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Detection of Breast Cancer from Histopathology Images Using Deep Learning

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ABSTRACT

The stated system presents pre-trained Convolution Neutral Network (CNN) model which is convolutional Neutral Network to verify pre-segmented Breast Cancer mass mammogram tumour as benign or malignant. Based on detailed researched and analysis, to overcome the limitations of infrequency of available training datasets, Data augmentation, particular pre-processing & transfer learning is applied to achieve results. To tackle the classification issues noted above, this processed system is built on a modified version of DESNET 201. The suggested architecture has undergone extensive training and testing. The Convolution Neutral Network (CNN) was trained using data from the RGB colour model, which included 2480 benign and 5429 malignant cases. The achieved accuracy is 0.97%, the precision achieved for benign is 0.99% and recall rate is 0.83%. An achieved precision for malignant 0.83% following recall rate is 0.99 %. Overall, the presented DENSENET201 model excelled the previously proposed method for this system in terms of accuracy.

Keywords – Convolutional Neural Network, Breast cancer, Dense NET201, Transfer learning, Breakhis

I. INTRODUCTION

Breast cancer is the most often diagnosed cancer and the leading cause of death among women globally, according to the World Health Organization. Breast cancer-related mortality are greater than any other type of cancer, according to a survey of women.

The tumours are classified in two types based on its characteristics and cell level behaviour Benign tumour and malignant tumour.

Breast cancer is identified by using biopsy method, where tissues is removed and studied under a microscope. In today's world, a pathologist must evaluate several aspects within photographs, such as patterns, texture, and various morphological properties, while evaluating with various magnifications factors, which necessitates panning, zooming, focusing, and scanning of each image completely. This is a time-consuming and exhausting technique, and as a result, manual diagnosis for breast cancer might be erroneous at times. Blossom malignant growth is one of the most unavoidable sorts of disease on the planet, thus early detection of blossom malignancy is the most effective means of saving lives because it increases endurance through effective treatment, lowering death rates. The most used imaging approach is Mammography for finding abnormality in tissues and screening for breast cancer. A radiologist can decide whether the mammography depicted has cancer or not, however the mistake rate is between 8% and 16%.[1]

Although current clinical procedures for detecting breast cancer have advanced significantly in recent years, the process is still time intensive and has numerous limitations, including unpredictability and time consumption. Deep learning, a form of machine learning, can be utilized to efficiently overcome such limitations in cancer detection and therapy. Several deep-learning-based techniques that use CNN have recently achieved outstanding results in the medical field, including chest pathology categorization, thoracoabdominal lymph node detection, and lung illness detection.[2]

Convolution Neutral Network can assist pathologist in breast cancer diagnosis by automatically filtering benign & malignant tissue biopsies which is more reliable. This method involves raw pixels to create labelled (Benign/Malignant) input images, which are subsequently used to distinguish between non-cancerous and malignant cells. A total of 2480 benign and 5429 malignant samples were used to train the CNN. RGB colour model is a colour model that uses three primary colours: red, green, and blue.[3]

Breast cancer is a prevalent disease that affects many women at some time in their life, but it can also strike men. According to the Breast Cancer Institute, breast cancer is one of the most fatal diseases for women in the World. Early detection is the most consistent and dependable method for effectively controlling cancer. Delaying diagnosis may cause cancer to spread throughout the body, making control and treatment more difficult. Furthermore, a delay in diagnosis reduces the likelihood of a successful treatment. Connective tissue, fat, glands, and ducts are all components of the breast that can be affected by cancer. Breast cancer can be discovered early using a variety of methods, including at-home self-examination, breast screening, and medical visits. Mortality rates will be reduced by these methods and will increase the likelihood of a successful treatment. The most common breast imaging techniques include ultrasound, computed tomography (CT), Magnetic resonance imaging (MRI), thermography, computed tomography (CT), thermography, mammography, and histopathological imaging. The most often used early breast cancer diagnostic tools that are used are ultrasound and mammography.

II. METHODOLOGY

Due to the availability of annotated datasets and (DCNN), CNN supports learning data-driven and hierarchical picture features from a large amount of training data, there has been exceptional progress in image recognition. Because of the availability of huge, datasets during the last decade, there has been a dominating technique to solving various image classification tasks.

A. *Computer-Aided Cancer Detection*

Computer aided detection (CAD) is a type of software that helps clinicians detect and diagnose cancer while also lowering death rates by automatic analysing of medical imaging data. CAD is a piece of software that is used to analyse medical photographs, classify them, and grade them into benign and malignant groups or stages. Artificial intelligence (AI) and its applications are exploding in popularity. Machine learning (ML), particularly deep learning, has been one of AI's most successful years (DL). Convolutional neural networks (CNNs) were one of the most impressive Deep learning triumphs, automatically capable of extracting information from images and to classify them with stunning precision. The CNN has been used in photos, audio, sound, text, and videos, as well as to create self-driving cars to classify.

It's a handy technique for detecting patterns in data to visual information in a number of cognitive applications, as well as extracting features to classify the photos automatically.[5]

Simple dataset is used for training of natural photos using the transfer learning approach shown in Figure 1

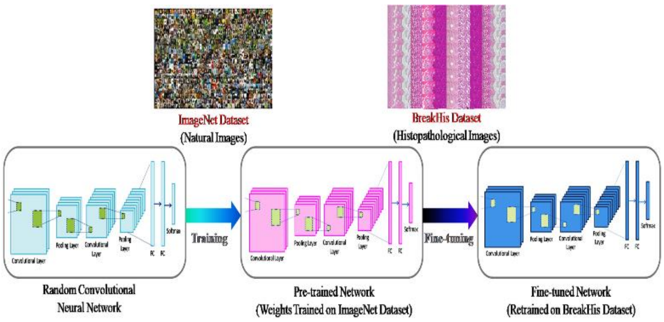

FIGURE 1 AN INSTANCE OF THE TRANSFER LEARNING METHOD

B. Convolutional Neural Networks

CNNs are often built up of many layers concatenated together. Each one is made up of several subunits, such as a bank of trained fitters, element wise non linearity, and a pooling operator to minimize dimensionality.[6]

CNN models are taught how to deduce a mapping from a set of data collection of training inputs to matching sets of outputs by minimizing a loss function such as cross entropy or mean square error through an optimizations process.[10]

C. Densenet

The Dense Net-201 is a 201-layer convolutional neutral network. This can load a pre-trained version of the networks from the image Net database, which has been trained on over one million photos. The network has been pre-trained to classify photos into 1000 object categories, including, pencils ,mice, keyboards, , and a variety of animals. As a result, the network has trained to represent a wide range of images with rich feature representation. The densenet201 architecture is as shown in Figure 2

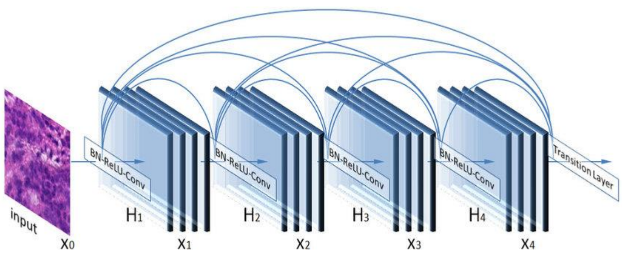

FIGURE 2 DENSENET201 ARCHITECTURE

D. Feature Learning Via Dense Net

Since the original last dense layer, which is a fully connected layer, was revised, structures must be modified, and originally it identifies 1000 objects. Some randomly selected classes are listed below:, Norwich terrier, chain link fence, spider, monkey, chair, ski,bikini,necklace, miniskirt, , maze, pencil box, radio, hyena,crab, beagle, zebra hair spray, and schipperke.[7]

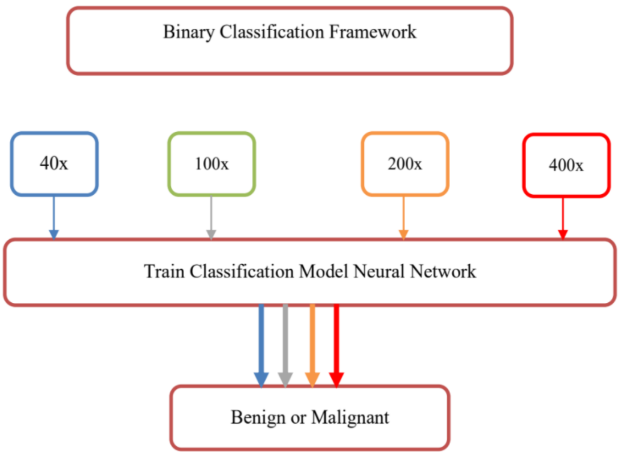

FIGURE 3 METHODOLOGY FOR BINARY CLASSIFICATION

E. Transfer Learning

The goal of transfer learning is transferring the information of a CNN model that has been trained on big datasets to a new dataset. Using a trained CNN model on diverse datasets and using it for the weight initialization for the classification issue can increase the performance of a CNN.

With a precision rate of 0.99 percent for benign and 0.83 percent for malignant, the proposed Dense Net model achieved a mean accuracy of 97 percent. The benign recall rate is 0.83 percent, while the malignant recall rate is 0.99 percent. In both cases, the F1 score remains at 0.91 percent. Support is 191 for benign and 159 for malignant cancers. We may infer from the results of the studies that the Dense Net architecture model operates well and effectively in systems.

III. IMPLEMENTATION

To implement the best cancer detector using Dense Net 201

A. Sequential Model

As we had only input and output tensor, sequential model is used, where sequential model is perfect for plain stack of layers.

B. Flatten

As any shape of tensor can be transform into one dimensional tensor with keeping all values same in the tensor, flatten can be used.

C. Dropout

Overfitting can be avoided by using a model with dropout layer. It's a regularization strategy in which a subset of neurons is neglected during training. They are dropped out at random, implying that their contribution to downstream neuron activation will be removed temporally on the forward pass, and any weight changes will not be applied to the neuron on the backward trip.

D. Batch Normalization

This is how a convolutional network gets regularised. In addition, batch normalization protects your convolutional network from vanishing gradient during training, which reduces training time and improves performance. Batch normalisation is a layer that makes every layer of the network to learn more independently and is used to normalise the output of the previous layers while building a convolutional architecture using batch normalisation. Learning becomes more efficient when batch normalisation is used. [8]

E. Pooling Layers

In our architecture, we partition the network into numerous densely connected dense blocks to assist down-sampling. Transition layers, which perform convolution and pooling, are referred as used. transition layers between blocks.

F. Data Pre-Processing

We had to size normalize the data before we could utilize it to ensure that it met the standards of various networks. To make sure that image sizes suit each pre-trained Convolutional Neural Network, data rescaling and cropping were used to resize input photos.

G. Data Augmentation

For parameter learning, CNN needs a good amount of data. In augmentation, a common technique is utilized to enlarge the training data set. Augmentation improves system performance by lowering the risk of overfitting and data imbalance. Augmenting data can be done in a number of ways. Random reflection, rotation, and horizontal or vertical translations are among them.[9] We used data augmentation on the train set; the test set was left unaltered. The transformations that were used to enhance our training set are shown.

IV. TESTING AND TRAINING

Python and Tensor Flow frameworks were used as development environments. The network was built using the Adam optimization approach, which is used for being rapid and successful for computer vision tasks.

In this study, we used transfer learning with a fine-tuning method. We used the weight values as initialization weight values in our testing after pre-training DenseNet201 with the public domain dataset Image Net.

We used 70 percent of patient data for training and 20% for testing in a randomized method. There was no categorization of the data by subject or magnification. To put it another way, When creating the datasets for training and validating, photos of various magnification factors from different patients were blended. These two sets of imaging data did not overlap in any way. The training set was used to fine-tune the individual neuron connection features and train the model. The test set was used to check classification accuracy and model reliability, while the validation set was utilised to determine the model. We conducted the experiment three times with randomised inputs each time to lessen the experiment's contingency.

In addition to the default network setup parameters, the following hyper parameters were changed for network training: 15 epochs, batch size 16, transformation rate = 0.05, validation sample size = 3000, training sample size = 4000 Dense Net k growth rate = 12, and r = 8 reduction rate. Based on different values, we divided the learning rate into two stages.

The initial learning rate was set at 1e-4 to speed up the network's training (1104). The learning rate was lowered by a factor of two after every 5 epochs. On the training dataset, fine-tuning with data augmentation was employed to improve classification performance, reduce over-fitting, and increase network robustness. To expand the initial training data by 5 times, we used rotation (90°/180°/270°) and flipping (horizontal mirror/vertical mirror).

V. RESULTS

We developed a Convolutional Neural Network approach for detecting breast cancer in this paper. We also used the Densenet201 Architecture for improving the accuracy. Using CNN and Densenet201 architecture we have achieved the accuracy is 0.97%, the precision achieved for benign is 0.99% and recall rate is 0.83%. An achieved precision for malignant 0.83% following recall rate is 0.99 %. Overall, the developed DENSENET201 model excelled the previously proposed method for this system in terms of accuracy.

A. Evaluation Matrix

The confusion matrix is a good tool for evaluating the binary classifier's performance Table 1 and Table 2 shows the binary classification confusion matrices and the evaluation matrices that were implemented in the experiment.

TABLE 1 CONFUSION MATRIX FOR BINARY CLASSIFICATION

	Benign Predicted	Malignant Predicted
Benign Actual	TP	FN
Malignant Actual	FP	TN

True Positive (TP): Breast cancer has been observed to be positive and is predicted to be positive.
False Negative (FN): The breast cancer is observed to be positive, although the prediction is negative.
True Negative (TN): Breast cancer observation has been negative and is likely to remain negative.
False Positive (FP): The breast cancer observation is negative, despite the fact that it is projected to be positive.

TABLE 2 EVALUATION METRICS.

Evaluation Metrics	Formula
Accuracy	$\frac{TP + TN}{TP + FP + TN + FN}$
Precision	$\frac{TP}{TP + FP}$
(TP)	$\frac{TP}{TP + FN}$
F1 Score	$\frac{2 * TP * Precision}{TP + Precision}$
(TN)	$\frac{TN}{FP + TN}$

Figure 4 shows the classification report generated by proposed DenseNet201 Model

```
accuracy
Precision: 0.862205
Recall: 0.995455
F1 score: 0.924051
Classification Report
              precision    recall  f1-score   support

      Benign       0.99      0.83      0.90       206
   Malignant       0.86      1.00      0.92       220

    accuracy                           0.92       426
   macro avg       0.93      0.91      0.91       426
weighted avg       0.93      0.92      0.91       426
```

FIGURE 4. CLASSIFICATION REPORT

VI. CONCLUSION

We built a semi-automatic breast cancer diagnostic system with a mean accuracy of 97 percent in this paper. The system's input is original mammography images, and its output is e-diagnostic results, which indicate whether the tumour is cancerous or not. DenseNET201 performed well in our tests.
With an increasing number of parameters, accuracy tends to improve consistently, with no signs of performance degradation or overfitting in our experiment.

When it came to categorizing benign and malignant tumours, breast-dense NET offered extremely accurate results. As a result, the predictor could be utilized as a second opinion to help radiologist diagnoses.

VII. FUTURE PROSPECTS

Despite the fact that we presented a semi-automated diagnosis system in this paper, there are a few aspects that might be improved. The first is that our approach is only applicable to binary categorization.

Our semi-automatic design, which limits our system's capabilities in real-world situations, should also be modified. In the world of medical pathology, the diagnosis of breast cancer using digital/digitized histopathology photos is a significant moment. It has also opened the door to new research prospects, as machine learning and deep learning approaches and tools can disclose many previously unknown regions. By changing the network design and characteristics, we may be able to achieve better outcomes. Instead of manually lowering image size, an auto encoder can be used to improve the proposed method. Because auto encoders can regenerate up to 90% of the original image, it can compress data without losing prominent characteristics. We can incorporate spectral imaging as a way of method improvement. Spectral imaging is a technique for obtaining images with a wide range of wavelengths, as opposed to the common three-channel RGB image. We can also integrate other imaging methods, such as MRI, CT scan, ultrasound, and mammographic pictures, to establish the overall results. Multimodel fusion is the term for this technique. Deep learning can easily tackle the problems mentioned above, and it can be utilized to conduct high-quality research that may yield even better outcomes.

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