Revolutioinizing Breast Cancer Prediction Through Efficientnet-Based Deep Learning Approach

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Abstract— **Breast Cance (BC) is one of the deadly diseases and most dangerous disease which affects the lives of millions of women all over the world. Eventually over time, the number of breast cancer cases had been rapidly increased. Therefore, preventing Breast Cancer is a difficult task but still survival rate would be improvised if the disease is treated in early stages. Lot of improvements in breast cancer can be seen using deep learning techniques. The most common type among breast cancer is invasive ductal carcinoma. Histopathology images are used to detect breast cancer. from overall images 78,786 are observed as idc positive images, and 148,738 images are observed as IDC negative images. Deep learning method uses several methods like keras, maxpooling, Dropout, fatten etc. And also, our model EfficientNet uses a special method called compound scaling. our research work is also compared with different models. Therefore, after evaluation EfficientNet model provided results around 97.2% of accuracy is observed.**

Keywords— Breast Cancer, Invasive Ductal Carcinoma, Computer Assisted Diagnostics, Specificity, Sensitivity, recall, F1-Score, Deep learning, Breast Histopathology Images, Microwave Imaging, K-nearest neighbor.

1. INTRODUCTION

Nowadays, Breast Cancer had been the significant issue in all over the world today.it is also important to diagnose the issue and one should concentrate to reduce it as well. According to W.H.O report, the number of people died due to breast cancer is around 9.6 million which was observed in the year 2018. And also accounts for 18.1 million new cases were registered.[1]. According to medical science it states that unchecked cell proliferation in breast tissue is the primary cause for breast cancer. Based on the spread of the breast cancer is typically divided into 3 categories, such as non-invasive, invasive and metastatic. The standard test for breast cancer is histopathology.[2]. AI and ML are subsets of DL. Later Computers read the data from the photos and also apply easy deep learning strategies to enhance various types of computer models.[3]. Therefore, basically two types of breast cancer are observed i.e. Benign and Malignant. In Benign tumor cells are not treated as cancer cells only few and minor changes are observed therefore it is invasive, whereas in Malignant tumors grow rapidly and released in the other organs i.e. it spreads to other organs as well.[4]. Mammograms are known as breast X rays which uses a very less amount of radiation.[5]. CNN which is a branch of DL, had made great remarks in the field of object detection and speech recognition, and also CNN model is used to provide better results compared to earlier networks like neural network, artificial neural network. [6]. mammograms are not only x-rays images but also used as a tool for early screening tool across worldwide.[7]. If early signs and symptoms are shown in induvial through screening, then early detection of breast cancer would be used.[8]. Tumors which are analyzed by high amount of water contains fluid by nature which results in altering the tissues in breast cells and therefore it uses MI to detect these kinds of tumors.[9]. Metastatis is the process where through this process BC can spread to various part of the body, and it is necessary to address the issue and diagnose using various technologies.[10]. DL network leverages CNN architecture which is one of the essential network which is best opted for medical images and all the other various DL algorithm results are interpreted based on calculating the evaluation metrics[11]. EfficinetNet model is more efficient because of its special property called as compound scaling. Various forms of breast cancers are mentioned below in Fig1:

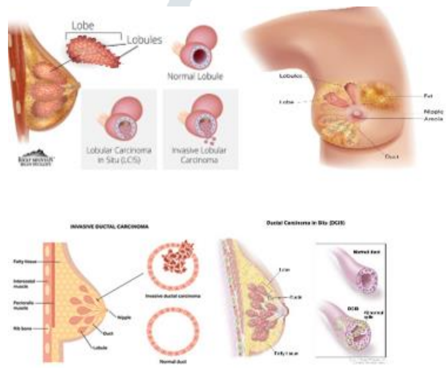


Fig1.Types of Breast Cancer

II. MOTIVATION

Our work aims to develop a deep learning classifier, which is used to detect the breast cancer, which supports to study complex patterns within the images. We would address the existing difficulties such as computational power issues pr complexities through unique training methodology. By using optimization technique to our model, we can increase the accuracy and efficiency rigorously which will empower the healthcare provinces and intern results in saving one's life. Through novel Strategies, one can overcome the limitations and can provide effective tools for early invention. our research is to provide better healthcare on basis of using several scalable methods and some precise detection which will have better outcome. Efficientnet is excellent in picture detection, image classification which will blend network depth, network width and image resolution. All these parameters are scaled up for better accuracy. Its compound scaling method balances size as well as accuracy across various datasets. Our primary contributions include:

2.1Designing and Implementing an EfficientNet based cancer detection model.

2.2Evaluating the performance of the proposed model against existing classifier models.

2.3Providing a robust and reliable tool for early diagnosis and ultimately enables for timely intervention and treatment.

III LITERATURE SURVEY

Maheshvar Chandrasekar, Mukkesh Ganesh, Saleena B, Prakash Balasubramanian [12]. Had worked on a paper, where in their work, researchers used EfficientNet model to improve the mammography images. They have used breakhis dataset for their research. The model achieved an accuracy around 100% and 100% of sensitivity while performing few binary classifications. both in training as well as in validation. However, it displays excellent accuracy in their study. Also, they have mentioned about future scope to work on GAN algorithm with more images and more samples and also with a greater number of data samples in order to enhance the accuracy and to interpret better results.

Yao Lu, Jia-Yu Li, Yu-Ting Su, An-An Liu [13]. Had worked a paper where they have studied about breast cancer medical images. In their work in order to diagnose the breast cancer they have proposed some commonly used imaging techniques for medical images. for the data collection, they have collected images from ultrasound, mammography and in histopathology. And also, they have worked on various datasets and the better results interpreted were on Camelyon dataset where they have used ScanNet method and got results around 96.69% of accuracy was obtained.

Ervin Halim, Pauline phoebe Halim, Marylise hebrard [14]. had worked on model by using ML model, here they have used segmentation process and also combined with knn algorithm, likewise, researchers have used various ML technologies and combined with various models to interpret the best results.in order to study about gene identification, and if it the identification has to be effective, then they should have studied 450 datasets of breast cancer in order to gain knowledge and it is gained through an experience of studying 450 datasets.

Pratyaksh Singh, Jaideep Nagill, Dr. Kavitha Saini [15]. had worked on a model where they have used multiple ML models and algorithms, such as KNN, Artificial Neural Network and Decision Tree. They had considered mammography images to detect breast cancer. The researchers had provided the better results which are nearer to perfection.as the future scope they have mentioned that they can work on different parameters in order to interpret better results.

Pranati V, Narendra Khatri, Harish Sharma, Praveen Kumar Shukla [16], had worked on a model in order to detect the breast cancer where they have used a DenseNet model which comes under DL and used a optimizer called an Adam optimizer, and 0.0001 learning rate was used in their work, and for mammography images they try to detect breast cancer created and obtained results around 100% of accuracy

Partho Ghose, Md. Ashraf Uddin, Mohammad Manzurul Islam, Manowarul Islam, Uzzal Kumar Acharjee, [17]. Had worked on a model, and dataset used for their work is to detect and classify breast cancer images Wisconsin Diagnostic Breast Cancer dataset. It checks several performance measures and determine the effectiveness of algorithm. Therefore, in their work they have used SVM model and obtained results around 98% of accuracy.

Soham Saha, Ahona Dutta, Sabarna Choudhury [18]. Had worked on a model to detect and classify the breast cancer images have used Wisconsin Diagnostic Breast images by combining DL and ML models, where they have used random forest algorithm to detect breast cancer and obtained results around 98.25% of accuracy was observed. They have also used few visualization tools and results are also viewed in scatterplot graphs too.

Darshana Rajput, Dr. Bejoy BJ [19]. Had worked on a model to detect and classify the breast cancer images have used, various datasets and many ML models to detect which model would provide better results and also results vary on different dataset and models among them they have achieved accuracy around 99.1 of accuracy and dataset used was Wisconsin diagnostic Breast Cancer and the algorithm used was Deep Convolution Neural Network and also they mentioned that results might vary in future due to the upgradations that are happening on algorithms more oftenly.

Ashish R. Dandekar, Dr. Avinash Sharma, Dr. Jitendrakumar Mishra [20]. Had worked on a model to detect the breast cancer images here also in their work they have merged optimization techniques as well as extraction methods. CBIS-DDSM datasets were used and images were extracted from this dataset. They have used neural network to detect breast cancer and the algorithm used are Random Forest and etc. The results achieved on this model is around 98.5% of accuracy. In their future work they have mentioned that further experiments can detect the truth if the dataset improves.

IV. METHODOLOGY

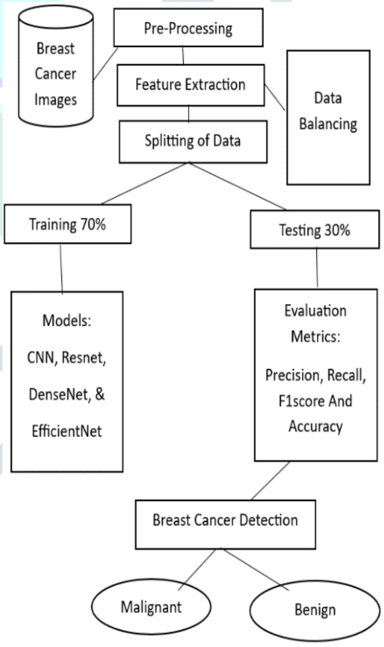
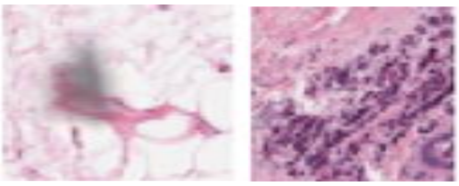


Fig.2: The Representation Of The Proposed Model

4.1 Dataset:

Histopathology breast cancer dataset is considered as the giant datasets compared to other datasets. The enormous Break His dataset was retrieved from the Kaggle. Many data analysts, data scientists are working in this platform. This collection includes 162 mount slide images in total, which are in the png format and were derived from 277,524 patches with a size of 50*50 pixels. Of them, 148,738 are negative and 78,786 are positive idc images. One of the datasets we use in our research is Break His, which has a variety of benefits like high-resolution photos, detailed annotations, standard benchmarks, and good diversity and magnification.



IDC (-) IDC (+)

Fig 4.1.1: Collection Of Histopathological Images

4.2 Data Preprocessing:
Data pre-processing is a primary step in ML. Where it can be defined as the process of converting raw data into usable form, which involves cleaning of data. Cleaning of data involves several tasks such as handling the missing values, scaling and normalization techniques. The preprocessing function used is resizing. Initial image size was 50X50 pixel was resized into 224 by 224 pixels. Therefore, data pre-processing is significant and plays a crucial role. Completeness of the data helps to increase the efficiency of the results and enhances the results, where it is useful to interpret the meaningful insights from the model.

Dataset Splitting:
The process of data splitting takes place in three steps such as, Divide the dataset into testing, validation, and training. During the training phase, the model will be trained, and in the validation phase, few parameters will be adjusted or finetuning of parameters takes place, and in testing phase the model will be trained on the unseen data.

4.3 Model Selection:
In order to determine the best model has to be selected for breast cancer detection can be done by considering some key points. The model has to comprehend with data, should have better transfer learning methods, should provide good evaluation metrics results, it should refine the model in a better way, all these parameters will help to have an efficient and enhanced results. In this paper we have worked on several models to know which algorithm would provide better results CNN, ResNet50, DenseNet, and EffiecientNet are the deep learning models from which the best-fit model is selected

4.4.1. CNN:
Convolutional Neural Network is what CNN stands for. Whereas CNN plays a important role in object detection and also useful in classification tasks. This is a core deep learning architecture that works especially well for feature extraction from photos. To discover spatial patterns in the data, it applies filters. Although this model is flexible, it might not be sufficiently tailored for particular tasks in your pomegranate yield forecast project, such as segmentation or object detection.

4.4.2. ResNet50:
Known for its exceptional accuracy and efficiency, ResNet50 is a particular pre-trained CNN architecture. It solves problems with vanishing gradients that are typical of deep networks. If you have limited computing power, it can be an excellent place to start when fine-tuning your pomegranate yield data. If you require segmentation or specialized functions like interpretability, though, it might not be the best option.

4.4.3. DenseNet

The name DenseNet itself indicates that, it comes from the fact that every layer in the architecture is connected to every other layer. It indicates that each layer uses the feature maps of all the layers before it as input, and each layer after it uses its own feature maps as input.

4.4.4. EfficeintNet:
EfficientNet is one of the models in deep learning, where it is efficient because of its compound scaling technique, where it basically works on idea of scaling of one dimension out of 3 dimensions, this EfficientNet algorithm is effective due to its compound scaling technique, which essentially works on the principle of scaling one dimension out of three. EfficientNet has three dimensions: depth, height, and image resolution. To read the best results, we can reduce any one of the dimensions. Finding a balance between a model's speed and accuracy can be challenging because there are many ways to get there, and there are drawbacks associated with every choice made. While the accuracy of the model increases with the number of dimensions, the results decrease at a certain point.

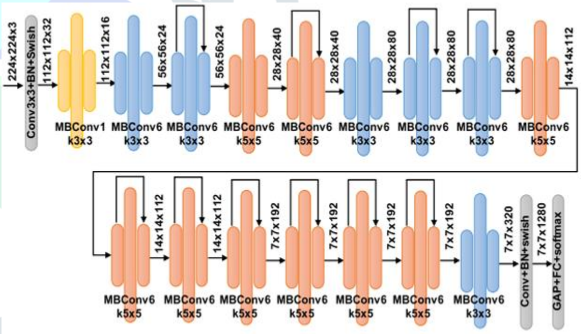


Fig 4.4.1 EfficientNet Architecture

The above Fig 4.4.1 is an EfficietnNetwork architecture which offers both network layer and pooling layer. A kernel of particular size is applied to the image by the CNN layer which extracts the additional information. Computation is quite challenging task here, hence in order to increase the speed up the computation pooling layer minimizes the Complex Matrix. Where in order to minimize the dimension, this layer is made up of kernels, filters and strides. At this particular point average and maximum pooling are the two types of pooling which is frequently used. Efficientnet architecture also has few parameters known as depth(d), width(w), resolution(r). it adds all these parameters on regular basis:

$d = \alpha Ø$

$w = \beta Ø$

$r = \gamma Ø$

By using the above scaling coefficients, it results in combined scaling [16].

V RESULTS AND DISCUSSION

This Area concentrates on the experimental results where we have worked on different models, and also tried to work on different models to interpret best results among various models. if we are concentrating to obtain a moderate result than we need to increase the number of tests and evaluate the results so that we can also know the performance of the model once it is evaluated properly. Results of various models are also considered and discussed in this section.

Table 5.1: Obtained Results by Building the Different Model of Deep Learning Techniques

MODELS	Train-test split ratio	Accuracy
CNN	80:20	80.85%
ResNet	60:40	92.28%
DenseNet	80:20	89.90%
EfficientNet	70:30	97.2%

All the models had been evaluated based on its training accuracy, test accuracy, f1-score, precision and recall. Let us define these terms:

•Training Accuracy: It can be defined as the accuracy of a model on examples it was constructed on and makes the correct predictions out of it.

• Testing Accuracy: It can be defined as the accuracy of a model on examples it has not seen.

• Precision: Precision refers to number of true positives divided by total number of positive predictions.

• Recall: It can be defined as how often a model correctly predicts true positives to the actual positives in the model

• F1-Score: it defines the model's accuracy on a dataset which is used to evaluate the binary classification system.

Table 5.2: Test Results of Data-Split Ratio

No	Train: Validation: Test	Accuracy
1	65:10:25	89.3%
2	70:10:20	97.2%
3	75:10:15	90.43%
4	80:10:10	86.11%

However, 5.2 table shows test results of data Split ratio. The dataset is classified into three different categories, one among them is validation, training and testing. where in validation s, finetuning of hyperparameters takes place, and in training period, the model is trained, and in testing period, it will assess on training model against new data. Various splits have been performed to analyze and interpret the best results. However, the best results were obtained around 97.2% when the dataset was splitted based on 70:10:20 ratio. By performing on various split ratios results were changing and the best results were obtained under 70:10:20 ratio. it is applied on the unseen data.

Table 5.3: Learning Rate Test Results

No	Learning Rate	Accuracy
1	0.1	55.43%
2	0.01	48.235
3	0.001	93.21%
4	0.0001	97.2%

Based on Table 5.3 above, the learning rate is one of the parameters which can be finetuned in order to obtain better results, therefore, learning rate parameter can also be considered as one of the hyperparameter In this paper the learning rate 0.0001 provides, 97.2% of accuracy in this research. This parameter is also used to calculate the correction of weights, during the training phase. Sometimes, results also depends on size of this parameter, because, if the size of this parameter is big, then the result interpreted would be small. And it works vice versa. i.e., if the size of this parameter is small, then the results interpreted would be large. Therefore, it is not always sure that smaller learning rate provides better performance to system. Therefore, it is not the fact that smaller learning rate would always provide better results and better performance to model. However, if model study too much of features in detail, then the model suffers from overfitting. From the above table it is observed that learning rate with 0.0001 had given best results and it is more opted for this model.

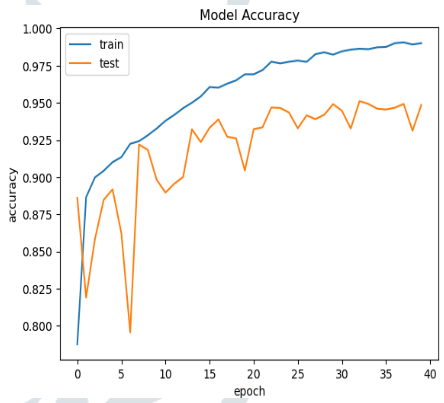


Fig5: Model Accuracy Graph

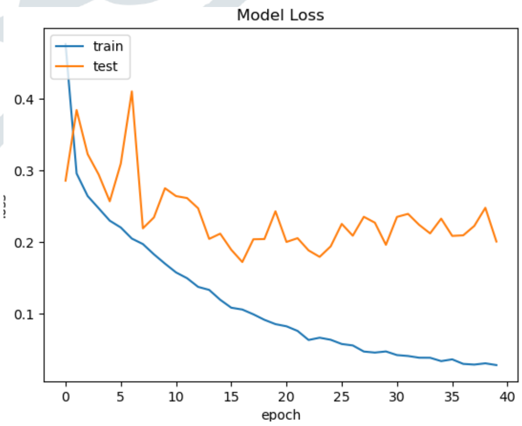


Fig5.1: Model Loss Graph

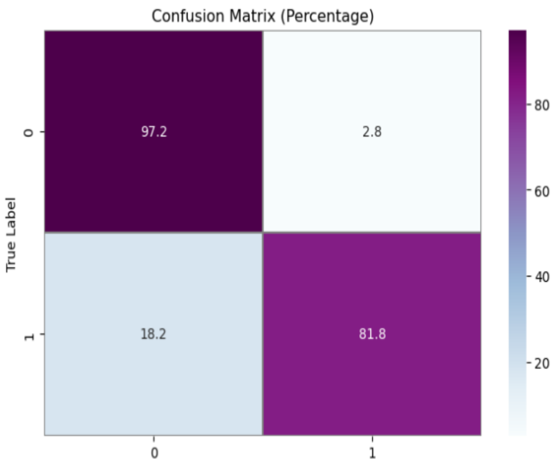


Fig 5.2: Representation Of Confusion Matrix for EfficientNet Model

Fig 5 and 5.1 shows graphs, which defines models' accuracy and models loss.it is observed that if the epochs are increased the training accuracy is also increased, whereas the validation and the training is decreasing which can be observed that as and when the epochs are increasing the model can learn more and as well it can classify the images more accurately. If we want to know the misclassified images, this will be shown in model loss graph, where it is quite evident that the number of misclassified images are decreasing when the number of epochs are getting increased. Whereas fig 5.2 talks about confusion matrix which describes about the rows which consists of true positive elements, true negative elements, false positive elements and false negative elements. More numbers in true positive indicates better accuracy whereas more values in false positive elements and false negative elements indicates more finetuning of hyperparameters required to generalize well on data..

VI Conclusion

The work was carried out by dividing dataset into training phase and testing phase. During training phase, the model gets trained, and in training phase model works on new data or on unseen data. Final parameter which yields better performance for the model is the train-test-validation split ratio of 70:10:20, image dimensions of 64X64 pixel, where it used learning rate of 0.0001 and optimizer used was Adam. Therefore, the performance of the model produces an accuracy around 97.2% which is achieved by using EfficientNet model which is one of the algorithms under DL. Therefore, it is concluded that Efficientnet architecture can detect breast cancer and, also not only an EfficientNet but also if this model is used along CNN will be a more efficient and it can classify the histopathology images properly.

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