SURVEY ON CLASSIFICATION OF BREAST CANCER IMAGES USING DEEP LEARNING MODELS

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Abstract:
Among female cancers, breast cancer has a high incidence rate. Cancers that don't cause any obvious symptoms in the early stages are called asymptomatic.Accordingly, a computerized approach for the detection of breast cancer in mammography will help radiologists with their diagnoses. Many people are curious about using deep learning to solve medical imaging challenges, especially those related to diagnosing breast cancer, thanks to the field's recent surge in popularity.Mammography has replaced other screening methods, allowing for earlier identification and more accurate diagnosis of breast cancer. The emergence and growth of deep learning models in recent years have the potential to improve their utility by building on their already impressive track records in a variety of contexts. In this paper, the authors develop the process of classification using deep learning in medical images. The study aims to study the classification accuracy using deep learning based residual learning in breast images.

Keywords: Breast cancer, Cancers, classification, deep learning

1. Introduction

Lung cancer is the most common type of cancer in women, breast cancer is the second most common, and clinical trials have shown that early identification of breast cancer greatly increases the survival rate. To detect and track breast cancer, radiologists have traditionally used a broad variety of imaging modalities, from tried-and-true methods to cutting-edge technologies.

Masses, microcalcifications, architectural distortions, and bilateral asymmetry are all examples of breast cancer anomalies that have been detected with remarkable sensitivity using these imaging modalities. Problems, such as breast tissue overlap, which conceals breast information and potentially harmful malignancies, are present.

Breast cancer can be classified into two main categories, in situ cancer and invasive ductal carcinoma (IDC). Although in-situ malignancies only account for roughly 20-30% of breast cancer, 80% of all breast cancer diagnoses are due to in-duct carcinoma. Active monitoring as an alternative to surgery for in-situ cancer has become more common in recent years, however this is not the case for the treatment of IDC. Therefore, prompt, and precise detection of the disease stage and whether it is in situ or invasive is crucial for patients.

Several distinct approaches to image processing have been studied in recent years. Methodologies like ML, AI, and neural networks fall within this category. Computer-assisted diagnosis (CAD) has produced a reliable system that can accurately distinguish between benign and malignant lesions while reducing the impact of experimental errors. The quality of images for human evaluation is enhanced while the process of reading and understanding them is simplified by these technologies. Several recent articles have explored the application of machine learning and AI techniques to the problems of breast cancer diagnosis, segmentation, and classification.

Progress in computer vision, and especially biomedical image processing, has been made recently thanks in large part to deep learning models. That mostly because these models can automatically pick up high-level details from images. Since then, several scientists have used similar algorithms to sort breast cancer histology images into various categories. Convolutional neural networks (CNNs) are commonly used for image-related tasks due to their ability to successfully transmit parameters across numerous layers within a deep learning model.

2. Breast Cancer Diagnosis

Several researchers have been motivated to employ deep learning in diagnosis because of the recent advances and remarkable performance of deep-learning algorithms. The improvement in deep-learning algorithms is to blame for this. One of the many benefits of this deep learning-based CAD technique is that it automatically classifies breast lumps as either malignant or benign, eliminating the need to segment lesions, compute image attributes, or select.

Artificial Neural Network (ANN)

Artificial Neural Network (ANN) refers to a hypothetical mathematical model that mimics the structure and behaviour of a real neural network. It receives data, processes it, and then sends the results to another area, much like the human brain. Artificial neural networks (ANNs) are a powerful technique for determining the presence of breast cancer. In the future, only radiologists who are experts at using ANN will be in demand. Radiologists are currently learning how to take use of ANNs while avoiding their pitfalls. Patients can rest easy knowing that radiologists will catch any false-positive results generated by artificial neural networks [1]. Even though it takes much longer to train, the performance of a multi-layered artificial neural network (ANN) dramatically improves for challenging tasks.

Abbass [2] makes a seminal contribution to the field. In the study, ANN was utilised to detect breast cancer using the numerical feature-based Wisconsin dataset. By contrasting their findings with those of an evolutionary programming approach and conventional back propagation.The authors were able to achieve this by comparing our findings to those of previous studies. Not a single principle of feature engineering was applied to this effort. Karabatak et al. [3] advocated using AR and a neural network for the automatic diagnosis of breast cancer. (NN). The feature vector was compressed using AR, and then the data was classified using NN.

The proposed model that mixes AR and NN outperformed the NN model. With only four inputs, the proposed approach achieved a classification accuracy of 95.6%, while with eight inputs, it achieved 97.4%. An example of this is the life-sensitive model proposed by Jafari-Marandi et al. [4]. (LS-SOED). The ANN capacity for making good decidementshas been enhanced.

Anton S. Becker [5] built an artificial neural network (ANN) architecture based on deep learning to detect breast cancer in the BCDR dataset. The accuracy attained by the ANN was on par with that attained by previously reported deep learning models. Surgery patients who deteriorated following their procedure were excluded from the study. Even though only a brief history of the patient was supplied, the BCDR dataset nevertheless contained patients who had very small changes, adding bias.

To distinguish benign from malignant modifications, Rouhi et al. [6] trained an ANN on a small dataset of images. To get the desired results in the segmentation process, both cellular neural networks and artificial neural networks (ANN) were used. The cellular neural network parameter values were arrived at with the help of a genetic algorithm.

Autoencoder

The autoencoder uses back-propagation, a type of unsupervised learning, to guarantee that outputs are in line with inputs. An autoencoder can take the input data and produce a hidden layer. The decoder then makes use of the hidden layer to reconstruct the original input. Denoisingautoencoders (DAEs), variationalautoencoders (VAEs), sparse autoencoders (SAEs) and contractive autoencoders (CAEs) are the four types of autoencoders. The decoder then makes use of the hidden layer to reconstruct the original input.

One variation of the stacked autoencoder that helps cut down on background noise is the stacked denoisingautoencoder. The terms stacked and denoising are what inspired its name (SDAE). With the help of auto-encoders, the authors can work with much smaller datasets. Training an autoencoder is a lengthy procedure that necessitates a large amount of data processing power, in addition to adjusting hyperparameters and validating the model. There are many similarities between the autoencoder and the Principle Component Analysis (PCA), however the autoencoder is more adaptable. Autoencoders can do both linear and non-linear transformations, while PCA can only perform linear transformations.

To categorise nucleus patches in breast cancer histopathology images, Xu et al. [7] develop a stacked sparse autoencoder (SSAE) consisting of two distinct sparse autoencoders. Within the SSAE architecture, unsupervised learning is utilised to find abstract characteristics that better characterise the original data. Overall, SSAE+ Softmax performed better than PCA+ Softmax and SAE+ Softmax when it came to classifying nucleus patches. However, only 17 patients were used to acquire the breast histopathology images.

Xu et al. [8] developed a model using 537 H&E-stained histopathological images. The findings from the previous study informed the second. Specifically, they suggested the SSAE framework be used to track for breast cancer nuclei. The pre-processing methods, however, were not considered. Kadam et al. [9] demonstrated that the SSAE+softmax architecture underperformed the suggested SSAE feature ensemble learning approach.

However, autoencodershave been used in only a few research projects to learn features via the process of dataset reconstruction. Feng et al. [10] offered a SDAE for learning critical features from image fragments. In cases where there are few labelled examples, it can help classify nuclei.

SDAE was utilised by Cheng et al. [11] to distinguish between lesions detected using breast ultrasonography and nodules detected via chest computed tomography. One of the benefits of the SDAE design is its ability to withstand background noise, and another is that it provides an automated means of discovering useful traits. Considering this, it is well suited for processing medical image data from several imaging modalities, all of which tend to be intrinsically noisy. Comparisons with two popular CADx algorithms showed that SDAE-based CADx was superior to the conventional technique. When more slices from individual nodules are provided as training data, SDAE discriminative abilities improve.

Deep Belief Network (DBN)

Unsupervised, generative, and devoid of human control, the Deep Belief Network (DBN) is a type of graphical model [12]. The Deep Belief Network (DBN) is a multi-layered belief network that is based on RBM. Starting with contrastive divergence (CD) to learn from visible units, a DBN is first taught a collection of features.

One major drawback is that RBMs could be challenging to train. The fundamental goal of RBM training is to optimise the model probability distribution to get a good fit with the training data. To achieve this, it is necessary to determine the most likely values for the parameters and then base them on the training data.

Using the DBN unsupervised phase and later its supervised backpropagation neural-network phase, Abdel-Zaher and Eldeib [13] suggested an approach for breast cancer identification. Methods that required data preparation were not implemented in this investigation.

Khademi and Nedialkov [14] processed microarray data to improve the accuracy because cancer is a genetic illness. Parameters and structure can be learned from microarray data by integrating genetic elements, but this approach is fraught with difficulty due to the curse of dimensionality and the difficulties posed by a limited sample size. The authors were able to fix these problems by using DBN to the microarray data.

The technique for identifying breast masses in mammography was developed by Dhungel et al. [15]. Segmentation describes this technique. The CRF model was also shown to have far shorter training and testing times than the SSVM model. Comparing the CRF model to the SSVM approach reveals that the CRF model has several benefits. Only a small fraction of these studies really used DBN to extract features and pick the most relevant features. However, training will take more time, even though this design outperforms its predecessors.

Convolutional Neural Network (CNN)

CNN main goal was to spot patterns in flat, two-dimensional images. Many layers make up a convolutional neural network, but the output, convolutional, and max-pooling layers are the most crucial. Due to its importance in breast cancer classification, a thorough introduction of the CNN is in order. Studies have shown that CNNs are the most effective technique for creating a trustworthy breast cancer classification model. The large range of imaging methods that employ CNNs is a testament to their efficacy with images. Unfortunately, a massive image-based data set is required to train a CNN. When working with a small sample size of images, achieving a satisfying result can be challenging. Unfortunately, it is difficult to gather enough data for training in the medical imaging industry due to the exorbitant cost of labelled datasets. However, CNN does have some positive aspects. When compared to other classification strategies, a ConvNet takes far less setup time. Features are extracted and classified using the same CNN architecture. For the most part, it can shrug off any stray geometrical or optical aberrations that may crop up in each area. Researchers analysed breast cancer classificationusing features collected from medical images using convolutional neural networks [16]. Common methods for classifying breast cancer data include TL-based CNNs, which have already been trained, and de-novo CNNs, which are trained from scratch [17].

Residual Learning (RL)

Residual learning has only been employed for breast cancer diagnosis in a handful of recent studies. Specifically, residual blocks are the fundamental structural elements of residual networks. To avoid the issue of fading gradients, it makes use of skip connections, which allow data to bypass an entire layer. Using residual blocks in a network instead of stacked CNN increases its representation power, hastens convergence, and reduces the amount of training errors. When processing DBT images, Singh et al. [18] suggest using a model that has already been trained on FFDM images. Two unique tuning strategies were used in this research: (1) focusing on the top two layers, and (2) focusing just on the layers that performed very well. Based on their comparison, which can be found below, the authors conclude that the best AUC was achieved by fine-tuning the final two layers.

For their part, Toacar et al. [19] introduced a brand-new method they called the BreastNet model. This strategy makes use of attention modules to form a residual architecture. Before being fed into the modelling procedure, the authors augmented each piece of image data that was culled from the BeakHis dataset. After that, the model used the image attention modules to zero in on and analyse its most crucial parts.

One such residual-learning-based method, Gour et al. [20], employs a convolutional neural network (CNN) of 152 layers. The model capacity to learn discriminative and rich features enables the classification of histology images. As a result of their new data-augmentation method, they outperformed their earlier efforts. Histopathology images retain any relevant contextual information since ResHist categorises the entire slide image. On the downside, it takes a long time and a lot of computing power to train. According to the authors of the study, their model achieved 82.12% accuracy in classifying 40x, 100x, 200x, and 400x images when only raw imagegraphs from BreakHis were utilised for training and evaluation. This was true back in the day when just raw images were used in the evaluation and training processes.

Hu et al. [21] proposed the CNN-derived MyResNet-34 network, which is built on a deep residual learning architecture. Accuracy ratings of 86.90%, 84.62%, 85.34%, and 81.06% were achieved for 40x, 100x, 200x, and 400x magnifications, respectively, when myResNet-34 was applied to the raw images of BreakHis.

Consequences [22] showed the superiority of their approach over ResHist, providing more proof of its viability. For images with a resolution of 40x40 pixels, the proposed augmented approach improved classification accuracy by 6.73 percentage points, bringing the total to 93.63% in testing.
The usefulness of residual learning in classifying breast density was investigated by Li et al. [23]. They were able to accomplish this by combining data from two sets of mammograms. The authors of the study used a combination of deep residual networks, integrated dilated convolutions, and attention methods. The purpose of these changes was to strengthen the network capacity for classification. The proposed method outperformed a widely accessible alternative on the team own data set.

Generative Adversarial Network (GAN)

The deep learning-based generative models are called generative adversarial networks (GANs). One model, the generator model, uses features learnt from the training data to generate new images that are like the original; another model, the discriminator model, uses the same features to identify whether the instances generated by the generator model are real. To produce new images that are comparable to the original, the generator model must be used.
To combat the high mortality rate associated with breast cancer, Shams et al. [24] developed an ensemble model using a deep generative multi-task (DiaGRAM). This action was taken so that the authors can reach our objective. DiaGRAM built-in mammography diagnosis methods are among the most precise in the industry. It was able to learn these features by synthesising a GAN.
Singh et al. [25] conducted a second investigation in which cGANwas employed for segmentation of region of interest (ROI). First, the generative model will use its learned detection to create a binary mask that may be used to zero in on the precise location of the tumour. Also, GANs have recently been applied to the problem of insufficient training data by being used as image-enhancement algorithms.
Guan and Loew [26] created a unique GAN-based mammographic image generator. Following that, CNN was used as the discriminator for the GAN they developed. When compared to the total efficiency of other image enhancing approaches, GAN was 3.6% more efficient.
To construct an image utilising GAN for anomaly identification, Swiecicki et al. [27] utilised data from tomosynthesis. The goal was to identify outliers; hence this was carried out. The results of this study showed promise for the anomaly detection method employed, since it was able to identify outliers without training images.
It was with the goal of enhancing the quality of chest CT images taken from breast cancer patients that Tien et al. [28] combined CycleGAN with Deblur-GAN to create the new algorithm Cycle-Deblur-GAN.

Extreme Learning Machine (ELM)

An artificial neural network called an extreme learning machine (ELM) has demonstrated promising results in breast cancer classification. The approach uses an analytical formula to compute the output weights after being seeded with random values for the input weights and biases. This means the ELM will not experience the negative consequences of having its settings changed by hand. In recent years, ELMs have gained notoriety for their prowess in a variety of difficult tasks. Their low processing costs and quick learning times have earned them this status.
A genetic method was utilised by NEMISSI et al. [29] to find the optimal parameters for an ELM for the hidden neurons. The purpose of doing so was to identify the best course of action. The efficiency of the generalisation process was increased as a direct result of applying the technique that was presented. However, the evaluation was flawed because only accuracy was used to determine the model final scores. By combining the robustness of ELM classification with the capabilities of CNN for feature extraction and representationwas developed. For starters, the authors use deep transfer learning and double-step deep transfer learning to get high-level features. The authors augment the high-level feature sets with regularisation terms to improve classification precision.
Wang et al. [30] presented a detecting mass model. Features were clustered using unsupervised (US-ELM) clustering and a convolutional neural network to identify their geographic origins. Next, the neural network was used to extract the features. Finally, the resulting composite features were passed

into an ELM classifier. Breast cancer detection performance was significantly boosted when ELM classification was combined with Fusion deep feature sets.

The author of [31] combined various models out of which the backpropagation algorithm was used to get these results. Classification accuracy can be improved when initial network weights are not generated at random but are instead set based on previous data. The term back propagation describes this phenomenon. Pre-training for DBN is only possible up to the last hidden layer, but the weights are chosen at random from the output layer and the one before it.

3. Summary

Breast cancer is the common cancer and poses a threat to women everywhere. This malignancy strikes females at an alarming rate, too. Comprehensive research, precise diagnosis, and effective management of patients and professionals can all contribute to bettering the current situation. Successful treatment is often achievable if the disease is detected early, and the patient is closely watched.

Cancer is a progressive disease, which is responsible for these shifts. Biomedical imaging from diagnostic tools like mammography and magnetic resonance imaging can be used to track cellular changes over time. However, it is notoriously difficult to decide the quality of these images, even for experts. Computer-aided diagnosis techniques, however, with an emphasis on machine learning, may analyse the images and provide a diagnosis based on the data they collect. Images can be used to help doctors diagnose cancer, for instance.

The results of this research show that early local feature extraction is crucial for the majority of widely used classifiers. Due to the dynamic nature of cancer, a model that relies on a static collection of regional features will not do well when applied to a different data set. However, recent advances in biological image classificationhave been made possible by modern deep neural networks, in particular CNN, due to the capabilities they offer. The kernel, the most essential part of the model, is what enables the CNN model to employ globally retrieved features. This gives the CNN model more leeway in how it searches images for hidden structure. That paves the way for future breakthroughs in the creative and cutting-edge achievement of classification. The model reliance on generic features means that this classifier approach should work with every dataset that comes up.

The paper provides evidence to back up the findings of previous studies showing that the ROI is the primary location for malignancy data storage. Information gleaned from the data segments, especially the ROI subset, can be used to significantly boost performance. Recent developments in deep neural network technology allow for not only recognition of the ROI but also data segmentation, both of which are used in the subsequent steps of the process for the classification of images.

4. Future Work

Efforts to enhance breast cancer patient treatment through the application of machine learning methods and technology have met with considerable success.The implementation of deep learning techniques has greatly contributed to this success. Our research aims to fine-tune the lightweight DNN model to lessen the burden on both time and computing resources. On the other hand, the current CNN model relies heavily on reinforcement learning methods and data augmentation to guarantee accurate results. The findings suggest that deep learning techniques are where machine learning is headed soon.

Initially, it was necessary to use the right tools to create the whole deep-learning model before using machine learning methodologies based on deep learning. And this was only one of the numerous effects. However, recent advances have led to the development of dependable software that may be used for breast image classification. In the future, the authors may be able to achieve more hopeful breast cancer projections if the authors integrate the DNN network with many additional learning approaches.

Overwhelming numbers of research papers have been published thus far due to the widespread interest in breast cancer. The availability of specialists who can offer sound advice on how to treat the condition is also limited. In some cases, there may be a long wait before the patient can visit a specialist due to a lack of available doctors with the necessary expertise. The patient experience may be enhanced if the diagnostic system were based on machine learning and could provide instantaneous feedback on the present state of the ailment.

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