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INTELLIGENT BREAST CANCER SCREENING BASED ON DEEP NEURAL NETWORKS

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Abstract- Image interpretation corresponds to the analysis of an image or a scene making it possible to describe the objects making up the scene and their relationships, i.e. to extract the semantics of the image, in order to better to understand. The problem of image interpretation is a problem of perception of the environment and decision-making. It is one of the most promising areas of research as it offers opportunities for diagnosis and treatment decisions in many diseases, including cancer. In particular, we are interested in breast cancer, which is the most feared disease among the female population. Our objective is to develop a diagnostic support system for mammography images adapted to the needs of doctors, experts and pathologists based on image processing. Our proposed method for detecting abnormalities is often based on the procedures performed by doctors during radiological examinations. First, we proposed an automatic segmentation using the neuro-fuzzy inference technique namely ANFIS (Adaptive Neuro-Fuzzy Inference System). Then we seek to separate breast mammograms from those containing probable tumors based on a deep neural network.

Keyswords: Mammography, Breast Cancer, Segmentation, ANFIS, Deep Neural Network, BI-RADS.

1. INTRODUCTION

Breast cancer ranks first among the most common cancers in women in Algeria, followed by that of the cervix. It accounts for 33% of all incident cancers in women. To be able to cure the disease and avoid or stop its progression, screening for breast cancer must be done in a systematic way that allows the patient to be treated to have a chance of returning to a normal life after treatment by avoiding extreme surgeries when the cancer is not yet at an advanced stage. It also reduces the mortality rate of those affected. Not being a diagnostic examination, screening mammography cannot definitively establish the existence of cancer, nor exclude it 100%, hence possible (but rare) errors of interpretation [1]. The low rate of cancers to be detected by analyzed mammography makes the task of the radiologist particularly difficult. Fortunately, recent technological advances in digital mammography, as well as advances in CAD methods, should provide appreciable assistance to the radiologist and make it possible to detect more cancers while reducing the number of patients called back for additional examinations (false positives).

Computer-aided detection methods are used to identify suspicious regions on a mammogram [2] with physical and perceptual characteristics similar to those of cancer. The objective of these methods is to help the radiologist identify suspicious lesions that might otherwise be sometimes missed, with the radiologist obviously retaining responsibility for the diagnosis. Advances in image processing, particularly in [3] the field of medical imaging, hold promise for the development of automated applications suitable for breast cancer detection and classification. Algorithms used in deep learning are able to recognize patterns [4] using layers of neural networks. Computer algorithms are becoming increasingly useful in the medical field [5]. Advances in image processing [6][7], particularly medical image processing, and raise hopes for designing appropriate automated applications for breast cancer detection and classification. Currently, deep learning is the most popular image classification algorithm [8]. For this, we opted for deep learning algorithms, which have the ability to use layers of neural networks to recognize patterns. The aim of this work is to propose a diagnostic aid system to differentiate between abnormal tissues and normal tissues in digital mammograms using deep learning networks.

2. SEGMENTATION OF BREAST MASSES FROM MAMMOGRAMS USING ADAPTATIVE NEURO-FUZZY INFERENCE SYSTEM

In this article, we propose a method of breast segmentation in digital mammography images using fuzzy neural inference technique called ANFIS (Adaptive Fuzzy Neural Inference System). The method proceeds in three stages: First, we start by removing noise and other artifacts from the given image by pre-processing the image using the median filter, the second step is an extraction of the breast region using OTSU and in the third and final step, an Adaptative Neuro-Fuzzy Inference System is applied to detect micro-calcifications and masses.

The Adaptive Neural Fuzzy Inference System (ANFIS) [9] is composed of a set of neurons connected to each other by direct connections. Each neuron models a parameterized function; changing the values of its parameters drags the change of the function, as well as the total behavior of the adaptive network [10]. All of the neurons that make up an adaptive network is distributed on all the neurons constituting it. All of the neurons that make up an adaptive network is distributed [11] on all the neurons constituting it. This during each neuron has a set of local parameters: if this set is empty then the associated neuron is represented by a circle and its function is fixed; fixed neuron, otherwise it is shown as a square and the values of these parameters affect the associated function; adaptive neuron.

In ANFIS, connections between neurons are only used [12] to specify the direction of propagation of stimuli from other neurons. For the structure of ANFIS is composed of five layers [13], two type of membership function (bell or Gaussian) and the rule of type so premise then consequent ANFIS is one of the first neuro-fuzzy systems that exist [14]. It is very much cited in the literature because it has proven its effectiveness over time with its simplified learning algorithm: the gradient descent method likewise the least squares approach.

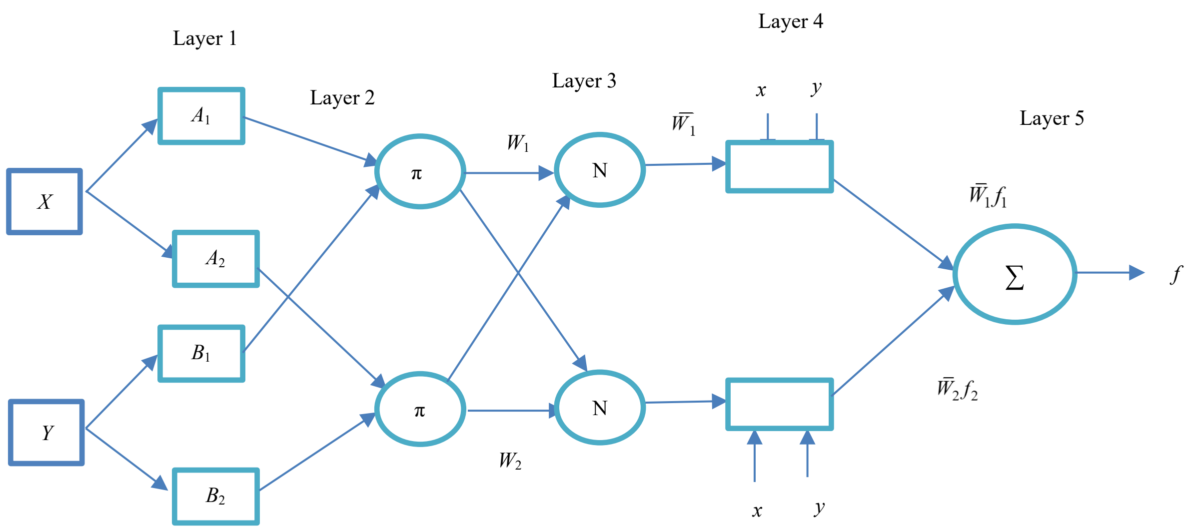

Figure 1. ANFIS Architecture [10]

The Figure 1 illustrates the ANFIS architecture with its layers, including the use of a 5-layer MLP-type neural network, each layer corresponding to a single-step implementation of the Takagi Sugeno-type fuzzy inference system. Each class is explained in detail below:

- The first layer: The adaptive neurons A_i (B_i) calculate the degrees of membership; the set of parameters characterizes the functions A_i (B_i). The corresponding parameters are called parameters of the premise $\{a_i, b_i, c_i\}$.
- The second layer outputs the product w_i inputs, this product represents the degree of activation of each Tule.
- The third layer calculates the normalized value:

$$l_{3,i} = \overline{w}_1 = \frac{w_i}{w_i + w_2} \tag{1}$$

where, $i = 1, 2$ of the degree of membership of each rule.
- The fourth layer realizes links filling the role of the consequence part of each rule, producing as output the value of the function:

$$l_{4,i} = \overline{w}_1 . f_i . \overline{w}_1 . f_i \left(x_1, x_2, \ldots x_N\right) \tag{2}$$

- The fifth layer is a fixed neuron, at a given input; it delivers the response of the network given by:

$$l_{5,i} = \sum_i \overline{w}_1 . f_i = \frac{\sum_i w_i . f_i}{\sum_i w_i} \tag{3}$$

The antecedent parameters were determined by the gradient descent method and the parameters were consistently identified by the least squares method.

3. BREAST MASS CLASSIFICATION FROM MAMMOGRAMS USING DEEP CONVOLUTIONAL NEURAL NETWORKS

In recent years, various Deep Learning-based systems [15] have been developed to improve the classification and prediction of breast cancer, and they depend on labeled data. In the following, we will first present the proposed architecture [16] Deep Convolutional Neural networks CNN that consists in distinguishing between normal and abnormal classes. The mammography database used to learn and evaluate the neural network proposed in this work is "DDSM" stands for Digital Database for Screening Mammography. There are 2620 cases total, of which 695 are considered normal cases, 141 mild cases without recall, 870 mild cases and 914 malignant cases.

The dataset images used have different sizes. Therefore, we resize them to 300x300. Then we split the data into two parts: 80% training data and 20% test data of the dataset. There are several types of layers used to build a CNN but the most relevant are [17]: the convolution layer, the Pooling layer, the activation layer, the flatten layer, the Fully Connected layer, Dropout [18].

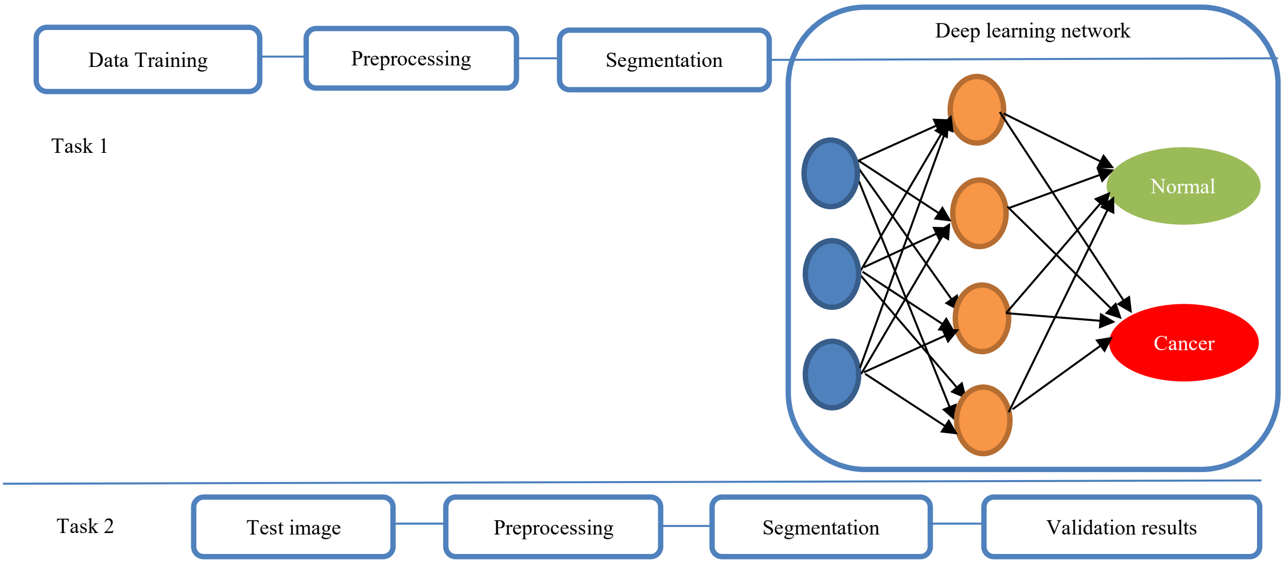

Figure 2. Proposed approach

We cite different architectures of CNNs used [19]:

• AlexNet: Alex-NET in tribute to Alex Krizhevsky, the first author of the ImageNet's revolutionary classification document. This network of neurons was the basis of the 'Scale Visual Recognition Challenge 2012'. AlexNet trained using the ImageNet database provided improved classification accuracy compared to AlexNet [20].

• VGG: There are several types of architectures of VGG 25 in different sizes, the number of layers of which is between 13 and 19 layers with a special architecture, which reduces the size of the filter and increases its depth. "Karen Simonyan" and "Andrew Zisserman" introduced the VGG from the "Visual Geometry" group of the Oxford University laboratory, in 2014 during the "ISLVRC" competition. There are several configurations of the VGG, the most used are VGG19 and VGG16.

• ResNet: The Resnet (residual neural network) model is the winner of the "ILSVRC 2015" competition with an error rate of 3.6% from 23. This gives it a level of performance, similar to that of a human being in the classification of images.

The Figures 3-5 provides a schematic illustration of the many models that were used.

4. RESULTS AND DISCUSSION

In order to achieve our approach, we used the Java language under the Eclipse environment on an i5 CPU @ 2.50 GHz machine with 8 GB of RAM. We start with a data preprocessing to remove the noise from the image acquisition system3. The next step consists in dividing all the examples of the database into several parts, a large part of the example data is intended for the training phase of the model (training data). The second part of the data (test data) is used to calculate the performance and accuracy of the learning model in order to observe and test the results obtained during training. Then we go to the data normalization stage, which is a data pre-processing method, it reduces the complexity of the database. It consists of rendering the values of the database between 1 and 0. To carry out the training of our proposed model, a configuration of several other parameters is necessary, it is summarized on the choice of the functions of activations of the various layers, an optimization function and a loss (error) function.

It remains difficult to compare the approaches contributed in digital health due to of several shortcomings. Indeed, the databases that researchers use are different and many of them are part of a hospital project between the university and a hospital. Of moreover, the sample images dedicated to the evaluation are always different. Without forgetting the parameter, setting point varies from approach to approach. All these points generate a difficulty for a fair comparison of the different approaches. In the field of digital health and during the evaluation of the progression of a disease, the data is generally in a very limited number. In fact, we only have on limited amount of prognostic information relating to patients. In this sense, validation crossover seems the most adequate remedy where the major issue is the division of the samples of data disjunctive folds.

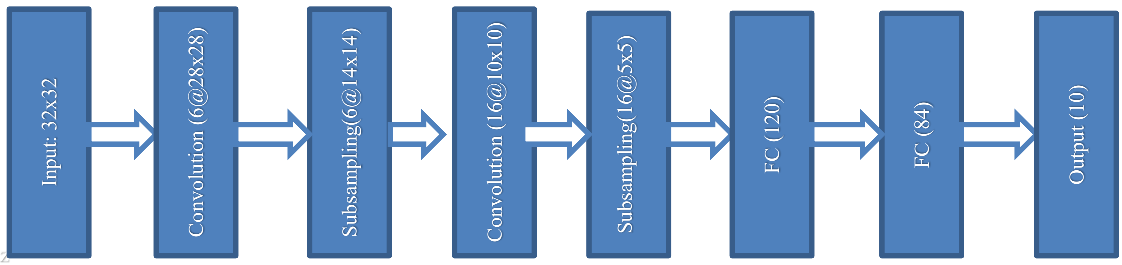

Figure 3. Architecture of AlexNet

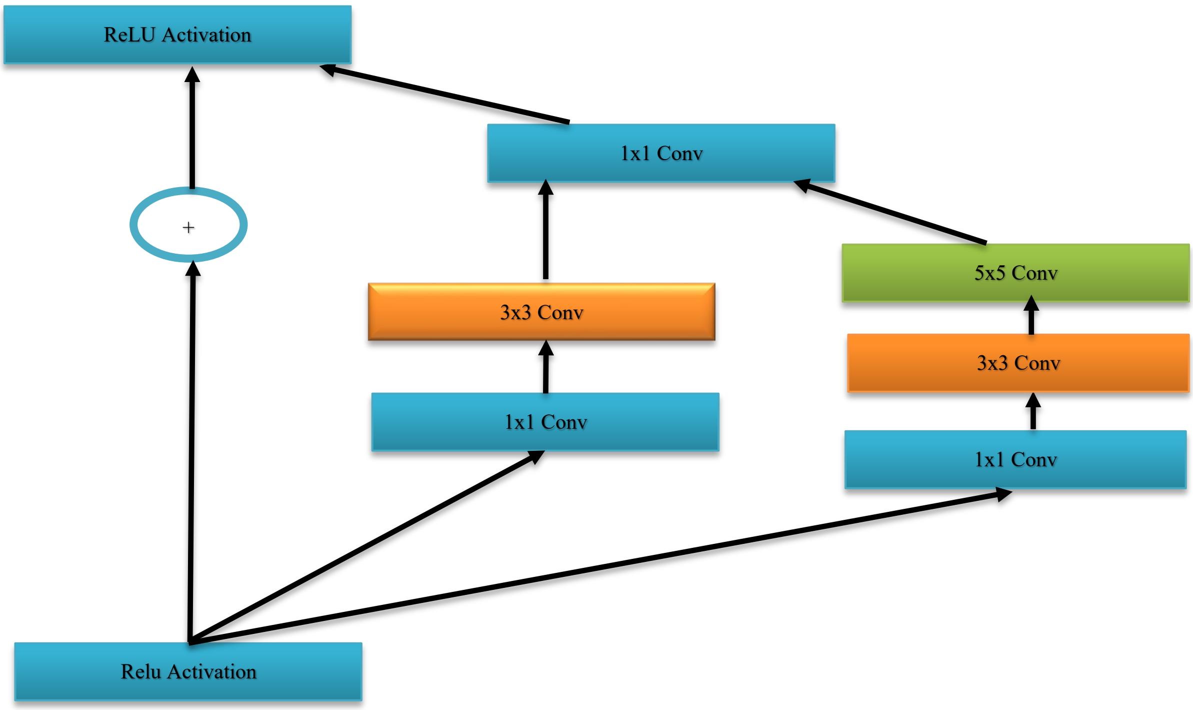

Figure 4. ResNets Architecture

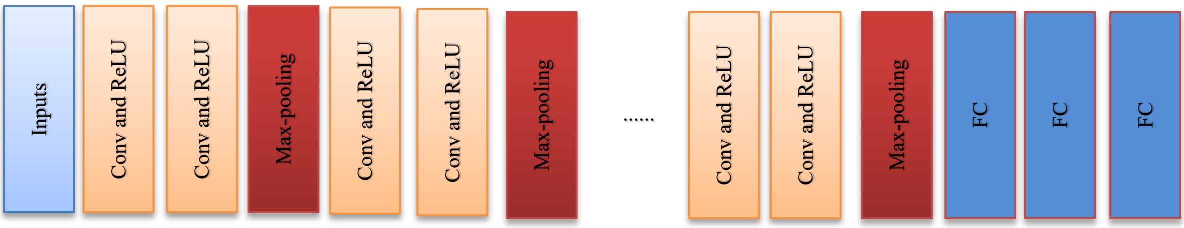

Figure 5. VGG-16 Architecture

Table 1. Report of classification assessment measures

Statistics								
Class	Rate (%)	*VP*	*VN*	*FP*	*FN*	*Precision*	*Recall*	F_measure
Normal	88.75%	58041.0	1194.0	124.0	6237.0	0.9978	0.90296	0.94804
Tumor	11.24%	64278.0	1258.0	1258.0	64278.0	0.9808	0.5	0.66234

Table 2. Comparison metrics

	Recognition rate	*Precision*	*Recall*	F-measure
Value	99.62%	98.7%	70.7%	80.8%

It remains difficult to compare the approaches contributed in digital health due to of several shortcomings. Indeed, the databases that researchers use are different and many of them are part of a hospital project between the university and a hospital. Moreover, the sample images dedicated to the evaluation are always different. Without forgetting the parameter, setting point varies from approach to approach. All these points generate a difficulty for a fair comparison of the different approaches. In the field of digital health and during the evaluation of the progression of a disease, the data is generally in a very limited number. In fact, we only have on limited amount of prognostic information relating to patients. In this sense, validation crossover seems the most adequate remedy where the major issue is the division of the samples of data disjunctive folds.

We used all the regions of interest segmented from the DDSM [21] database during the classification process into: normal class or tumor class to demonstrate the power of discrimination of the descriptor vector between pathological tissues. The four performance indices (True positive, True negative, False positive and False negative) of Table 1 are calculated to summarize the test results obtained with the three models used. The recognition rate value, which is 99.62%, indicates that our class was accurately predicted in the dataset. It can be said that both classes were planned. In the dataset, normal and tumor classes have good and reasonable accuracy. In addition, the system has a high possibility of correctly predicting both classes, with an accuracy of 98.7%.

5. CONCLUSION

Early detection of breast cancer is very useful because it reduces the mortality rate and the cost of treatment. Among the screening techniques and the most important is mammography, which presents an X-ray of the breasts, allowing obtaining images of the interior of the breast using X-rays and thus detecting possible anomalies. It is in this context that our work falls, which aims to classify mammography images in order to detect images containing masses and calcifications. In order to complete our research, we first applied segmentation to separate the interest regions before using Radiologists analyze mammography images. However, there are where the specialist radiologist cannot detect small anomalies such as micro calcifications, lumps or certain masses, which leads to an increase in the error rate. Convolutional neural networks to classify the regions into two groups: positive class (those with cancer) and negative class (those without cancer).

We talked about the foundations of machine learning, as well as general and convolutional neural networks. By describing the various classification layer types (convolution layer, activation layer, pooling layer, dropout, batch normalization, and fully connected layer), we introduced these convolutional neural networks. The results obtained at the end of execution show the effectiveness of the chosen model which can encourage to continue the improvement of this solution. The use of GPUs (graphics processor) can further improve the classification results by training all the images in the database.

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