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Feasibility of Breast Cancer Detection Through a Convolutional Neural Network in Mammographs

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Abstract

In the Iraq female samples, the malignant neoplasm type with the highest mortality rate is breast cancer. When the disease is detected early, the success rate is higher, resulting in improved prognosis and, consequently, cure. The present study aims to analyse the viability of a system capable of detecting breast cancer through convolutional neural networks, classifying a mammogram into five classes: non-cancer; benign calcification; malignant calcification; benign mass; and evil mass. Processing was carried out on the database containing 55,890 images, in which the data was converted from records structure to image format, which is necessary when using the neural network. After this stage, the images were classified into the five categories mentioned to enable tests to be carried out to verify the accuracy of the machine learning algorithm in identifying and classifying breast cancer. Using a small partition of 10% of images from the total database to verify the initial results presented in this work, it was possible to obtain 44% of global accuracy, highlighting the ability to expedite the early and rapid detection of breast cancer using artificial intelligence.

Keywords: Breast Cancer. Artificial intelligence. Convolutional Neural Network. Health Informatics.

1. Introduction

Breast cancer currently represents the leading cause of death from cancer in Iraq women and is, therefore, a significant public health problem. Iraq has experienced high rates of breast cancer incidence and mortality annually. Despite this scenario, the necessary measures for preventing, diagnosing, and controlling the disease do not follow the increase in cases [1].

Breast cancer diagnostic methods have undergone significant technological advances, allowing for more assertive results [2]. Despite this, breast cancer diagnosis still faces barriers such as difficult access to health services, especially in less favored regions of the country, such as the North and Northeast.

The best way to detect breast cancer is mammography, which has a detection rate of 90%. However, according to the Ministry of Health (Iraq), mammography was used in only 24% of cases in 2018, thus explaining the increase in mortality and late diagnosis[3].

The situation is even more worrying if the patient depends on care from the Unified Health System (UHS). According to a study by Romeiro Lopes et al. (2017)[14], it takes approximately thirty-six days between the first medical consultation at the Family Health Strategy (FHS) and the mammogram date. After this first step, it is necessary to wait a period of forty-six days to obtain the result of the mammogram and a consultation with a specialist doctor. After consulting with the specialist, it is necessary to wait another thirty-nine days to be able to perform the biopsy with the specialist doctor and finally wait another thirty-three days to have the diagnosis of the biopsy in hand to be referred to the most appropriate treatment indicated finally.

In addition, according to each region, there is a variation in the queue to start treatment after the last step mentioned above. According to WHO, the average interval in Iraq is approximately fifty-nine days [5].

Therefore, from the first appointment to the start of treatment, a UHS patient needs to wait approximately two hundred and twelve days, a much higher number than that recommended by the Ministry of Health (Iraq) [3, 5], which is sixty days. This rate, 3.5 times higher than recommended, added to the wait, causes the patient to develop a more pronounced clinical picture of the disease.

The high incidence of breast cancer in the female universe and the considerable waiting time, especially for patients dependent on the, underscores the urgency of effective methods for efficient and rapid diagnosis. In this scenario, techniques based on computational support have gained significant prominence. In a study with deep learning techniques developed by the Massachusetts Institute of Technology (MIT), an agreement level of 90% was obtained among specialist physicians, with the great benefit that data processing takes seconds to issue results [6].

Computing has been widely used in recent times in all areas, including with significant penetration in the health area. Therefore, it is necessary to look for tools that can also help in the diagnosis of breast cancer. Thus, the present study seeks to develop and apply methods that allow agility in the diagnostic process of the pathology in question and early initiation of treatment to reduce the mortality rate from breast cancer [7]. In this work, machine learning algorithms were applied using one of the concepts of Artificial Neural Networks (ANN) and Artificial Intelligence (AI), which is called Convolutional Neural Networks (CNN). The term convolutional is employed because such tools have been developed for image classification.

This work used images of mammograms obtained from open databases such as the Digital Database for Screening Mammography (DDSM - Mammography), made available by the company Cancer Image Archives3, were used. The CNNs allow calculations of mathematical functions based on the recognition of previously learned patterns and perform spatial processing, thus helping to speed up breast cancer diagnoses without the need to wait for a biopsy.

The present study aims to address the possible technological advances in the oncology area, more precisely in breast cancer, by analyzing the effectiveness that an CNN can achieve. The central hypothesis of this work is that from the development of an CNN, it is possible to carry out the early and assertive detection of breast cancer, thus allowing treatments to be instituted even in the initial phase of cancer, improving the patient's prognosis.

For this, the following specific objectives were developed: data collection in the DDSM-Mammography database; transformation and decoding of collected information into images so that artificial intelligence can perform convolution processing; analysis of how an CNN extracts information from the image and how the categorization is carried out through the established characteristics; comparison with state of the art proving the efficiency of CNNs in the use of mammography images for the detection of breast cancer; identification of the accuracy that machine learning algorithms can achieve using a sample partition of the proposed database [8].

Changes in the appearance of the breast were analyzed in each image, such as orange-peel skin, serosanguineous secretion in the areola, cervical, supraclavicular, and axillary lymphadenopathy, characteristics and consistency of the nodule, texture, perimeter, amount of concavities in the contour of the nodule, symmetry, fractal dimension of the lesion, calcifications, infiltrations, angiogenesis, and quadrant in which it is located.

2. Contextualization and Methodology

Each cell in the human organism has genetic information that regulates growth processes, mitotic divisions, cell lifespan and apoptosis. When these cells change their genetic structure, these mechanisms become unbalanced, resulting in rampant cell proliferation without programmed cell death.

Therefore, such changes result in neoplasia, which is called cancer when it acquires characteristics such as loss of the relationship between nucleus and cytoplasm, infiltration of the underlying tissue and high mitotic levels. When a malignant neoplasm begins in epithelial tissue, such as skin and mucous membranes, it is called carcinoma.

2.1 Breast Cancer

The mutations described in the previous section can occur in breast cells, resulting in breast cancer. This type of carcinoma is subdivided into fibroadenoma (benign neoplasm), ductal carcinoma, and lobular carcinoma (malignant neoplasm). For the detection of breast cancer, several clinical exams are performed, the most frequently found in clinical practice being self-examination, followed by complementary exams such as mammography and ultrasound [9].

Because it is a procedure that uses radiation, mammography is indicated for women over 35 years old; an ultrasound is performed for patients below that age. In addition, mammography has low sensitivity in young women, given the high density of breast tissue and the scarcity of adipose tissue, which makes it challenging to visualize possible existing alterations when examining.

Mammography is an imaging exam where the mammography device, the device used to perform the mammography, applies small portions of X-rays, thus generating a radiograph of the breasts [10]. Several alterations are identified through it, such as microcalcifications, asymmetries, nodules, and cysts, among other breast lesions.

Mammography uses the BI-RANDS scale (Breast Imaging Reporting and Data System. 2014), measuring the proportion of fatty and fibroglandular tissue, classifying breast density as follows: BIR-I, predominantly rich; BIR-II, containing scattered areas with fibroglandular tissue; BIR-III, heterogeneously dense and finally BIR-IV, extremely dense[11].

2.2 Health Informatics

The use of systems is present in all branches of activity, in the most diverse areas, so it adapts to each branch of action to obtain the best possible result. One of the areas that has been benefiting from technological advances is medicine. Several health professionals use an information system to help them with processes and routines, whether for decision-making, collection, and storage of data regarding patients, medications, or other information.

Expert systems are also used in the health area, artificial intelligence, to help health professionals make decisions, as demonstrated by El-Dahshan *et al*. (2014)[12]. These expert systems are developed to solve the problem in the same way as the professional since the problem solution has already been taught to the expert system.

2.3 Artificial Neural Networks (ANN)

When the ANN algorithms were designed, Haykin (1999) [13] described them as having the same principle as the human brain, which can be considered the most powerful computer that exists, which performs parallel and non-linear information processing, realizing pattern knowledge. , perceptions, and motor control with higher quality than a conventional computer; that is, the ANNs, are developed to emulate the functioning structure of human neurons.

The ANN, as well as the Human Neural Network on which it was based, is composed of neurons connected by synaptic connections, as seen in Figure 1. Each connection has different weights; obtaining the desired knowledge only occurs by updating these weights.

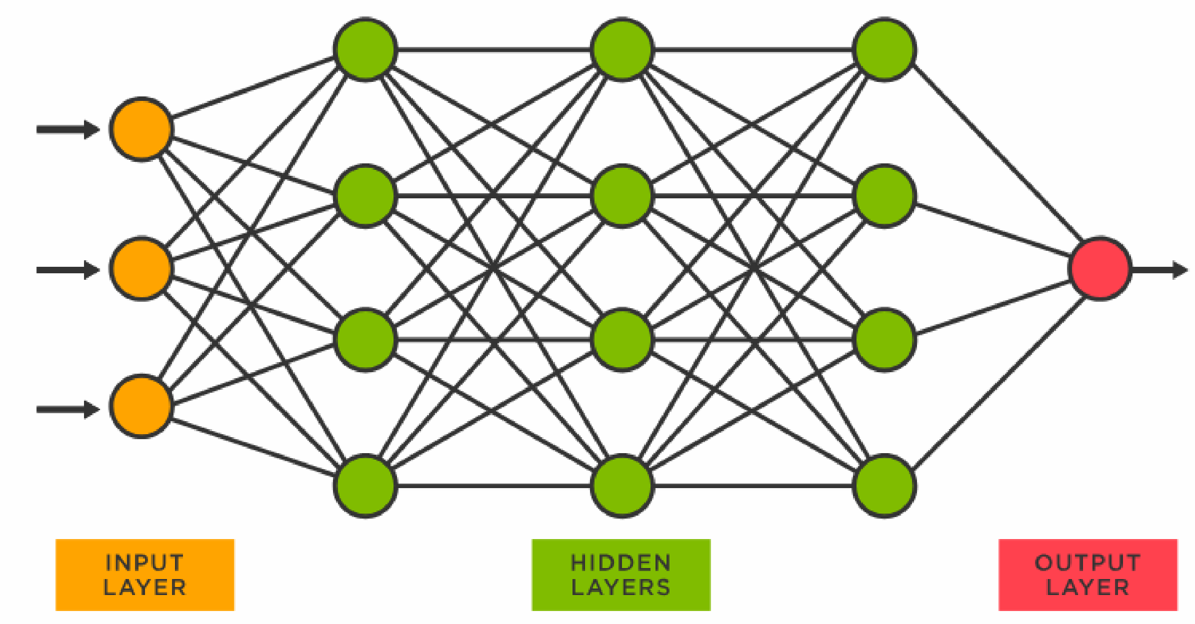

Figure 1: Artificial Neural Network [14]

According to Haykin (1999), the interest in artificial neural networks has been motivated by the growing knowledge about the human brain. This can process information in a complex, parallel and non-linear way. It can be said that ANNs seek to simulate the functioning processes of a human neural network, such as learning, generalization, association, and abstraction. The process of functioning an artificial neural network consists firstly in the step of learning through experience and, later, using the learning to make inferences about new experiences that were previously unknown.

ANNs can solve problems of approximation, categorization, optimization, classification, and prediction of what will happen in the future [15]. For an artificial Neural Network to perform satisfactorily, it needs to be tolerant of controlled imprecision and have excellent training with a representative database, so it can show a preview of how the final result will be, whether for image recognition or voices, time series processing, recognition of purchase desire, pandemic simulation, medical diagnoses and among several purposes for which it is used.

2.4 Convolutional Neural Network (CNN)

CNNs have been known methods for several years, but they have been gaining prominence recently due to the great computational capacity never seen before. Such algorithms have proven to be very effective in the processing and analysis of digital images due to the fact that they natively evaluate spatial information.

LeCun *et al*. (1998)[16] developed the CNNs in such a way that their layers performed linear and non-linear operations. Its nomenclature comes from the main operator responsible for its execution, the morphological convolutional operator. As can be seen in Figure 2, there are convolutional filters that extract features from images. Its use on the image makes it possible to return the desired characteristics, its filters are applied in several layers, and its value is assimilated by the network itself, determining which are the relevant characteristics to obtain the output solution.

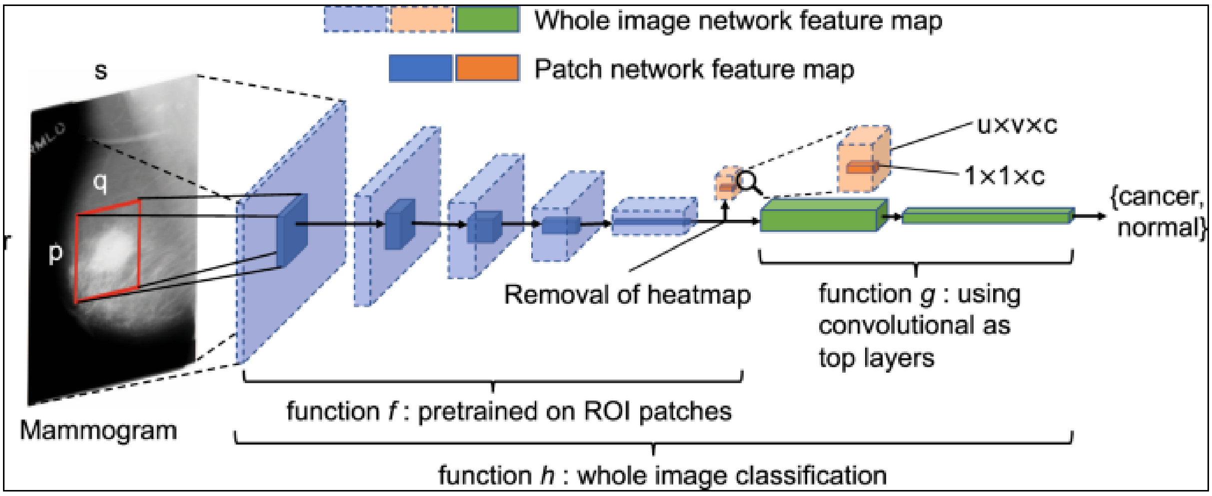

Figure 2: Exemplification of Convolutional Neural Network [17]

Convolutional neural networks act very similarly to ANNs, but the results related to their image applications are much superior since they can evaluate spatial information; another difference is that artificial neural networks use vectors, whereas the CNNs use both input and output structures. The structures can have up to three dimensions; at the entrance, the amount of dimensions are linked to the pigmentation of the image to be used, monochromatic images use two dimensions, and polychromatic images use three dimensions.

2.4.1 Convolution: The most used composition in CNNs is convolution because it has great efficiency when used in image processing areas. Each layer comprises several neurons; each neuron uses a kind of mask in a certain image region. This feature is called a structuring element, as can be seen in Figure 3, in which a 3x3 structuring element is applied to the original image to generate the pixel in the output image.

Figure 3: Convolution process generating new information from neighboring information in the input image [10]

Figure 4 shows the steps of a convolution operation using a 5x5 pixel matrix with a structuring element of 3x3 pixels, which element will be responsible for applying the convolution operation. In the example, only the calculation of the first line of the output image is used.

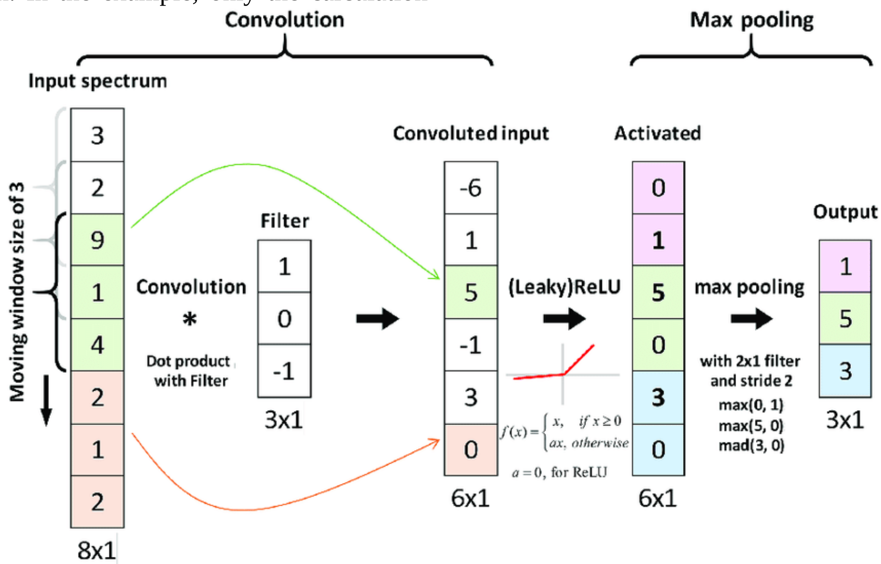

Figure 4: Example of Max Pooling performing the transformation process of image values from the Convolutional Filter [17]

The output image displayed in Figure 4 shown above resulted in a 3x3 matrix; we can see that each value of the output matrix is the result of the sum of the multiplication that occurs between the input image by the structuring elements.

The structure of convolution uses the same principle of ANN, where it is possible to form other layers with other neurons. This layer receives a weight matrix; these weights come from the training that occurs when receiving the database. The fact that CNN uses spatial structure offers a great advantage for processing large images, a resource that artificial neural networks do not have since they assume a linear structure of a single dimension.

3. Method

The development of the CNN used in this work took place in the Google Collaboratory4 environment, which enables the creation and execution of codes written in the Python language on Google's cloud infrastructure. The tool does not require installation and runs in the cloud online, and is free of charge.

Before starting the development of the convolutional neural network, it is necessary to convert the database since the images provided by Cancer Image Archive are available in records format, and it is necessary that the images are in JPG or PNG format. The records file format is a simple format used to store a sequence of binary files, while the JPG or PNG format is a more used format for images.

In parallel with the conversion of the images to the desired format (JPG), two other processes took place: the first is the division and classification into five groups of folders based on the original records: healthy breast; benign calcification; benign mass; malignant calcification; and finally, evil mass. The second process is the storage of the images, where Google's own cloud storage service, Google Drive, will be used.

Each folder referring to each classification group, after the processing mentioned above, stored about 11,000 images; therefore, the image bank to be used for the development of the convolutional neural network contains more than 55,000 images. For the initial experiments addressed in this work, it was decided to use 10% of the database, about 5,500 images for sampling, thus allowing the first tests to be done quickly without depending on a long processing time. In this way, it will be possible to verify the analysis of the initial performance that the neural network will achieve with a reduced set of images.

The use of a sample of information happens due to the fact that when the machine learning algorithm is executed and programmed with the complete image bank, it becomes a very costly and time-consuming process for training, thus making its use almost unfeasible for the users. Initial tests, as throughout its development, many adjustments are necessary. It is noteworthy that the long process is precisely the training of the CNN, a step in which the network will learn the image patterns, and after this learning, any classification of a new image is performed in real-time, highlighting the great

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performance gain compared to the human analysis and diagnosis.

For the selection of images that make up the sample universe, some guidelines were followed: completely random choice, the guarantee of non-repetition of the images, and each subclass (group of folders) must have the same level of contribution to the sample bank, that is, a guarantee of the equivalent representation of each group.

The performance of a neural network model must always be evaluated based on data not visualized in the training stage, that is, unpublished for CNN. Thus, the sampling was divided into two sets: the first, called the test set with 30% of images, and the second, the training set with the rest of the sample set. This is due to the fact that the training set is used for machine learning. After training this model, the learned features are used to make predictions on the test set, thus verifying the performance of the convolutional neural network. For this purpose, the ImageDataGenerator method was used, which allows for determining what percentage of the sample bank will be used for testing and what will be the other part to be used in training.

After finishing the adjustments of the images, the process of creating the CNN began, with two layers of connections using the geometric progression of base two. Such connections are interconnected by a fully connected layer, enabling the occurrence of the first machine learning training proposed in this study.

4. Results

After completing the step above, tests are started to verify the result of the convolutional neural network. For this, labels with truth class verification and visual display are used, as can be seen in Figure 5, to facilitate the visualization of the initial accuracy obtained.

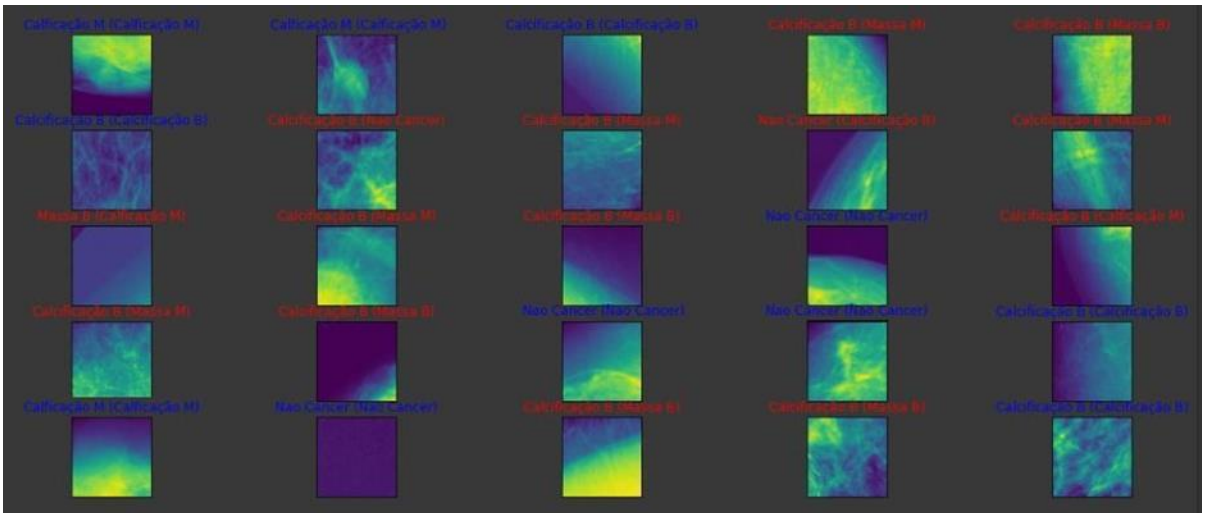

Figure 5: Demonstration of output layers.

The figures plotted with a blue legend represent the hits of the convolutional neural network. The figures with red captions represent the images in which the presented neural network error occurred.

With the sample bank used, an accuracy of 44% was achieved; that is, this is the probability of success of the machine learning when faced with a mammogram never seen before. It is possible to analyze that underfitting occurred in machine learning since there was no success when the image had a malignant mass or malignant calcification. This may have occurred due to some factors, such as; a reduced number of images in the sample bank; necessary adjustments in the connection layers; this error is noticeable because when the convolutional neural network was unable to perform the correct classification of the image based on the previously learned characteristics, it returned as a benign calcification.

5. Conclusions

It is possible to infer that machine learning and NCR algorithms are resources with great potential to be used to assist health professionals in possible therapeutic approaches.

The data from the analyzed image bank (DDSM-Mammography) proved to be extremely important for the convolutional neural network. This data set presents a characteristic of great quality for use in artificial intelligence environments. The conversion to the necessary format, JPEG, also obtained a satisfactory result and an important contribution to any process that uses neural networks.

The convolutional neural network developed and presented in this work obtained an accuracy of 44% for classifying images not known by the CNNs. The presented accuracy is lower than expected but can be justified by the reduced set of images used, corresponding to 10% of the total number of images that the database has.

Finally, it can be concluded that the accuracy of the CNN will increase when the entire database is used since, with more than 55,000 images, there are good prospects for better and more assertive accuracy in the diagnosis of breast cancer. Even in the face of an experimental scenario for carrying out rapid tests, the 44% accuracy presented already represents an excellent scenario with the possibility of offering greater agility in the early diagnosis of breast cancer from a fully automatic process supported by artificial intelligence, a fact that can be essential for improving the quality and speed of care in health systems

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