Breast Cancer Detection using Deep Convolutional Neural Network

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Abstract: Deep Convolutional Neural Network (DCNN) is considered as a popular and powerful deep learning algorithm in image classification. However, there are not many DCNN applications used in medical imaging, because large dataset for medical images is not always available. In this paper, we present two DCNN architectures, a shallow DCNN and a pre-trained DCNN model: AlexNet, to detect breast cancer from 8000 mammographic images extracted from the Digital Database for Screening Mammography. In order to validate the performance of DCNN in breast cancer detection using a big data , we carried out a comparative study with a second deep learning algorithm Stacked AutoEncoders (SAE) in terms accuracy, sensitivity and specificity. The DCNN method achieved the best results with 89.23% of accuracy, 91.11% of sensitivity and 87.75% of specificity.

1 INTRODUCTION

According to theWorld Health Organization (WHO) reports, breast cancer is the most common cancer among women. This pathology is the first major cause of death in all cancers among women, such as 570000 women died from breast cancer in 2015 (World Health Organisation). The early detection of breast cancer is needed for effective diagnosis and treatment.

Currently, mammography is the most widely used imaging modality for detection and diagnosis of breast tumors. A large number if mammography is realized every day, which make the task of analysis of image difficult because a radiologist can not analyzes hundreds of images with the same accuracy and a minimal time.

Therefore, the development of Computer Aided-Diagnosis systems (CAD) (Tang et al., 2009) which can assist medical personnel with the early detection of cancer, pose a crucial alternative.

Deep learning (Hinton et al., 2006; Ranzato et al., 2006) is a new area of machine learning. In recent years, deep learning has attracted attention in various research areas such as computer vision, image classification and big data analysis. This method achieved a record results in many challenges like ImageNet Large Scale Visual Recognition Competition (ILSVRC) (Russakovsky et al., 2015).

The DCNN (Lecun et al., 1998) is one of the most successful techniques in deep learning which achieved outstanding performance on challenging tasks such as image classification (Rawat and Zenghui, 2017), visual object recognition (Radovic et al., 2017), Segmentation (Long et al., 2017).

In this study, we aim to use DCNN to detect breast cancer from a large number of mammographic images (8000 mammography). We implemented two different DCNN models with the mammographic image features based CAD system. To assess the performance of our method with the big data, we compared the results of our models with a second deep learning algorithm Stacked AutoEncoders (SAE) (Vareka and Mautner, 2017).

The paper is organized as follows: in Section 2, we present a previous study of breast cancer detection and classification using deep convolutional neural network architecture. Section 3 describes deep convolutional neural network. Section 4 presents our approach such as DCNN models architecture. Section 5 reports our experiments and results. Finally, Section 6 concludes the work presenting some possibilities for further researches.

2 RELATED WORKS

DCNN has achieved interesting results in images processing. Recently, this network began to prove its per-

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formance in medical tasks, particularly the analysis of medical imaging.

In the context of our study to detect breast cancer automatically in early stages, several studies addresses the problems of detection and classification of breast masses based on DCNN. In (Posada et al., 2015) they used two DCNN models AlexNet and VGGNet as a features extractor and the SVM as a classifier to detect and diagnose breast cancer with 64.52% of accuracy. This system is applied to a dataset containing 600 mammography where 360 for training and 240 for test. Michal Zejmo et al (Zejmo et al., 2017) classified breast microscopic images for 50 patients using GoogLeNet and AlexNet which achieved respectively 83% and 80% accuracy. The authors of (Zhou et al., 2016) analyzed the effeciency of DCNNin determining the existence of breast masses using 322 mammographic images. This analysis gave an accuracy equal to 60.9%. In (Jadoon et al., 2017), the authors classified 2796 mammography into three classes normal, begnin and malign using DCNN to obtain 83.74% of accuracy.

Although research in this context has used deep DCNN models and has achieved interesting results, the dataset used in evaluation are small despite the large number of mammography performed every day. For this, our work consists mainly of creating a computer aided breast cancer diagnosis using a big number of mammographic images (8000 images).

3 DEEP CONVOLUTIONAL NEURAL NETWORK

The deep convolutional neural network is the most popular kind of deep learning models, as it is used in large scale image recognition tasks and especially in the medical imaging analysis. The DCNN architecture is a stack of three main layers: convolutional layer, pooling layer and fully connected layer.

- The convolutional layer is the principal building block of the DCNN. The layer parameters are a set of weights called filter or kernel. The input feature map is divided into small regions called receptive fields, and each receptive field will be multiplied by the filter to produce the output feature map. The stride is the distance between the applications of filters that if this hyperparameter is smaller than filter size, the convolution is applied in overlapping windows.
- The pooling layer is responsible for downsampling the spatial dimension of the input. The main objectives of this layer type are the reduction progressively of the spatial size of the representation and the reduction of the number of parameters and computations required by the network. Despite the availability of various types of pooling function like average pooling, L2-norm pooling, the max pooling is the most used as it consists to compute the maximum in the input patch.
- The fully connected layer is a traditional Multi Layer Perceptron that uses a softmax activation function in the output layer. The neurons of this layer have full connections to all activations in the previous layer. The purpose of the fully connected layer is to classify the input image using the highlevel features extracted from convolutional and pooling layers.

4 METHODS

In this section, we describe our approach to breast cancer detection from a big number of mammography images.

4.1 DCNN Architecture

We train two different DCNN architectures for breast cancer detection which are shown in figures 1 and 2, and analyze the effect of model choices that describe the below. We evaluate two models, a shallow DCNN (the baseline model) and a pre-trained model AlexNet (a deeper model) (Krizhevsky et al., 2012).

The baseline model architecture includes a convolutional layer, a max-pooling layer, a fully connected layer and a soft- max classifier for a binary classification. The convolutional layer is composed of 20 filters of size 5*5 and stride of 2, where receptive field were no overlapping. The final layer contains two units fully connected with the previous layer (fully connected layer), one neuron activated by soft-max regression which produce a value between 0 and 1 to interpret cancer or not.

The AlexNet model is designed in the context of ILSVRC 2012. It is the winner of this challenge with 57% for top-1 accuracy and 80.3% for top-5 accuracy. The network takes a 227*227*3 as input and produces as output a distribution of predicted probabilities across the 1000 classes for ImageNet classification. AlexNet architecture is a set of stacked 5 convolutional layers followed by 3 fully connected layers and ending with a soft-max layer. Concerning the first two convolutional layers are followed by a normalization and max-pooling layer. The last convolutional layer is followed by a maxpooling layer, and the last fully connected layer has two outputs in our adapted version of AlexNet (equaling to the number of classes in our dataset). This DCNN model uses a Rectified Linear Unit (ReLU) as a neural activation function and a dropout (Srivastava et al., 2014) as a regularization technique.

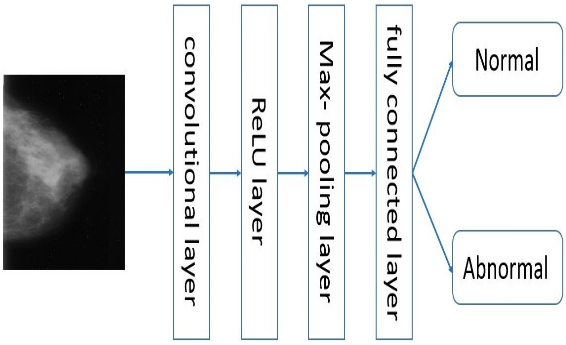

Figure 1: The shallow DCNN architecture.

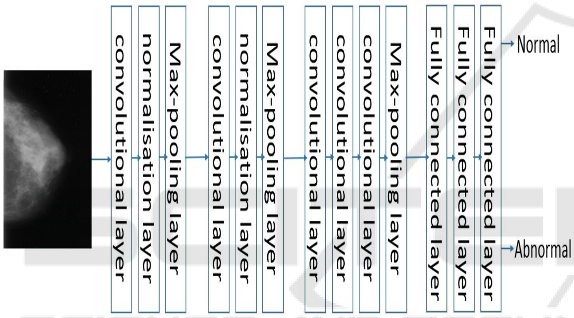

Figure 2: The AlexNet architecture.

4.2 Preprocessing Images

Simple preprocessing of mammographic images is performed. Firstly, we resized images to 28*28 and 227*227 pixels, the input image size for each DCNN model. Secondly, images are converted to an RGB images.

4.3 Data Augmentation

We study the performance of DCNN in breast cancer detection from a big number of mammographic images (8000 images). The dataset available are small, for that, we use rotation to increase the size of our dataset. Each image was rotated 45, 90 and 180. This augmentation is justified because masses have no inherent orientation and their diagnosis is invariant to the transformation.

5 EXPERIMENTS AND RESULTS

5.1 Dataset Description

The mammography used in this work are extracted from the Digital Database for Screening Mammography (DDSM) (Digital Database for Screening Mammography). This database contains 2620 studies, each containing both Cranio Caudal (CC) and Medio Lateral Oblique (MLO) view of each breast. Each image is a grayscale. This database also includes information about patient (age at time of study,ACR breast density rate...) and the image (spatial resolution...).

In this work, we only used 2000 mammographic images CC which are normal and abnormal (containing tumor). The images of our dataset are randomly split into training and testing sets respectively 70% and 30% of the full dataset.

5.2 Performances Metrics

In order to evaluate the performance of DCNN in breast cancer detection, we compared the experimental results in terms of accuracy, sensitivity and specificity. Accuracy, sensitivity and specificity are described in terms of TP, TN, FP and FN.

- True Positive (TP): if the condition is positive and the prediction (the ratio of sick people with a positive test).
- True Negative (TN): if the condition is negative and the prediction (the ratio of healthy people with a negative test).
- False Positive (FP): if the condition is negative and the prediction is positive (the ratio of sick people with a negative test).
- False Negative (FN): if the condition is positive and the prediction is negative (the ratio of healthy people with a positive test).
- Accuracy, sensitivity and specificity are the main metrics for the performance evaluation of a system. N is the number of tests performed.
- Accuracy: is the percentage of mammography correctly classified.

$$\begin{aligned} Accuracy &= (TP+TN)/(TP+FN+FP+TN) \\ Overall\ Accuracy &= \frac{1}{N}\sum_{i=1}^{N} Accuracy_i \end{aligned} \quad (1)$$

- Sensitivity is the percentage of abnormal mammography (with cancer) correctly classified.

$$
\begin{aligned}
Sensitivity &= (TP)/(TP+FN) \\
Overall\ Sensitivity &= \frac{1}{N}\sum_{i=1}^{N} Sensitivity_i
\end{aligned}
\tag{2}
$$

- Specificity is the percentage of normal mammography (without cancer) correctly classified.

$$
\begin{aligned}
Specificity &= (TN)/(TN+FP) \\
Overall\ Specificity &= \frac{1}{N}\sum_{i=1}^{N} pecificity_i
\end{aligned}
\tag{3}
$$

5.3 Experiment Description

DCNN is being widely used to carry out image classification due to its outstanding performance compared to other classification techniques. DCNN has become an emerging alternative in the CAD field.

Our work consists to create a computer aided breast cancer diagnosis based on DCNN using a large number of mammographic images (big data). The main goal of this system is to distinguish between two classes, mammographic image normal (without cancer) and abnormal (with cancer).

In this work, two experiments are carried out. Firstly, two DCNN models, a shallow model and a pretrained model AlexNet that we saw their architectures previously, are used. Secondly, the results of the two DCNN models are compared to a second deep learning algorithm SAE using accuracy, sensitivity and specificity.

In this experiment, to evaluate our methodology, 8000 mammography are selected from the data augmentation operation. We performed 10 tests for both DCNN models. In each test, our dataset is randomly divided into training (5600 images) and test (2400 images) sets, in which a different training and test sets are used in each test. This technique is called cross validation which allows the evaluation of machine learning algorithms performance in making predictions on new datasets that it has not been trained on.

5.4 Results

In figure 3, the accuracy rate of the 10 tests is compared between the two DCNN models in which AlexNet has the best results. The AlexNet accuracy results in all the tests are very close that are varied between 88.04% and 89.83%, while the maximum accuracy value of the shallow DCNN does not exceed 80.47%.

Figure 4 shows the comparison sensitivity rate in the 10 tests using the two DCNN models where AlexNet outperformed the shallow DCNN. The AlexNet gives sensitivity results between 87.37% and 93.68%, whereas the shallow DCNN gives sensitivity results in the interval [60.02%, 90.83%].

Figure 5 presents the comparison specificity rate in the 10 tests for both DCNN models in which AlexNet specificity results are between 83.68% and 91.23% and the shallow DCNN specificity results are in the interval [61.37%, 87.95%]. This results demonstrate that the deeper DCNN model performed better than the shallow model in all the tests in terms accuracy, sensitivity and specificity.

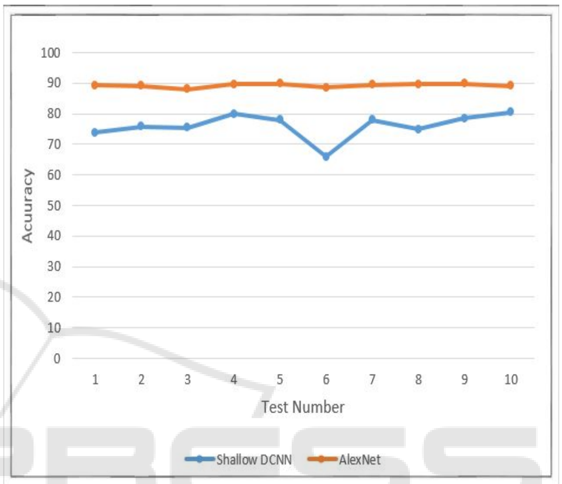

Figure 3: The accuracy comparison of the shallow DCNN and AlexNet.

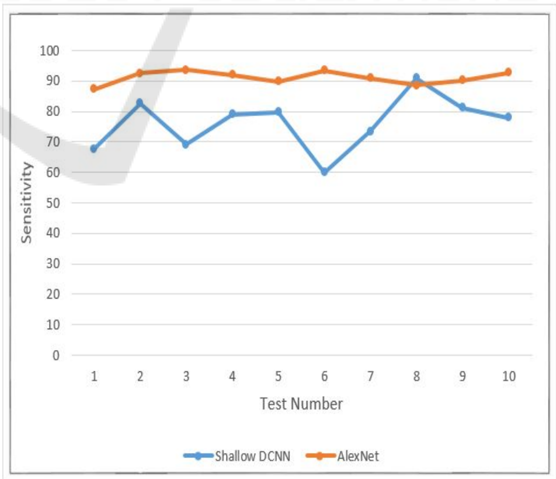

Figure 4: The sensitivity comparison of the shallow DCNN and AlexNet.

Table 1 shows the overall accuracy, overall sensitivity and overall specificity of the two DCNN models. The deeper model AlexNet achieved the best results where gives 89.23% of overall accuracy, 91.11% of overall sensitivity and 87.75% of overall specificity.

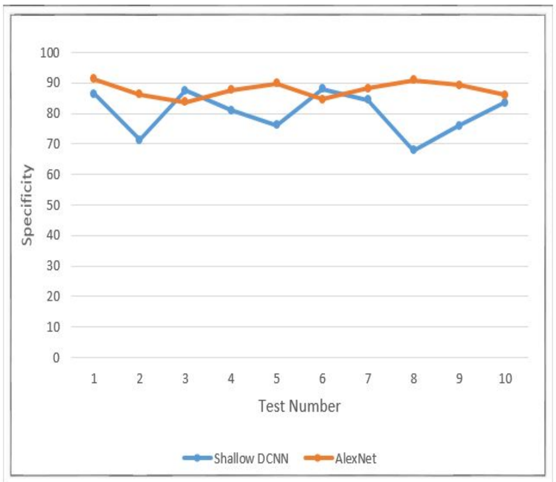

Figure 5: The specificity comparison of the shallow DCNN and AlexNet.

This results presents the importance of the number of layers in breast cancer detection and especially when we use a big data for analysis (8000 mammographic images).

Table 1: Comparison of Results of DCNN Models.

	Shallow DCNN	AlexNet
Accuracy	76.05%	89.23%
Sensitivity	76.19%	91.11%
Specificity	80.28%	87.75%

6 COMPARISON WITH SAE

In order to validate the performance of DCNN in computer aided breast cancer diagnosis system using a big number of mammography, we carried out a comparative study with the SAE algorithm.

The SAE model consists of two autoencoders, each autoencoder stacked on top of each other. There are 300 hidden layers in each autoencoder.This model is applied on the same dataset.

The figure 6 shows the confusion matrix of SAE which gives 63.7% of accuracy, 44.8% of sensitivity and 82.8% of specificity.

Figure 7 presents the comparison accuracy, sensitivity and specificity between DCNN models and SAE. This graph shows the accuracy, sensitivity and specificity results by three classifiers. The difference between the results of DCNN and SAE is huge in terms of three parameters such as DCNN with its simple architecture, its easy learning and its shared weight has achieved better results than SAE and especially AlexNet.

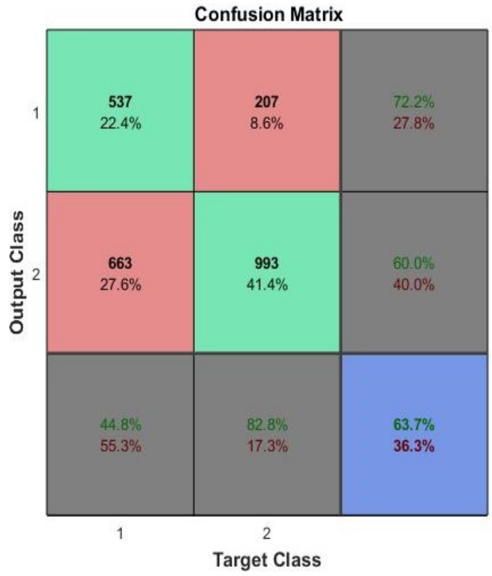

Figure 6: The confusion matrix of the SAE model.

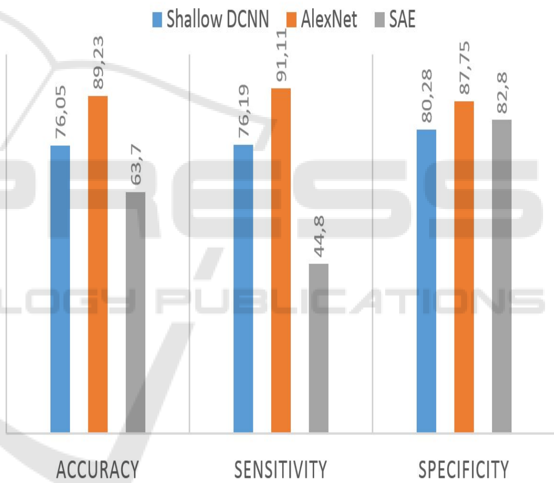

Figure 7: The comparison of DCNN and SAE models.

According to these results DCNN present a promising methodology for a computer aided breast cancer diagnosis system using a big number of mammography which the automatically extracted features by DCNN are effective in mammographic images anlysis as compared to SAE.

7 CONCLUSION

The performance of DCNN in object recognition and image classification has made tremendous progress in the past few years. Recently, many studies are based on DCNN in medical imaging analysis like breast cancer detection by analyzing mammography images, and they achieved interesting results.

The big data present the philosophy of measuring all sorts of things, and today a large number of mammography is performed every day. For this, we attempted to expand our dataset using data augmentation operation to have 8000 mammography, in order to test the feasibility of using DCNN in breast cancer detection using big data (8000 mammography).

In this study, we present the performance of DCNN for computer aided breast cancer diagnosis system using a big number of mammography (8000 mammographic images). We implemented and compared the performance of two different deep learning algorithms: DCNN (a shallow model, AlexNet) and SAE, and the highest results we get are 89.23% for accuracy, 91.11% for sensitivity, and 87.75% for specificity.

The comparison results demonstrated the great potential for DCNN and computer learned features used in the medical imaging area. So the DCNN is a promising methodology for mammographic CAD system, especially the deeper model AlexNet.

Since the reliability of the system is pertinent, it is desirable to increase accuracy more than 89.23%. For this, we propose to use a deeper DCNN model such as GoogLeNet (Szegedy, 2015) and ResNet (He et al., 2015) which have achieved very high accuracy for image recognition in ILSVRC. In addition, we propose to increase the number of mammography, to use another type of classifier in task of classification in DCNN like SVM, and test another deep learning algorithm such as Deep Belief Network, Deep Boltzmann Machine... .

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