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Medical diagnostic support system based on breast thermography using Raspberry Pi and cloud computing

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ABSTRACT

Breast thermography is a promising medical imaging technique for the detection of breast cancer. However, providing a robust and portable computer-aided diagnostic system for breast thermography remains a tedious task. In this paper, a computer-aided diagnostic system based on breast thermography is developed and implemented on a Raspberry Pi 4 using the cloud computing services to provide the computing power needed for machine learning algorithms. Image processing techniques such as pre-processing and segmentation are employed to achieve an adequate feature extraction task. The support vector machine classifier is used in the final stage to classify the breast as normal or abnormal. According to the experimental results, the proposed computer-aided diagnostic system has shown high performance in both the segmentation and classification steps. Furthermore, a low computation time was obtained when using the high computing capabilities of the cloud with the Raspberry Pi. We conclude that the implementation of such a decision support system on the Raspberry Pi especially when using the cloud computing services, can be a reliable tool for radiologists to predict breast abnormalities even in the rural backcountry where there is lack of health services.

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1. INTRODUCTION

Nowadays, breast cancer is the most common type of cancer among women [1], [2]. The World Health Organization estimates that more than one million new cases are diagnosed each year and more than 500,000 deaths are related to breast cancer worldwide [1]. In order to reduce the number of women deaths from breast cancer, the use of early diagnosis is a must. Mammography is the main known standard for diagnosing breast cancer [2]. However, some researchers claim that this technique can harm the health of the patient when using it, due to exposure to x-rays [3].

Infrared thermography is another non-invasive, non-ionizing medical imaging technique for breast cancer detection that uses a thermal camera to detect infrared radiation emitted by the skin of the breast [4], [5]. In a study conducted on patients with breast cancer, Gamagami [6] reports that 15% of cancers go unnoticed on mammography, but are detected by thermography. When thermal imaging is combined with mammography, the reported sensitivity rate of 85% for mammography increases to 95%. Thus, it is clear that infrared imaging can detect small tumors leading to early diagnosis [6].

However, when using a computer aided diagnostic system, some of the major problems using thermography, are the accurate segmentation of the breast area as well as the correct discrimination of the breast being normal or abnormal [7]. On the other hand, the use of artificial intelligence algorithms, requiring high levels of responsiveness and intensive computing resources, introduces the need to define new methods to facilitate the use of such algorithms and help reduce latency.

Different types of research have focused on identifying breast cancer from thermography. Here we consider the most relevant published research. Zadeh *et al.* [8] applied fuzzy active contour to automatically detect return on investment (ROI) in the breast thermograms. 85% of sensitivity and 91.98% of accuracy were respectively achieved using a limited data set. Golestani *et al.* [9] discussed and compared three breast thermogram segmentation techniques: k-means, fuzzy c-means and level set. Pramanik *et al.* [10] applied discrete wavelet transform and artificial neural network to automatically detect breast abnormalities. The authors achieved an accuracy of 90.48%. Francis and Sasikala obtained 85.1% of accuracy by focusing on the asymmetry in temperature between the right and the left breasts [11]. Regarding the implementation on an Raspberry Pi, Salvi and Kadam, [12] used CNN to classify the breast into benign and malignant, then send the results to doctor via cloud computing using the Raspberry Pi. Similarly, Elouerghi *et al.* [13] realized an embedded system using Rasperry Pi offering the possibility of communicating via a server to store and consult breast thermograms.

2. PROPOSED METHOD

Proposed method to detect breast abnormalities employs image-processing techniques, machine learning algorithms, embedded implementation and cloud computing services. Compared with other related works, the method will be used not only to store and visualise breast thermograms on the Internet, but also to fully process all image processing steps on the Raspberry Pi, even high computational algorithms like deep learning. Figure 1 presents the main steps involved in the proposed method. An automated diagnosis system is designed including image preprocessing, image segmentation and classification of breast thermograms as either normal or abnormal. This algorithm is then implemented on a Raspberry Pi using the cloud wich will enhance the computing capability of the Raspberry Pi and thus help decrease latency in machine learning steps that require high comptuing power.

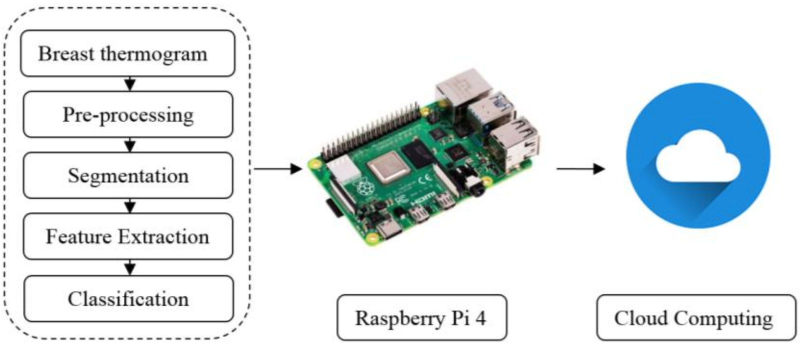


Figure 1. Main steps and computing resources involved in the proposed method

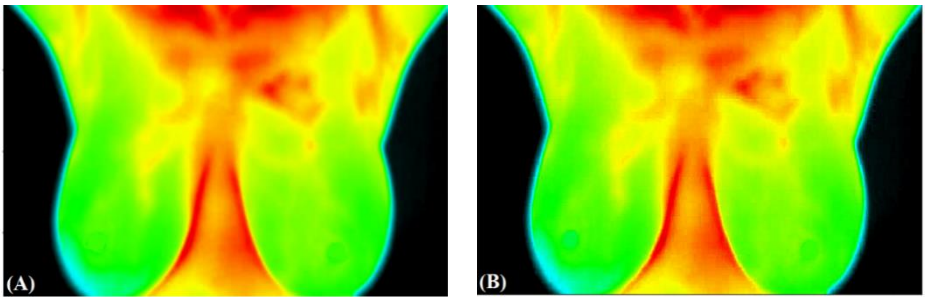
3. METHOD

3.1. Database acquisition and preprocessing

To evaluate the proposed method, several tests were conducted using breast thermograms from an open source online database [14]. One hundred and seventy images from female patients including normal and abnormal breasts are involved in the data collection procedure. In order to enhance the quality of blurred thermograms, we apply a sharpening filter as a high pass filter, which will increase the contrast between bright and dark regions. Figure 2 shows the effect of the preprocessing step on the collected breast thermograms. In Figure 2(a) is effect of sharpening filter before processing and Figure 2(b) after processing.

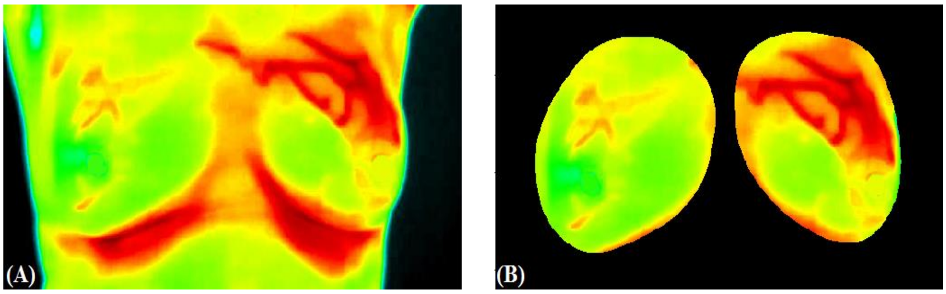
3.2. Segmentation

One of the major problems with the use of thermography, especially when using a computer aided diagnostic system, is the precise segmentation of the region of interest (right and left breast) from the background (extra mammary organs). Several segmentation techniques have been proposed in the literature to solve this problem, but they obtained moderate success rates [6], [15]. In an attempt to properly segment the breast regions, we used a deep learning U-net algorithm [16] which has showed great performance in similar pattern recognition and computer vision tasks [11], [17]–[19]. Figure 3 illustrates the result of this segmentation operation on breast thermograms. In Figure 3(a) before processing and Fogure 3(b) after processing. More details on segmentation, model architectures and training configuration can be found in our previous work [16].



(a) (b)

Figure 2. Effect of sharpening filter (a) before processing and (b) after processing



(a) (b)

Figure 3. The result of the segmentation process on a breast thermogram; (a) before processing and (b) after processing

3.3. Feature extraction and classification

In order to obtain high accuracy in the classification step, the most relevant characteristics of interest in the image are extracted, in particular statistical and textural features [6], [16], [20]. Several supervised learning techniques were then tested as classifiers for the proposed computer aided detection (CAD) system using the extracted features. The one that has shown great performance is the support vector machine (SVM) due to its high ability to generalize data. SVM builds a model capable of distinguishing the belonging class (normal or abnormal breast) of any future data based on the support vectors obtained by the training dataset [20], [21]. More details on feature extraction and classification steps can be found in our previous work [16].

3.4. Implementation on the Raspberry Pi

Raspberry Pi is a small single-board minicomputer based on a low-cost system-on-a-chip (SoC) [22], [23]. In the proposed approach, we used the latest Raspberry Pi 4 Model B, which is mainly depended on Broadcom BCM2711 SoC with a 1.5 GHz quad-core, a memory of 2 GigaB SDRAM LPDDR4, a videocore VI graphical processing unit (GPU) supporting OpenGL ES 3.0 and a 4K HEVC decoding at 60 fps.

The Raspberry Pi 4 shown in Figure 4 officially works with Raspberry Pi OS, which is based on Linux. However, the Pi 4 can run other operating systems such as Windows 10 IoT Core, Ubuntu, Risc, or even a special version of android called Lineage OS. In the proposed method, we used the Lineage OS as the operating system in order to access the cloud computing facilities through an Android application. To correctly achieve this task, the algorithm [16] was written on the Pycharm integrated development environment using the python language.

3.5. Cloud computing

Cloud computing designates a parallel and distributed computing environment made up of a set of interconnected and virtualized computers [24]. These computers are dynamically provisioned and presented as unified computing resources, offering services that can be rented by users via the internet such as power high computing power, high-speed internet connection, and massive storage space.

There are three main service models in the cloud paradigm, software as a service (SaaS) (Gmail, Google Docs, Facebook), platform as a service (PaaS) (Google App Engine, Windows Azure, Engine Yard), and infrastructure as a service (IaaS) (Google Compute Engine (GCE), Blade Shadow, Amazon EC2, IBM Blue Cloud). In the present work, we used blade shadow [25] as a cloud computing service which allowed us to attain very interesting computing power on the low cost minicomputer Raspberry Pi, providing a 1080 GTX 8G GPU, 4 cores/8 threads processor, 12 GigaB SDRAM and a 64-bits Windows 10 operating system. Shadow is a French company specializing in cloud computing it was created in 2015 by E. Freund, S. Héliot and A. Kagan.

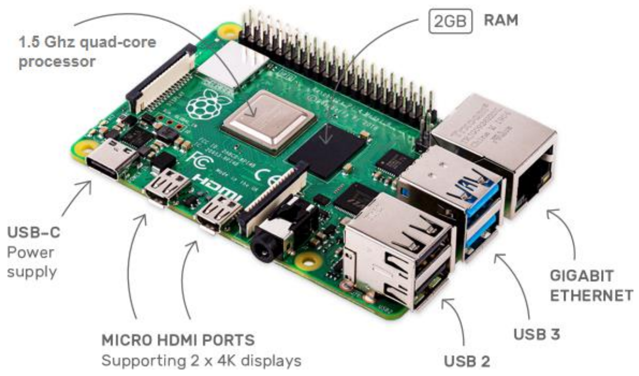


Figure 4. The Raspberry Pi 4 Model B

4. RESULTS AND DISCUSSION

We carried out several tests for the different stages of the proposed approach. The performance metrics obtained are presented in what follow. 1- Intersection over Union IoU [16], [26] was calculated to assess the segmentation accuracy. As illustrated in Figure 5, this parameter computes the ratio of the superimposed zone divided by the union area in order to compare the truth region with the predicted one.

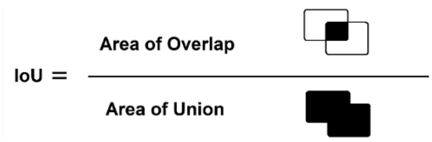


Figure 5. Intersection over Union IoU

After several tests, the performance of the learning network reached an average IoU of 0.8884 (88.84%). Figure 6 shows the result on a breast thermogram sample of this segmentation operation with its corresponding IoU. The second computed metric is the accuracy of the classifier. This parameter is measured in the classification step in order to quantify the classifier performance capacity [16], [27]. Indeed, after several attempts, we obtained an interesting accuracy of 94.4% using SVM. This good result is due to the fact that SVM has great generalization capability and does not need lot of data to work appropriately.

The third metric measured concerns the processing time of segmentation and classification steps. This parameter is calculated with and without the use of the cloud in the Raspberry Pi. Table 1 summarizes the obtained results. It is obvious from Table 1 that the processing time of the proposed method is significantly less when using the Raspberry Pi with the cloud. This is due to the high computing power of the hardware part provided by the Shadow cloud services, in particular the part in charge of the image processing task which is done on a 1080 Geforce GTX GPU. Therefore, it can be concluded that the use of the Raspberry Pi with the Shadow cloud computing services is very suitable to carry out a powerful and portable medical diagnostic support system for breast thermography.

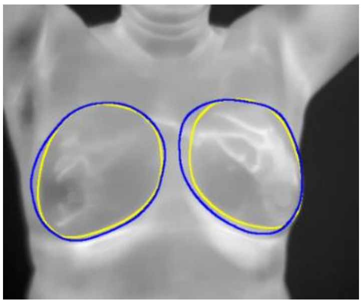


Figure 6. Segmentation result on a breast thermogram sample (predicted region in blue and truth region in yellow)

Table 1. Processing time of the segmentation and classification steps

Step	Raspberry Pi 4	Raspberry Pi 4 + Shadow Cloud Computing
Segmentation (learning phase with 400 epochs)	28400 s (7.8 h)	147 s (2.45 min)
Segmentation (predicting phase)	3.34 s	0.38 s
Classification	0.84 s	0.2 s

5. CONCLUSION

In this paper, we have proposed a portable medical decision support system for the diagnosis of breast abnormalities based on thermography. Image processing steps were performed including preprocessing, segmentation of breast region, feature extraction and supervised classification. Additionally, the hardware implementation was performed on the Raspberry Pi 4 Model B adding cloud computing services to overcome the limited computing power performance of the Raspberry Pi. Experimental results confirm the efficiency of the proposed system, giving a high accuracy and a low computation time especially when using the Shadow cloud computing services on the Rasperry Pi. According to the obtained results, it appears that the implementation of the proposed medical support system on the Raspberry Pi, when using the cloud computing services, can help to provide a robust and powerful device, handing a valuable support for radiologists for the prediction of breast cancer at an early stage even in the rural backcountry where there is lack of health services. Future work includes the incorporation of an infrared camera module on the Raspberry Pi for real acquisition of breast thermograms, increasing data for the training process in the segmentation and classification stages, and cloud data security assessment.

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