Automatic Detection of Breast Cancerusing Deep Learning

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ABSTRACT
Breast cancer is being discovered in women with cancer at an alarmingly high rate in India. In the future, these numbers will significantly rise, and the majority of Indians between the ages of 20 and 34 will see this increase. Since a late-stage diagnosis reduces the probability of a cure, breast cancer claims more lives among women globally than any other disease. The processing and learning capabilities of AI have increased recently. Using photos, researchers are able to detect cancer using machine learning. Furthermore, judging the health of tissues using digital images provides a second opinion faster. Here, our attention will be on applying Keras and deep learning techniques to identify cancer using histopathology pictures.

Keywords
Breast Cancer Detection, Convolution Neural Network (CNN), Invasive Ductile Carcinoma (IDC).

1. INTRODUCTION
About 25% of all breast cancer diagnoses conducted worldwide returned a positive result. In addition, out of the 23 lakh cancer patients, 12.5% have breast cancer as their primary cancer location. 6.85 lakh deaths were formally registered in 2020. Unsatisfactory medical care and late-stage diagnosis have resulted in a sizable incidence of mortality. This problem will worsen before it gets better if nothing is done to halt it. According to a survey that was published in, there are 7.12 lakh female cancer sufferers in India alone. These figures are expected to rise to 8 lakh over the next five years, with breast cancer accounting for one in three instances. Following in order, with 1 out of 7 cases, is infected lung cancer, followed by oral cancer, with 1 out of 8 patients. [4]

When breast cancer is diagnosed early and therapeutically, treatment chances are quite favorable. However, only 20 to 50 percent of cases in second- and third-generation world countries are discovered early. Therefore, the great majority of patients still risk harm even after receiving a cancer diagnosis. The poor standard of care, the lack of physicians, and the financial burden that patients and their families are face are the main causes of this. So that therapy may begin immediately away, it is vital to develop approaches that will enhance the diagnosis process. The method used to collect the data must be accurate and well-verified. [5]

1.1 Tumors
Tumors from breast cancer (BC) tissues fall into one of two categories.

A non-cancerous tumor is one that is benign. Because they do not invade neighboring tissues, they are frequently considered to be non-cancerous. The sac, a particular kind of immune system, must identify these cells from the body's healthy cells and eliminate them.

Malignant cells are cancerous cells. Compared to the nucleus of a conventional cell, their nucleus is more important. Additionally, they aim at the nearby tissue.. Human life is at danger as a result of their growth. They regenerate faster as well as was already said, tissue is composed of normal, malignant, and non-cancerous cells. Consequently, a tissue sample with a benign tumor nearby may also have a conventional tumor there. Cancer diagnosis is therefore challenging. Technology that can make decisions thus offers a better grasp of the issue. These educational models incorporate digital visuals as input.

2. LITERATURE REVIEW
This section will display the literature of finished works along with the results they generated. Let's have a look at some potential solutions using the image datasets we used as our base: In this study, breast tumours are automatically classified using deep learning and fine needle cytology. The system's main objective is to distinguish between benign and malignant cases using microscopic pictures. In this paper, cytological images were mostly employed. Over global characteristics, higher layer CNN models were implemented, such as the Google Net and Alex Net models; the Google Net model produced the best accuracy at 83%. [1]

By utilizing a neural network, the authors hope to improve the capabilities of ultrasonographic (US) technology for the differential diagnosis of breast tumors. An auto correlated neural network classifier was used to assess whether the tumour was benign or malignant. Ultrasound images are used in this. For diagnosing cancers, neural networks have sensitivity, specificity, and accuracy of 98%, 93%, and 95.0%, respectively. [3]

The authors analyse the Naive Bayes Classifier, Support Vector Machine (SVM) Classifier, Bi-clustering, R-CNN Classifier, and Bidirectional Recurrent Neural Networks, which are the most frequently used BC detection methods. (HA-Bi) RNN. Also mentioned is a novel method known as Deep Neural Network with Support Value (DNNS), which results in exceptionally high-quality images. The author incorporates historical-related photos in this. The suggested DNNS is demonstrably superior to the current approaches, according to experimental findings. [4]

The best Shear-let transform over RGB picture sensitivity, specificity, and accuracy scores are 89%, 94%, and 88%, respectively. The results are subpar compared to mammography or ultrasound. [9]

As defining characteristics, we employed mean, median, S.D., skewness, kurtosis, and entropy range. For this, we used thermographic photos. We propose to breakdown each image using multi-resolution wavelets. This wasn't the case, either, with the highest outcome being 0.87 normalized accuracy, 0.83 sensitivity, and 0.85 specificity. Because of its rapid learning and high accuracy rate, our recommended model is The results for mammography images using different techniques and feature extraction are displayed below. CNN yields superior outcomes in comparison to other conventional classifiers. Mammogram images are made up of weak X-rays. These intensities were supposed to serve as an information model. The energy in the corners of the images was quantified and used as a feature in addition to intensity. This model was used to identify the contaminated photographs. The measured precision was 0.92, and the measured accuracy was 0.96 when normalized. [2]

Ultrasound imaging is becoming more used as a method of clinical diagnosis. First was the segmented infected tissue. The output is then produced using a hybrid gravitational method using an SVM and search algorithm model. The accuracy of this model or system increased by 93%. [7]

It is difficult to automate breast cancer screening to improve patient care. In this study, we compare and contrast the methodologies of support vector machines, K-nearest neighbour, and logistic regression. The current work provides a CNN approach that analyses the IDC tissue region in WSis in order to automatically detect these cancers. In this study, three distinct CNN architectures are described. The suggested model outperformed the algorithm's results in accuracy by 8%. The accuracy rate of the proposed system is 87%. [8]

A hybrid system that incorporated an SVM model and a Bayesian classifier resulted in an AUC of 0.903 for the dataset. The accuracy was 0.8368.[12]

In this study, the distinction between benign and aggressive breast cancer is made using convolutional neural networks with sigmoid and relu activation functions. To improve accuracy, employ a number of optimizes, including the Adam Optimizer and others. In this, images of the histology are taken. This strategy achieves 90% accuracy.[13]

In this study, Masud et al. propose the use of convolutional neural network (CNN)-based models for the diagnosis of breast cancer. The authors explore the potential of CNNs in accurately classifying breast cancer cases using medical imaging data. Their work aims to improve the accuracy and efficiency of breast cancer diagnosis, potentially leading to more effective treatment and improved patient outcomes.[14]

In this review paper, Kaur et al. provide an overview of the advancements in histopathological image analysis techniques for breast cancer detection, diagnosis, and grading. The authors discuss the challenges associated with manual interpretation of histopathological slides and the potential of computer-aided analysis to improve accuracy and efficiency in breast cancer diagnosis. They review various methods and algorithms employed for different tasks, such as tumor detection, segmentation, feature extraction, and classification, with a focus on the analysis of histopathological images. The paper provides insights into the current state-of-the-art techniques, including machine learning and deep learning approaches, and highlights the advancements in digital pathology and image analysis technologies. The authors also discuss the limitations and future directions of research in this field.[19].

In this research, Cruz-Roa et al. focus on the automatic detection of invasive ductal carcinoma, a type of breast cancer, in whole slide images using convolutional neural networks (CNN). The authors aim to develop an automated system that can accurately identify invasive ductal carcinoma, providing a more efficient and reliable method for diagnosis. The paper likely presents the methodology employed, including the CNN architecture and training process, as well as the evaluation results and potential implications of the findings in the field of digital pathology and breast cancer diagnosis.[15]

In this paper, Hamidinekoo et al. present an overview of deep learning applications in mammography and breast histology. The authors discuss the advancements in deep learning techniques and their potential for improving breast cancer detection, diagnosis, and prognosis. They review various deep learning architectures and methodologies used for processing mammography images and breast histology slides. The paper highlights the performance of deep learning models in comparison to traditional machine learning approaches and manual interpretation by pathologists. The authors also discuss the challenges and limitations of deep learning in this context, such as the need for large annotated datasets and potential biases in the training data.[20]

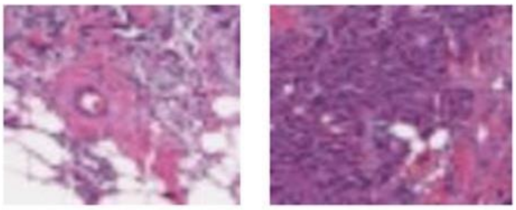
3. PROPOSED METHODOLOGY

The early diagnosis of cancer should be our primary goal because it can help with effective cancer therapy. Data from Kaggle is used in this job. Breast cancer treatment prospects are extremely good when diagnosed early and therapeutically. The CNN design is standardized and includes different sorts of layers. The convolutional layer, which gives the image's input components a weighted average, produces the output. By employing pooling layers, the dimensionality can be reduced. The last layer, which is fully connected, outputs each label to a class while monitoring the variety of discoveries from earlier levels. We'll start with a seven-layer learning architecture that has two completely linked layers and five convolutional layers. The image size is (50, 50, 3), while the stride dimensions are initially kept huge (5x5). The stride dimensions are reduced to (3x3) in the following two topologies. The model slows from first to second as computation grows and the amount of time required to examine a picture increases due to a decrease in stride size. Each model has a comparable design, with smaller stride sizes and an equivalent number of output characteristics. Every model is further altered by the addition of new layers. They are built using Max- pooling with top-layer sigmoid and relu activation. Binary cross-entropy is employed to compute loss.

3.1 DATASETS

Working with sets of histopathology imaging data will be our task. The datasets are valid for the binary classification of ductal carcinoma (IDC/DC) tissues and only contain IDC tissue with a significant number of images. The most frequent sub-type of breast cancer is invasive ductal carcinoma (IDC). Pathologists usually focus on the regions that contain the IDC when assessing the aggressiveness of a whole mount sample. As a result, one of the frequent pre-processing procedures for automatic aggressiveness assessment is locating the precise IDC zones inside a full mount slide. This dataset was acquired via Kaggle. [6]

Because of the public domain licensing, these pictures were taken from gleason.case.edu. To produce such a big number, a biopsy of 162 people was performed at a 40-times magnification and size (50, 50). There are 78K IDC (+) images and 198K (-) images in this collection. The class represents the IDC (+) if the value is 1 and IDC (-) if the value is 0, and coordinates are the x-y coordinates of the original image from which the patch was segmented. PID stands for the patient identification number.



Non-Cancerous Image **Cancerous Image**

Figure 1. Benign and Malign images from Datasets

3.2 IMAGE PREPROCESSING

When using image data, image pre-processing is an essential stage in deep learning. It includes a number of methods for converting unprocessed photos into a format better suited to deep learning systems. In order to improve the features, eliminate noise, and normalize the data, picture preprocessing is done. This improves the accuracy and resilience of the deep learning model. Re-scaling, filtering, normalization, cropping, and re-sizing are typical techniques used in deep learning. The process of image analysis generally starts with image processing. It can considerably improve the performance.

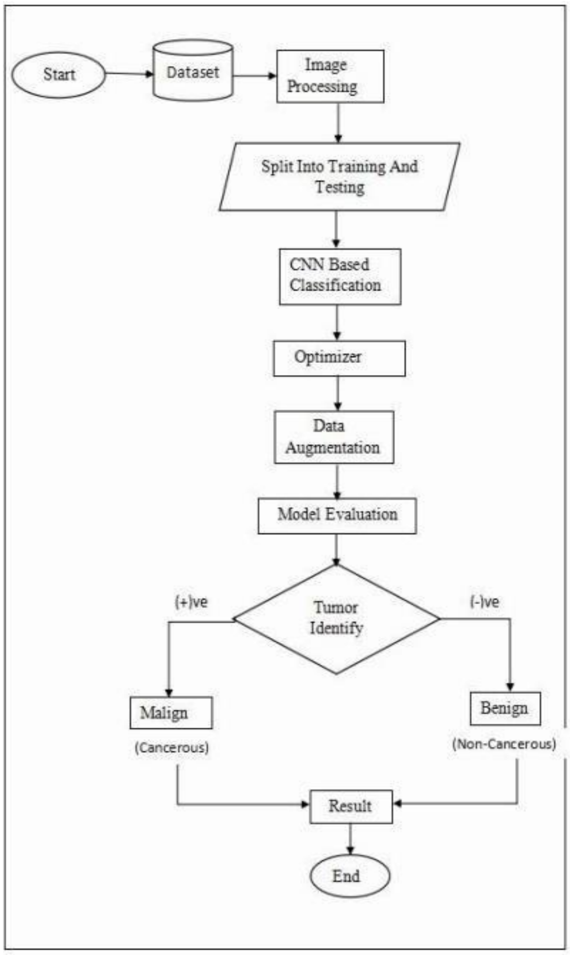


Figure 2. Diagram showing how breast cancer can be automatically found in Images from histopathology

3.3 Classifier Used

Many layers can be successfully trained using convolutional neural networks (CNN), one of the most popular deep learning techniques.Because research has shown it to be quite successful, computer vision programmes typically employ it. CNN can be used to build a computational framework that converts unstructured image inputs into the appropriate output categories for categorization.The overall CNN design is composed of numerous different layer types. The convolution layer, which weighs each input component, produces the image output. It is possible to use pooling layers to reduce the dimension. The last completely linked layer, which also keeps account of the discoveries made by earlier layers, outputs each label to a class. First, the stride widths are kept wide. As a result, all models have the same number of output characteristics and a similar design with decreasing stride size.

Layer of input: The layer of input is where the input imagesand their pixel values are kept.

1. Convolution layer: A CNN generates several feature maps by employing kernels in the convolution layers to transform thebest feature maps and the entire object.

2. Pooling layer: The size of feature maps and network parameters can be decreased by using the pooling layer, whichfrequently comes after a convolutional layer. Pooling layers are similarly invariant in interpretation to convolutional layerssince they incorporate neighbouring pixels into their calculations. The two most widely used techniques are averagemaximal_pooling.

3. Non-linear layer: The convolution neural network categoriesthe hidden layer by altering the input in a non-linear way. In the CNN framework, rectified linear units are utilized (Relu). In non-linear transformations, rectified linear units are frequently utilized. By utilizing a threshold to set any input value less than zero to zero, this type of layer performs a straightforward action.

5. Fully connected layer: The data eventually reaches the fully connected node, which is the top layer of the convolution neuralnetwork, after numerous cycles of the lower layers. The neurons in the completely connected network and those in the two adjacent layers are directly coupled.

6. Normalized layer: The suggested system will use an automated batch normal-zation layer as the normalization layer.Any channel can be normalized using the batch normalization layer form, which makes use of a tiny batch. You might consequently become less sensitive to data changes as aresult.

7. Soft-max layer: Interpreting network performance might bechallenging. The CNN commonly concludes with a soft max function when categorization problems exist.

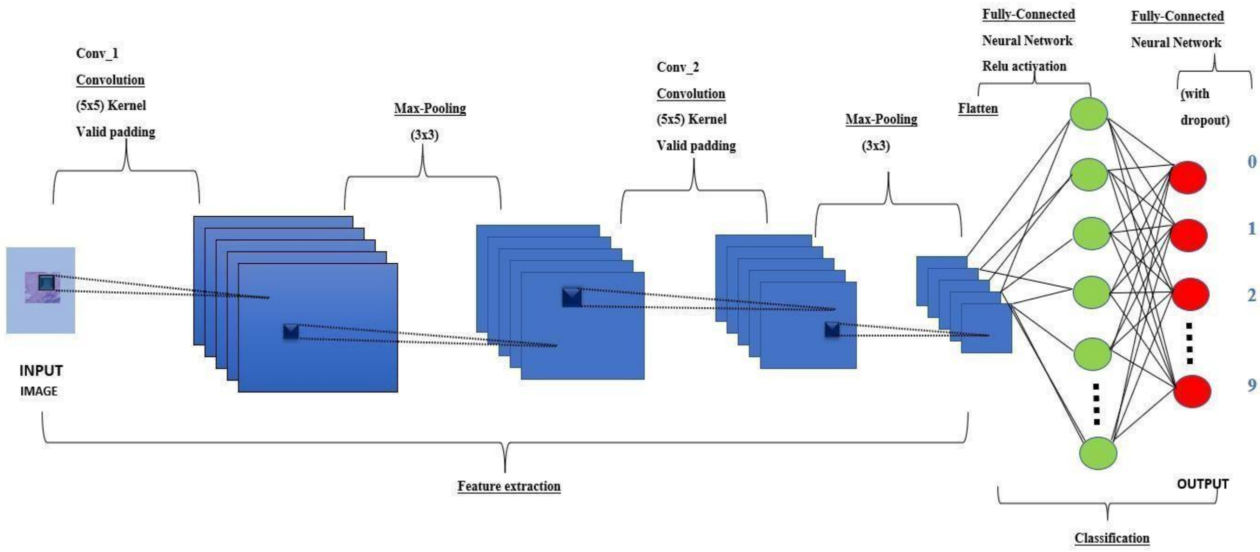


Figure 3. CNN based Architecture.

3.4 SGD Optimizer

One of the most used optimization techniques in deep learning is stochastic gradient descent (SGD). To identifythe weights of a neural network that minimize the loss function, a first-order optimization approach is applied. The fundamental principle of SGD is to incrementally adjust the neural network's weights after handling each training batch.

4. EXPERIMENTAL RESULT

The scikit-learn framework was utilized for Python implementation. The majority of data scientists use Scikit-learn. The Numpy, Matplotlib, and Seaborn frameworks, among other requirements for running the scikit-learn function, have been used to create the suggested system.

4.1 HANDLING IMBALANCING PROBLEM

A class imbalance can be troublesome for machine learning model training since it can result in predictions that are biased in favour of the dominant class. If one classhas noticeably more samples than the other in the dataset, there may be a class imbalance that can be identified usingthis fig.

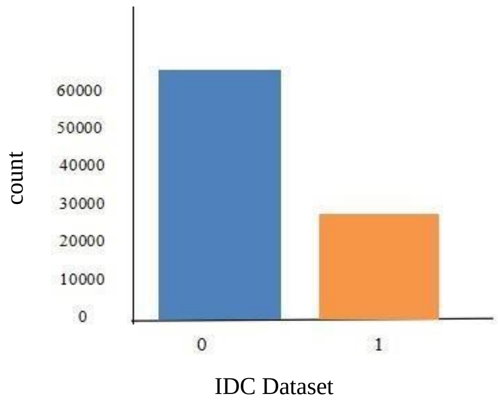


Figure 4. Imbalance datasets shown in a bar graph

When one or more classes have a disproportionately small number of samples compared to the other classes, handling class imbalance is a common difficulty in machine learning. Oversampling is a technique that can be used to address this problem. In oversampling, the minority class is replicated to increase its representation in the dataset. This can be done by either duplicating the existing samples or generating new samples synthetically. By increasing the number of samples in the minority class, the model is exposed to more examples, which helps to prevent it from being biased towards the majority class.

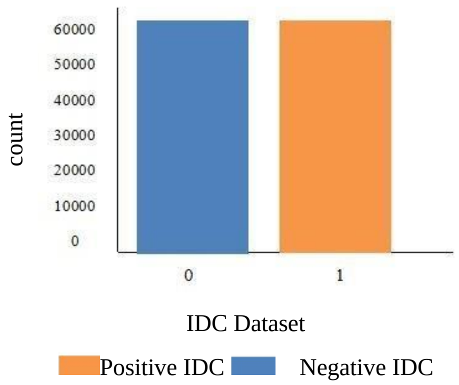


Figure 5. Balance datasets shown in a bar graph.

4.2 HYPER TUNING

Hyper-parameter modification is essential in deep learning algorithms because the values of a model's hyper-parameters have a significant impact on the model's performance. Neural networks are capable of autonomously learning input and output connections. Some of these connections perform admirably during training butfall short when put to the test on actual data. This leads to

model performance degradation and over-fitting. This makes one of the important jobs the hyper-tuning of the parameters. By tweaking the model's parameters, we increase performance. It used dropout. We used dropout 0.2 to prevent the model from being over-fitted.

- Dropout: 0.2
- Epoch: 25
- Optimizer: SGD Batch size: 256 Learning rate: 1e-3
- Convolutional neural network with 5 convolutional layers, max pooling, and 2 dense layers.
- Increased the filters for the convolution layers (32-64-128-256).

4.3 Image Augmentation

The dataset is expanded using image augmentation, which nvolves creating new, changed images. utilizing the Keras library's ImageDataGenerator. We produce fresh, enhanced histopathology pictures. We guarantee that our neural network will train more effectively at each step andepoch by using fresh augmented photos. Images are first provided to ImageDataGenerator, which rotates, transforms, and otherwise alters each image. The augmented photographs' parameters are:

- Range of zoom:0.2,
- Height_shift_range: 0.2,
- width_shift_range: 0.2,
- shear range: 0.2.

4.4 PERFORMANCE ANALYSIS

After 25 epochs of training on the balanced training set with a 256-person batch size, the model is evaluated on the balanced testing set. Utilizing Matplotlib, graph model 1 training and validation accuracy with time. Fig.6 illustrates the first subplot, which depicts the training and testing accuracy over epochs. Additionally, the second subplot in fig.7 displays the training and validation loss over epochs.

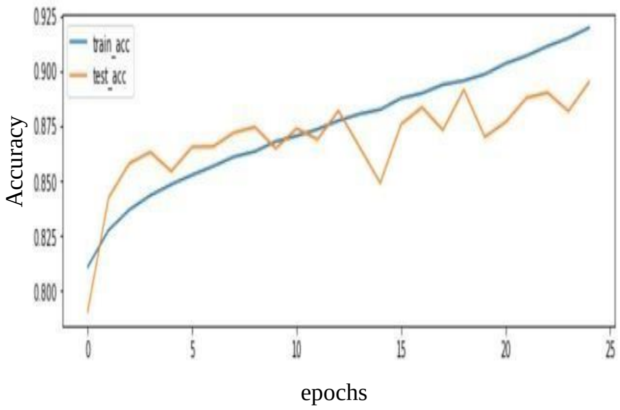


Figure 6. Accuracy testing and training over epochs

Table 1: The summary table of CNN Model

Layer	Output shape	Param #
Input_1 (InputLayer)	(None, 50, 50, 3)	0
conv2d_1 (Conv2D)	(None, 50, 50, 32)	896
max_pooling2d_1(MaxPooling2D)	(None, 25, 25, 32)	0
batch_normalization_1(Batch)	(None, 25, 25, 32)	128
conv2d_2 (Conv2D)	(None, 25, 25, 64)	18496
max_pooling2d_2(MaxPooling2D)	(None, 12, 12, 64)	0
batch_normalization_2(Batch)	(None, 12, 12, 64)	256
conv2d_3 (Conv2D)	(None, 12, 12, 128)	73856
max_pooling2d_3(MaxPooling2D)	(None, 6, 6, 128)	0
batch_normalization_3(Batch)	(None, 6, 6, 128)	512
conv2d_4 (Conv2D)	(None, 6, 6, 128)	147584
max_pooling2d_4(MaxPooling2D)	(None, 3, 3, 128)	0
flatten_1 (Flatten)	(None, 1152)	0
dense_1 (Dense)	(None, 128)	147584
dense_2 (Dense)	(None, 1)	129

Total params: 389,441
Trainable params: 388,993
Non-trainable params: 448

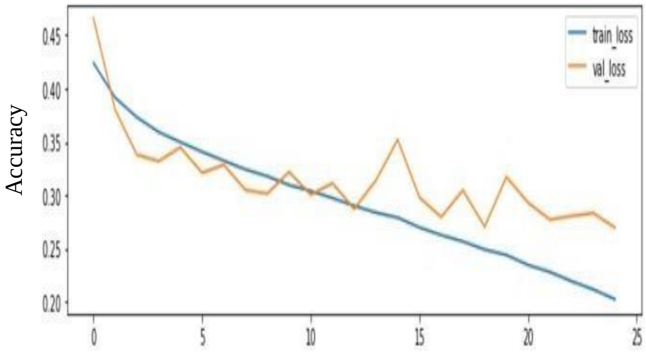


Figure 7. Training and testing accuracy over epochs

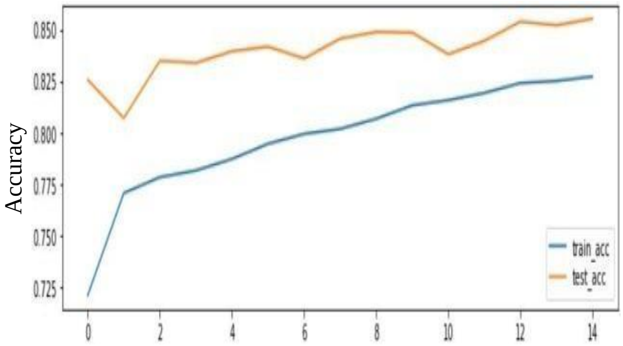


Figure 8. Training and testing accuracy over epochs

The programme builds a CNN model with Keras layers, stochastically gradient descent, binary cross-entropy loss, accuracy metrics, and learning rates of 1e-3 and 0.9. The model is 15 epochs of balanced training set training and balanced testing set validation. Model 2 plots the training and validation accuracy over epochs using Matplotlib. Fig.8 illustrates the first subplot, which displays training accuracy and testing accuracy over epochs, and Fig.9 illustrates the second subplot, which shows training loss and validation loss over epochs.

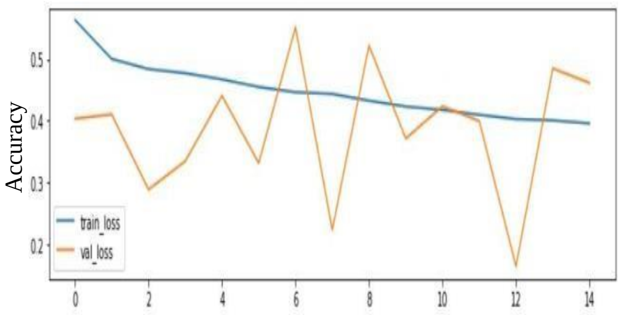


Figure 9. Loss during training and validation across epochs

This classification report analyses a binary classification model's effectiveness. The precision of accurate prognoses is measured. It is the proportion of actual positive results to all expected positive results.In this instance, 93% of the cases were correctly identified as class 0 and 87% as class 1, respectively, by the model.

Recall gauges the model's sensitivity, or its capacity to spot real positives. It is the proportion of actual positives to all genuine positives. In this instance, 93% of the instances that belong to class 1 and 86% of the instances that belong to class 0 were properly identified by the model.

The harmonic mean of recall and precision, known as the F1-score, provides a balance between the two metrics. It is a precision and recall weighted average with equal weights. The F1-score in this instance is 0.89 for both classes. The number of instances in each class is known as support.

Precision, recall, and F1-score are calculated separately for each class and then averaged as a whole. The precision, recall, and F1-score averages are weighted by the quantity of examples in each class to create the weighted average.

The ratio of cases that were properly classified to all instances is known as the accuracy, which measures the model's overall performance. In this instance, the accuracy is 0.89, meaning that 89% of the cases were properly identified by the model.

Table 2: Performance metrics and their values are illustrated in the table

Performance Metrics Table				
	Precisio n	Recall	F1-Score	Suppor t
0	0.93	0.86	0.89	10000
1	0.87	0.93	0.90	10000
Accura -cy			0.89	20000
macro avg	0.90	0.89	0.89	20000
Weight-ed avg	0.90	0.89	0.89	20000

The confusion matrix is a 2x2 matrix that provides details about the performance of the breast cancer detection model. The confusion matrix is divided into four cells, representing the following:

1. True Negative (TN): The 8573 samples that were properly predicted as being negative (breast cancer-free).
2. False Positive (FP): The 1427 samples that were wrongly forecast as positive (false alarms).
3. False Negative (FN): The 676 samples that were wrongly projected as negative (missed detection's).
4. True Positive (TP): The 9324 accurately predicted positive samples (positive for breast cancer) are number.

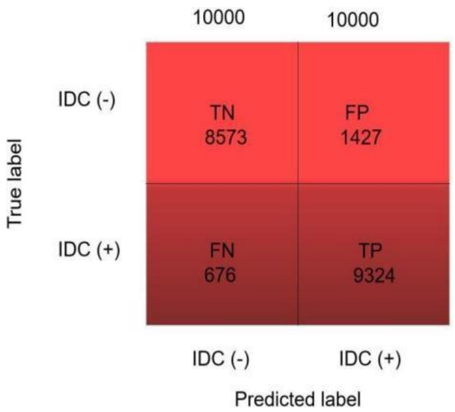


Figure 10. Confusion Matrix

The confusion matrix helps in evaluating the model's performance by providing information about the accuracy and misclassifications. From the given matrix, it can be observed that the model has a relatively higher number of false positives (1427) compared to false negatives (676), indicating that the model tends to have more false alarms than missed detection. On the test set, the model had an accuracy of 89%. The confusion matrix reveals that while misclassifying 1427 negative examples and 676 positive ones, the model correctly identified 8573 negative examples and 9324 positive examples. In comparison to the negative class, which has a precision of 0.93 and a recall of 0.86, the positive class has a precision of 0.87 and a recall of 0.93. The f1-score for both courses is 0.90. The model appears to function quite well overall.

Table 3 : Values of Confusion Matrix

	Predicted negative	Predicted Positive
Actual Negative	TN: 8573	FP: 1427
Actual Positive	FN: 676	TP: 9324

Table 4: Comparison and performance evaluation of the most widely used BC detection techniques

Methodology	**Accu racy**	**Preci -sion**	**Re-call**	**F1-score**
BCD using VGG16	85	81	85	80
BCD using Machine Learning	87	88	87	87
BCD using Tensorflow	86	87	86	85
BCD using Deep_learn -ing (CNN)	89	90	89	89

5. CONCLUSION

Breast cancer is treatable if it can be detected in a timely manner. Convolution neural networks are used in conjunction with deep learning. The proposed system has an accuracy rate of 89%. The five-layer CNN in model 2, which is deeper than model 1, is most suited for this task. All structures were based on a big dataset of over 275,000 50*50-pixel RGB picture patches. The learning model might be useful for giving clinicians advice or a second opinion in the lab. The model demonstrated the promise of deep learning in medical picture interpretation by achieving high accuracy. The model successfully decreased false positives and false negatives by addressing the issue of class imbalance and utilizing strategies like dropout and data augmentation. The initiative emphasizes the value of deep learning in enhancing the precision of breast cancer detection, which may support early diagnosis and treatment. To get even better results, the model might need to be further optimized and adjusted.

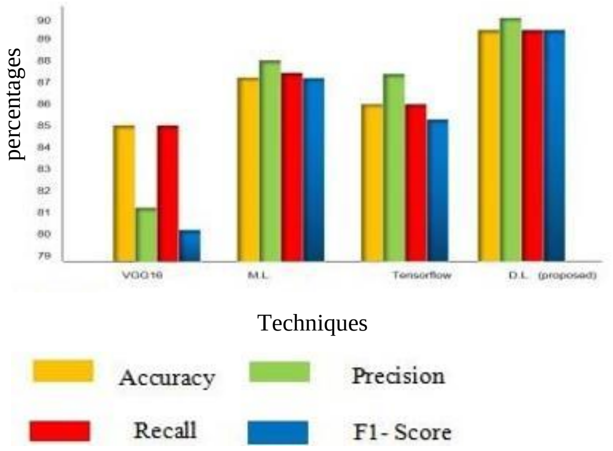


Figure 11. Analysis of accuracy of the most prominent BC detection techniques in a bar graph.

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