

# Classification of Breast Cancer Cell Images using Multiple Convolution Neural Network Architectures

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**Abstract**—Breast cancer is a malignant tumor that affects women. It is the most prevalent cancer in women, affecting about 10% of all women at any point in their lives. The development of breast cancer begins in the lobules or ducts of the cells. Early detection and prevention are the best ways to stop this cancer from spreading. In this study, five Convolution Neural Network (CNN) models are used to process image data of breast cells. AlexNet, InceptionV3, GoogLeNet, VGG19 and Xception models are used for the classification of Invasive Ductal Carcinoma, IDC and Non-Invasive Ductal Carcinoma (Non-IDC) cells. The models are trained and tested at different epochs to record the learning rate. It is observed from the study that with higher epochs, the data loss decreases and accuracy increases. The accuracy of InceptionV3 and Xception is 92.48% and 90.72% respectively. Likewise, VGG19 and AlexNet have fairly close accuracy of 94.83% and 96.74%. However, GoogLeNet dominates over the other implemented models with the highest accuracy of 97.80%. The GoogLeNet model performs with high accuracy and precision in detecting IDC cells responsible for breast cancer.

**Keywords**—Breast cancer; IDC; non-IDC; AlexNet; VGG19; Inception sV3; GoogLeNet; Xception; accuracy

## I. INTRODUCTION

Cancer, also known as a malignant neoplasm, is a group of more than a hundred diseases marked by irregular cell development with the ability to spread to the body's underlying tissues. IDC is a kind of breast cancer that started in the ducts of the breast and has progressed to fibrous or fatty tissue outside of the duct. IDC is the most prevalent kind of breast cancer, accounting for 80% of all occurrences. Breast cancer is the most common kind of cancer in women worldwide [1]. Many imaging techniques have been developed to aid in the early diagnosis and treatment of breast cancer, as well as the reduction of breast cancer-related mortality. To improve diagnostic precision and accuracy, many assisted breast cancer diagnosis methods have been employed [2-4]. Fig. 1 shows breast cancer cases around the world.

To classify and predict breast cancer, machine learning algorithms with image processing have become quite famous for their accuracy in detecting the disease at an early stage. Ciresan et al. [5] classified each pixel into mitotic and non-mitotic groups using an 11-layered CNN. The predictions were made using likelihood ratings allocated to each pixel depending on its distance from the mitosis centroid. A related

study [6] used Transfer Learning in CNNs to identify and segment brain and colon cancer images, and the findings were cutting-edge. It used AlexNet (pre-trained on ImageNet) to train a Support Vector Machine with the features extracted from the last FC layer Support Vector Machine (SVM). Gao et al. used CNN to identify interstitial lung infections [7] and discovered that a pre-trained model converged categorization faster than a randomly initialized network. It is possible to automate cell counting in microscope pictures. Weidi et al. [8] took a regression approach to the issue, which eliminates the need for previous identification or segmentation. They regressed a density surface generated by the superposition of Gaussians using completely convolutional regression networks (FCRN). The dot annotations of each cell given as the ground truth for the training set are expressed by these Gaussians. To identify the best-supervised learning classifier, Vikas Chaurasia and Saurabh Pal [9] evaluate the performance criteria of Naive Bayes, SVM-RBF kernel, RBF neural networks, Decision trees, and basic CART in breast cancer datasets. The experimental results indicate that the SVM-RBF kernel outperforms other classifiers, scoring 96.84% accuracy in the Wisconsin Breast Cancer (original) datasets. Djebbari et al. [10] investigate the impact of an ensemble of machine learning approaches on breast cancer survival period prediction. When compared to prior results, their methodology is more accurate on their breast cancer data collection. S. Aruna and L. V Nandakishore [11] compare the findings of C4.5, Naive Bayes, Support Vector Machine (SVM), and K-Nearest Neighbor to find the appropriate classifier in WBC (K-NN). SVM is the most accurate classifier, with a 96.99% accuracy rate. Angeline Christobel. Y. [12] use a decision tree classifier (CART) to obtain an accuracy of 69.23% in breast cancer datasets. The accuracy of data mining algorithms SVM, IBK, and BF Tree is compared by A. Pradesh [13]. SMO outperforms other classifiers in terms of performance. T.Joachims [14] uses neuron fuzzy methods to reach a precision of 95.06 % by utilizing Wisconsin Breast Cancer (original) datasets. In this study, a hybrid method is proposed to increase the classification accuracy of Wisconsin Breast Cancer (original) datasets using 10-fold cross-validation. Liu Ya-Qin, W. Cheng, and Z. Lu [15] used the C5 algorithm with picking to produce additional data for training from the initial array using variations of repetitions to yield multisets of the same scale as the original data to predict breast cancer survivability. Delen et al. Lu [16] pre-classified 202,932 breast

cancer medical records into two groups: those who "survived" (93,273) and those who "didn't" (93,272). (109,659). The precision of the prediction of survivability was in the region of 93%.

Estimated number of new cases in 2020, worldwide, females, all ages

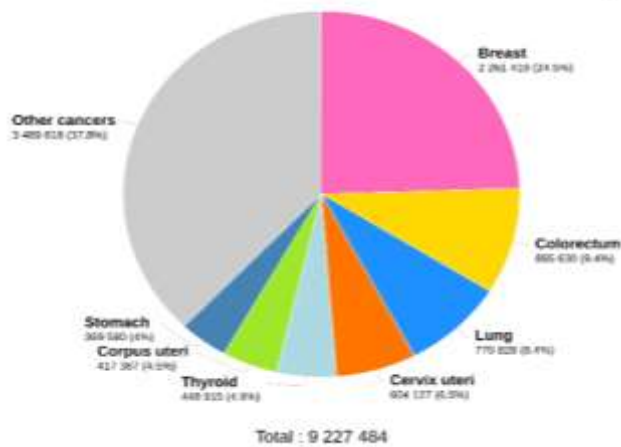


Fig. 1. The Distribution of the Confirmed Breast Cancer Cases around the World (2020). (Source: World Health Organization).

In this work, to detect cancer cells in time for fast treatment, CNN models are used to classify the IDC cells in the breast to determine breast cancer. The CNN models proposed for the study are AlexNet, GoogLeNet, VGG19, Xception and InceptionV3. The aim is to classify IDC from Non-IDC breast cell images from the dataset. Furthermore, the accuracy of the models is compared with each other to determine which model performs best.

The remainder of this paper is organized as follows. Section II contains the overall view of the system. It gives an

idea of how the study is conducted in each step. Section III comprises the materials and the methods in detail. It also explains the criteria under which the performance of the implemented models will be evaluated. Section IV summarizes the experimental studies and the obtained results. Section V provides a comparison of the proposed system with the existing studies to show that the proposed system has superior performance over others. Finally, Section VI presents the conclusion of the study.

## II. PROPOSED SYSTEM

Early detection of breast cancer is a critical field on which researchers are working since it may improve the rate of diagnosis, care, and recovery of affected women. Early identification is the most important measure in reducing this condition's clinical and social risks, given the high expense of care and the high incidence of the disease among women worldwide. There are several approaches and techniques for detecting this form of cancer, each with its own set of benefits and drawbacks. When cancer has spread through the later phases, it is usually identified and diagnosed. This is especially bad since cancer risks have metastasized by the time it is discovered are large, leaving the chances of treating it very low. Self-testing is rarely done, which tends to cancer detection in its latter stages. A lump or mass on the breast, self-examination, or mammography is the most common way to diagnose breast cancer.

In the proposed system, image data of breast cells are used to predict breast cancer. For that, the images are classified to identify which cells cause cancer. The models used for the prediction are AlexNet, IceptionV3, VGG19, Xception and GoogLeNet. An overall flow diagram of the study is presented in Fig. 2.

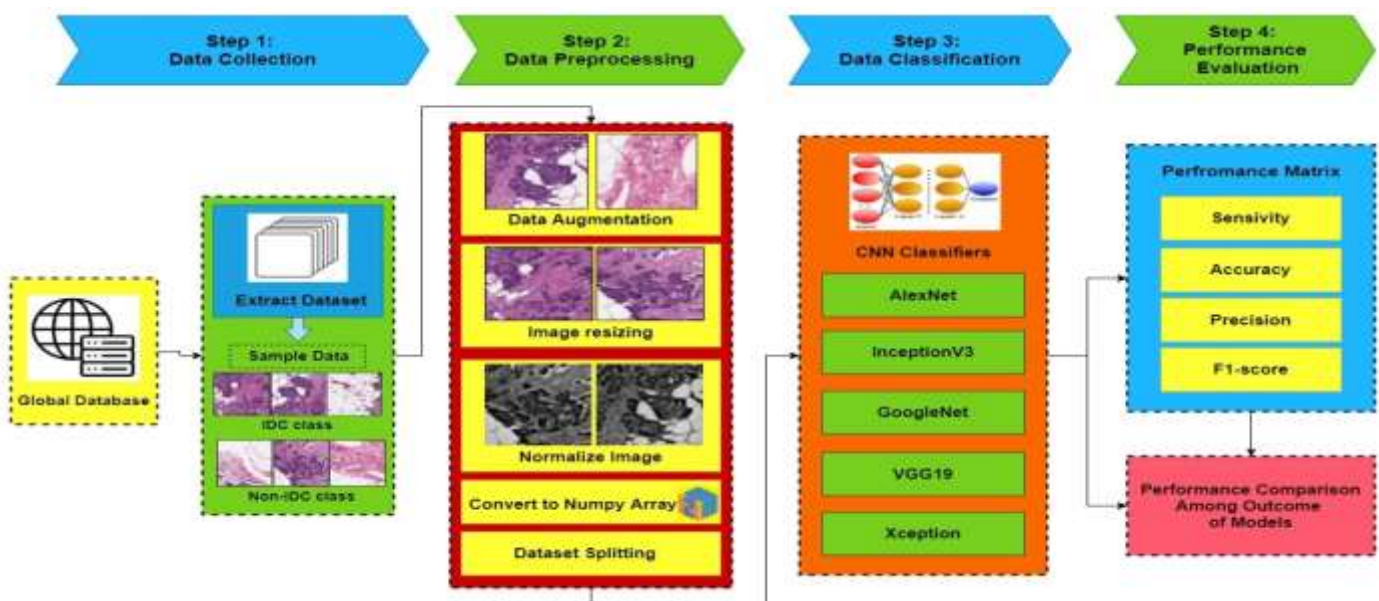


Fig. 2. System Flow Diagram of the Proposed Study.

### III. SYSTEM OPERATION

#### A. Data Description

The image used in this study is of breast cells to diagnose Breast cancer. The dataset was retrieved from "https://www.kaggle.com/paultimothymooney/breast-histopathology-images/discussion/130203". For training and testing the machine learning models, 27800 image data are used. The images are categorized into two categories,

- Non-IDC: categorized as "class0".
- IDC: categorized as "class1".

It will help specify IDC (Malignant (cells are abnormal and grow uncontrollably)) and Non-IDC (Benign (if the cells are normal just overgrown)).

Several IDC and non-IDC image data were added for better training of the models to enrich the dataset. Fig. 3 and Fig. 4 contain some of the IDC and non-IDC class images that were added to the dataset, respectively.

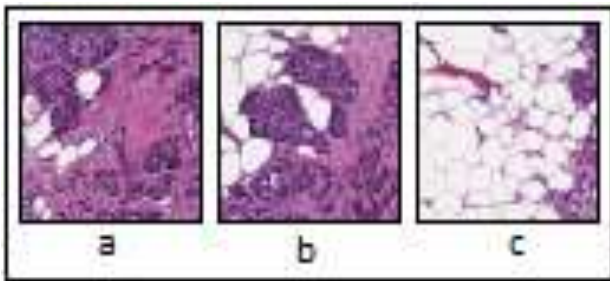


Fig. 3. Image Data of IDC Class.

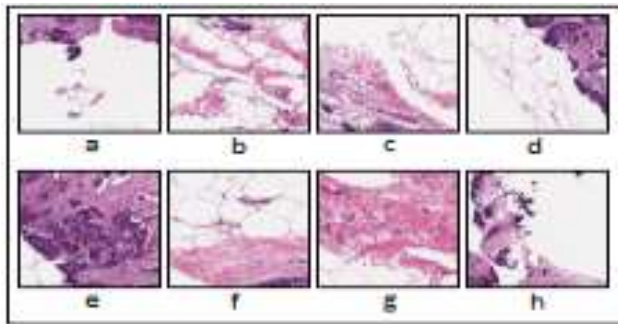


Fig. 4. Image Data of non-IDC Class.

#### B. Data Pre-processing

The dataset contains raw image data that are not fit for models to be trained and tested. To bring all the raw data into the same scale, data pre-processing is done on the dataset used in the work. The steps of the pre-processing stage are as follows.

- Generating augmented image: to train any machine learning algorithms, a large dataset is required. To increase the dataset volume, augmented images are generated using the ImageDataGenerator class in the Keras library. Table I holds the attributes used for image generation.

- Resize image: Since all images in the dataset are not in the same size, all the images are reshaped to 128 X 128 pixels.
- Normalize image: since all the images are in RGB, converting to greyscale images is being divided by 255 for normalization.
- Convert to NumPy array: image data a converted to NumPy array for faster computation.
- Dataset Splitting: the dataset is split into 80:20 for training and testing the models.

TABLE I. IMAGEDATAGENERATOR ATTRIBUTES

<i>Shear_Range</i>	0.3
<i>Zoom_Range</i>	0.2
<i>Horizontal_Flip</i>	True
<i>Vertical_Flip</i>	True
<i>Rescale</i>	1/255

#### C. CNN Models of Classification

1) *AlexNet*: AlexNet [17] is an 8-layered network with 5 convolutional layers and 3 Max Pooling layers [18]. ReLU activation is used. 96 filter sizes with a stride of 4 give the first Convolution sheet. After that, the 3X3 inputs go into the Max Pooling Sheet, with a stride of 2. Then, the data is sent to the second convolution layer with stride one and padding two, with a total of 256 5.x/2. The data is then followed by a second datasheet, where the stride is 2 and the filter size is 3. Three Convolution layers with 384, 384, 384, and 256 kernels are then applied to the input results, followed by an Activation layer with 3 X 3 kernels, followed by a Reshape layer with 512 kernels and a padding value of 1. With pool size 3, the final MaxPooling is implemented. If all the operations have been performed, the results are transferred to three connected layers, which are eventually converted into totally connected layers. In Fig. 5, the architecture is seen.

2) *InceptionV3*: InceptionV3 [19] is the third iteration of Google's Inception Convolutional Neural Network, which was first shown at the ImageNet Recognition Challenge. It includes Label Smoothing, Factorized 7X7 Convolution, RMSProp Optimizer, BatchNorm in the Auxillary Classifiers and a downscaling classifier to identify and add information from smoothed label sequences. This is shown in Fig. 6.

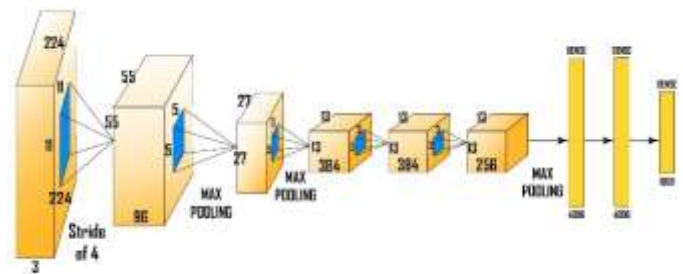


Fig. 5. AlexNet Architecture.



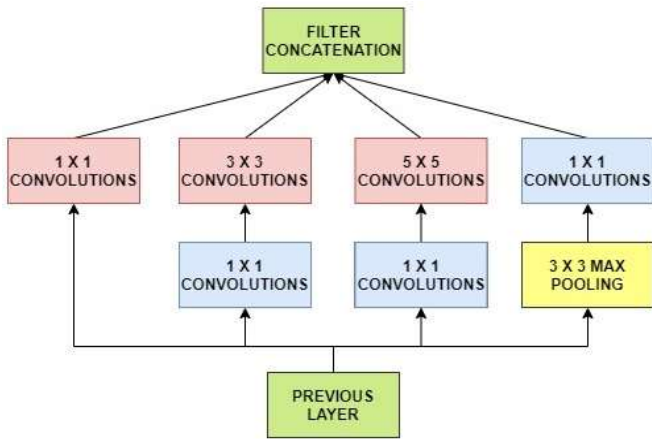


Fig. 6. Implemented InceptionV3 Structure.

3) *GoogLeNet*: Since 'InceptionV1' [20] is sometimes referred to as *GoogLeNet* [21]. There are 47 stages of aggregation and several pooling layers in *GoogLeNet*. A result is that, to sum up, the nine Inception modules are lined one after another. In the case of *GoogLeNet*, the stochastic descent algorithm is employed. The following Fig. 7 is an example.

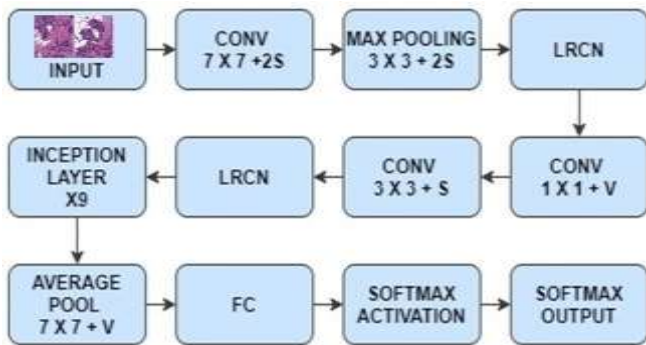


Fig. 7. GoogLeNet Model.

4) *VGG19*: *VGG19* is a version of the *VGG* model that includes 16 convolutional layers, three fully connected layers, five MaxPool layers, and one SoftMax layer as shown in Fig. 8. A fixed-size RGB picture was used as the input to this network, which also has a matrix of the same size. Max pooling was done using stride 2 across a 2 \* 2 pixel window. This was followed by the Rectified linear unit (ReLU) to add non-linearity into the model in order to enhance classification and computing speed. Three completely linked layers were implemented. And finally, a softmax function is used as the last layer.

5) *Xception*: The *Xception* model's base layer is initially frozen with the command (include top=False), followed by the trainable layer as shown in Fig. 9. The trainable layer employs images that have undergone the Average Pooling procedure. The Average Pooling pool size is (7,7), and there are 128 hidden nodes accessible in this layer. The Adam Stochastic gradient descent method is utilized for optimization, and the ReLU activation function is employed in that layer. Following that, in the output layer, the Softmax activation function is

utilized to identify IDC cells using two nodes. A learning rate of 0.01 is specified for backpropagation.

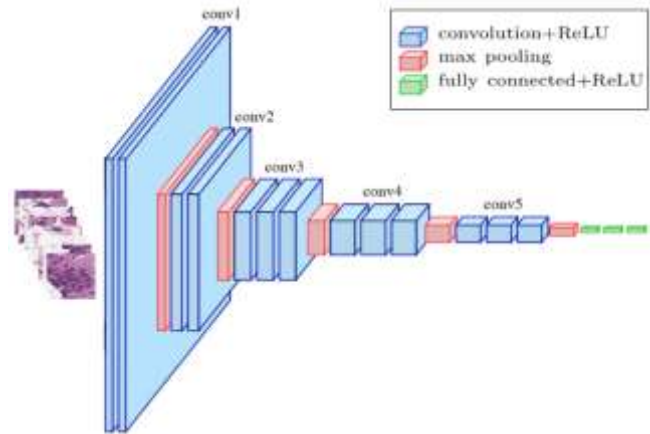


Fig. 8. Applied InceptionV3 Structure.

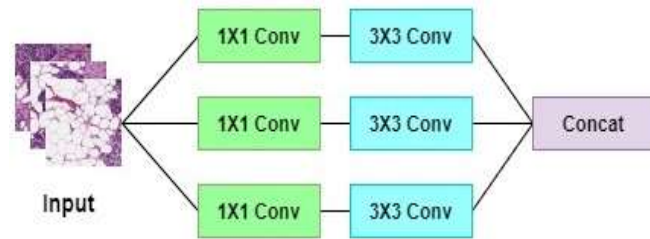


Fig. 9. Implemented Xception Model.

#### D. Performance Evaluation

After completing the training and testing process, the performance of the models is calculated [22, 23]. The evaluation criteria are precision, recall, f1-score, and accuracy, as described in Eq. 1, 2, 3, and 4.

$$Precision = \frac{TP}{TP+FP} \quad (1)$$

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (3)$$

$$F1 - Score = \frac{Recall * Precision}{Recall + Precision} \quad (4)$$

#### IV. RESULT AND ANALYSIS

Using the CNN models *Vgg19*, *Xception*, *AlexNet*, *InceptionV3*, and *GoogLeNet*, breast cancer prediction can be done successfully. The models can efficiently classify IDC cells and non-IDC cells. However, not all the models perform the same. Some show more accuracy than others.

The outcome was recorded for up to 10 epochs. Table II illustrates the recorded data for the *InceptionV3* model where the highest accuracy is 92.48%.

Table III contains the record of accuracy and data loss of the *GoogLeNet* model for the epoch. It can be observed from the table that with every new epoch, the rate of data loss gradually decreases and the accuracy increase for both the training and test set.

TABLE II. TRAINING AND TESTING OUTCOME FOR INCEPTION V3

Epochs	Training Data Loss	Training accuracy in %	Testing Data loss	Testing accuracy in %
1	13.29	77.34	10.21	83.42
2	11.02	81.93	6.46	89.94
3	7.76	85.67	6.39	90.24
4	7.39	86.76	6.23	90.73
5	7.56	88.34	5.93	91.23
6	7.26	87.99	5.74	91.47
7	6.98	89.23	5.46	91.78
8	7.23	88.80	5.28	92.12
9	7.34	88.23	4.97	92.48
10	7.03	88.57	5.01	92.10

TABLE III. TRAINING AND TESTING OUTCOME FOR GOOGLNET

Epochs	Training Data Loss	Training accuracy in %	Testing Data loss	Testing accuracy in %
1	9.39	93.53	7.14	94.54
2	5.28	95.39	4.24	96.83
3	5.19	95.73	4.19	97.23
4	5.03	95.93	3.95	97.53
5	4.83	96.23	3.69	97.46
6	4.90	96.15	3.53	97.94
7	4.85	96.39	3.45	97.45
8	4.72	96.32	3.33	97.23
9	4.79	96.83	3.49	97.42
10	4.67	96.45	3.19	97.80

The record of outcome accuracy of AlexNet has stated in Table IV with data loss in every epoch. The highest rate of accuracy rate of AlexNet model is 96.74% in the test set with a data loss rate of 9.59% at the 10<sup>th</sup> epoch. At the same epoch, it achieved the highest accuracy rate on the training set as well with 96.34%.

TABLE IV. TRAINING AND TESTING OUTCOME FOR ALEXNET

Epochs	Training Data Loss	Training accuracy in %	Testing Data loss	Testing accuracy in %
1	29.26	89.93	25.77	91.01
2	25.18	91.37	20.54	92.80
3	22.06	92.32	17.28	93.59
4	20.62	93.34	15.66	94.11
5	17.97	93.73	15.23	94.21
6	14.49	95.06	14.98	95.87
7	14.44	95.45	10.10	96.23
8	10.29	96.11	9.89	96.19
9	9.87	96.72	9.48	96.33
10	9.93	96.34	9.59	96.74

Table V contains the record of accuracy and data loss of VGG19 model with respect to epoch. The rate of data loss gradually decreases as the accuracy increase for both the training and test set. The model gives an accuracy of 94.83% with 5.1 data loss.

Table VI contains the record of outcome accuracy of the Xception model implemented in the dataset, along with data loss for each epoch. Xception model achieves an accuracy rate of 90.72% in the test set, with a data loss rate of 7.21 at the 8<sup>th</sup> epoch.

From the recorded data is can be observed that on the 10<sup>th</sup> epoch, all the models show the highest accuracy and lowest data loss for both train and testing data. A graphical comparison of the accuracy for training (a) and testing (b) data for the models are depicted in Fig. 10 as well.

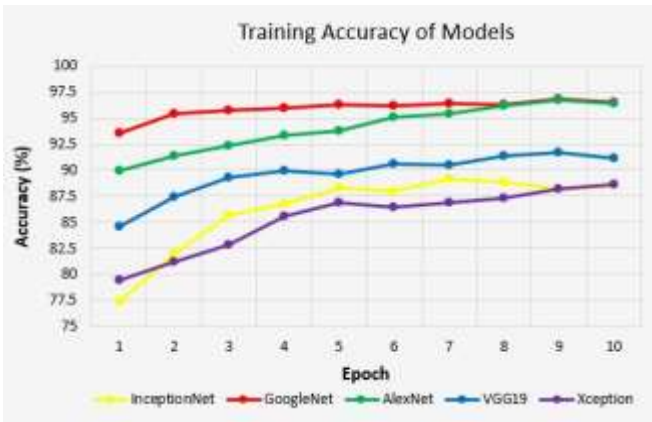
The data loss rate for the models decreases for both training and test set with every increasing epoch for all the models. The graphs in Fig. 11 show the rate of data loss obtained in each epoch as the model learns from the training (a) and testing (b), the less data it losses.

TABLE V. TRAINING AND TESTING OUTCOME FOR VGG19

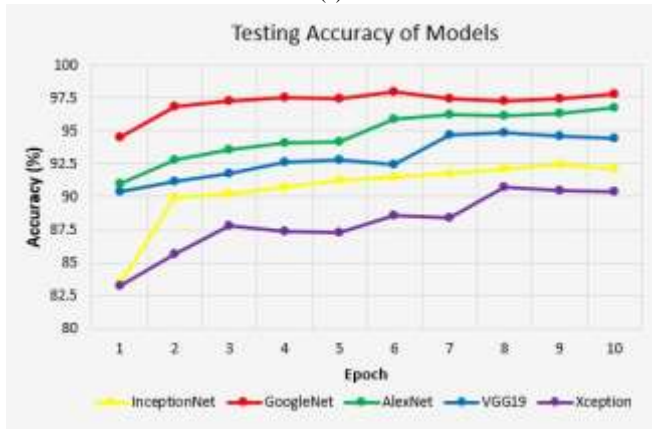
Epochs	Training Data Loss	Training accuracy in %	Testing Data loss	Testing accuracy in %
1	13.85	84.63	9.85	90.36
2	11.53	87.44	9.37	91.18
3	10.55	89.27	8.77	91.74
4	9.45	89.94	7.23	92.58
5	9.46	89.66	7.19	92.83
6	8.57	90.57	7.85	92.47
7	9.35	90.48	5.55	94.66
8	8.35	91.38	5.10	94.83
9	8.02	91.65	6.02	94.57
10	8.33	91.19	6.16	94.46

TABLE VI. TRAINING AND TESTING OUTCOME FOR XCEPTION

Epochs	Training Data Loss	Training accuracy in %	Testing Data loss	Testing accuracy in %
1	16.46	79.46	12.34	83.26
2	15.33	81.24	10.73	85.63
3	14.63	82.84	9.27	87.78
4	10.53	85.59	9.74	87.38
5	10.12	86.94	9.49	87.26
6	10.11	86.47	8.74	88.57
7	9.73	86.88	8.37	88.39
8	9.48	87.37	7.21	90.72
9	9.46	88.24	7.64	90.48
10	9.53	88.63	7.48	90.38

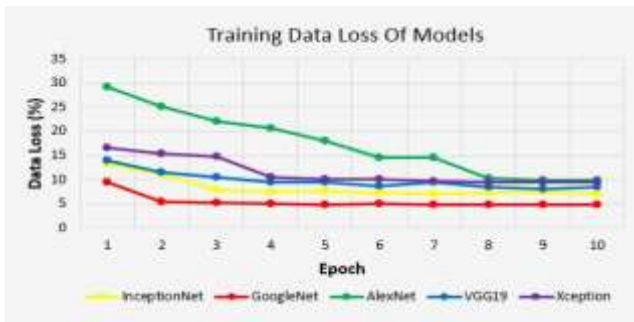


(a)

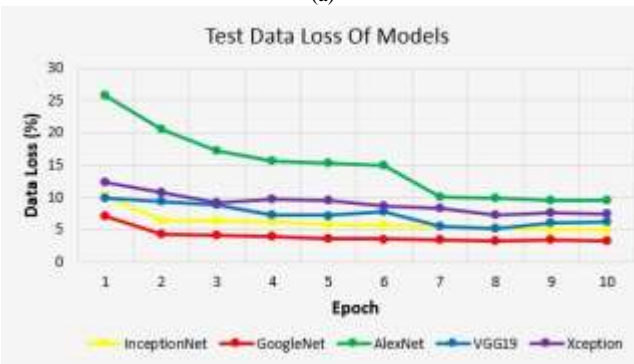


(b)

Fig. 10. Accuracy Comparison for (a) Training Data and (b) Testing Data of the Models.



(a)



(b)

Fig. 11. Data Loss Comparison for (a) Training Data and (b) Testing Data of the Models.

From the comparison, it is understood that GoogLeNet demonstrates much higher accuracy in predicting breast cancer and classifying cancer cells over other models. For further clarity, and overall performance measurement of the models is calculated in Table VII.

From Fig. 12, it can be deduced that GoogLeNet shows a higher rate for precision, recall and F1-score (97.34%, 96.46%, and 96.46%) along with the highest accuracy in predicting breast cancer.

GoogLeNet shows much superior classification performance over InceptionV3 and AlexNet. The models can successfully classify IDC and Non-IDC cells with 97.8% accuracy. A classification outcome of GoogLeNet for both classes is demonstrated in Fig. 13.

TABLE VII. CLASSIFICATION REPORT OF TEST DATA

Models	Performance Measures			
	Precision	Recall	Accuracy	F1-score
Inception v3	89.84%	90.12%	92.48%	89.54%
GoogLeNet	97.34%	96.46%	97.80%	96.46%
Alexnet	95.12%	93.54%	96.74%	94.65%
VGG19	93.63%	92.47%	94.83%	91.36%
Xception	89.49%	91.33%	90.72%	90.03%

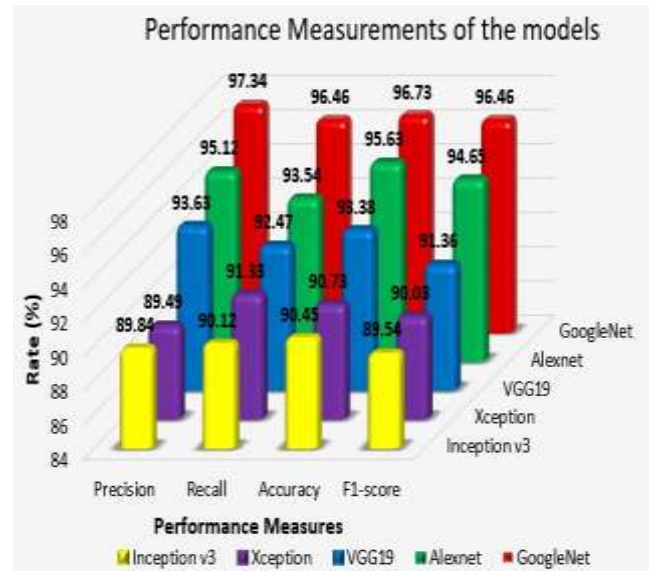


Fig. 12. Performance Evaluation of the Models.

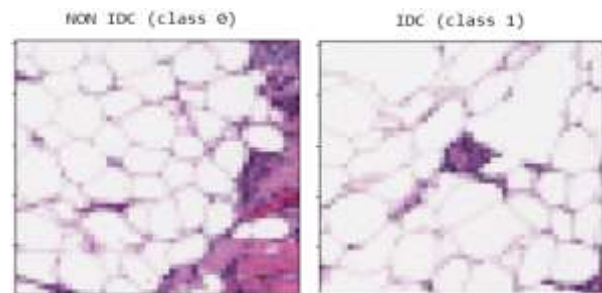


Fig. 13. Classified Classes by GoogLeNet.

## V. COMPARATIVE ANALYSIS

## REFERENCES

As mentioned before, many studies have been performed to predict Breast cancer using machine learning, deep learning, and other techniques based on different imaging data of cancer cells. The following table VIII compares the suggested technique to many other methods used by researchers on various datasets. Despite the fact that previous studies have shown a high degree of accuracy in predicting breast cancer, the proposed method surpassed prediction accuracy.

TABLE VIII. COMPARISON OF PREVIOUS METHODS AND THE PROPOSED METHOD

Studies	Datasets	Models	Accuracy
Proposed study	Breast histopathology images from kaggle	AlexNet	96.74%
		VGG19	94.83%
		Xception	90.72%
		InceptionV3	92.48%
		<b>GoogLeNet</b>	<b>97.80%</b>
[9]	Wisconsin Breast Cancer (original) datasets	SVM-RBF	96.84%
[11]	-	SVM	96.99%
[12]	Breast cancer datasets	Decision tree	69.23%
[14]	Wisconsin Breast Cancer (original) datasets	Neuron fuzzy methods	95.06%
[24]	Wisconsin Breast Cancer (original) datasets	SVM	97.13%
[25]	Image data from Mayo Clinic	SD-CNN	90%
[26]	Kaggle 162 H&E	CNN	87%

## VI. CONCLUSION

Breast cancer is a deadly disease that has claimed the lives of many people in both emerging and industrialized countries around the world. Breast cancer is the second leading cause of cancer death among females in industrialized countries and the first among females in developing countries. According to recent estimates, one of every eight people in Bangladesh will grow breast cancer over their lifetime. As a result, the fight against cancer is far from over. The main focus of this paper is to detect breast cancer that an early stage using the images of IDC cells in the breast. To complete the work, CNN models are used to classify the image data. AlexNet, InceptionV3, VGG19, Xception and GoogLeNet are the algorithms used in the classification process. The algorithms separately are successful in predicting the disease. However, they vary in accuracy of the prediction. It is seen that GoogLeNet has a much higher accuracy rate of 97.80% compared to the AlexNet and InceptionV3 with 96.74% and 92.48%. And VGG19 and Xception with 94.83 % and 90.72 %. GoogLeNet has higher Precision, Recall, and F1 scores than the other two models. However the models are only tested for the data images available in the Breast histopathology images dataset. The models will further be studied on more dataset to ensure that they can be universally used to detect breast cancer. Using the same process, it is also to be studied that other diseases such as liver cancer, colon cancer, ovarian cancer, etc., can be diagnosed efficiently and with high accuracy at a very early stage.

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