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Classification of Breast Cancer Histopathology Image using Deep Learning Neural Network

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ABSTRACT:
Globally the major and well known reason for Cancer associated deaths in ladies is the breast cancer. Accurate and early findings of breast cancer growth will expand the endurance pace of patients. In the perspective of computer-aided diagnosis (CADx) of breast cancer usually Deep learning tools such as Convolutional neural networks (CNNs) are explored. This paper is classifies the histopathology images of breast cancer into cancerous and noncancerous utilizing the technique of Convolution neural network. The project aims at automated, deep learning based methods where descriptive features are taken out with the help of Deep Convolutional neural networks (DCNNs). The project is expected to accelerate the analysis by helping experts in diagnosis and classification process of the breast cancer. Experts sometimes do not agree with the decisions of radiologists of successful detection of cancerous tumors from histopathology images, though they have several years of experiences. Subsequent choice for image diagnosis is Computer-aided diagnosis, which will improve the consistency of specialist supervisory. Clinically identifying cancerous tumors from histopathology images plays a vital role in automatic and accurate taxonomy of breast cancer images. This project of ours comprises a novel design of convolutional neural network, made up of fully connected layers. The two class classification results show that the model achieved the best classification accuracy of 84% with CNN.

Key words: *Computer-aided detection (CAD), Convolutional Neural Network (CNN), Deep Convolutional Neural Networks (DCNNs)*

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I. INTRODUCTION

Cancers are one of main sources of human death universally. The recent studies say that the breast cancer among all types of cancers in women is very common [1]. The Indian women accounts for 14% of cancers in India and a new patient is diagnosed for breast cancer in a span of four minutes. Also worldwide, the deaths related to breast cancer in women are higher (34%) contrasted with other kinds of malignant growth related deaths in each year [2]. Lack of knowledge, proper screening at early stages and diagnosis are some of the causes for poor survival rate of women suffering from breast cancer.

The development of breast cancer in the breast tissue is identified by bulge in breast in addition to other modifications from standard conditions [3]. Mammography [4], breast ultrasound [5], biopsy [6] and other are few medical examinations methods. A biopsy [6] is the only faithful diagnostic methodology to rely on whether the suspicious region is carcinogenic or not. The pathologists diagnose it by keeping the histological slides under the microscope for visual assessment, which is assumed as best quality level for diagnosis [7]. The customary manual diagnosis needs expertise and concentrated work duties by professionals. The diagnostic inaccuracy may occur with the pathologists that have not enough diagnostic experience. The death rate can be reduced only if at early stages of development of breast cancer, is detected and assessed. Computer-aided detection (CAD) and diagnosis systems not only offer vital assistance in the decision-making process of the radiologists but also provide more idea and accurate diagnosis results to doctors. Such systems may significantly reduce the efforts needed for assessment of lesion in clinical practices, and also minimizing the number of false positives which leads to superfluous and discomforting biopsies.

Despite the fact, that it is the most curable malignances if diagnosed at early stages. Breast cancer detection techniques are necessary to develop, as early diagnosis could improve treatment outcomes and also longer survival period for breast cancer patients. Deep Learning is a growing technology of machine learning and various researcher are utilizing this tool for their research [8].

II. DEEP LEARNING NEURAL NETWORK

From past decades, Deep learning is a well known technology of machine learning and has exhibited excellent results in a mixture of types of object prognosis, diagnosis and classification. As opposed to conventional machine learning strategies, deep learning techniques acclimatize to be trained from the input data with suitable feature extraction process for the desired output. The monotonous process of investigation and engineering of dissimilarity of the features is eliminated and the reproducibility of the methodologies is facilitated. After the advent of deep learning various researches have been published utilizing deep architectures [9]. In deep learning architecture the common and frequent used tool is Convolutional Neural Network (CNN). The features from images were extracted automatically and executed for classification of images. Arevalo et al. [10] experimented different CNNs and compared them with two hand-crafted descriptors for the task of mass diagnosis. The experiment was performed on the BCDR-FM dataset.

PROBLEM STATEMENT

Keras an open source library provides learning application of Convolutional Neural Network, to get insight into the types of medical images and breast cancer, used for classification using neural network tool. Machine learning and image classification use ImageNet Classification with Deep Convolutional Networks [11]. Number of techniques applied on various model have references from [11]. These techniques are generally used for preprocessing of raw data. we can find some works also focuses on taxonomy of histopathology of breast cancer. In the past decade the recent version is by utilizing CNN for histopathology image classification [12]. Breast cancer is predicted and classified using artificial neural networks [13]. Wavelet Neural network can also be implemented for the diagnosis of the breast cancer [14].

III. DATA PREPROCESSING

3.1 Data Collection:

A well-defined dataset is a vital key to the research on breast lesions detection/classification. The dataset was collected from Kaggle [15].The database consisted of 200 folders consisting of 1000 images each labeled with one of two different classes.

3.2 Dataset Extraction:

Data augmentation is an effective process to enhance the volume of the dataset by allowing the network to observe more differentiated, yet at the same time focuses, on data points during training. An image data generator was created to get the data from the folders and into Keras in an automated way. To enlarge the training set and to open more clarity in the images, the project applied image rotations, flipping, zooming and shearing of images to make it diversified dataset and analyze the critical points with more clarity.

3.3 Data Visualisation

We used "***matplotlib***" library as it is impossible to view our data directly. Also data can be developed into 2D space and visualized. Plotting data can be helpful for the people belonging to non technical background as it is difficult for them to understand data.

IV. METHODOLOGY

4.1 Convolutional Neural Network

As the input is an image, Convolutional Neural Networks take benefit of the images by holding back the architecture into a more rational way. **ConvNet** uses unique type of multi-layer neural networks which are designed to identify visual patterns directly from pixel images employing minimum preprocessing. The Fig. 1 below shows the neurons arranged into height, width and depth in three dimensions into the layers of a CNN.

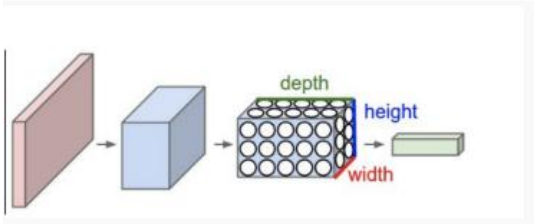

Fig. 1. A Convolutional Neural Network neuron arrangement [16]

Different type of architectures viz. AlexNet, ResNet is used by CNN. The motivation behind this layer is to receive a feature map which is done using Conv2D. It is an arrangement of various types of layers. The Convolutional and Rectified Linear Unit (ReLU) layers are included into the hidden layer. Commonly, the hidden layer comprises of Fully-connected and pooling layer as shown in the Fig. 2.

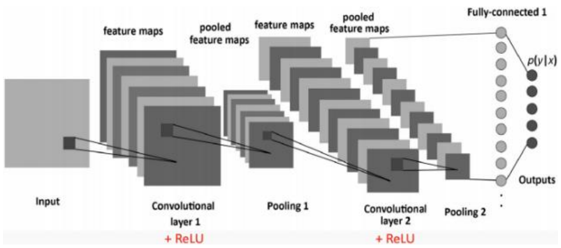

Fig. 2. Convolutional Neural Network Process

Convolution filters in specific number are applied to the image by Convolutional layer. The layer executes a set of numerical process to generate one value in the feature map of output as shown in Fig.2. To introduce nonlinearities into the sequential model, the convolutional layers distinctively apply a ReLU activation function to the designed output. We used 32 filters with a 3x3 matrix to make up the feature map. The input is scanned with the filter of a given size and matrix computations applied in turn to obtain the feature map.

4.1.1 Pooling

Thiss layer offers spatial variance, which implies that the framework will be capable of distinguishing an object even though its appearance varies in some other way. A MaxPooling 2D 2x2 pool size is used to reduce the feature map down towards the essential features (Fig.3).

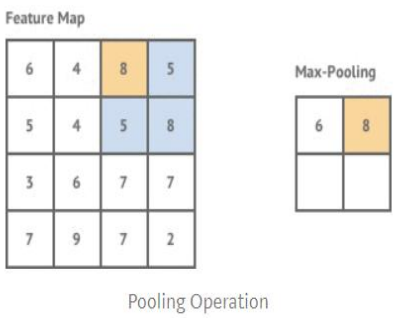

Fig. 3 Pooling operation

4.1.2 Process

In ConvNet architecture, 2 Conv2D layers were used with an activation map ReLu and Sigmoid and 32 filters with 3*3 matrix with 3 MaxPooling2D layers with pool size 2*2. It makes use of the flatten function which converts the feature maps from 3-Dimensional to 1-Dimensional feature vectors which are essential for classification.

The model uses dense layer with 64 neurons for 2 output classes i.e. Cancerous and Non-Cancerous with ReLU and Sigmoid as an activation functions. The “rmsprop” is used for optimizer and for Loss function “binary_cross_entropy” is implemented with precision measurements. To prevent overfitting of the model “dropout layer” regularization technique is used.

4.2VGG16:

The VGG network is characterized by its simplicity, using only 3×3 Convolutional layers stacked on top of each other in increasing depth. Max pooling is used to reduce the filter size. One fully-connected layer, followed by dense 256 layers with ReLU as activation map and 50% dropout value is then followed by Sigmoid activation map. VGG 16 Net was pertained where the smaller networks were converged and used for initializing the bigger and deeper networks. But VGG Net is slow and also the network architecture weights itself quite large.

4.2.1 Process:

In VGG-16, Bottleneck features were used as the last activation map before the fully-connected layers as shown in the Fig.4. If we use the VGG16 model upto the fully-connected layers, then we can convert the input image X (50 x 50 x 3) into the output image Y (224 x 224 x 3). By this way a simple CNN with fully connected layers using Y as input and categorical values Z as output is trained. We used ReLU and Sigmoid as activation maps with dense layer 256 and dropout value 0.5 which prevented overfitting of model. Moreover, we have used “rmsprop” as an optimizer and trained the model for 10 epochs.

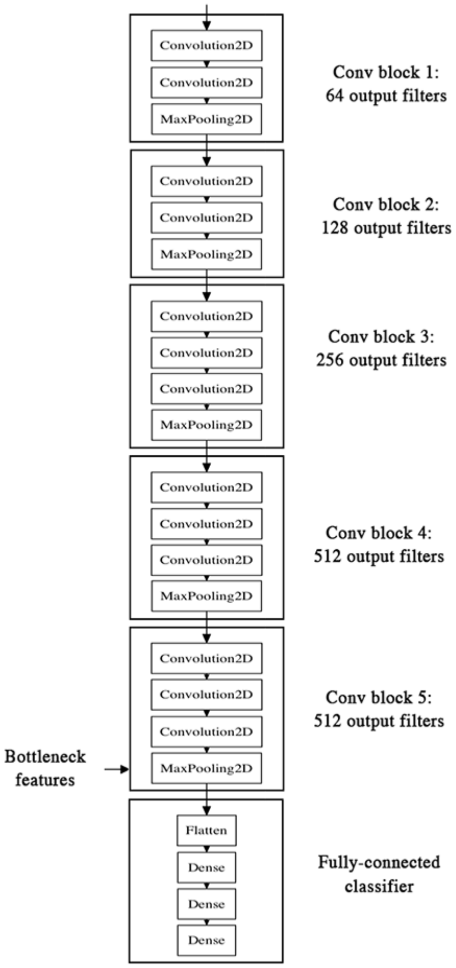

Fig.4A visualization of the VGG-16 architecture with bottleneck features

4.3Xception:

Xception stands for “extreme inception.” and it reframes the way we look at neural nets and Convnets in particular. It is a deep Convolutional neural network architecture which involves Depthwise Separable Convolutions as shown in the Fig.5. It maps the spatial correlations for each output channel individually, and then performs a 1×1 depthwise convolution to capture cross-channel correlation followed by pointwise convolution (1×1 convolution across channels).

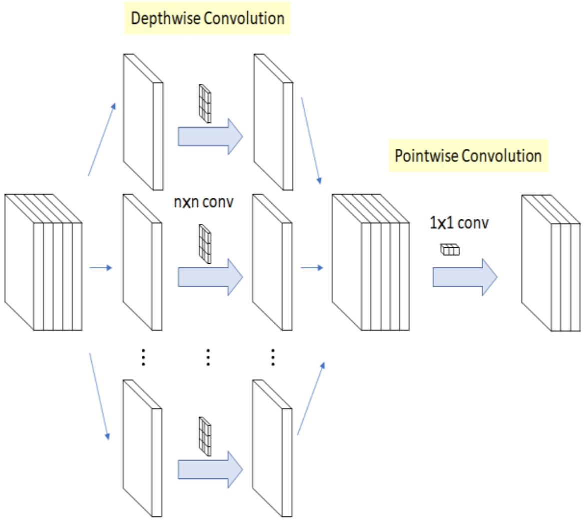

Fig. 5 Architecture of Xception model (Extreme inception)

Xception is an efficient architecture and it relies on:

1. Depthwise Separable Convolution which is much more efficient in the context of computation time.

4.3.1 Process:

Our image input size is 299x299x3 and a pretrained model with weights Imagenet is used. Fully connected layer of CNN is replaced with Global average pooling 2D. Batch normalization is implemented to lessen the effect of unstable gradients within deep Neural Nets. A dense layer with 256 neurons and ReLU as an activation function with dropout value of 0.5 followed by Softmax activation map. The model uses Regularizers as Kernel and Bias regularizer l2 to prevent it from overfitting. Thus the pre trained layers are frozen to prevent overfitting of model. An Optimizer “Adam” with learning rate 1e-3 and loss function Sparse Categorical Cross Entropy is used. Early stopping is used for performance measure and check points to store the best results.

V. RESULTS AND DISCUSSION

In comparison to a regular Neural Network which uses 48x48x1 = 2304 weight parameters for processing our data. We have used CNN model with 32 feature map having 3x3 channels. Three version of CNN is created. The number of trainable parameters is 5,046,369 for CNN

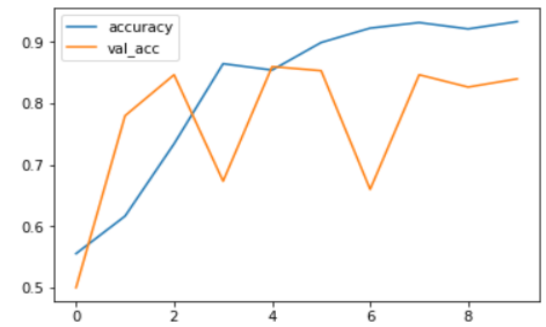

Fig. 6(a)Accuracy curve (epoch =10, optimizer = "rmsprop")

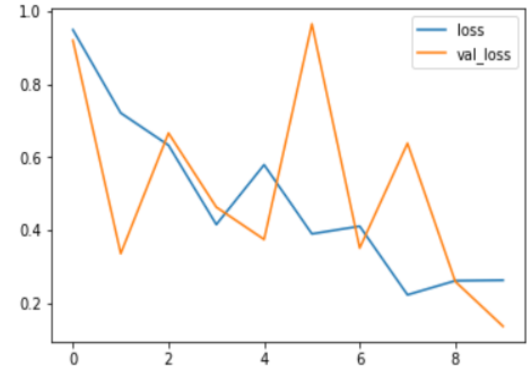

Fig. 6(b) Loss curve (epoch =10, optimizer = "rmsprop")

```
In [43]: from keras.preprocessing import image
         import numpy as np
         test_image = \
             image.load_img('./test/8864_idx5_x1801_y2451_class1.png',
                            target_size=(300,300))
         test_image = image.img_to_array(test_image)
         test_image = np.expand_dims(test_image,axis =0)
         result = model.predict(test_image)
         train_generator.class_indices
         if result[0][0] == 1:
             print('noncancer')
         else:
             print('cancer')

         cancer

In [44]: test_image = \
             image.load_img('./test/8864_idx5_x201_y2301_class0.png',
                            target_size=(300,300))
         test_image = image.img_to_array(test_image)
         test_image = np.expand_dims(test_image,axis =0)
         result = model.predict(test_image)
         train_generator.class_indices
         if result[0][0] == 1:
             print('noncancer')
         else:
             print('cancer')

         cancer
```

Fig.7 Testing Code for Cancerous image

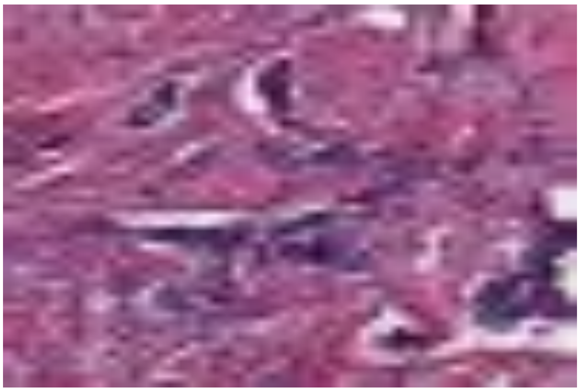

Fig. 8 Classified Cancerous image

```
In [45]: test_image = \
             image.load_img('./test/8864_idx5_x51_y2201_class0.png',
                            target_size=(300,300))
         test_image = image.img_to_array(test_image)
         test_image = np.expand_dims(test_image,axis =0)
         result = model.predict(test_image)
         train_generator.class_indices
         if result[0][0] == 1:
             print('noncancer')
         else:
             print('cancer')

         noncancer

In [46]: test_image = \
             image.load_img('./test/8864_idx5_x601_y2151_class0.png',
                            target_size=(300,300))
         test_image = image.img_to_array(test_image)
         test_image = np.expand_dims(test_image,axis =0)
         result = model.predict(test_image)
         train_generator.class_indices
         if result[0][0] == 1:
             print('noncancer')
         else:
             print('cancer')

         noncancer
```

Fig. 9.Testing Code for Non Cancerous image

Fig. 10 Classified Non - Cancerous image

TABLE 1: CLASSIFICATION REPORT OF CNN ARCHITECTURE

	precision	recall	f1-score	support
cancer	0.65	0.89	0.75	400
noncancer	0.83	0.52	0.64	400
micro avg	0.71	0.71	0.71	800
macro avg	0.74	0.71	0.70	800
weighted avg	0.74	0.71	0.70	800

F1=(2*(Recall*Precision))/(Recall+Precision)

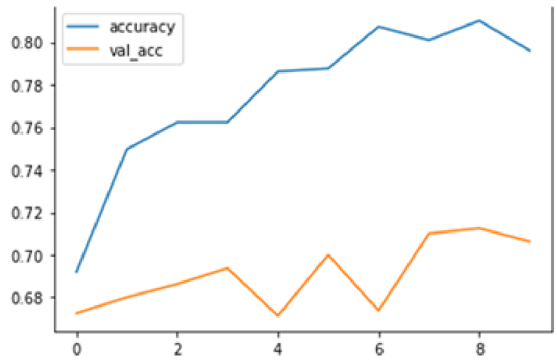

Fig. 11(a) Accuracy curve (epoch =10, optimizer = “rmsprop”)

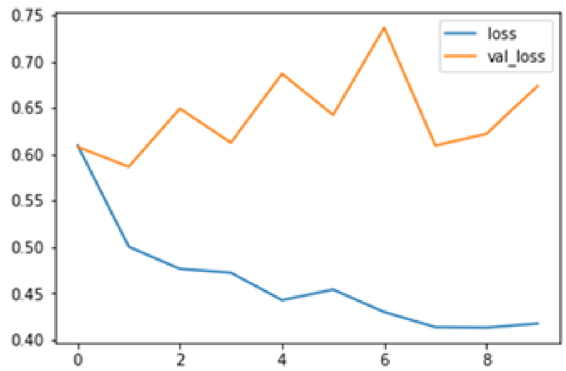

Fig. 11(b)Loss curve (epoch =10, optimizer = “rmsprop”)

TABLE 2: CLASSIFICATION REPORT OF VGG16 ARCHITECTURE

	precision	recall	f1-score	support
noncancer	0.66	0.83	0.74	400
cancer	0.77	0.57	0.66	400
micro avg	0.70	0.70	0.70	800
macro avg	0.72	0.70	0.70	800
weighted avg	0.72	0.70	0.70	800

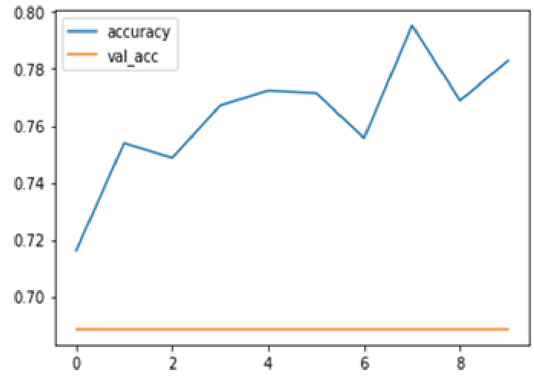

Fig. 12(a) Accuracy curve (epoch =10, optimizer = “Adam”)

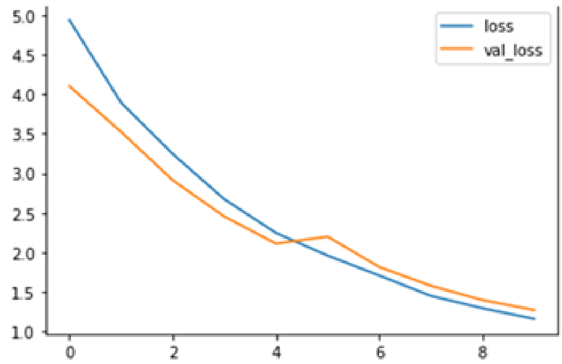

Fig. 12(b)Loss curve (epoch =10, optimizer = “Adam”)

TABLE 3: CLASSIFICATION REPORT FOR XCEPTION ARCHITECTURE

	precision	recall	f1-score	support
noncancer	0.00	0.00	0.00	38
cancer	0.69	1.00	0.82	84
micro avg	0.69	0.69	0.69	122
macro avg	0.34	0.50	0.41	122
weighted avg	0.47	0.69	0.56	122

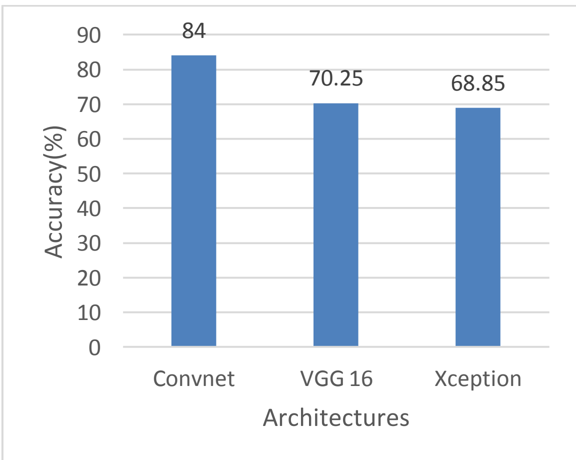

Fig.13 Comparison of three models in terms of Accuracy

VI. CONCLUSION

A modified Deep Convolutional Neural Network has been proposed and developed for breast cancer detection. Three different architectures is used here. The Convnet classifies the histopathology images into two classes cancerous and non cancerous with a success rate of 84% whereas the minimum accuracy of 69% is achieved with Xception model. The whole process of image prediction takes few minutes to complete without time limit unless there is need of some parameters to be changed. In this case, the model is retrained for few days.

This project can help and assist the doctors or trained nurses to fast and correct diagnose thereby overcoming the shortage of medical experts. The method involves preprocessing of the histopathology images into an image easily identified by a computer. This model identifies the difference between all labeled data by using various types of feature extraction process from the image. After 10 epochs, the model is able to classify input images into promising outputs. To summarize, 2200 of histopathology images of breast cancer is successfully detected, classified and examined by using Deep Convolutional Neural Network. We have been able to develop an accurate and fast method for the diagnosis of breast cancer.

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