A Computer-Aided Diagnosis System for Breast Cancer Using Deep Convolutional Neural Networks

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Abstract The computer-aided diagnosis for breast cancer is coming more and more sought due to the exponential increase of performing mammograms. Particularly, diagnosis and classification of the mammary masses are of significant importance today. For this reason, numerous studies have been carried out in this field and many techniques have been suggested. This paper proposes a convolutional neural network (CNN) approach for automatic detection of breast cancer using the segmented data from digital database for screening mammography (DDSM). We develop a network with CNN architecture that avoids the extracting traditional handcrafted feature phase by processing the extraction of features and classification at one time within the same network of neurons. Therefore, it provides an automatic diagnosis without the user admission. The proposed method offers better classification rates, which allows a more secure diagnosis of breast cancer.

Keywords Convolutional neural networks · CNN · Deep learning
Image classification · Breast cancer · Mammography · Diagnosis

1 Introduction

Cancer in general is a tumor related to the anarchic and indefinite proliferation of genetically modified cells. This proliferation is at the origin of the destruction of the base tissue and the extension of the tumor. In this case, the organism is not able to put it under control. The multiplication of tumor cells in one place constitutes a

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malignant tumor or cancer. The propagation of cancer cells from the local tumor to other parts of the corps is a metastasis. In particular, breast cancer is the most repeated cause of death among women worldwide.

Breast cancer is among the most frequent and grievous cancers in the domain of public health, or so one in ten women is touched by this sickness during their lifetime [1]. However, the reduction of the mortality rate caused by this type of cancer as well as the promotion of the chances of recovery is possible only if the tumor has been taken care of in the first time its appearance. So as to ensure the early detection of such a tumor, radiologists have been led to increase the frequency of mammography, especially for the age group most concerned. In addition, each year, a large volume of mammography images must be analyzed, which requires intense work, a huge amount of time, and several interventions of different radiologists in order to help one another in decision-making. For it, several research studies have been directed toward the automation of mammography reading and decision-making [2].

The first work on automated mammography imaging systems is aimed at providing a second interpretation to radiologists to help them detect/diagnose at an early-stage malignant lesion regardless of their mass or microcalcifications. They are termed the computer-aided detection/diagnosis (CAD) systems.

The main purpose of automated system is to improve the diagnosis accuracy. In fact, CAD is used as a second opinion by the physicians to get the final diagnosis [3, 4], which can decrease human errors, and therefore to provide a uniform screening on a large scale and a better price.

The computers once trained can get much faster classifications, so this helps doctors in real-time classification. Machine learning for breast cancer diagnosis has achieved great development in recent years [5].

Deep learning is a branch of machine learning and can be applied to many problems such as image classification, voice recognition, and natural language processing. Convolutional neural networks (CNNs) are widespread, representing deep learning architectures, have encouraging results for image recognition applications, including medical imaging. CNNs were already used in the 1970s [6], have demonstrated an impressive record for difficult applications such as handwritten character recognition [7], and have improved the recognition rate for better computing approaches [8].

CNNs have demonstrated a qualitative and supreme evolution of technology to perform many complex image classification tasks, like the annual ImageNet challenges [9, 10].

The main functions of a computer-aided diagnosis system are defined as follows: segmentation, feature extraction, and classification which is the basic step in this process in order to obtain an end result.

This study introduces an image recognition system that utilizes a CNN so as to detect and classify abnormalities in mammograms. In general, a mammogram is classified as either normal, benign, or malignant (Fig. 1 shows an example).

The last two steps are merged into deep neural networks which perform both the automatic feature extraction and their classification. This paper is organized as

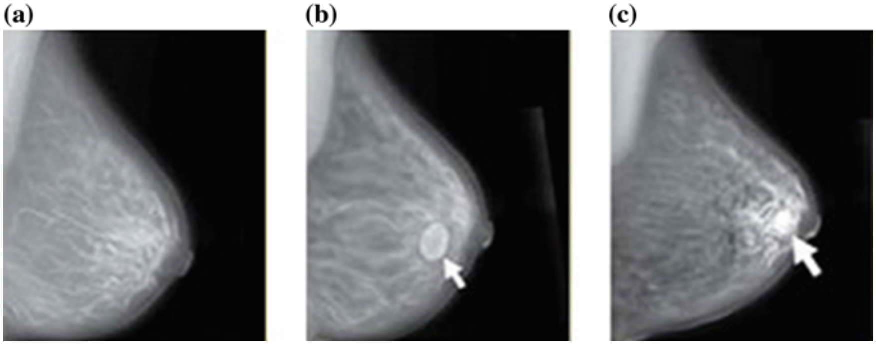


Fig. 1 Breast cancer mammogram images: **a** normal; **b** benign—not cancer; **c** cancer

follows. An overview of the related work presented in Sect. 2. Section 3 explains our method of preprocessing our data and represents our CNN architecture. In Sect. 4, we illustrate the results of our work. Finally, Sect. 5 presents a conclusion of this study as well as a general discussion of the results obtained.

2 Related Work

All women can be affected by breast cancer. Breast cancer is the leading cause of death in women. As such, several studies have been carried out to develop tools to diagnose this cancerous disease. Automated breast cancer detection has been achieved using different machine learning (ML) techniques.

In 2008, Verma [11] presented a new method for the classification of mammary masses for the diagnosis of breast cancer. The proposed methodology is based on the insertion of new neurons into the hidden layer. The classification rate is 94%.

In 2016, Sayd, A.M et al. [12] used magnetic resonance images in order to extract features for classifying mammography images into two classes: malignant, benign, used both KNN and LDA algorithms.

Also in 2016, Zhang, Qi et al. [13] used two unsupervised learning algorithms: the restricted Boltzmann machine (RBM) and the point-wise gated Boltzmann machine (PGBM) using deep learning to automatically extract the image features for the classification of breast cancer; the results showed an accuracy of 93.4%.

And also in 2016, Sidney ML of de Lima et al. [14] used two different types of data, images and texture and have extracted the features of each type of data using Zernike moments and multiresolution wavelets. The proposed approach combines the results of the both SVM and ELM algorithms for breast cancer classification with an accuracy of 94.11%.

In 2017, Alharbi, A. and Tchier, F. [15] proposed an automatic system for the detection of breast cancer based on the Saudi Arabian database by merging the results of the fuzzy and genetic algorithms.

These approaches mentioned above need a prior artistic step of extracting the characteristics of the images before the main recognition step, and they are not applicable in real time that a CNN. According to our knowledge, this is the first work using deep convolutional neural networks for computer-aided diagnosis system for breast cancers. This work is a continuation of our previous tasks [16–18].

3 Proposed Method

The creation of our network by the proposed approach, illustrated in Fig. 2, was obtained after several experiments and after a deep study of the literature for other tasks of pattern recognition. A preliminary step of manual segmentation on the database was carried out in order to extract the masses.

3.1 Segmentation

In our method, a manual segmentation of the mass of the learning base (our base includes mass images encircled by a red circle) is performed in order to extract the contour of the form to be analyzed using the ImageJ tool (Figure 3 shows an example).

3.2 CNN Architecture and Conception

We use 6 layers in our CNN architecture which are organized as follows: convolutional layer C1, subsampling layer S1, convolutional layer C2, subsampling

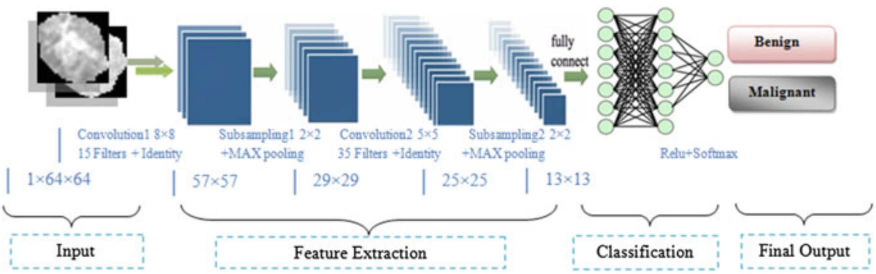


Fig. 2 Network architecture

Fig. 3 Example of extraction of the mass [19]

Fig. 4 Model and training information

Model and Training Information

Model Type	MultiLayerNetwork
Layers	6
Total Parameters	431080
Start Time	
Total Runtime	
Last Update	2017-06-23 15:58:13
Total Parameter Updates	938
Updates/sec	2,38
Examples/sec	76,01

layer S2, dense layer D and finally output layer O (see Fig. 2). The main model parameters and training information of proposed CNN architecture are described in Fig. 4.

We develop a network with CNN architecture that avoids the phase of extracting traditional handcrafted features by processing the extraction of features and classification at one time within the same network of neurons and therefore provides an automatic diagnosis without the user admission.

The convolutional neural networks are currently the most powerful models for classifying images. They have two distinct parts. At the input, an image is provided in the form of a matrix of pixels. It has two dimensions of a grayscale image.

The first part of a CNN is the conventional part itself. It functions as an extractor of image characteristics. An image is passed through a succession of filters, or convoluted nuclei, creating new images called convolution maps. Some intermediate filters reduce the resolution of the image by a local maximum operation.

In the end, the convolution maps are combined in a feature vector, called a CNN code. This code CNN got out of it from the convolutive party is then connected in the entry of a second part, constituted by completely connected layers (multilayer perceptron). The role of this part is to combine the characteristics of the code CNN to classify the image. The output is a last layer with one neuron per category.

3.3 Training

Our neural network is performed after several performance tests. We start through the convolution blocks creation; a batch normalization step is applied after each convolutional layer to decrease the number of feature maps. A stochastic gradient descent is used with a momentum value of 0.9. L2 regularization method is also applied for weight and biases with a threshold equal to 0.0005. Finally, a low learning rate is fixed at 0.0001 to train our neural network.

We use two convolution layers of and two subsampling layers (see Fig. 2) using each one the identity activation function. A stride parameters are fixed at (1*1) and

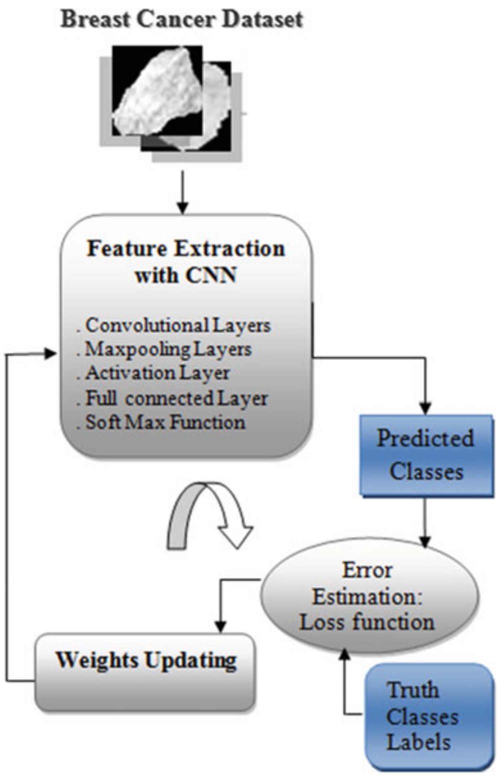


Fig. 5 Supervised training process of CNN classifier

(2*2) for convolutional and subsampling layers respectively. The MAX-pooling function is used with kernel size 2×2. For the dense layer, we use the widely used ReLU function; also the mean square error (MSE) function has been used to optimize the loss function. Finally, for the classification we use the function Softmax widely used.

Figure 5 shows the training process of CNN.

The proposed approach for breast cancer detection and classification uses a sample of 190 images from DDSM mammographic images database. Out of these, 95 images are benign and 95 images are malignant. In order to evaluate our approach, we use the cross-validation method of k-fold. After 13 epochs and 10 iterations, CNN was able to detect normal and abnormal classes of breast cancer with accuracy of **97.89%**.

4 Results

In our experiments, we use the digital database for screening mammography (DDSM) [20]; our database was developed, with 190 images, including 95 benign images and 95 malignant images. The implementation of the proposed work was done with Deeplearning4j. Deeplearning4j[1] is the first commercial-grade, open-source, distributed deep-learning library written for Java and Scala.

As shown in Table 1, **92** breast cancer images are correctly detected as malignant image by the proposed approach, and **94** non-cancer images were correctly classified as benign images.

In summary, 186 images were accurately labeled by the proposed method, resulting in **97.89% accuracy** with **sensitivity 98.9%, specificity 96.9%,** positive predictive value (**PPV**) **96.8%**, negative predictive value (**NPV**) **98,9%,** and **AUC 98.2%.** The sensitivity, specificity, PPV, NPV, and accuracy are defined in Eqs. 1, 2, 3, 4, and 5 [21]:

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{1}$$

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{2}$$

$$\text{PPV} = \frac{TP}{TP + FP} \tag{3}$$

$$\text{NPV} = \frac{TN}{TN + FN} \tag{4}$$

[1]https://deeplearning4j.org/

Table 1 Confusion matrix of CNN results

	Malignant	Benign
Malignant	92	1
Benign	3	94

Table 2 Obtained results of the proposed method

	Sensitivity	Specificity	PPV	NPV	AUC
Proposed CNN architecture	98.9	96.9	96.8	98.9	98.2

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{5}$$

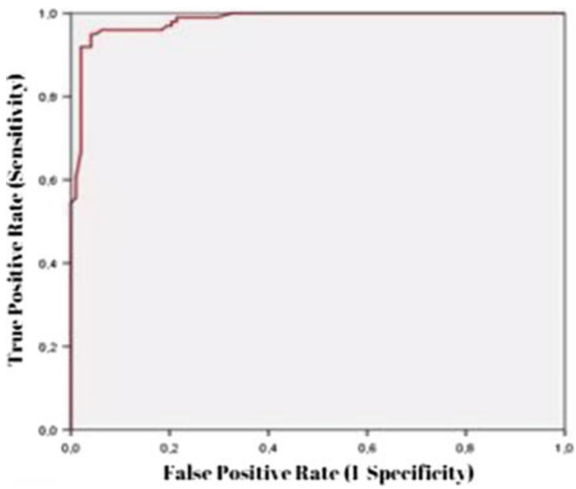
True positive (TP) describes the number of diseased individuals with a positive test, true negative (TN) describes the number of people not sick with a negative test, false positive (FP) is the number of non-diseased individuals with a positive test, and false negative (FN) is the number of diseased people with a negative test.

Table 2 summarizes the obtained results of the proposed CNN architecture.

The proposed approach was also evaluated according to the ROC curves [22], and the operational characteristic curve of the receiver (ROC) of our method has been plotted in Fig. 6. The area under the ROC (AUC) curve was **98.2,** and all the points of the curve are on the top half part of the ROC space; therefore, we can conclude that the proposed model has a good ROC curve.

Figure 7 shows model score versus iteration of our CNN; this is the value of the loss function on the current minibatch.

Fig. 6 ROC curve



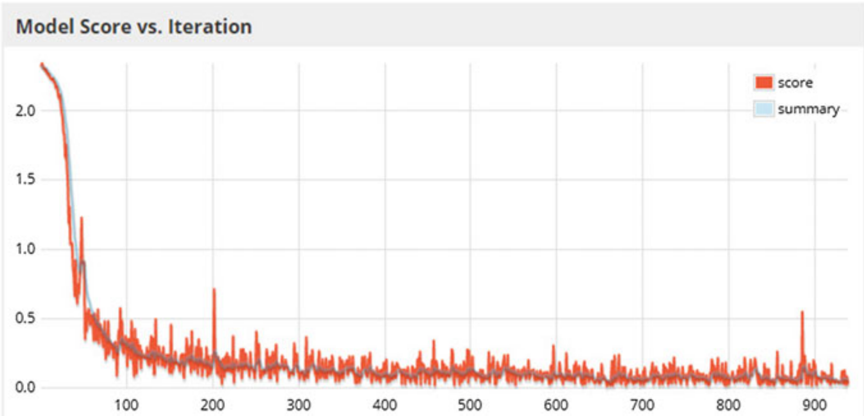


Fig. 7 Model score versus iteration

5 Discussion and Conclusion

Breast cancer is the leading cause of death in women. All women can be affected by this disease. Several studies in mammography imaging have been carried out to develop tools to diagnose this cancerous disease. Automated breast cancer detection has been achieved using different machine learning (ML) techniques.

In this study, we proposed a diagnostic aid system by classifying mammographic images in order to detect the nature of tumors (malignant/benign) using a convolutional neural network (CNN) as a binary classifier, with an image of the tumors (Malignant/Benign). The digital database for screening mammography (DDSM) is used to validate the robustness of our approach.

Proposed approach in this article avoids the design and/or the manual extraction of characteristics. Typical approaches are typically faced with difficult problems such as the conception of robust and easy methods and algorithms to calculate features, the assessment of these features and their relevance for the separation of classes, and the more general case of the selection of relevant features. Our approach based on convolutional neural networks circumvents these difficulties and avoids the delicate step associated with the features.

To conclude, proposed approach provides an automated breast cancer detection computer-aided system that enables the radiologists and the gynecologist in early diagnosis of breast cancer patients with high accuracy, comparing with state-of-the-art results using the same database (DDSM).

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