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Mammogram classification using Deep learning features

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Abstract— **This paper presents a method for classification of normal and abnormal tissues in mammograms using a deep learning approach. VGG-16 CNN deep learning architecture with convolutional filter of (3x3) is implemented on mammograms ROIs from the IRMA dataset. The deep feature matrix is computed from first fully connected layer. The results are evaluated using 10 fold cross validation on SVM, binary trees, simple logistics and KNN (with k=1, 3, 5) classifiers. The method produced 100% classification accuracies with AUC 1.0.**

Keywords: Deep learning, VGG-16, Convolutional neural network, Mammogram Classification.

I. INTRODUCTION

Breast cancer is one of the most common types of cancer diagnosed in women around the world. Its one of the leading causes of deaths in females worldwide. World Health Organization (WHO); International agency for cancer research(IARC) and American cancer society report that 14.1 million new cancer cases were recorded in 2012 worldwide[1]. Generally, breast cancer cells are divided based on geometric shape as microcalcification, masses and architectural distortions. In most of the cases the breast cancer cells are either masses or microcalcifications [2]. Early detection and treatment can reduce the breast cancer mortality rate quiet considerably. Unfortunately, in breast cancer the signs are very subtle and vary in appearance at early stages [2].

To visualize the internal breast structures a low dose x-ray of the breasts are performed, this procedure in medical terms in known as Mammography. It is one of the most suitable techniques to detect breast cancer. Mammograms today expose the breast to much lower doses of radiation compared with devices used in the past[3]. In recent years it has proved to be one of the most reliable tools for screening and a key method for the early detection of breast cancer[4],[5].

In literature, it can be seen that various researchers have utilized local and global texture information from the mammograms using techniques such as local binary pattern[6],[7] grey level co-occurrence matrices[8] and shape properties etc. Others have exploited multiresolution techniques such as wavelets[9], curvelet for feature extraction[10],[11] and classifications of mammograms.

Although, over the years there has been advancements in improvements in performance of current CAD systems using these feature driven techniques, but still require further investigation for large scale dataset. Recently, many researchers have presented a new deep learning approach for segmentations and classification of images[12],[13] .

Dhungel et al.[14] presented an approach to detect and classify the candidate regions into normal and abnormal using deep learning approach. The method detects the suspected regions using cascade deep learning combined with Bayesian optimizations. The method utilizes the 1N breast dataset for experimentation. The classification of the regions is achieved using pre-trained deep learning classifier. The results show that their method successfully detected 90% of mass cases with classification sensitivity of 98 % and specificity of 70% for benign and malignant cases. Ahn et al.[15] used convolutional neural network (CNN) for estimation of breast densities in mammographic images. Their method classified the images into dense and fatty tissue types using local and global features extracted by the CNN deep learning approach. The proposed method was implemented on 397 digital mammograms from Seoul National university Hospital in Korea. The dataset was divided into 297 twining and 100 test cases. Their method showed high correlation coefficient value of 0.96 amongst, the manual classified densities and the estimated by CNN. Agrwal and Carson [16] proposed to predict the semantic features such as type of lesion and pathology in mammograms using the deep convolutional neural networks. Wang et al.[17] presented a deep learning approach to discriminate the micro-calcifications cases in breast cancer dataset. The method was tested using two scenarios one having micro-calcification and second microcalcifacitons and masses together. Their method achieved 87.3% discriminative accuracy for identifying calcifications and 85.3% classification accuracy using SVM classifier.

In this paper we present potential application of Visual geometry group (VGG) based CNN model for mammogram classifications into normal and abnormal classes. In section II a brief introduction of VGG model and its parameters is presented. In Section III implementation of VGG, dataset details and classifiers used are presented. Results and discussion is presented in section IV. The conclusion is presented in section V.

II. VGG NETWORK : A BRIEF INTRODUCTION

K. Simonyan and A. Zisserman [18] proposed a VGG model based on convolutional neural network(CNN) principle for large scale image recognition. VGG provides evaluation of networks with increased depth of layers providing significant improvement in performance of system. The group have designed a number of VGG model e.g.; VGG19, VGG16, VGG13, VGG11 etc.as shown in Fig.1 The best of them obtained 92.7% top-5 test accuracy in ImageNet Dataset, that comprises of over 14 million images having to 1000 classes.

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Figure.1: VGG ConvNet Configuration [18]

III. IMPLEMENTATION

A. Dataset

In the current study, we utilized the manual cropped ROIs from the Image retrieval in Medical Applications (IRMA) dataset[19]. IRMA is project initiated by Aachen University Germany to collect mammogram images from different databases and build a large scale mammogram database. It is provided with ground truth, prepared by experts radiologists, which provide the information on lesion types, tissues densities and radii measures for masses as well. In the current study 2795 mammogram ROIs from IRMA were used with 1863 abnormal and 932 normal cases. Each ROI is 128 x128 pixels in size and were extracted by experts from the original images. The abnormal class included abnormalities such as masses, spiculated masses, circumscribed masses and architectural distortions.

B. Implementation of VGG16

In this paper we have used the macroarchitecture of VGG16 can be seen in Fig. 2. The ROIs from the IRMA are resized to 224 × 224 pixels as the VGG ConvNets has fixed-size 224 × 224 for the images.

The input images are passed through a stack of convolutional (conv.) layers, with filters with receptive field of 3 × 3 (that the lilliputian size to capture the notion of left/right, up/down, center). The convolution stride is fixed to 1 pixel; the spatial padding of conv. layer input is such that the spatial resolution is preserved after convolution, i.e. the padding is 1 pixel for 3 × 3 conv. layers. Spatial pooling is carried out by five max-pooling layers, which follow some of the conv. layers (not all the conv. layers are followed by max-pooling). Max-pooling is performed over a 2 × 2 pixel window, with stride 2. A stack of convolutional layers (which has a different depth in different architectures) is followed by three Fully-Connected (FC) layers: the first two have 4096 channels each, the third performs 1000- way ILSVRC classification and thus contains 1000 channels (one for each class). The final layer is the soft-max layer. The configuration of the fully connected layers is the same in all networks. All hidden layers are equipped with the rectification (ReLU) non-linearity[12].

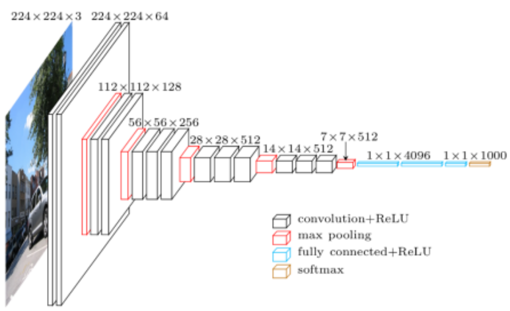

Figure.2 Microarchitecture of VGG16

C. Classification

The classification task of the deep learning feature matrix is performed using four different classifiers i.e. Simple logistic classifier, Binary decision tree classifier, Support vector machine (SVM) classifier with polynomial kernel function and K nearest neighbor (KNN) classifier with k=1,3,5 were used separately on the features matrix. For each case 10 folds cross validation applied. The classification results for each case are noted for comparison.

IV. Results and Discussion

The VGG 16 was implemented on 2795 ROIs of size 224 × 224 pixels each. As can be seen in Fig.2, an input of 224 × 224 × 3 using a series of Conv. layers and pooling layers the image activation volume has reduced to 7 × 7 × 512 which is achieved by using 5 pooling layers with a down sample by factor of 2. The 7 × 7 × 512 conv.layer ,with stride 1 and padding 0 results in fully connected layer of 1× 1 × 4096. There are three fully connected layer in VGG 16. After 1st and 2nd fully connected layers, feature matrix of size 1x4096 has been captured respectively as shown in Fig.2 and feature matrix size of size 1x1000 after 3rd fully connected layer . These features matrix used by the classifier to differentiate between different regions.

Thus the feature matrix of size 2795 × 4096 is obtained from the first fully connected layer. The classification task was performed using 10-fold cross validation for four different classifiers and results were recorded as in table 1.

Table.1 Mammograms classifications using different classifiers

Classifier	SVM	KNN K=1,3,5	Binary decision tree	Simple Logistic
Accuracy	100%	100%	100%	99.8%
AUC	1.0	1.0	1.0	1.0

Table.1 shows that we are getting 100% accuracy using SVM, KNN (1, 3, 5) and binary decision tree. While, only in case of Simple Logistic classifier we are getting slightly less accuracy of 99.8%. Moreover all the classifiers produced AUC value of 1.0.

V. Conclusion

In this paper we applied a deep convolutional network VGG16 with 16 weight layers for classification of normal and abnormal mammogram ROIs. It can be seen that VGG16 conv. network presentation of depth is very efficient and we achieved 100% accuracies for four different classifiers i.e., SVM, KNN, binary decision trees and simple logistic.

Although VGG16 conv.net has produced excellent results, yet we need to investigate further on issues of over fitting. We suspect that smaller set of images might have caused in an over fitting of sample in feature space. Thus, implementation of VGG16 on larger dataset is under investigation and results would be presented in near future.

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