Chapter

Artificial Intelligence at the Service of Medical Imaging in the Detection of Breast Tumors

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Abstract

Artificial intelligence is currently capable of imitating clinical reasoning in order to make a diagnosis, in particular that of breast cancer. This is possible, thanks to the exponential increase in medical images. Indeed, artificial intelligence systems are used to assist doctors and not replace them. Breast cancer is a cancerous tumor that can invade and destroy nearby tissue. Therefore, early and reliable detection of this disease is a great asset for the medical field. Some people use medical imaging techniques to diagnose this disease. Given the drawbacks of these techniques, diagnostic errors of doctors related to fatigue or inexperience, this work consists of showing how artificial intelligence methods, in particular artificial neural networks (ANN), deep learning (DL), support vector machines (SVM), expert systems, fuzzy logic can be applied on breast imaging, with the aim of improving the detection of this global scourge. Finally, the proposed system is composed of two (2) essential steps: the tumor detection phase and the diagnostic phase allowing the latter to decide whether the tumor is benign or malignant.

Keywords: breast cancer, artificial intelligence, artificial neural network, deep learning, expert system, fuzzy logic, medical imaging, big data

1. Introduction

Breast cancer is a disease in which cells in breast tissue change and divide in an uncontrolled manner, usually producing a lump or lump. Most breast cancers start in the lobules (mammary glands) or in the ducts that connect the lobules to the nipple. If not diagnosed early, it can lead to death. It can be divided into two (2) groups: normal and abnormal and it can also be divided into two (2) categories: benign (not dangerous) and cancerous (malignant). Benign tumors grow quite slowly and do not invade neighboring tissues or spread to different parts of the body [1]. The early and reliable detection of it focuses on reviewing data from past diagnoses and gathering valuable information from past data. Currently, the early detection and diagnosis of tumors using image processing techniques and artificial learning can be of great help in improving the accuracy of a breast cancer diagnosis. Secondly, medical imaging plays a major role in the clinical diagnosis of diseases, the evaluation of treatment and the detection of abnormalities in different organs of the body such as [2, 3]. In addition, several researchers have focused intensively on the production and interpretation of medical images to identify the majority of diseases including breast cancer. These images thus facilitate the identification of the disease and help in the detection of a pathological lesion, in the clinical treatment of the patient. Artificial intelligence has played a major role in the medical field, such as the analysis of medical images. It is the most effective way to detect breast cancer, with regular use of different modalities such as MRI, mammography, computed tomography and radiographic ultrasound. The most frequently used images are mammography, ultrasound, MRI, histology and thermography [4]. Mammography can detect and diagnose breast cancer in women. Mammography images can be examined by professional radiologists to determine if there are any abnormalities in the breast. She may show breast changes for up to a year or two before the patient or the doctor sees the symptoms. The American Cancer Society (2019–2020) recommends a mammogram once a year for all women over 40. Dense breast tissue during a mammogram may appear white or light gray. This may make it easier to view mammograms in younger women who appear to have thicker breasts. Therefore, it is ineffective in patients under 40 years of age, with dense breasts and less sensitive to small tumors. Most breast diseases look like signs of cancer and require tests to identify them, and often a biopsy [5]. Another method of breast cancer screening is ultrasound imaging which can be used to supplement mammography by determining the liquid or solid nature of a lesion, especially in women with large breasts [6]. Magnetic resonance imaging (MRI) is another technique for early detection of cancer cells, in addition to ultrasound and mammography techniques [7]. Despite rapid advances in medical research, the benchmark for cancer diagnosis remains histopathological diagnosis [8]. Another breast cancer imaging modality is thermography or thermal imaging of the breast which is a painless and non-invasive method that is often used to detect changes in the breast that may indicate this global scourge [9]. Finally, the use of artificial intelligence makes it possible to identify candidate biomarkers for medical imaging [10].

2. Artificial intelligence and medical imaging

Artificial intelligence is at the crossroads of several fields. Among these fields we can cite computer science, mathematics, medicine, physics, philosophy, etc. Early detection plays a very important role in the diagnosis of cancer, especially the diagnosis of breast cancer. It can promote the chances of recovery from it, therefore it is able to improve the long-term survival rates of patients. Note that, medical imaging has long been used to perform early detection of breast cancer, its monitoring and post-treatment follow-up, nevertheless, the direct interpretation of a large number of medical images is a difficult task. and depends on the expertise of the radiologist. In fact, the interpretation of medical images still relies today on the eye of the radiologist or the doctor. Several imperfections mar this process. The human eye is fallible, fatigable, subject to many cognitive biases, and its performance depends on its experience. In addition, its relevance depends on the visibility (salience) of the images to be located. A large lesion, of which the contrast is high will be easily detected, this is not the case when the lesion is small and of low contrast and if it is located outside the nosological field questioned. To solve this problem, ordinary assisted diagnostic systems were developed as early as the early 1980s. Initially, from the 1970s to the 1990s, medical image analysis was performed from sequential treatments from the treatments of. low level (denoising, contrast enhancement, detection of edges and lines, segmentation of regions) up to pattern recognition through mathematical modeling. Then, to develop automatic analysis systems, the researchers drew inspiration from the human brain to build expert systems, which use artificial intelligence techniques [11, 12].

AI applied to medicine aims to:

- automate the detection of pathological images;
- treat large cohorts of patients;
- allow the detection of incidental lesions, not sought "a priori";
- make the interpretation of images more reliable;
- identify patterns, allowing the classification of lesions;
- establish standardized reports.

Finally, "supervised" artificial intelligence requires a large amount of data allowing the learning of AI methods. The French society of Radiology and the National Federation of Radiological Doctors have decided to create an "ecosystem" of 500 million imaging files thus making a medical imaging database available to researchers [13, 14]. 400 million would be truly exploitable for the development of AI algorithms. This database should also be continuously updated. The potential French database has many advantages and is recognized internationally [15].

3. Artificial intelligence and big data

The exponential increase or the quantitative explosion of data has forced researchers in data science, then in medical science, to transform the way they see and analyze the world. In medicine, this increase is caused by the number of medical images produced. Thus, for mammographic examinations, two (2) or four (4) mammograms are performed per patient and this at the rate of one or two mammograms per breast. Therefore, a woman can have at least two (2) medical images in this context. In this case, it is about understanding new ways to capture, search, share, store, analyze and present data whose order of magnitude grows exponentially. These large-scale data (Big Data) are generally analyzed using artificial intelligence methods. Note that these two (2) concepts are increasingly applied in medical research [16]. There are several sources of medical " big data ", we can cite clinical data from databases such as health insurance, private mutuals or the pooling of cohort data, or even digital traces (keywords typed into an internet server); but also data from medical imaging (a single imaging test that may contain millions of pixels), or even biological data. So, for better data exploitation, Big Data is analyzed by methods derived from AI and its sub-specialty, artificial learning (Machine Learning) [17, 18].

4. Artificial intelligence and data mining

The ability to make good use of data, particularly that of medical imaging, is at the heart of the challenges of tomorrow's medicine. We can cite the development of diagnostic aid tools, radiomics which consists in extracting quantitative data in order to identify potential imaging biomarkers, the development of in-silico models making it possible to accelerate medical research, formulation and validation of hypotheses from the retrospective use of several independent cohorts, patient screening to better target patients eligible for a clinical trial [19]. Indeed, data exists in abundance, nevertheless the exploitation of this "big data" is a very difficult task for doctors and other actors in their specific fields.

5. Artificial intelligence and cognitive psychology

It is certain that the observation, modeling, understanding of cognitive activity and intelligence are, as natural sciences, the responsibility of cognitive psychology, or more generally of cognitive ethology. According to Margaret Bogden artificial intelligence is the art of simulating intelligence using a computer, this clearly falls under the science of the artificial. Insofar as it draws its inspiration from cognitive psychology and cares about psychological realism, it can be an experimental counterpoint all the richer for cognitive psychology (or cognitive ethology) as experimentation using software does not pose the ethical problems posed by human or even animal experimentation. Indeed, cognitive psychology and artificial intelligence present themselves as sister disciplines. AI will have two sides [20]:

- predominantly psychological, it is above all concerned with the realism of simulations of the functioning of the human mind;

- redominantly computer science, it seeks intelligent global behavior, human or not; In addition to purely practical reasons, we can also consider that the human mind probably does not have a monopoly on intelligence, and would benefit from being helped by other forms of intelligence.

6. Artificial intelligence in computer vision

Computer vision is an AI technology. There are interactions between artificial intelligence and computer vision, from the point of view of knowledge-based systems for the interpretation of images and scenes, and for the recognition of shapes, structures or objects in images. The general objective of these approaches is to add semantics to images, by associating visual information extracted from images on the one hand and knowledge or models on the other hand [21].

7. The use of artificial intelligence in clinical practice

The analysis of current medical imaging applications using artificial intelligence for current clinical use provides information on the directions of scientific research to be considered in this field. The first half of 2018 was marked by the arrival of three

(3) AI players in imagery. Their solutions have all been approved, for the first time, by the United States Food and Drug Administration (FDA). This is especially the application Viz.ai (San Francisco, CA, USA) for acute stroke, using the deep learning (Deep Learning) for automatic detection of occlusion of cerebral vessels to the angio-CT and the immediate call of the interventional radiologist on call. This is also the case with the IDx-DR software capable of detecting diabetic retinopathy on the fundus without even the intervention of an ophthalmologist. This app can be used in theory by paramedics for early detection action. According to these authors, its reliability is high. It relates to a clinical study (NCT02963441) of eye funds on 10 American centers with 900 diabetic patients in whom, in 90\% of cases, the IDx-DR solution (Coralville, Iowa, USA) allowed the correct diagnosis [22]. Finally, Osteodetect from the company Imagen (New York, USA) is another tool which makes it possible to accelerate the detection of wrist fractures on standard 2D digitized radiologies. This assisted detection uses artificial intelligence techniques to enable faster diagnosis based on an initial retrospective analysis of 1000 images per second at 24 centers. The device has been announced by its developer to be dedicated above all to non-radiologist nursing staff (general practitioners, emergency physicians, resuscitators, etc.). The site emphasizes that it is a complementary tool and not a software to replace the expertise of radiologists. In [23], these three (3) examples confirm the importance of AI methods in clinical practice.

8. Role of artificial intelligence in medical imaging

The aim of artificial intelligence systems is not to replace radiologists but rather, to provide them with convincing help. So, let the practicing doctors handle the use of artificial intelligence in their specialty [24]. The fields of application of AI techniques in medical imaging are numerous: the creation of examination protocols, improvement of image quality and reduction of the irradiation dose, reduction of acquisition times in MRI, optimization of programming, presentation of images for interpretation, development of detection assistance tools, post-processing assistance, quantification tools, segmentation, image registration, analysis the quality of the images produced, realized production [25].

9. Some definitions

Here are some definitions of artificial intelligence (AI) techniques [26–29]:

- Artificial Neural Networks (ANNs): These are AI techniques aimed at simulating the functioning of neural cells to mimic the functioning of the human brain. They are mainly used in the recognition of speech and images. These techniques can be simulated in software or with specialized electronic circuits.

- Deep learning (DL): it is an extension of artificial learning integrating supervised learning and self-learning functions based on complex and multidimensional data representation models. It is an evolution of the ANNs which have multiple layers and sub-layers of neurons.

- The support vector machine (SVM): it is an algorithm which will classify data according to a linear threshold and whose objective is to solve the problems of classification or discrimination in two classes. Note that there is a modification of this algorithm which allows it to be used for the regression.

- Expert systems: these are AI systems based on high-level knowledge modeling with predicate logics (if this then that, if the patient has her symptoms then the patient has breast cancer, etc.) and rule engines.

- Fuzzy logic: it is an AI technique created by Lofti Zadeh in the 1960s and representing information not in binary form but in fuzzy form between 0 and 1. It is sometimes used in rules engines of expert systems.

10. The application of artificial neural networks

This artificial intelligence technique is used to detect breast cancer. In [30], breast cancer is detected using two electronic noses (EN) to analyze breath and urine samples. Exhaled breath samples were taken from 48 breast cancer patients and 45 healthy patients who served as a control group while urine samples were taken from 37 breast cancer patients. Breast based on mammographic tests and 36 healthy patients. These two ENs made it possible to analyze exhaled respiration on the one hand, and on the other hand the authors used gas chromatography mass spectrometry (GC-MC) to analyze the substances present in the urine. The first EN used was the MK4 model. The second EN used was Cyranose 320. Indeed, the model obtained, that is to say the artificial neural network on the basis of the analysis carried out by the MK4 and Cyranose 320, made it possible to classify the patients suffering from dystrophy. ‘breast cancer with an accuracy, on average, of more than 95%.

In [31], the proposed method is based on the representation of images using discrete Haar wavelets. Then, they are introduced into artificial neural networks. These digital images are obtained by biopsy from the Near East University Hospital. The images are classified using two classifiers including the Backward Propagation Neural Network (BPNN) and the Radial Basis Function Network (RBFN).

In [32], to help radiologists quickly detect breast cancer, these authors proposed a computational model based on an artificial neural network. This is able to detect the presence or absence of an abnormality on a mammogram. In order to train or train their model, they used a database of digital mammograms generated by MIAS (Mammographic Image Analysis Society). Then, they used 60 images divided into 30 normal images and 30 images including anomalies. This has been confirmed by expert radiologists. The artificial neural network model created in this study has the following advantages: simplicity of extracting the descriptive parameters of each mammogram, automatic and rapid detection of the presence or not of an anomaly on a mammogram, possibility of adapting the template to other images from different medical bases with different resolutions. Finally, they demonstrated the performance of the model obtained for the detection of breast cancer on a mammogram with a correct recognition rate of 91.66%.

11. The application of deep learning

Deep learning is another form of artificial neural networks. It is the most widely used artificial intelligence method when it comes to the classification of breast cancer on medical images. In [5], in order to help medical experts quickly diagnose breast cancer, the authors presented the Convolutional Neural Network Improvement Algorithm for Breast Cancer Classification (CNNI-BCC). Indeed, the sensitivity of the convolutional neural network (CNN) to radiological images prompted the authors to improve CNN. To detect and categorize into malignant, benign, and normal, the CNNI-BCC method uses data extension by functionality (FWDA) algorithms, convolutional neural network-based classification (CNNBS), and lesion locator based on interactive detection (IDBLL). This model can be incorporated on portable devices such as smartphones. The materials used in this work are digital mammography databases. These bases were prepared and supplied by MIAS. Then the experiments are applied to 21 mild cases, 17 malignant cases and 183 normal cases. CNNI-BCC has achieved an accuracy of 90.50%.

In [33], to alleviate the lack of early detection of breast cancer, the authors proposed a cancer detection approach based on a convolutional neural network (CNNs). This technique can simultaneously locate and classify the mass as benign or malignant on a mammogram image. Then, to train or train, validate and test the method, datasets were collected at various sites, in particular at St Gebriel Hospital, Grum Hospital, Betezatha Hospital, Korean Hospital, Kadisco Hospital and at Pioneer Diagnostic. Indeed, the mammogram images were collected with their document reports that show the results of screening and diagnosis of the patients. Overall, the proposed approach includes the following steps:

- Data collection in different hospitals in Ethiopia,

- Preprocessing mammographic images to improve data quality and prepare them appropriately for deep learning,

- After the preprocessing, the noise on the images is eliminated by applying Gaussian filtering, median filtering and bilateral filtering,

- And later images were enhanced using Adaptive Contrast Limited Histogram Equalization (CLAHE),

- Finally, a morphological operation is performed to extract the breast region from the background and to remove part of the mammographic image such as artifacts, labels, patient profiles and the like.

Ultimately, the model was trained and evaluated via mammographic images and achieved an accuracy of 91.86%.

In [34], in order to help radiologists more precisely diagnose breast cancer, this research proposes the development and validation of a new scheme called SD-CNN (Shallow-Deep Convolutional Neural). This method combines image processing and machine learning techniques to improve diagnosis using full field digital mammography (FFDM) by leveraging information available from contrast enhanced digital mammography (CEDM). The first hypothesis posed by the authors is that the application of a deep CNN (Deep-CNN) to CEDM is able to take advantage of recombinant imaging to improve the classification of breast lesions. Second, with the aim of extending the advantages of the CEDM imaging modality to the FFDM imaging modality, they hypothesized that a shallow CNN (Shallow-CNN) is capable of uncovering non-mapping. Linear between the LE images that is to say the low energy (LE) and recombined images. The objective of this study is to validate these two hypotheses using a single study procedure and two separate data sets, including a data set acquired from a tertiary medical center (Mayo Clinic Ari-zona) and a set public data file from INbreast. They first developed a CEDM Shallow-CNN to discover the relationships between LE images and recombinant images. This Shallow-CNN is then applied to FFDM to restore "virtual" recombined images. In collaboration with FFDM, a trained Deep-CNN is introduced for feature extraction, followed by classification models for diagnosis. The approach proposed by the authors had an accuracy of 90%.

In [35], manual segmentation is time consuming and does not take into account the appearance of anatomical structures. So to solve this problem the authors proposed a method of auto-segmentation of the clinical target volume (CTV) called deeply dilated residual network (DD-ResNet). It performs automatic segmentation in order to plan the computed tomography or scanner. They used data from early-stage breast cancer patients who only underwent breast-conserving therapy from January 2013 to December 2016 at the Radiation Oncology Department of the Cancer Hospital of the Chinese Academy of Medical Sciences. To evaluate their method, they performed a comparison between self-segmentation and manual segmentation. This comparison is based on images from different patients and also of different sizes. The results show that the self-segmented contours of the CTV were close to the manually segmented contours in shape, volume and location. The deep learning algorithm (DD-ResNet) proposed by the authors, could be used to improve consistency in bypassing and streamlining breast cancer radiotherapy processes.

12. The application of support vector machines

This method is also useful in the detection of breast cancer. In [36], the authors propose a wide-margin separation technique to perform the stain classification in the context of breast cancer detection. This method is called, the Support Vector Machine (SVM). In this study, they also dealt with character extraction using the Hough transform. The latter makes it possible to detect the characteristics of the mammographic image in order to provide the values to the classifier, that is to say SVM. The mammography images used are collected from the Mammography Image Analysis Database Company (MIAS). Among the 322 images of this company, 95 images were taken to carry out this work. Note that SVM has a success rate of 94%.

In [37], the use of machine learning algorithms such as Support Vector Machine (SVM), decision trees (C4.5), Naive Bayes (NB) and K nearest neighbors (K-NN for K-Nearest Neighbor in English) in medical sciences can classify and predict breast cancer. The authors compared the performance of these algorithms using Wisconsin breast cancer datasets from the UCI machine learning repository. They managed to prove that SVM has the highest accuracy (97.13%) and the lowest error rate (2%).

13. The application of expert systems

This technique is useful in the diagnosis of breast cancer. In [38], the need for a powerful diagnostic tool motivated the authors to create an expert system for breast cancer diagnosis called Ex-DBC to effectively diagnose breast cancer. To perform the diagnosis, the system uses fuzzy rules. In this study, the mammography mass dataset is provided by the UCI Machine Learning Repository. This dataset can be used to predict the severity (benign or malignant) of a mammographic mass lesion from the attributes of the Breast Imaging Recording And Data System (BI-RADS) and the patient's age. It contains a BIRADS assessment, the patient's age and the three BI-RADS attributes as well as the ground truth (the gravity field) for 516 benign masses and 445 malignant masses that were identified on mammographic images collected at the radiology institute of Erlangen-Nuremberg University between 2003 and 2006. Note that the expert system Ex-DBC has a powerful inference engine containing fuzzy rules that can detect hidden relationships in the unrecognized case by the human expert. The goal of the Ex-DBC is to minimize human error by capturing and interpreting points that may not be recognized by the radiologist. Ultimately, the expert system created in this study can make an important contribution to the prevention of unnecessary biopsy in the diagnosis of breast cancer and it can also be useful in training medical students.

14. The application of fuzzy logic

This technique can detect and diagnose breast cancer. In [39], it is difficult to improve the image and remove noise at the s-ame time. This prompted the authors to propose a new contrast enhancement algorithm based on fuzzy logic and fuzzy entropy. The principle of maximum fuzzy entropy is used to map the original image, then the characteristics of the American image are taken into account. More precisely, the edge and texture information is extracted to evaluate the characteristics of the lesions and the phenomenon of diffusion of the American images and the local information is used to define the enhancement criterion. The algorithm improves the details and characteristics of lesions using local fuzzy information. The proposed method includes the following steps: image normalization, image fuzzification, edge information extraction, texture information extraction and contrast enhancement. Indeed, the images of the American breasts used in this study were provided by the Second Affiliated Hospital of Harbin Medical University (HMU). The database included a total of 86 images from 49 cases, and each unique lesion is in an image. Of the 49 cases, 14 were benign solid lesions (30 images) and 35 were malignant solid lesions (56 images). Finally, the proposed approach will be useful for the analysis of images of the breast of American women and computer-aided diagnostic systems.

15. Architecture of the proposed system

Figure 1 shows the architecture of our system.

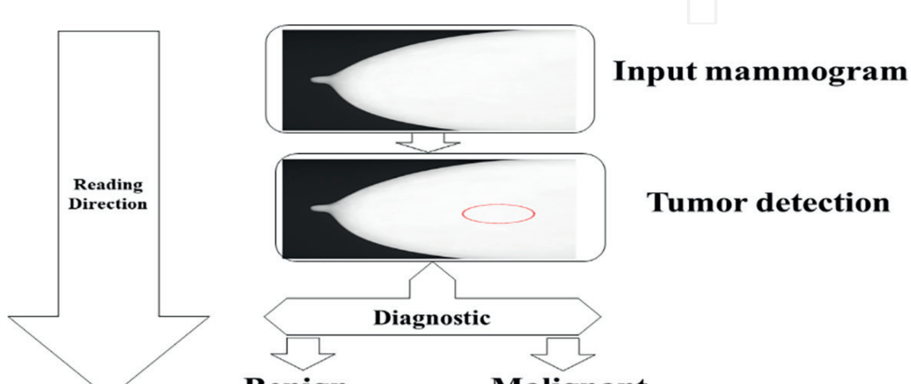

Figure 1.
Architecture of the proposed system (SI2AD for artificial intelligence system aided detection and Diagnosiss).

16. Description of the database used in this study

To carry out our comparative study between artificial intelligence techniques, we chose a breast cancer database extracted from the UCI repository https://archive.ics.uci.edu/ml/datasets/Breast+Cancer+Wisconsin+%28Diagnosi29. This database describes the characteristics of the cell nuclei present in the image. A few of the images can be found at http://www.cs.wisc.edu/~street/images/. Here is the information about this breast cancer database:

- Number of instances: 569
- Number of attributes: 32 (ID, diagnosis, 30 real-valued input features)
- Attribute information:
  - ID number
  - Diagnosis (M = malignant, B = benign) 3–32

Ten real-valued features are computed for each cell nucleus:

a. radius (mean of distances from center to points on the perimeter).

b. texture (standard deviation of gray-scale values).

c. perimeter.

d. area.

e. smoothness (local variation in radius lengths).

f. compactness (perimeter^2/area - 1.0).

g. concavity (severity of concave portions of the contour).

h. concave points (number of concave portions of the contour).

i. symmetry.

j. fractal dimension (“coastline approximation” - 1)

- Class distribution: 357 benign, 212 malignant

17. Performance evaluation measure

$$\text{Accuracy} = \frac{correct\ predictions}{all\ predictions}\ or\ \frac{True\ Positive + True\ Negative}{all\ predictions} \tag{1}$$

18. Results

In this section, we will present our comparative study. We compared artificial intelligence techniques: Logistic Regression, Gradient Boosting Classifier, Random Forest, XGB Classifier, Support Vector Machine, Decision tree, KNeighbors and ANN. The choice of these techniques is based on their very frequent use in the literature.

Artificial Intelligence Methods	Accuracy
ANN	0.97
Decision Tree Classifier	0.94
XGB	0.95
SVM	0.98
Kneighbors Classifier	0.94
Ramdom Forest Classifier	0.95
Gradient Boosting Classifier	0.96
Logistic Regression	0.97

19. Discussion

This work put more emphasis on one of the most powerful algorithms in artificial intelligence. These are convolutional neural networks (CNN). This technique is part of deep learning algorithms. The choice of this method is based on its power, notably allowing the recognition of images by automatically attributing to each image provided as input, a label corresponding to its class of membership. Then, in **Figure 1**, there is the absence of the feature extraction step, this proves that we chose CNN over other AI methods, not by preference but rather on convincing arguments. We know that Artificial Neural Networks (ANNs) like Multilayer Perceptron only contain a classification part, so in systems that use ANNs and want to extract features, it is necessary before applying ANNs before perform a feature extraction step while the CNN contains the two parts: a convolutional part whose final objective is to extract the characteristics specific to each image and a classification part allowing to classify the image. Also, it is sure and certain and all data scientists will tell you that deep learning methods are data and computationally intensive. However, today we see the exponential growth of data in all fields, in particular that of health, in particular with the exponential increase in the number of mammographic images produced. The use and improvement of this method is therefore possible thanks to this big data and the computing power. Here are the essential steps of our proposed system: a tumor detection phase and a diagnostic phase to classify the tumor (benign or malignant). In addition, the proper functioning of our system will be validated in collaboration with experts, in particular doctors, or by using a local database or others. This step is called the validation phase. Finally, our results obtained show that artificial neural networks are efficient, even if the database used in this study is very small.

20. Conclusion

Ultimately, artificial intelligence can play an important role in the early detection of diseases, especially breast cancer. Currently, we are witnessing an exponential increase in large-scale data (or Big Data) in our hospitals. This is caused by the number of medical images produced, the vast majority by women. Thus, in this study, we have shown that it is possible to create robust artificial intelligence systems from medical imaging databases. These systems use machine learning methods in particular deep learning in image classification. In order to facilitate the detection and early diagnosis of breast cancer, we have proposed an aid system called SI2AD as future work.

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