthier living.

- *Dataset:*

Datasets from the Digital Database for Screening Mammography were utilized in this project (DDSM). It has mammography scans that have been digitally saved. Researchers and scientists utilize these images for their study.

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The database's primary contributors are the Massachusetts General Hospital, the University of South Florida's Department of Computer Science and Engineering, and the Sandia National Laboratories. There are over 2,500 exercises in it. Each investigation includes two images of each breast, some information about the affected person, such as age at the time of the investigation, a rating of breast density, etc., and mammogram image records, such as information about the scanner, information about spatial resolution, and other things.

The dataset is divided into three categories: benign, cancer, and normal.

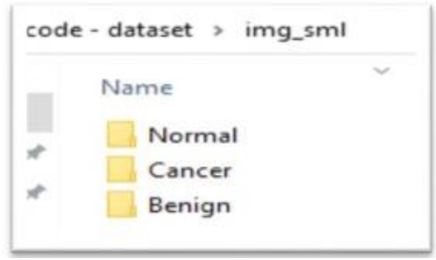

Fig 1:- Dataset Attribute

The first category is normal, which indicates that no more "work up" is necessary. The second one is benign; it is in the suspicious stage and pathological results are not required. Cancer falls within the last category; pathology evidence supports its presence. There are 4 different image angles in our dataset.

- Left CC refers to Left Crane Caudal.
- Left MLO refers to Left Mediolateral Oblique.
- Right CC refers to Right crane caudal.
- Right MLO refers to Right Mediolateral Oblique.

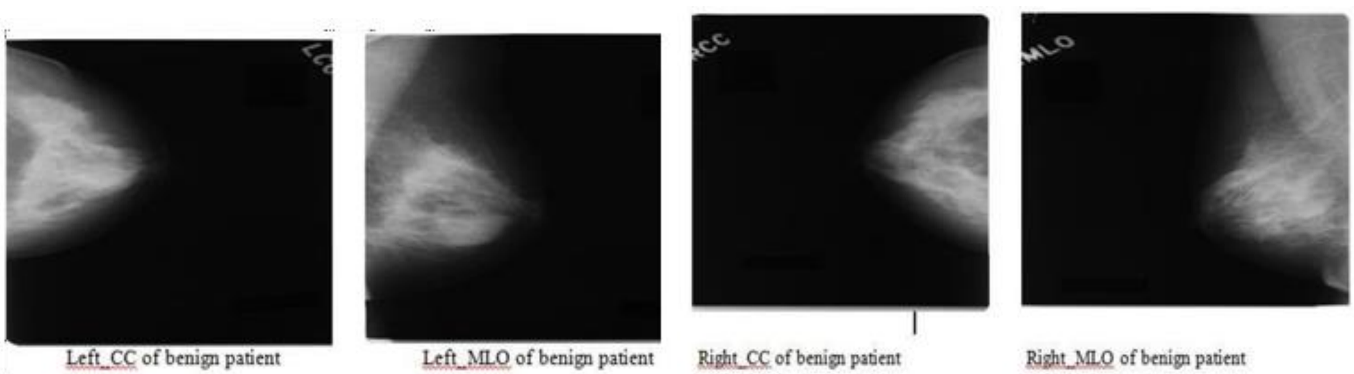

Fig 2:-Scan Images

It also includes patient information and masking images in addition to these angle images. To delineate the necessary portion of the breast from the mammography image, masking images are utilized. We don't need the patient information or masking images for our project. Only the 4 angle images are required.

II. LITERATURE SURVEY

➢ *A Technical Review of Convolutional Neural Network-Based Mammographic Breast Cancer Diagnosis[1].*

The article [1] describes how CNN is used in a specific area of mammographic breast cancer diagnosis (MBCD). It intends to provide instructions on how to use a CNN for similar tasks. The long-standing problem of MBCD has led to the suggestion of huge CAD models. CNN can be used to divide MBCD into three types. The first strategy is to configure shallow models or modify existing models to reduce the time expenditure as well as the number of preparation sessions. The second strategy is to use a pre-trained CNN model by transfer learning strategy to fine-tune the model. The third and final strategy is to use CNN models for feature extraction, and the distinction between benign ones and injuries is satisfied by using ML classifiers.

➢ *An Alternative Approach to Detect Breast Cancer using Digital Image Processing Techniques [2].*

In the modern era, computerized image processing is essential in many creative fields, according to an article [2]. Advanced Image Processing is used to manage computerized images and extract useful qualities from the data, which may subsequently be applied to make simple decisions with high accuracy. These techniques are also applied in the clinical setting, such as in the detection of mammary gland cancer. Breast cancer is currently one of the leading causes of death among women worldwide, and it is difficult to predict breast cancer because its underlying causes are yet unknown. All things considered, the distinct mammogram-detectable masses andmicrocalcifications are the hallmark of bosom illness. It can beused for early detection and will help women who might also be at risk of getting harmful malignancies. Mammography is the primary method used for breast cancer screening and early detection. For the expectation of breast cancer growth, the best research of the clinical report is necessary.

- *Breast Cancer Detection in Mammograms using Convolutional Neural Network[7].*

In a variety of malignancies, breast cancer is among the second worst diseases in the world. According to them, bosom malignant development is currently the most widely recognized disease among all women. Regarding clinical imaging, advancement is constantly necessary. The risk of death can be reduced if we detect cancer in its early stages and administer a suitable treatment. Clinical professionals can benefit from machine learning (ML) to identify infections more quickly and accurately. Whereas Neural Networks (NN) or Deep Learning (DL) is one of the cutting-edge techniques that can be used to determine the location of benign and malignant breast tumors. The location of cancerous growths in the bosom can be determined using convolutional neural networks (CNN).

		Class	
		Normal	Abnormal
Images	Training Samples (70%)	132	93
	Test Samples (30%)	57	40

Table 1:- Specifications of Mias Dataset and Its Division Into Train And Test Set in The Proposed System

For this experiment, they used the mammograms-MIAS dataset. Three hundred twenty-two (322) mammography images, around one hundred eighty-nine (189) benign images, and one hundred thirty-three (133) malignant images make up this dataset. Numerous exploratory findings have been made, demonstrating the effectiveness of Deep Learning (DL) models for detecting breast cancer using mammogram images.These findings also support the use of Deep Learning (DL)- based most recent component extraction and classifying techniques in various clinical imaging applications, particularly in the area of detecting breast cancer using mammogram images. The research is still in its early stages, and new developments are being made by improving the CNN design and employing additional pre-trained network models, which should result in improved accuracy measurements.

Effective feature extraction and classification require the use of appropriate segmentation techniques. On the MIAS dataset, an accuracy of 65% was attained.

III. METHODOLOGY

A. Module Description

In aspects of manuscripts, this composition presents a Computer-Aided Diagnosis and Detection (CAD) framework for organizing normal and dangerous mass sores from mammogram image tests using various Deep Learning (DL) design models and evaluating their performance. Residual Networks, also known as ResNet, VGG, GoogLeNet/Inception, and AlexNet, will be used in this case.

In figure 3, we are taking the digitally stored mammogram images from the publicly available database known as DDSM (Digital Database for Screening Mammography). The project's next step is to pre-process the mammogram images. The undesirable articles, which include explanations about the image, marks, and noise in the image, are removed from the mammogram images during the image preprocessing step. The preprocessing step allows for the localization of the area to be searched for irregularities.

The fragmentation zone is crucial for the mammary gland's unusual tissue detection and feature extraction processes, thus it needs to be extremely precise and concentrated. In this way, it is crucial to divide the image into its parts to extract an ROI that provides an accurate evaluation of the breast region's normal and anomalous sections. The crucial process of separating the breast area from the background and making plans to separate the bosom regions from other objects is included in the picture segmentation step.

Following image segmentation, we feed the image through various CNN models and modify their layered parameters. The CNN models will examine the features of mammography pictures and take the features out of them. As an illustration, the training mammography pictures are fed into a ResNet CNN model. This pre-trained model is capable of extracting an image's features after receiving the input. Consequently, we extract the characteristics from a mammography image using the transfer learning technique.

The categorization of the image phase completely depends on other intermediate steps, including segmenting and extracting features from mammography images. Following training, our model will be fully knowledgeable about photos and their many classes. They may therefore precisely classify those photos by themselves. We can incorporate additional classification methods, such as SVM, into those models if we need to further improve their classification accuracy. Since we are employing a transfer learning strategy, we can alter the characteristics of CNN models, i.e., the characteristics of each layer, to obtain different results for the CNN models. Then, we can assess each model's performances, which will make it easier to conduct a useful comparative study.

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➢ *Pre-Procesing*

Unwanted objects such as annotations, labels, and background noises are removed from mammograms during the preprocessing step.

Preprocessing aids in the localization of regions for abnormality detection.

➢ *Enhancement*

Image enhancement techniques are used to improve the quality of the mammogram by increasing contrast and readability.

It improves the system's detection of mammographic lesions with poor visibility and contrast.

The primary goal of mammogram enhancement is to improve image quality on low contrast mammograms.

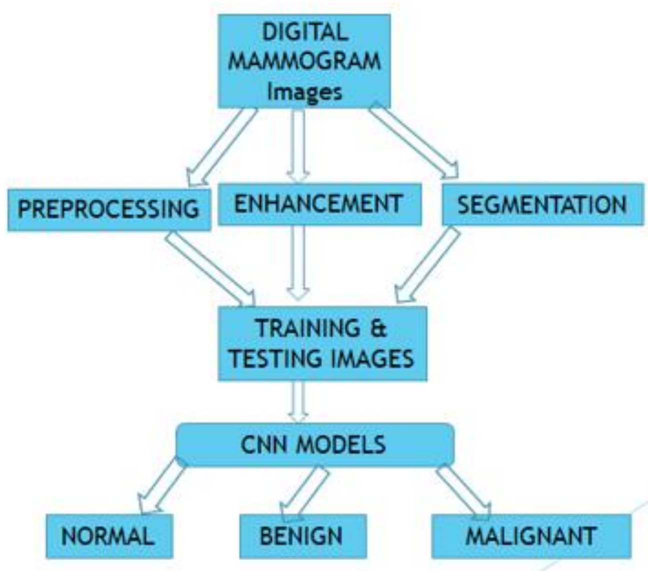

Fig 3:- Pictorial representation of Module Description

➢ *Segmentation*

The segmented region is critical for feature extraction and detecting abnormal breast tissues, and it must be well focused and precise.

As a result, segmentation is critical in order to obtain a ROI that provides a precise measurement of breast regions with abnormalities and normal regions.

Segmentation begins with separating the breast region from the background and progresses to separating the breast regionsfrom other objects.

B. Basic CNN Model Architecture

In recent years, there has been a significant increase in demand for a skill set known as DL. It is a component of ML and functions similarly to our brain, i.e., DL is made up of neurons similar to our brain, hence the name neural network. These neural networks teach our systems to do what comes naturally to humans. DL is made up of various models such as Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), Autoencoders, and so on. CNN is a model that emerged from these models and has made significant contributions to the field of computer vision and image analysis.

Convolutional Neural Networks (CNN) are a subset of Deep Neural Networks that can detect and classify features in images; thus, CNNs are used to analyse visual images. These CNN models have a wide range of applications in medical image analysis, image and video analysis, image classification, natural language processing (NLP), and computer vision, among others.CNN architecture is divided into two parts. The first is a convolution tool that will identify and analyse the image's various features. This is known as feature extraction. The second layer is a fully connected layer that processes the output from the convolutional layers. Following that, it predicts the image class using the features extracted from the previous convolutional layers.

➢ *Layers of CNN architecture*

There are three types of layers in CNN. Convolutional layers are the first, pooling layers are the second, and fully connected layers are the third. By stacking these models, we can create a CNN architecture. Along with these layers, two additional parameters are important: dropout layers and activation functions.

- *Layer of Convolution*

Convolutional layers are the first layers in a CNN model that are used to extract different features from an input image. Convolution was performed mathematically between the input image and filters of size MxM in this case.

The dot product between the filters and the input image is calculated using a sliding filter over the input image. The convolution operation is a type of linear operation in which two functions are multiplied to produce a third function that expresses how the shape of one function is modified by the other. For example, if two images that can be represented as matrices are multiplied, an output that can be used to extract features from the image is produced.

A CNN's input is a tensor of the form (number of images) x (image height) x (image width) x (input channels). The image is transformed into a feature map after passing through a convolutional layer, with the dimensions (number of images) x (feature map height) x (feature map width) x (feature map channels).

- *Pooling*

A Pooling layer follows a convolutional layer in CNN. This pooling layer is used to reduce the size of the convolved feature map in order to reduce computational costs. We can perform these operations by reducing the connection between layers and operating independently on each feature map. There are various pooling techniques available based on different methods. Some pooling techniques include maximum pooling, average pooling, sum pooling, and so on. The Max pooling technique is named after the largest element extracted from the feature map. The average pooling technique is defined as calculating the average of elements in a predefined sized image section. The Sum pooling technique is used to calculate the sum of the predefined sized image sections. In general, the pooling layer serves as a link between the convolutional layer and the FC layer.

- *Fully connected layer*

Fully connected layers are the next layer of CNN. It includes bias and weights in addition to neurons. It is used to connect neurons from two different layers. FC layers are added at the end of CNN, in front of the output layer and from the final few layers. The last layers' input image is flattened and forwarded to the fully connected layers. This flattened vector is then passed through a few more fully connected layers, where some mathematical operations are performed. The classification process then begins.

➢ *Classification*

The final step is to determine whether the lesion under observation is normal or cancerous. The classification step is heavily reliant on previous intermediate steps, particularly segmentation and feature extraction. Support vector machine (SVM), artificial neural network (ANN), k-nearest neighbour (KNN), binary decision tree, and simple logistic classifier are all examples of artificial neural networks.

- *The Dropout Layer*

When all of the features are connected to the fully connected layer, an error called overfitting of the training dataset may occur. Overfitting occurs when the model learns every single detail of the input. Assume that if our model learns the noise in our image, it will have a negative impact. When we provide new input to the model, it will consider the noise properties and produce an incorrect result. A dropout layer is used in our model to avoid the overfitting problem. While training the models, a few neurons are dropped from theneural network to perform this dropout function. It will shrink the model's size.

- *Activation Function*

These functions are important parameters in a CNN. Activation functions are used to learn and approximate complex and continuous relationships between network variables. This activation function will determine which model information should move forward and which information should not at the network's end. When building a CNN model, several activation functions are used. Activation functions include the ReLu, LeakyRelu, Softmax, Sigmoid, tanH, and Softmax functions. Each of these activation functions has a distinct purpose. For example, if we need to perform binary classification in our CNN model, we prefer sigmoid and softmax functions, and softmax is used for multi-class classification.

C. Architecture

We used digitally stored breast mammogram image datasets from the Digital Database for Screening Mammography in figure 4. (DDSM). We divided the images into training and testing image datasets after performing preprocessing tasks such as noise removal, annotation removal, contrast stretch, and adaptive histogram enhancement. We feed the preprocessed training dataset into CNN models such as ResNet, VGG 16 and 19, GoogLeNet, and AlexNet. After training these models with training data, the models examine the properties of images and effectively extract the features. The model can then be tested using the test image dataset, and each model can be compared.

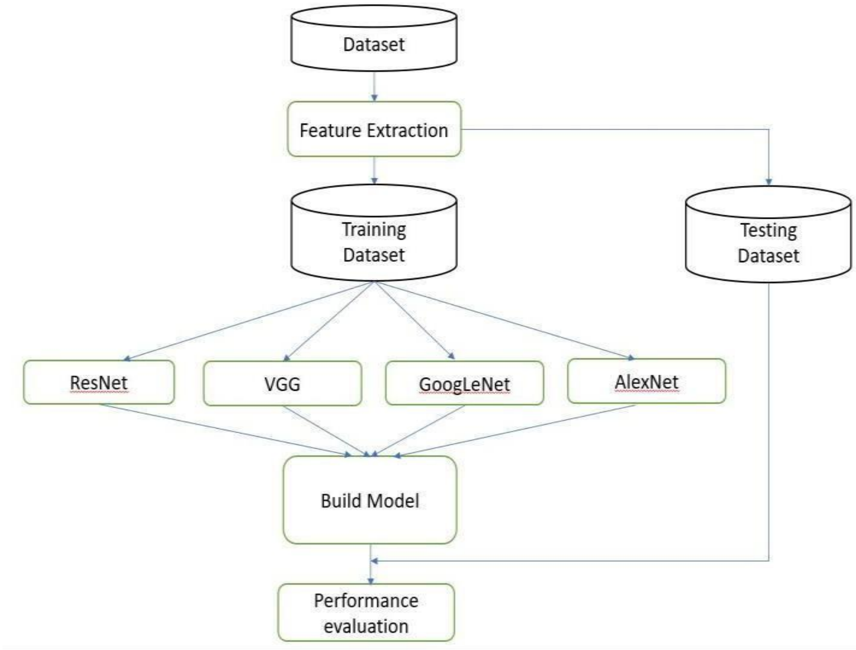

Fig 4:- Architecture diagram

There are two types of users in our project. The first is the developer, who works on the entire project. The developer is in charge of the pre-processing operations. We must perform pre-processing on our mammogram image dataset for this project. Image enhancement and contrast stretch operations are examples of pre-processing tasks. Following these pre-processing operations, developers build the CNN models. AlexNet, ResNet, VGG-16, GoogLeNet, and a customised Xception model are used here. These CNN models can detect and classify images, so by providing pre-processed mammogram images, the model can study the properties of those images. The developer then tests these models with testing images, evaluating each model's performance and accuracy.The user is the second. Users have access to CNN models as well as the evaluation section. A user could be a doctor or a radiographer, for example. These users can directly access the best CNN model after taking the mammogram image. When a user uploads a testing mammogram image to the model, it will classify the image into one of three categories: normal, malignant, or benign.

The benign result indicates that the patient does not have breast cancer but is at risk of developing it. We can cure it if I get the right treatment. The normal category indicates that the patient has no cancer cells and should not be concerned. Cancer is the final category.

D. Implemenatation and Result

Here to implement this project, python code in Jupyter Notebook platform is used. Tensor flow Keras and some basic packages are used to perform this project.

When compared to other CNN models, the custom-made Xception model provides higher test accuracy.

S.No:	Model	Test Accuracy
1	Alex Net	52%
2	VGG-16	65%
3	ResNet	51%
4	GoogleNet	62%
5	Xception	70%

Table 2:- Test Accuracy Table

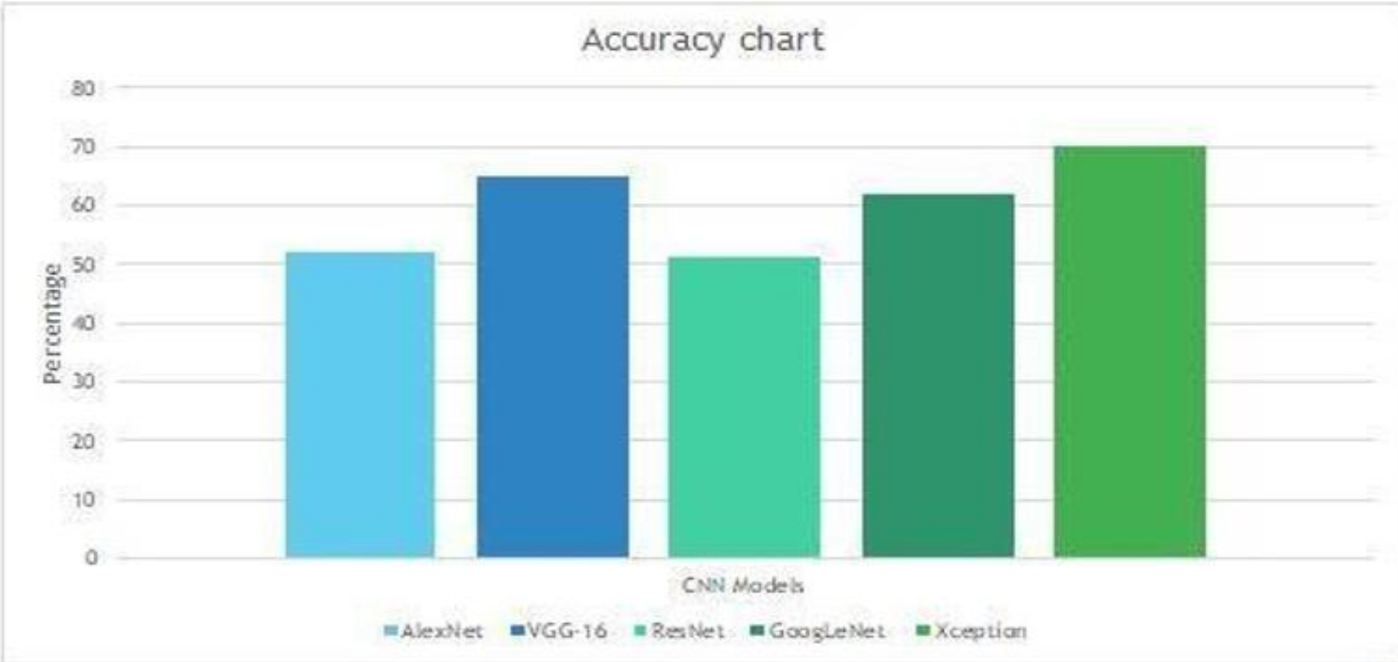

Fig 5:- CNN model performance

The bar diagram of model performance is shown in Figure 5. The X-axis of the chart represents the CNNmodels that we used in our project, and the Y-axis represents the percentage of test accuracy.

According to the graph, our customized Xception model has a higher accuracy of 70%. The ResNet modelhas the lowest accuracy of 51%.

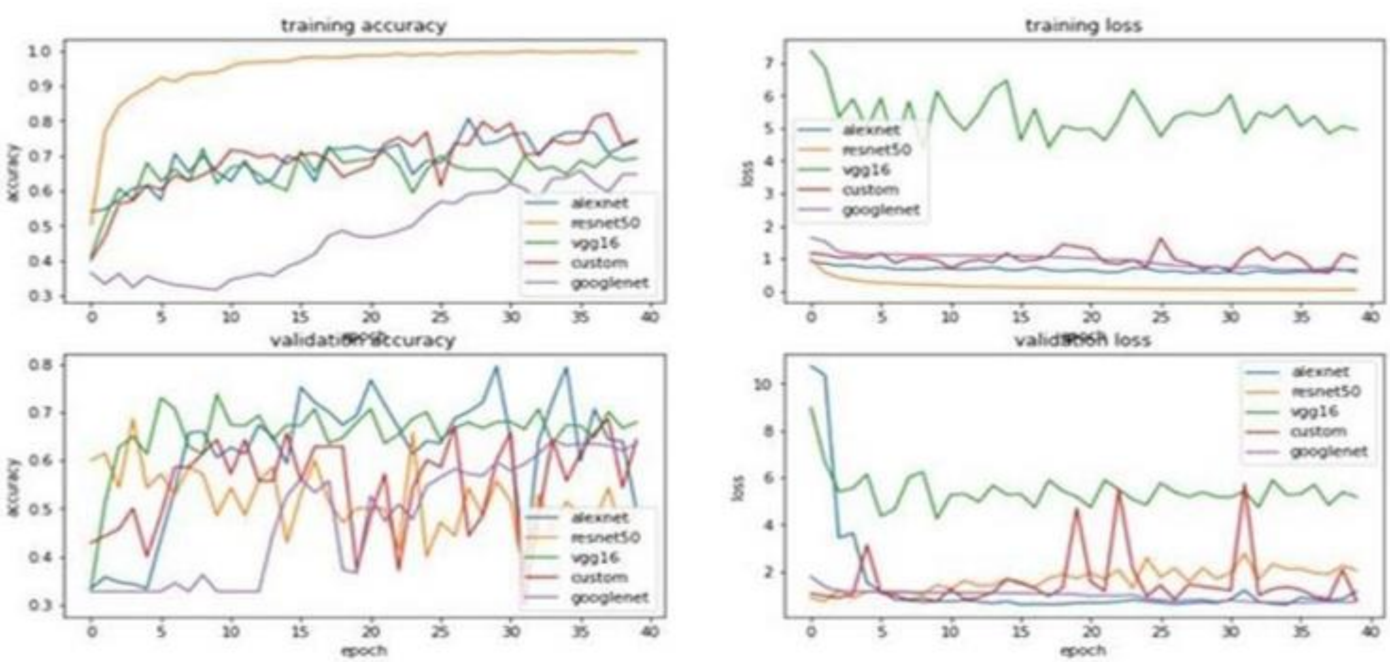

Fig 6:- Graphical representation of CNN model performance

Figure 6 shows a graphical representation of our various CNN models. Each model's training accuracyand training loss, as well as its validation accuracy and validation losses, are depicted in the graph.

IV. CONCLUSION

In today's world, advanced image preprocessing is extremely important in a variety of fields of innovative work. Advanced Image Processing is used to process computerised images and extract useful qualities from the data, which can then be used to make basic decisions with high precision. These procedures are also being used in the clinical field, specifically in the detection of mammary gland cancer. Breast cancer is one of the leading causes of death among women today, and it is difficult to prevent bosom disease because the primary causes of hidden bosom cancer remain unknown.

However, certain characteristics of breast cancer, such as masses and micro calcifications visible in mammogram images, can be used for early detection and are thus extremely beneficial for ladies who may be at risk of mammary gland cancer. Previously, physicians would analyse mammogram images and draw conclusions based on them, but now, with the help of Deep Learning (DL), we can determine whether it is benign or malignant in a shorter time frame and with greater accuracy. In this study, we used various Deep Learning (DL) architecture models to assess their performance in cancer prediction.

We created a custom model from the various models using the Xception model architecture, and this model outperforms the other CNN models in terms of testing accuracy. This Xception model has a testing accuracy of approximately 70%, which is higher than other CNN models.

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