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The Contribution of Artificial Intelligence Approaches in Early Stages of Breast Cancer

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Abstract

Breast Cancer is prevalent most diagnosed cancer type and remains a public-health issue as second leading cause of cancer death that affects women on a global scale. This type of cancer, that starts in the breast could decline the mortality rate even detected in early stages. A last decades, the only progress that can be attributed to the deployment of innovative management pathways, from early detection to treatment. Machine learning and artificial intelligence, can assist breast cancer to achieve prognostic information, and has a potential, practice of precision medicine. There is an important aspect for computer aided systems offers assistance and support to radiologists in the interpretation of medical images through deep belief network that automatically detects breast mass region.

Keywords: Artificial neural networks; Breast cancer; Computer aided diagnosis; Artificial intelligence; Machine learning; Healthcare system.

Aim of our work

The present paper aims to explore and validate with both clinical and biological data may be beneficial thus, research needs to explore a computational framework, using clinical and biological tests in a computer aided system, that assist physicians to take decisions swiftly. In the literature review led us to the selection of this topic, which focuses on a computer aided diagnosis technology, for detection of breast cancer to show how to improve the actions of radiologists by increasing sensitivity rate in a cost-effective way.

Objectives

As stated in the introduction, our main objective was to summarise various reviews on diagnosis of breast cancer with benefit of artificial neural networks as decision-making tools of breast cancer. This paper seeks to address a new look at the contents of recently published literature with attention to techniques and states of the art of artificial neural networks in a medical imaging. Most of the previous medical cases have focused on one of the diagnostic methods to differentiate begin from malignant lesions. There is still a need for fundamental knowledge from both medical and computational studies to improve computer aided diagnostics systems for breast cancer. We aim to address these and general description of the essential available information, few researchers have addressed the issue, by asking the following points:

1. Which is the current situation of breast cancer?

2. In order to identify, to improve the quality of methods for diagnosis that have been used for building computer aided diagnosis systems?

3. Which are the current computational approaches that have been used to build a breast cancer computer aided diagnosis system?

Methodology

In our review, methodology used was through the survey of simple review of relevant literature, research, technical articles, case studies, in the field of computer science, medicine and health science. Until now this research has only been focused on more recent publications as we have personal observation and interview with experts were added. The criteria for selecting the subject were as a follow the evaluation of screening modalities, especially in the community setting, is a challenging for methodological, clinical, and ethical reasons.

Introduction

Recently there has been renewed interest in the use of machine learning in medicine, nowadays becoming more and more important, in the context of breast cancer for early detection to develop algorithms for interpreting screening mammograms to potentially improve breast cancer screening by reducing “false – positives”. Most of the studies of artificial intelligence in breast cancer diagnostics have only been carried out on extends to imaging modalities to identification of metastatic breast cancer in whole imagines of sentinel lymph node biopsy [14,15].

A large sample size of imaging modalities and detection tools, mammography is reviewed the most cost-effective methods at early stages of detection. At the last two decades computer aided detection schemes, aims to provide radiological data with a precious “second opinion” to detect more breast abnormalities in early stages. Although cancer includes different types of diseases, they all begin since, abnormal cells grow out of control, without treatment cancer can cause serious health problems and even death [9,11,12].

A recent review of the literature on this topic in computer technologies and storage capabilities have produced an incredible amount of data and information from many sources such as social networks, databases, and information systems [8,13,15]. Nowadays, many countries around the world are changing the way of implementing health care to the patients and the people by utilising the benefits of advancements in computer technologies and communications through electronic health.

The etiology of cancer is still an area extensively subjected to medical research. Incidence of cancer is characterised by an uncontrolled cell division and cell mortality rates, which occur due to a genetic problem in the DNA of the body cells. The term of breast cancer is referred to a malignant tumour that has developed from cells in the breast [20,21,22].

A lot of different tests designed for the diagnosis at early stages. These tests are classified into two main types, the clinical and biological. In the clinical test, physician looks for external changes, such as, redness of the breast, variations in the texture of the skin, or an internal change such as, the presence of a mass within the breast tissue, which usually is detected by a mammography or ultrasound. Biological test looks for biological changes such as the development in the white blood cells, molecular biology of breast fluids or the presence of genetic mutations that lead to the development of breast cancer [23,24,26]. During the early stages of cancer, noticeable changes of a patient's breast or health are absent when the number of cancer cells is still small. In most patients, the first sign is the presence of a lump inside the breast tissues, which could be either tangible, can be felt by hand, or intangible, seen by breast imaging methods. In both instances the number of cancer cells present may exceed millions. Following changes in the breast have been identified as possible signs of breast cancer:

Thickening or swelling of part of the breast.

Irritation of breast skin.

Redness or flaky skin in the nipple area or the breast.

Pulling in of the nipple or pain in the nipple area.

Nipple discharge.

Any change in the breast size or shape.

Pain in any area of the breast.

Oedema and ``peau d`orange``

All these signs are shared with other breast diseases too, but it is highly recommended for women with one of the above signs to consult her physician. Referring outside the paper, the guidelines of the American oncologic society recommend against self-examination because the low rate of accuracy.

Machine Learning Approaches in breast cancer detection

Over the last of decades, machine learning algorithm have been widely, used in breast cancer detection to gain different insights from data samples. A variety of statistical, probabilistic and other sophisticated tools learn and improve performance from complex dimensional data, extracting key features and rules, which can be difficult to be discovered using traditional statistical methods. Machine learning, throughout the past decades might have been algorithms in breast cancer prognosis, diagnosis and treatment information gap on a different understands from data samples. A combination of skills, approaching and allowing computers to move forward behaviours based on empirical data thorough sensor data or databases, comprehension of the learning process and to implant study abilities in computer system [28,29].

Artificial intelligence uses a scale of statistical, probabilistic and optimization tools to study and make a better performance automatically from new data samples and past experiences, without explicitly programmed instructions. Typically, machine learning capable of extracting key features and potential rules which might be difficult to be discovered using traditional statistics methods. Knowledge is a referred to learning from data set or feature set. There are many methods of knowledge from statistical data analysis, for supervised, unsupervised support learning methods [8,9,10].

Artificial intelligence in breast cancer

When artificial intelligence entered the scene some years ago, the radiology community was in an uproar, because the implications and consequences of artificial intelligence were unclear, and radiologists were without purpose by reports of their imminent replacement by machines. Artificial intelligence developed systems that reliably interpret mammogram data and intuitively translate patient's charts into diagnostic information which accurately predicts breast cancer risk. Currently, artificial intelligence seems to be most promising in very specific fields or niches like screening digital mammography. Further studies on the current topic are therefore recommended from the American cancer society in order to screening guidelines for a woman 40-45 years old each year until the patient is in good health, on the contrary in the screening is recommended in women from 50-74 years old each 2 years, a digital mammography is considered the most important improvement in breast imaging [3,4,23].

Techniques that depend on the principle of intelligent systems such as neural networks, nearest neighbour methods, computer aided diagnosis algorithms, fuzzy logic approach, decision trees and linear programming methods. Currently "Cure Metrix" algorithm, "it bra", "natural language processing", "software genes", to system breast cancer databases and "triple negative" breast cancer database is an intelligent system are used for breast cancer detection.

Most of studies have only focused on artificial intelligence system than can be assist physicians by providing up-to-date medical information, reduce a diagnostic and a therapeutic error that are inevitable in the human clinical practice to inform proper patient care [8,10,11,13]. Moreover, an artificial intelligence system can extract useful data from a large patient population as they assist a real-time inference for health risk alert and health outcome prediction.

Challenges of Artificial Neural Network in Breast Cancer

In breast cancer diagnosis, the most commonly use artificial neural networks, which are a multilayer, whose concept is derived from biological neural networks. A collection of processing elements that are highly interconnected and transform a set of inputs to a set of desired outputs. The result of transformation is determined by the characteristics of the elements and the weights associated with the interconnections among them.

The construction of neural network involves three different layers with feed forward architecture. The input layer of this network is a set of input units, which accept the elements of input feature vectors. Automated classifiers may be useful for radiologists in distinguishing between benign and malignant patterns [11,15]. An artificial neural network which can be served as an automated classifier is investigated. In medical image processing, artificial neural networks have been applied to a variety of data-classification and pattern recognition tasks and become a promising classification tool in breast cancer [22,14]. Image features can be distinguished in many aspects, such as texture, colour, shape, and spatial relations. They can reflect the subtle variance in many degrees. Thus, different selections of image features will result in different classification decisions. These classifications can be divided into three types: first, the method based on statistics, such as support vector machine; second, the method based on rule, such as decision-tree and rough sets; and third, artificial neural network [8,9,15]. Artificial neural network model is the most used in computer - aided diagnosis for mammography interpretation and biopsy decision-making. There are two ways used in Artificial Neural Network to assist in mammography interpretation: first, applying classifier directly to the region of interest image data and second, understanding the situation from the features extracted from the pre-processed image signals [9,12].

In late 90's, the application of an artificial neural network in computer aided diagnosis mammography was found to have limitation in terms of data overfitting. Thus, bayesian belief network was compared with an artificial neural network's classification method to identify the positive mass regions based on a set of computed features in computer aided diagnosis [22]. The same database was used in artificial neural network and a bayesian neural network with topologies optimization using a genetic algorithm to test the performance and robustness of the artificial neural network and bayesian neural network [12,13].

Compared to artificial neural networks, bayesian belief networks have certain unique advantages, in addition to their ability to work with incomplete information, mentioned above. One such advantage is that they can provide explanations of their decisions [18,19,21]. Because they provide a flexible capability for specifying dependence and independence of variables, in a natural way through the network topology, their structure tends to reflect the logical structure inherent in a decision task [7]. In contrast, neural networks can be viewed, to a large extent, as a black box whose 'machine learned' internal decision structure is generally incomprehensible to human observers.

Mammograms are checked carefully by radiologists to make an accurate decision. The process is started by searching for a region(s) or mass that appears different from other regions of the same and the opposite breast [1,12]. If the radiologist finds such a region then s/he determines whether the region or mass has a 'normal' appearance or not. If the abnormality cannot be differentiated with certainty from 'normal', it is classified as 'Suspicious' and will need further investigation. 'Suspicious' areas generally fall within asymmetric density, architectural distortion and calcifications mammography is limited by the density of the breast, which makes it difficult to detect the abnormality in women with dense breasts. [2,3,6]

Detection of breast cancer on screening mammography is challenging as an image classification task because the tumors themselves occupy only a small portion of the image of the entire breast. Image processing is an important step in any attempt to help practitioners in the field by providing computer aided diagnosis of breast cancer [14,18]. Essentially, all computer aided diagnosis systems work with digital images. Whenever they are obtained from mammography, moreover the image processing step is crucial for the quality of the result [2,3,4]. Depending on the concrete approach and purpose there are various image processing techniques that can be used in computer aided diagnosis systems that focus on breast cancer.

Computer – Aided Diagnosis Systems for Breast Cancer

Using the computer aided diagnosis system in most studies have only focused on improved breast cancer detection as the major field in medical imaging and diagnostic radiology. Few studies have been published in increases diagnostic performance, particularly sensitivity to detect potential malignancies in the breast, so the detection algorithms were heavily biased towards sensitivity, thereby sacrificing the specificity of any mark [8,12]. At fundamental level, most of computer aided diagnosis systems rely on image segmentation followed by feature extraction and classification to characterize the lesion.

A challenge facing computer aided systems is the high number of false – positive markings into medical education as radiologists making more accurate interpretations should be encouraged. We have obtained accurate diagnosis which is deductive "process" that a physician's links symptoms to diseases.

A computerised detection and classification algorithm [19,20] has been reported for differentiating malignant from benign masses based on ultrasound images. The study used the sharpness of mass margin, Normalised Radial Gradient (NRG) along the margin, standard deviation of grey level value and gradient of lesion, posterior acoustic shadow and auto correlation depth (R) as 41 inputs for a classifier [15,21].

Artificial neural networks and receiver operating characteristic curves have been used for classification and evaluation, respectively, based on 400 cases for training and 458 cases for testing. The resulting areas under the receiver operating characteristic curve (Az values) were 0.87 and 0.81 with the training and testing respectively. A further study used the same algorithm and features for evaluating 609 cases obtained from two different datasets that were acquired from two different ultrasound platforms [2,4]. The (Az values) achieved by the study were between 0.8 and 0.86.

Another study evaluated an artificial neural network, several times using age and three ultrasound features (margin sharpness, intensity of absorbed sound waves by the mass margin and angular continuity of the margin) [24,25]. The study obtained an accuracy of 0.856 ± 0.058 in the different tests of artificial neural networks.

Decision trees had been used to diagnose breast tumours using texture features with 95.5% accuracy [19]. Furthermore, linear discriminant analysis has been used using six features; two of these features are geometric (compactness and orientation) and the others are echo features (intensity ratios of the regions below the two sides of a mass (side shadow of mass), intensity ratios of the regions below the mass (below shadow of mass) and homogeneity). The present study used receiver operating characteristic for evaluation and for the area under the curve, the Az value was 92% [1,2,7,17,21].

Another study used eight morphological features including shape, orientation, margin, lesion boundary, echo pattern, and posterior acoustic for building a breast cancer computer aided diagnostic system. A binary logistic regression model was used as a classifier to relate those features and pathological results. The system evaluated 265 samples (180 benign and 85 malignant cases), as the overall accuracy of the computer assisted diagnosis system was about 91% [25,26,27].

Exploring Bayesian Networks for Prognosis of Breast Cancer

We investigated the use of bayesian networks for the interpretation of mammograms which can express the relationships between diagnoses, physical findings, laboratory test results and imaging study findings. Since, bayesian networks represent uncertainty using standard probability, one can collect the necessary data for the domain model by drawing directly on published statistical studies.

Reviewing past literature, bayesian networks developed for real-life applications in biomedicine and healthcare have been constructed by hand, i.e., they are based on medical background knowledge. Manual constructions of a bayesian network require access to the knowledge of human experts and, are quite time consuming. With the increasing availability of clinical and biologic data, machine learning is clearly the more feasible alternative for developing a Bayesian network [5,6,7].

Mentioning positive aspects of others' work, integrating background knowledge and evidence derived from past data is also supported by Bayesian networks. Missing data can be handled both in the construction process and in using a Bayesian network model.

The bayesian network is a powerful tool to describe the uncertainty and complexity of many problems in the real world having rigorously justified mathematical basis.

They deal in a natural way with uncertainty (modelled as a joint probability distribution).

They are easy to understand because of their graphical representation.

It is possible to represent a large instance in a bayesian network using little space, and it is possible to perform probabilistic inference among the features in an acceptable amount of time.

The graphical nature of bayesian network gives us a much better intuitive grasp of the relationships among the features.

Discussion

It may be the case, that clinical diagnosis and decision making, patient outcomes, and workflow areas in breast cancer, as well as breast image screening are referred in many of the articles reviewed here as having potential for improvement by artificial intelligence, with expectations for what the future might hold and the extent to which anticipated limitations may impede development. In conclusion, it would appear that the published evidence on artificial intelligence for breast cancer detection was concentrated around model "algorithmic development", rarely independently of real world clinical or screening evaluation, and on the whole of the evidence does not indicate the readiness of artificial intelligence systems for "real – world breast screening trials" or for stand-alone screen reading [5,10,12]. A challenging issue is an emerging from these findings:

1. There are large-scale projects developing artificial intelligence for breast cancer screening;

2. The data and statistical sciences driving artificial intelligence development have advanced substantially in recent years, as has digital imaging data capture and archiving;

3. Mammography, the only imaging modality to date shown to reduce breast cancer mortality, has evolved into digital breast tomosynthesis or 3-D mammography technology which contains richer imaging data than conventional mammography; and

4. The increasing burden of resourcing screen-reading in population-based screening programs that practice double-reading of mammography.

This suggests that real-world implementation studies of artificial intelligence in breast screening may be lagging developments in the artificial intelligence industry or may not be available yet in the peer-reviewed literature. [3,22,24]

We discussed the usage of artificial intelligent and neural network in a different medical imaging application, to highlight that neural network is not limited to few areas of medicine. A lot of types with a neural network are used, along with the various types of feeding data, have been reviewed. Further studies on the current topic are address to hybrid neural networks in adaptation of breast cancer detection [11,12].

A key problem, of the last few decades, number of computer-aided diagnosis techniques have been developed in mammographic examination of breast cancer to assist radiologist in taken as a whole image analysis and to highlight suspicious areas that need further observation and notice. It can assist radiologist to find a tumor which cannot be spotted with make of use a naked eye. The neural networks based on a clinical support system that provide the medical experts with a second opinion thus removing the need for biopsy, excision and reduce the unnecessary expenditure, in detection of carcinogenic conditions in the breast cancer.

Conclusion

The evidence of the literature review provides a various challenges and opportunities of machine learning in early stages of detection in breast cancer. However, the question remains as to which implications our findings have on the treatment for it, which slowdowns the disease progression, improves patient's quality of life and further reduces the economic burden involved in healthcare management.

Although, lots of algorithms have achieved very high accuracy in wisconsin breast cancer database, the development of improved algorithms is still necessary. Classification accuracy is an important assessment criterion, but it is not the one. Different algorithms consider different aspects and have different mechanisms. These observations have many implications dominated in breast cancer diagnosis, prognosis and treatment; more recently alternative machine learning methods have been applied to intelligent healthcare systems to provide many options to physicians.

Next, we will work, and test particle swarm optimisation algorithms can be applied to support vector machine in with artificial neural network via tuning weights to find out whether we can achieve a higher classification accuracy with Wisconsin breast cancer database. Furthermore, we are going to process a set of rare datasets obtained from health care system and the corresponding results will be published in future papers.

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