Tracking Knowledge Evolution, Hotspots and future directions of Breast Cancer Detection using Deep Learning: A bibliometrics Review

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ABSTRACT

In the medical field, it has been necessary to provide resources to detect early-stage diseases, including breast cancer. Deep learning is immersed in all aspects of medical image analysis, catapulting it as a possible dominant autonomous technology. In this systematic review, a total of 250 results were located, of which 40 were selected, for which a quantitative methodology with a descriptive basis was chosen. The objective of this bibliometric review is to analyze models in image processing for the early detection of breast cancer using deep learning. As result, digital mammography is the most effective method for detecting abnormalities in images. The research concludes that the application of CNN (Convolutional Neural Networks) is the most preferred choice of experts for medical image analysis due to its powerful pattern recognition and feature classifier.

Keywords: Breast cancer, Deep learning, Image medical, Convolution neural networks.

INTRODUCTION

Breast cancer is generated by a mutation in the genes of the nucleus of cells, which, instead of remaking dead cells by other healthy cells, will generate an exponential and uncontrolled number of equal cells forming a mass of tissue called a tumor (American Cancer Society, s.f.). Although breast cancer is much more common in women, it also occurs in men between the ages of 60 and 70 more often (Sha, 2020). The importance of effective prognosis and treatment of early-stage disease is vital (Li, 2019). The identification of cancer depends on the doctor's interpretation from information obtained from the patients, this information is presented by different detection methods, for example, the processing of medical images. The most successful Artificial Intelligent Architectures for image analysis to date are Convolutional Neural Networks (CNN). In particular, they lead to a notable impact on image examination and understanding, especially segmentation, classification, and image analysis (Litjens, 2017). These approaches are very successful in automating complex tasks, especially in the medicinal field, including diabetes, using technology for drug control, and patient food consumption (Swapna, 2018). In medical imaging, deep learning is used for breast density segmentation and texture scoring and extracting features from the image (Kallenberg, 2016). Automatic detection of breast abnormalities from various imaging modalities is a challenging task due to the variation in size, texture, and contrast of breast abnormalities (Rashed, 2019). To carry out this study, a systematic review is carried out in the main search engines based on different inclusion and exclusion criteria, the goal is to analyze what type of image processing models exist for the early detection of breast cancer using deep learning. The results indicate that digital mammography is the most efficient modality in the detection of anomalies. The research concludes that CNN is the most popular alternative for researchers for the analysis of medical images.

DEEPENING

To carry out this analysis, it’s important to know the main components and methods that support the study of images for the early detection of breast cancer.

Starting from the concept of deep learning as the set of computational, algorithmic processes that allow a computerized system to learn by itself and develop its criteria for making and executing decisions (Universidad de Alcalá, s.f.). This technique has the utility of recognizing objects in images, transferring dissertations in writings, selecting relevant results in searches (LeCun, 2015).

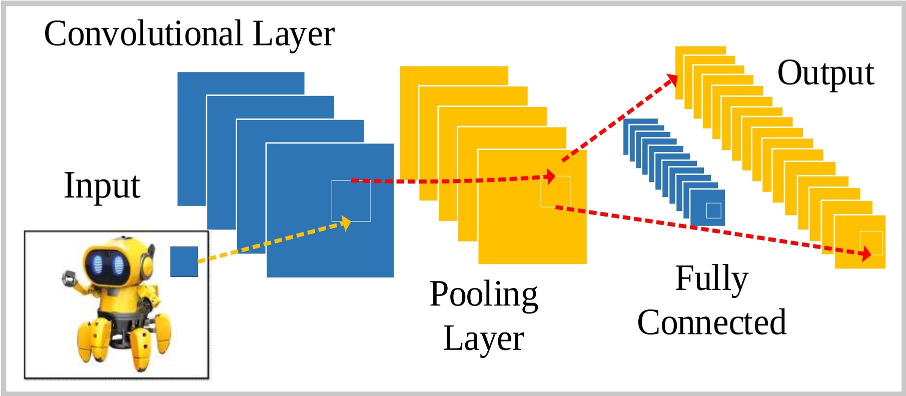

Figure. 1. Deep learning algorithm.

The image arrives in the form of an arrangement of pixels; in the first layer, the characteristics that one aspires to learn are the absence or presence of edges and specific locations in the image. The second layer detects particular edge arrangements until the output is passed to a "fully connected" layer that performs the final sorting (Ou, 2021).

NN (Neural Networks) are processing systems that consist of a large number of neurons that are organized in layers. CNN consists of adding more layers at the beginning of the network, which will be in charge of manipulating the pixels of the images (Ahmir Malik, s.f.).

RESULTS

Experts have studied many diagnostic methods, including mammography, MRI, and ultrasound, among others. Next, Table 1 presents the scope and limitations of the different imaging modalities in detecting breast cancer.

Table 1. Imaging modality scopes and limitations

Image modality	**Scope**	**Limitations**
Digital mammography	It's the most efficient imaging modality (Liu, 2018).	The number of false negatives is high (Liu, 2018).
	Digital images are easily stored and retrieved (University of Rochester, s.f.).	The presence of dense tissue can affect visibility (Healthwise, s.f.)
Ultrasound	Unlike mammography, ultrasound doesn't require ionizing radiation (Becker, 2017).	It's operator-dependent (Bray, 2018).
	Reduces unnecessary biopsies (Bray, 2018).	Low resolution and poor image (Akkus, 2019).
Magnetic resonance imaging	High sensitivity (Zhu, 2018).	It's not recommended in pregnant women (Mayo clinic, s.f.).
	It's used for clinical diagnosis (Debelee, 2019).	It can miss some tumors that a mammogram can detect (Mayo clinic, s.f.).
Digital tomosynthesis	It detects invasive cancers (Hooley, 2017).	It's costly (Mall, 2017).
	High sensitivity (Mayo clinic, s.f.).	Ionizing radiation (Diagnostico Maipú, s.f.).
Infrared thermography	It reveals changes in skin temperature that could indicate a tumor (Hannah., s.f.).	Not suitable for older women with large breasts (Milosevic, 2015).
	It can detect tumors up to 1.28 cm, while mammography can detect up to 1.66 cm (Breastcancer.org, s.f.).	Sensitivity and specificity are not yet comparable to mammography (Milosevic, 2015).

In the following image, you can see the application of deep learning in medical images, establishing the tasks where CNN achieves successful results.

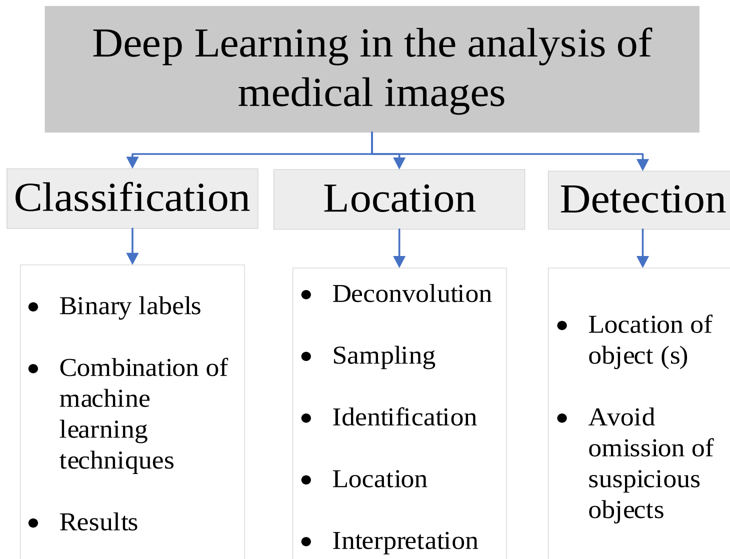

Figure 2. Analysis of medical images through deep learning.

Tree important groups were established that make up the elementary phases within the analysis of medical images: the "Classification" of the medical image is the main task in deep learning. Medical imaging normal and abnormal binary labels are set. The "Location" consists of extracting the importance of each object to focus only on the interesting object and discard the noise. Deconvolution restores and corrects degraded data extracted and classified to provide a better description of the analysis, while sampling is responsible for selecting the objects that need to be interpreted. "Detection" refers to the location of one or more target objects that belong to different categories in an image and marking them with a bounding box (Yunchao, 2019).

Below, different CNN architectural models designed over the years are presented.

Table 2. CNN architectures

Model	**Layers**	**Top-5 error rate.**	**Parameters**	**Year**
LeNet	7	-	60 K	1998

AlexNet	8	15.3 %	60 M	2012
ZFNet	19	14.8 %	60 M	2013
VGGNet	16	7.3 %	138 M	2014
GoogLeNet	22	6.67 %	5 M	2014
ResNet	152	3.57 %	23 M	2015
Inception V3	42	3.58 %	29.3 M	2015
DenseNet	264	5.17 %	15.3 M	2017
PyramidalNet	200	4.7 %	116.4 M	2017
Squeeze & Excitation Networks	152	3.79	27,5 M	2017
CMPESE-WRN-28	152	3.58 %	36.92 M	2018

Table 2 illustrates the various architectural models of CNN over the last 23 years; advances and efficiency are reflected as the technology is improved and updated. The number of layers that each algorithm uses for learning stands out. The term top-5 error rate refers to the method of comparing machine learning models, where performance is evaluated or labelled by percentages, the exposed architectures, utilizing contests. The parameters establish the amount of input data (set of images) required for training the models.

CONCLUSIONS

According to the literature reviewed, deep learning has permeated all aspects of the analysis of medical images; the shortcomings are evident, mainly, the number of parameters (samples) that are required for the processing and analysis of medical images. Digital mammography is presented as the best alternative and medical imaging modality for the training of networks and algorithmic processing in deep learning. This study concludes that CNNs were the most popular choice of researchers because it has the best performance among all the architectures reviewed. Given that deep neural architectures are advanced and optimizing their learning methods over the years, reaching lower rates and error rates. It suggested including the exploration of optical imaging, a modality that is under investigation.

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