Breast Cancer Automatic Diagnosis System using Faster Regional Convolutional Neural Networks

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Keywords: Breast Cancer, Mammography, Deep Learning, Convolutional Neural Network, Faster Regional Convolutional Neural Network, Medical Image Analysis.

Abstract: Breast cancer is one of the most frequent causes of mortality in women. For the early detection of breast cancer, the mammography is used as the most efficient technique to identify abnormalities such as tumors. Automatic detection of tumors in mammograms has become a big challenge and can play a crucial role to assist doctors in order to achieve an accurate diagnosis. State-of-the-art Deep Learning algorithms such as Faster Regional Convolutional Neural Networks are able to determine the presence of an object and also its position inside the image in a reduced computation time. In this work, we evaluate these algorithms to detect tumors in mammogram images and propose a detection system that contains: (1) a preprocessing step performed on mammograms taken from the Digital Database for Screening Mammography (DDSM) and (2) the Neural Network model, which performs feature extraction over the mammograms in order to locate tumors within each image and classify them as malignant or benign. The results obtained show that the proposed algorithm has an accuracy of 97.375%. These results show that the system could be very useful for aiding physicians when detecting tumors from mammogram images.

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1 INTRODUCTION

Breast cancer is the most prevalent cancer among women and the leading cause of cancer death. According to Global Cancer Observatory (GLOBOCAN), there have been around 2.1 million diagnosed female breast cancer cases in 2018, representing almost one for every four cancer cases among women (Bray et al., 2018). There are several types of abnormalities in breast cancer such as tumors and microcalcifications, which are the main indicators of malignancy. Tumors are attributed to any lesion or protuberance in the breast, which may be benign or malignant; while microcalcifications are areas with a large amount of calcium accumulation. The early detection of these abnormalities is crucial to improve women's quality of life and also the survival rate in critical cases.

Mammography is the most effective screening tool for the diagnosis of breast cancer. When using this technique, the traditional method to perform the diagnose consists in the evaluation by a physician. However, due to certain reasons, the diagnosis of breast cancer may be susceptible to failure. On the one hand, the experience of the physician and his expertise, and also the fatigue occasioned after examining many consecutive mammograms are some of the reasons for failure. On the other hand, there may be other reasons beyond the ones related to the specialist. Tumors could be confusing and hard to classify as benign or malignant depending on the characteristics shown in the mammograms due to their high similarity. To this end, a computer-aided diagnosis (CAD) could provide a second opinion in order to assist physicians to make the decision, which could reduce false negative diagnoses and, therefore, minimize the possibility of making a mistake.

In this work, a CAD system for detecting and classifying tumors in mammograms using a type of Deep Learning-based algorithm called Regional Convolutional Neural Networks (R-CNN) is presented. The purpose of R-CNNs is to locate an object inside an

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Breast Cancer Automatic Diagnosis System using Faster Regional Convolutional Neural Networks.
DOI: 10.5220/0008494304440448
In *Proceedings of the 11th International Joint Conference on Computational Intelligence (IJCCI 2019)*, pages 444-448
ISBN: 978-989-758-384-1
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image by proposing possible regions of interest and classifying them later. Faster Regional Convolutional Neural Network (Faster R-CNN) (Ren et al., 2015) is one of the most recent developed algorithms based on the R-CNN architecture. Faster R-CNN was developed in 2015 and its objective was to reduce its predecessors computation time. This algorithm has already been used for different context, proving its ability to detect objects successfully. Face detection (Jiang and Learned-Miller, 2017), polyp detection in gastrointestinal images, driver's cell-phone usage, hands on steering wheel detection (Hoang Ngan Le et al., 2016) and wildland forest fire smoke detection (Zhang et al., 2018) are some application examples.

In this paper, we report our study of an automated computerized system for locating and classifying tumors as malignant or benign in mammograms using a Faster R-CNN algorithm.

The rest of the paper is structured as follows: Section 2 is organized in two main subsections: Dataset (2.1), which consists of Image Acquisition (2.1.1) and Data Preprocessing (2.1.2), and Neural Network (2.2). Then, the results achieved in this approach are presented and discussed in Section 3. Finally, the conclusions of this work are presented in Section 4.

2 METHODOLOGY

In this section, we present the methods that are used in the approach that has been carried out. First, the used dataset is explained from its acquisition to its preprocessing. Finally, the Faster R-CNN is presented, along with the architecture, training and testing of the neural network that has been used in this work, and also, the performance evaluation metrics.

2.1 Dataset

2.1.1 Image Acquisition

In this work, the database of mammograms from Digital Database for Screening Mammography (DDSM)[1] was used. The DDSM (Heath et al., 2000), (Heath et al., 1998) was created by the University of South Florida. It has become a very useful tool in the development of decision support systems for breast cancer diagnosis. DDSM contains more than 2620 scanned grayscale mammogram images which include normal, benign and malignant cases with verified pathological information (see Fig. 1). For each case, four

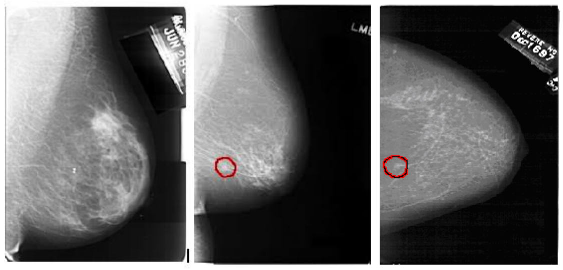

Figure 1: Mammograms taken from the DDSM. From left to right: breast without evidence of abnormality, breast with presence of malignant tumor and breast with benign tumor both of them shown in red.

mammograms are taken with two different views: bilateral craniocaudal (CC) and mediolateral oblique (MLO). In benign and malignant cases, ground truth information is given with the location of the abnormality.

2.1.2 Data Preprocessing

A preprocessing step was applied to the images in order to enhance the performance of the system and, therefore, improve the results of the detection (see Fig. 2).

Grayscale images tend to have a compressed histogram distribution, meaning that the details are not easy to observe. By modifying the histogram, the grayscale interval can be extended, increasing the contrast in order to better distinguish details contained in the image. Therefore, a contrast enhancement method called contrast-limited adaptative histogram equalization (CLAHE) was used to enhance image details. CLAHE is able to define the shape of the histogram that produces the best quality result (Maitra et al., 2012).

Another problem that has to be considered is the noise, since during the mammogram acquisition it is one of the effects that is going to be present. Therefore, we performed the spatial transformation using the median filter in order to reduce noise (Ponraj et al., 2011). This technique generates a new image where each pixel gets its intensity from the median of neighboring pixels.

Mammograms of the DDSM have different size, thus the preprocessed dataset was resized to 600 width and 900 pixels height. Also, a normalization process was applied reducing the range of values to [0,1] in order to achieve a better performance.

[1] http://www.eng.usf.edu/cvprg/Mammography/Database.html

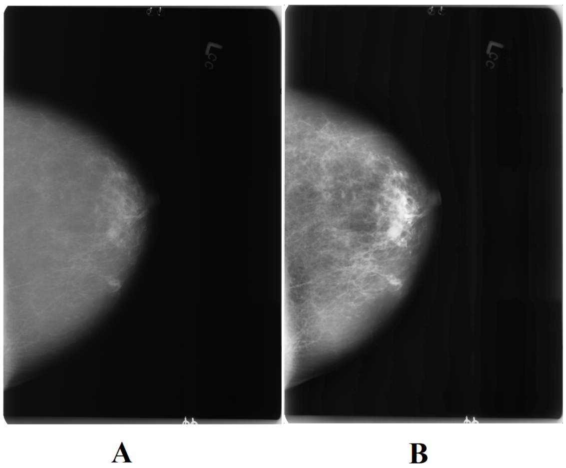

Figure 2: Preprocessing step applied to the original mammograms. (A) shows an original mammogram sample, while (B) shows the same mammogram after being preprocessed.

2.2 Neural Network Model for Breast Cancer Detection

As mentioned before, Faster R-CNN is an algorithm whose purpose is to detect and classify the regions of interest, locating them in the image. This algorithm consists of two parts (see Fig. 3): the region proposal network (RPN) which generates proposal regions of interest and the detector network whose purpose is to perform the classification over the proposed region (Ren et al., 2015).

RPN receives an image from the dataset as an input. Then, it extracts feature maps and analyzes them to propose the regions that most likely contains a tumor. The novel step that this architecture introduces is the way to determine the regions of interest, by using a Convolutional Neural Network that takes advantage of the mathematical operations made in the convolution layers. In this study, ResNet50 (He et al., 2016) was used as the CNN model.

The proposed regions of interest generated by the RPN are the input of the detector network, called Faster R-CNN detector, which performs two main tasks: a classification and a regression. The output of the regression determines a predicted bounding-box where the object could be located, while the output of the classification sub-network is the probability (confidence value) that the box contains the object.

For the training step, all the images obtained after performing the preprocessing step were randomly mixed in order to avoid any classification bias.

To evaluate the accuracy and robustness of Faster R-CNN in the detection, 85% of the preprocessed dataset was used to train and validate the network, while the remaining 15% was used to test its performance. These two folders did not contain mammograms from the same patient, meaning that the performance of the system was not tested using images from patients that were previously used in the training step.

In this study, TensorFlow[2] together with Keras[3] have been used to design, train and test the network.

3 RESULTS AND DISCUSSION

In this section, the results obtained after testing the trained network with the images from the dataset are presented.

In order to evaluate the results, the accuracy was defined using the following equation:

$$Accuracy = 100 \times \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Where TP means true positives, TN means true negatives, FP means false positives, and FN means false negatives.

Every time that the training step used the whole amount of images that were selected for training the network as input, the system performed a test over the a validation set. After training the network until the loss value was minimum, the classifier achieved a mean accuracy of 97.375% over the two classes that has been studied in this work: benign and malignant tumor.

After obtaining these results, the output images from the network were analyzed in order to see the bounding boxes that the system proposed over the original images. Fig. 4 shows the results of our recognition system in terms of precision when detecting tumors inside the samples from the dataset that were considered for testing it. Images in the left part of Fig. 4 correspond to the output of our system, where the bounding boxes are marked in blue; and, in the right part, their corresponding mark images are presented, indicating where tumors are located, considering that as ground truth.

Most of the tumors inside the set of images were not located exactly in the same area as the ground truth, which could be caused by some factors. First of all, the amount of images that were considered for training the network was very low, which could lead to the fact that the network has not learned how to detect tumors properly. Also, training the network takes several days, which didn't let us experiment enough

[2]https://www.tensorflow.org/?hl=es

[3]https://keras.io/

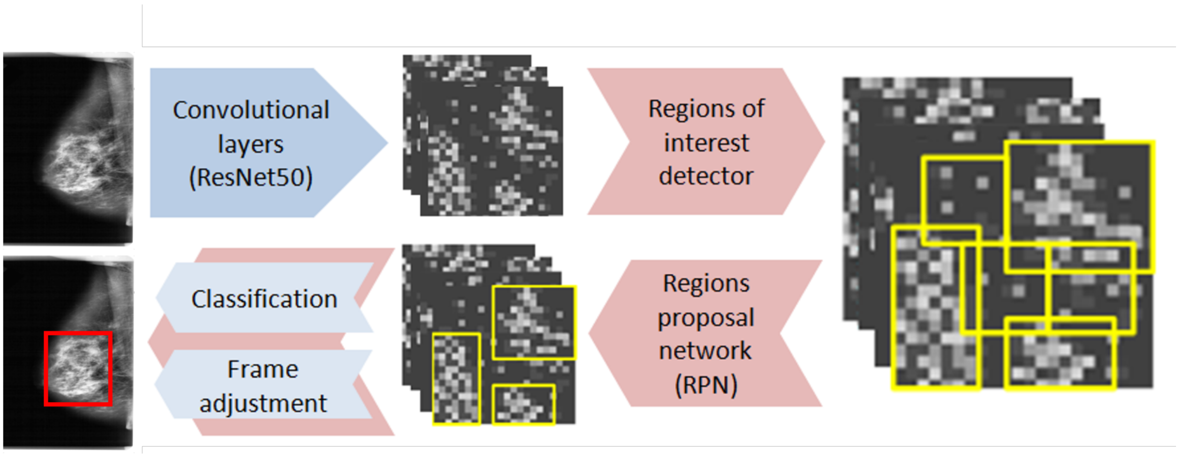

Figure 3: Faster R-CNN architecture.

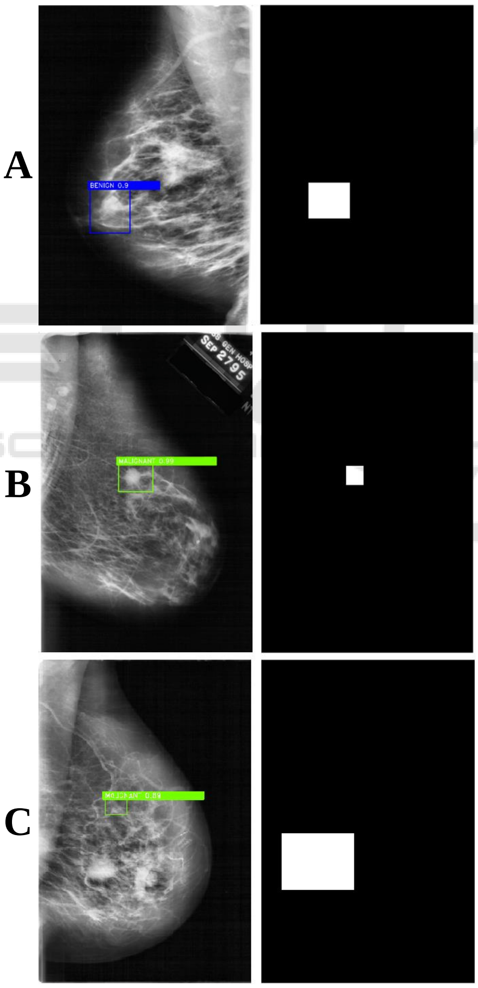

Figure 4: Results of the network performance. At the left, mammograms with the predicted tumors and its corresponding confidence values (benign tumor shown in blue, malignant tumors shown in green). At the right, ground truth images indicating where the tumors are located. A and B were correctly predicted whereas C was not.

to optimize the hyperparameters for this task. Finally, only the ResNet50 model was used, leaving the door open for many other different architectures.

Other approaches as Ayelet Akselrod-Ballin et al. (Akselrod-Ballin et al., 2016) developed a modified algorithm based on Faster R-CNN whose purpose is to detect and classify the major clinical classes in breast cancer, malignant and benign tumors. As opposed to our implementation, that architecture uses VGG16 as CNN for the extraction of features and proposal of regions of interest. This system uses multi-center clinical dataset with a total of 4750 images. After training their modified network, they obtained a 77% accuracy.

The preliminary results that are presented in this work already prove that, if we take into consideration the drawbacks that were mentioned before, the system is already able to classify if the mammogram has a benign or a malignant tumor with an accuracy that is higher than 97%.

4 CONCLUSIONS

In this study, a computerized-aided diagnosis method based on Faster R-CNN used for detecting and classifying tumors in mammograms is presented. Firstly, the images to train the network were obtained from the public database DDSM, which were preprocessed in order to improve the results. This preprocessing step consisted of an enhancement of the images by increasing the contrast with the CLAHE technique, a noise reduction with the median filter and a resize and normalization processes. Then, the network was trained and validated with the 85% of the preprocessed dataset, which extracts features over the mammogram images, proposes regions of interest where tumors could be located, and, finally classifies each of them based on the probability that they contain a tumor. Using the detection metrics, the performance of the network was measured with the remaining 15% of the dataset in order to evaluate its robustness. After training the network, the results show that this proposed computer-aided diagnosis method achieved a mean accuracy of 97.375% proving that the system could aid specialized doctors to recognize cancerous signs when analyzing mammograms, improving patients' quality of life.

In future works, the authors will study different CNNs models and also other network architectures like Mask R-CNNs instead of Faster R-CNNs in order to not only locate the tumor inside the mammogram, but also to create a mask with its shape. This way, the size of the tumor can be estimated more precisely and taken into account in the decision making task.

ACKNOWLEDGEMENTS

This work was supported by the excellence project from the Spanish government grant (with support from the European Regional Development Fund) COFNET (TEC2016-77785-P).

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