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Detection of Breast Cancer in Thermal Images Using Convolutional Neural Network

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Abstract. Worldwide, breast cancer is the most commonly diagnosed cancer in women. Early detection of this type of cancer can help women to have a more appropriate treatment and, consequently, reduce the mortality rate. Today, there are several techniques and algorithms for the diagnosis of breast cancer, but techniques that provide greater agility in diagnosis and precision in results are still widely studied. Thermography is a recent technique to record the image of the breast, measuring the temperature based on infrared radiation, and has been an attraction for research. In this context, a Convolutional Neural Network (CNN) was set up to process a data set of thermal breast image inputs in order to classify healthy and breast cancer patients with good accuracy. The data were obtained from the Mastology Database (DMR), with a total of 5,602 images divided into 80% for training and 20% for validation. The CNN architectures used in the experiments were Xception, ResNet101, ResNet101V2, MobileNet, MobileNetV2, DenseNet201 and InceptionV3. Each architecture had the same configurations, with a learning rate of 0.001, using SGD and a maximum of 20 times. The results found showed that the best proposed CNN architecture was Xception with an accuracy of 95.89%, while InceptionV3 obtained an accuracy of 94.73% and DenseNet201 had an accuracy of 93.22%.

Keywords: Cancer, Diagnosis, Thermal Image, Convolutional Neural Network.

1 Introduction

Breast cancer is the leading cause of cancer mortality among women [1]. In INCA [2] we can see an estimate of 66,280 new cases of breast cancer in 2020, which represents about 29.7% of all new cancer cases estimated in women in Brazil, but also in 2018 in the Atlas of Cancer mortality, 17,572 women died.The early detection of breast cancer has great value in increasing the cure and survival rate of a patient, being considered the most important step in reducing the complications of this disease [3].

The main method of screening for breast cancer is mammography. However, this method has low efficiency for young patients, because of dense breasts. However, new methods have been suggested in recent years to improve detection of breast cancer early, such as thermography [4]. Thus, thermography is a totally non-invasive and non-contact imaging technique, widely used in the medical field, being an alternative to detect cancer lesions in different types of breasts [3].

As early detection can increase the chances of treatment and cure, contributing to decrease this mortality rate, an efficient way for this approach is to propose non-invasive methodologies for automatic detection of breast cancer using image processing algorithms and techniques for learning machine [1, 3, 4].

Here, we propose a non-invasive diagnostic method using Convolutional Neural Networks (CNN) to detect breast cancer using thermal images. The proposed methodology compares different architectures of CNN to show their efficiency in detecting breast cancer.

2 Convolutional Neural Networks

Artificial Neural Networks (ANN) are based on the human brain for computational modeling, mainly used to solve problems involving time variations, speech recognition and text processing [5]. ANNs similar to natural neural networks have several layers of neurons connected together by synapses (connection links). The simplest ANN architecture is Perceptron, used to classify linearly separable problems [6].

Convolutional Neural Networks (CNN) is also an ANN architecture, but a variation of the multilayer perceptron (where neurons are organized in two or more layers). CNNs are similar to other neural networks in terms of feed advance, the organization of neurons in layers, with the output of each layer being fed into the next layer for further processing; in addition to learning via rear propagation, using a Loss Function to calculate the margin of error between the actual output and the desired output, updating the weights. The applications of CNNs are generally detection, classification and recognition of images and videos [5].

In Vargas et al. [7] CNN is said to have three main stages: Entry, Convolution and Classification. Figure 1 presents an example of CNN architecture. CNN's standard architecture has a structure containing an input layer, alternating convolutional layers, pooling layers and non-linear layers. After the image is loaded at the network entrance, it goes through a series of layers to extract features and finally, completely connected neurons are used for classification.

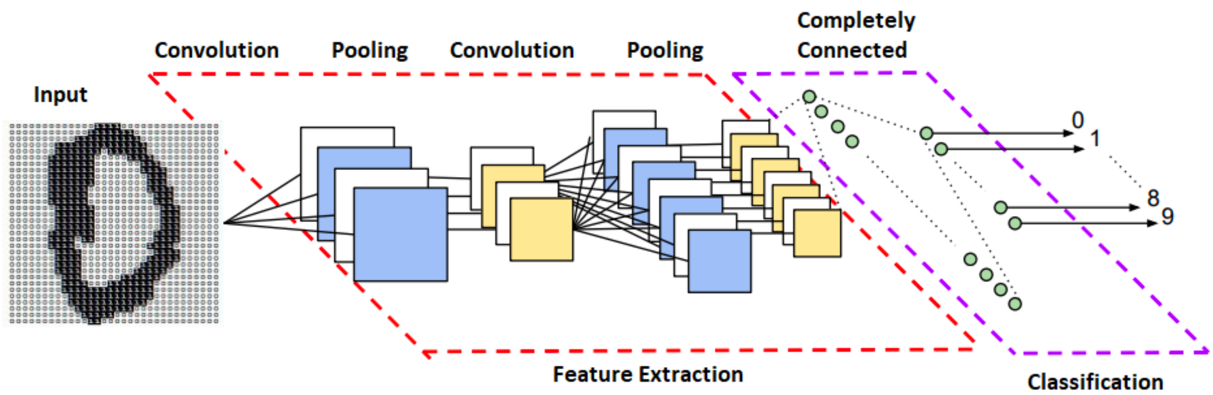

Figure 1. Example of a standard CNN. Taken from Vargas [7]

CNN has a number of advantages over other neural network applications for the detection of breast cancer. What differentiates the CNN architectures used is the number of layers and the number of filters for the feature extraction step. Thus, different configurations may be ideal for detecting and classifying breast cancer.

3 Methodology

The methodology proposed in this work consists of five stages, described in the figure 2.

In the first stage, the collection of thermal images of the breast is referred to, for this, a python program was developed to download the images and thermal matrices from the database [8].

In the second stage, the database was divided with 80% of the images for training the convolutional neural network and 20% of the images for validation. The images divided in this step are used for all tested networks.

In the third stage, training images are used to train the convolutional neural network. In the fourth step, validation is performed in the separate database for testing. Then, the results are obtained, the metrics described in the previous topic.

From the third stage, the process is repeated for seven different convolutional neural network architectures, in order to verify the best architecture proposed in the data analysis.

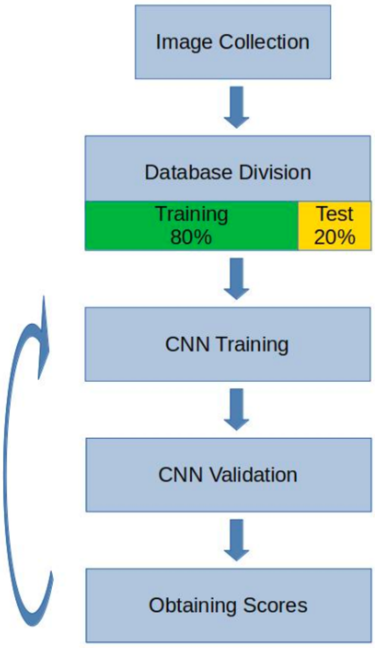

Figure 2. Steps of the proposed methodology.

3.1 Data base

The *Database For Mastology Research (DMR)* platform was used, in Silva et al. [8], which stores and manages mastological images for the early detection of breast cancer.

The database is composed of 218 patients, aged between 21 and 80 years, 176 of whom are healthy and 42 have malignant breast cancer. The diagnosis was confirmed by mammography, ultrasound and biopsies. A total of 5602 images, being 1,123 images of sick patients and 4,479 images of healthy patients, from the static and dynamic protocols. The thermal camera for capturing the images was the FLIR SC-620, with 640 x 480 resolution. In the static protocol, a single image captured in five positions after 10 to 15 minutes of thermal stabilization during the patient's rest. While in the dynamic protocol it is a series of images captured every 15 seconds for five minutes [8].

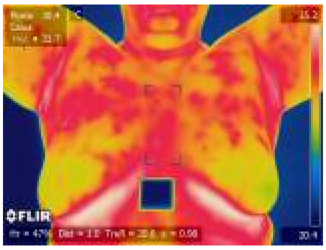

Figure 3. Sample image of healthy patient 24. Taken from Silva et al. [8]

The figures 3 and 4 are examples of the entry of the convolutional neural network of healthy patient and sick patient, respectively.

Figure 4. Sample image of the 138 sick patient. Taken from Silva et al. [8]

3.2 Metrics

The results evaluation measures considered in this work were: Accuracy, Sensitivity, Specificity and F1-Score. Expressions taken from Zuluaga-Gomez et al. [1]. In this way, the frequencies of the classifications for images are counted. Being, True Positive (TP), the number of sick cases correctly classified as sick cases; True Negative (TN), the number of healthy cases correctly classified as healthy cases; False Positive (FP), the number of healthy cases that were incorrectly classified as sick cases; False Negative (FN), the number of sick cases incorrectly classified as healthy cases.

The Accuracy represents correctly classified instances among all classified ones indicating the general performance of the model and can be calculated using the following equation:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

Sensitivity is obtained from cases of cancer patients classified correctly as cancer, used to correctly diagnose sick patients:

$$Sensitivity = \frac{TP}{TP + FN} \tag{2}$$

Unlike the Sensitivity to Specificity is obtained through cases of cancer-free (normal) patients who are correctly classified as non-cancer, used to correctly diagnose healthy patients:

$$Specificity = \frac{TN}{TN + FP} \tag{3}$$

And finally, the F1-Score metric is the harmonic average between Sensitivity and Specificity, indicating the general quality of the proposed model (network architecture):

$$F1 - Score = \frac{2 * TP}{2 * TP + FP + TN} \tag{4}$$

4 Results and discussions

To perform the work, the python programming language was used with the tensorflow and keras libraries in the Google Colab Pro environment, which provides the following hardware: Tesla P100-PCIE-16GB GPU, Intel Xeon @ 2x 2GHz CPU, 13021MiB RAM, 70GB HD and Ubuntu 18.04 Linux 4.19.104. The experimental set was composed of seven tested network architectures. All network architectures had the following configurations: 20 epochs, batch normalization size of 32, Softmax activation function, learning rate 0.001 and Stochastic Gradient Descent (SGD) optimizer.

The performance results of the breast cancer classification are shown in table 1. Looking at the results, it can be noted that the best results are presented in the Xception network architectures with 95.89% accuracy, 98.63% accuracy specificity, 85.95% sensitivity and 90.0% F1-score; the InceptionV3 network architecture presented 94.73% accuracy, 98.06% specificity, 82.64% sensitivity and 87.14% F1-score.

Table 1. Resultados da performance das sete arquiteturas para classificação do câncer de mama.

Network	Accuracy	Specificity	Sensitivity	F1-Score	Duration (s)
Xception	0.958965	0.986348	0.859504	0.900433	1345.33
ResNet101	0.828724	0.996587	0.219008	0.355705	1872.93
ResNet101V2	0.928635	0.959044	0.818182	0.831933	1691.3
MobileNet	0.853702	0.954494	0.487603	0.59	1072.78
MobileNetV2	0.784121	1.0	0.0	0.0	1143.48
DenseNet201	0.932203	0.94198	0.896694	0.85098	2445.32
InceptionV3	0.947368	0.98066	0.826446	0.87146	1149.58

The third best accuracy found was from the DenseNet201 network with 93.22%, with 94.19% specificity, 89.66% sensitivity and 85.09% F1-score. The InceptionV3 network is 1.51% more accurate than the DenseNet201 network, but the DenseNet201 network takes slightly more than twice the test of the InceptionV3 network. In this sense, the best network architecture with good results and the best computational cost is Xception. And the worst network architecture among the architectures tested for this problem, was MobileNetV2 with 78.41% accuracy.

In a similar work, using the same database (DMR) [8] and testing several other network architectures, it showed a lower result for the InceptionV3 architecture, than those presented in this work, with an accuracy of 80%, F1-score of 80%, accuracy of 82% and sensitivity of 78% [1]. In another study, using the authors' own configuration, but based on thermal data, superior results were obtained with 98 % breast cancer classification accuracy cite ekici.

5 Final considerations

Thermography is a good alternative to assess the detection of breast cancer, as it has a better location of cancer cells, due to the temperature difference. Here, we present a methodological approach of seven distinct architectures to assess the accuracy of breast cancer detection. We found that the Xception, InceptionV3 and DenseNet201 architectures were more appropriate for our approach, having an accuracy of 95.89%, 94.73% and 93.22%, respectively. For future work it is intended to test other architectures of convolutional neural networks (CNN), also configuring a particular architecture to those available in the literature.

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