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Breast Cancer Detection Using Deep Learning Technique

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Abstract: Breast cancer is the leading cause of cancer death in women. Early detection and diagnosis is the best and most effective strategy to control the tumor progression. Mammography is the currently recommended imaging method for early determination and diagnosis of breast malignancy. Classifications of masses in mammograms are still a big challenge and play crucial role to assist radiologist for accurate diagnosis. In this paper, we propose convolution neural network (CNN) based classification technique which is one of the deep learning technique. The architectural models of CNN like Mobile Net and Inception V3 are used for classification of mammogram images into normal and abnormal. A comparative study on these two models has been discussed in this paper.

Keywords- Mammography, deep learning, CNN, MobileNet, Inception V3

I. INTRODUCTION

OVERVIEW

Breast cancer has become one of the commonly occurring forms of cancer in women. In 2016, about 246,660 women were diagnosed with breast cancer which is considered as the highest level of 29% among other kinds of cancer. For the expected deaths, breast cancer is the second highest in a woman which is alone accounted 14% against other cancer types. Approximately 40,000 breast cancer patients die each year in the U.S. Early detection with correct diagnosis is extremely important to increase the survival rate. In clinical practice, mammography is a widely used diagnostic tool to screen breast cancer [1]. Mammography entails exposing a patient's breasts to low levels of X-ray radiation. Breast cancer are identifiable from mammograms thanks to the different X-ray absorption rates of normal and abnormal tissues. Tumors can appear as masses, distortions, asymmetry, speculated masses or micro-calcifications on mammograms [2]. To correctly detect and diagnose breast cancer (i.e., normal and abnormal), radiologists face challenges due to the large amount of breast images they have to examine daily and the difficulty of reading the images (i.e., detecting the breast masses and Correctly diagnosing them) [3]. Thus, computer-aided detection and diagnosis (CAD) are essential through which a second opinion can be provided to physicians to aid and support their decisions [4].

Deep learning is a currently developing field which explores areas of artificial intelligence and machine learning to learn features directly from the data, using multiple nonlinear processing layers [5]. Deep learning with Convolutional Neural Networks has emerged as one of the most powerful machine-learning tools in Image classification, surpassing the accuracy of almost

all other traditional classification methods and even human ability [6, 7]. The convolutional process can simplify an image containing millions of pixels to a set of small feature maps, thereby reducing the dimension of input data while retaining the most-important differential features [8]. We are using two CNN architectures, Mobile-Net and Inception V3 to classify the whole mammograms. Mobile-Net are class of CNN designed by researchers at Google. Mobile-Nets are based on streamlined architecture that uses depth wise separable convolution to build light weight deep neural networks. The main difference between Mobile-Net architecture and traditional CNN's is instead of a single 3X3 convolution layer followed by batch norm and ReLU, Mobile-Net splits the convolution into 3X3 depth wise conv and a 1X1 point wise conv. The Inception architecture was first introduced by Szegedy et al. in 2014. The goal of the inception module is to act as a "multi-level feature extractor" by computing 1x1, 3x3, and 5x5 convolutions within the same module of the network. The output of these filters are then stacked along the channel dimension and before being fed into the next layer in the network.

II. OBJECTIVE

- Training the Mobile-Net and Inception V3 Models by using MIAS database
- Testing the Mobile-Net and Inception V3 Models
- Classification of given mammograms images into normal and abnormal.

III. LITERATURE SURVEY

IV. METHODOLOGY

“The role various modalities in breast imaging” by Sachin Prasad N and Dana Houserkova, 2007. Mammography is the only reliable screening test proven in breast imaging.

“Identification of Preprocessing Technique for Enhancement of Mammogram Images” by Jaya Sherma, R P Tewari and J K Rai, 2014.

Determining best preprocessing technique on the basis of peak signal to noise ratio for set of mammogram images.

“Classification of Mammogram Images by using CNN Classifier” by Ketan Sharma and Bobbin Preet, 2016. In this paper they proposed a computer aided diagnosis(CAD) system named as CNN. . They had also compared of CNN with Logistic Regression algorithm.

“Whole Mammogram Image Classification with Convolutional Neural Networks” by Nathan Jacobs, Jinze Liu and Erik Y. Han, 2017. This paper reports preliminary work on developing and optimizing machine learning models for whole image classification mammograms. They evaluated 7 different CNN architectures and conclude that combining both data augmentation and transfer learning method with a CNN is the most effective in improving classification performance.

“Preprocessing Filters for Mammogram Images” by Kshema and Jayesh George M, 2017. Preprocessing is the most vital and essential step in the mammogram analysis to improve mammogram picture quality. It is important to redress the mammogram images for further processing and analysis. Filters are utilized to enhance picture quality, evacuate the clamor, saves the edges inside a picture, improve and smoothen the image. Mammogram image corrupted with speckle noise can be better reconstructed with Gaussian filter, wiener filter and mean filter. Mean filter, median filter and adaptive median filter works better for salt and pepper noise.

“Mass Classification In Mammograms Using Neural Network ” by Effa Adrina Azli, Salina Abdul Samad and Mohd Faisal Ibrahim, 2017. Different features affects performance of the classifier so it is important to extract the useful features that are able distinguish between benign and malignant classes. Besides that the architecture of neural network affects the overall performance of the classification. The architecture with 100 hidden nodes consistently improves the classifier performance by 10% compare to the architecture with only 3 hidden nodes regardless of the input feature fed into the classifier.

CNN Architecture:

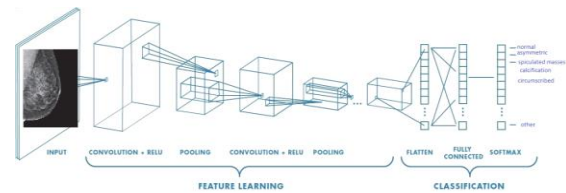


Fig 1: CNN Architecture.

Convolutional neural network are the leading architecture in deep learning that are used to solve an image classification problem. The goal of this paper is to tell which class the input image belongs to. The process of building a convolutional neural network always involves 4 major steps

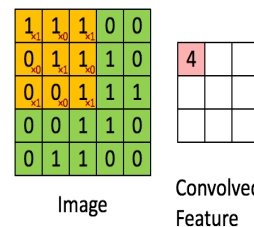
- Convolution
- Pooling
- Flattening
- Fully connected layer

Types of layers:

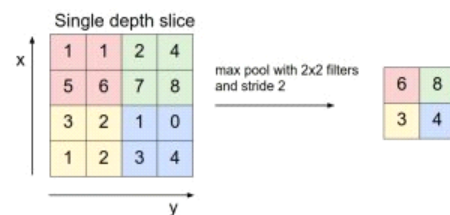
All neurons in one layer, do similar kind of mathematical operations that is how that layer gets its name.

1. Convolution layer:

Convolution is the mathematical operation that is used in image processing to filter signal, find pattern in signal etc. All neurons in this layer perform convolution on inputs. The most important parameter in a convolutional neuron is the filter size. We shall slide convolution filter over whole input image to calculate this output across the image and here we slide our window by 1 pixel at time this number is called Stride. Typically we use more than 1 filter in one convolution layer.



2. Pooling layer:



Pooling layer is mostly used immediately after the convolutional layer to reduce the spatial size(only width and height, not depth). This reduces the number of parameters, hence computation is reduced. Also, less number of parameters avoid over fitting. The most common form of pooling is **Max pooling** where we take a filter of size 3X3 and apply the maximum operation over the 3X3 sized part of the image.

3. Fully Connected Layer:

If each neuron in a layer receives input from all the neurons in the previous layer, then this layer is called fully connected layer. The output of this layer is computed by matrix multiplication followed by bias offset.

Training and Testing the CNN using original data

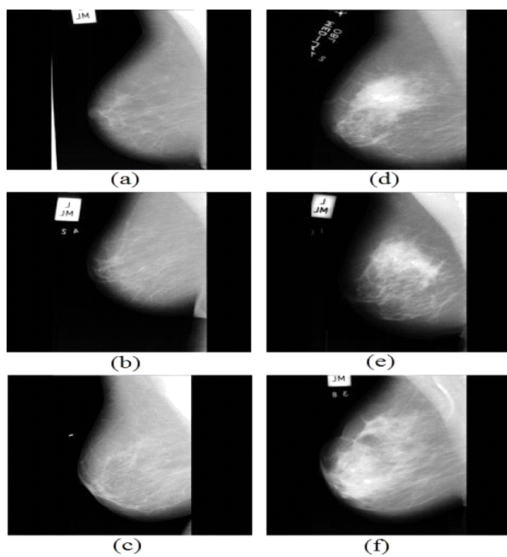


Fig 2. Sample images from MIA’s mammograms dataset. (a-c) Normal images, (d) Asymmetry, (e) Calcification, (f) Spiculated mass.

Original data was of size 1024-by-1024. We performed Training by first dividing the dataset into 2 classes as normal and abnormal. Filters were used of different sizes (2, 3, 5). The data trained randomly yield better results as compared to without randomizing it automatically. Proposed method is good and it has introduced deep learning for breast cancer detection. It is an ongoing research and further developments are underway by optimizing the CNN architecture and also employing pre-trained networks which will probably lead to higher accuracy. Dataset was pre-processed where the images were of size 1024-by-1024 were resized to 224-by-224. Dataset was further divided into 7 sub-classes, 6 among them included different types of abnormalities and 1 class containing normal images. The classes were named according to abnormalities like architectural distortion, asymmetry, calcification, spiculated masses, circumscribed masses and miscellaneous (images which were neither recognized as benign or malignant). Here we trained and tested the pre-processed dataset with same 3 filter sizes (2,

3, 5) where we also tested the data with and without randomizing it.

V. RESULTS

Satisfactory results have been obtained using the CNN based proposed breast cancer detection method. The dataset was sub-divided into 7 classes in total in which the abnormal classes were further sub-divided into 6 more classes. Training and testing was done through two methods, in first method the dataset was divided into two classes named normal and abnormal. While the second method included further sub-division of the abnormal classes, that included six types of abnormalities found in breasts such as asymmetry, calcification, spiculated masses, circumscribed masses, architectural distortion and miscellaneous. Miscellaneous contained those images where there was lack of surety that either the images were benign or malignant. Pre-processing is done to get better performance and faster learning of neural networks. Accuracy of the raw images obtained by using different filter sizes in CNNs. Accuracy is determined when the model parameters are learned and fixed and no further learning takes place.

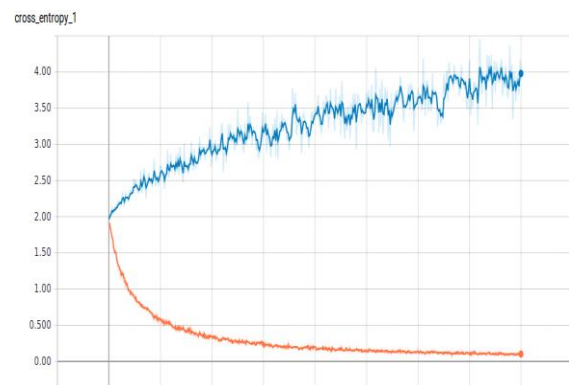
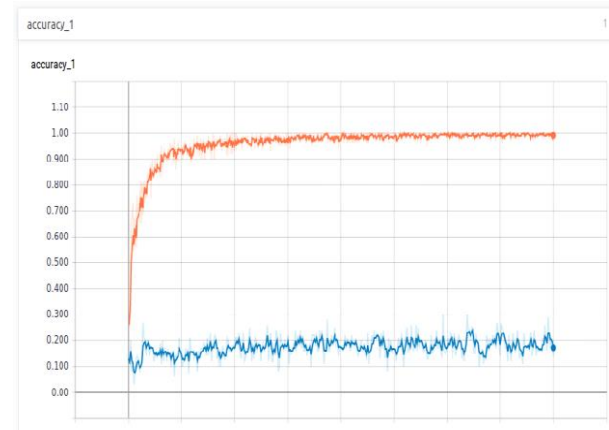
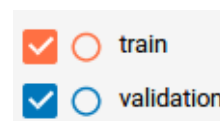


Fig 3. Train accuracy, validation accuracy and cross entropy



Architecture Inception V3	Accuracy obtained 83%
Mobilenet	58%

Fig 4. Comparison between mobilenet and inceptionv3 models

CONCLUSION

In this paper we proposed a computer – aided diagnosis (CAD) system named as convolution neural network. This convolution neural networks used on mammograms for detection of normal and abnormal mammograms. It is always preferable to detect cancer at early stage and advise the patient to treat it. By using inception V3 architecture we detect breast cancer with 83% accuracy.

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