Detection of Breast Cancer using ultrasonic images through Machine learning algorithms

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Abstract

The cancer is a disease in which cells multiply uncontrollably and these cell crowd out normal cells. Breast cancer (BC) is one of the most common types of cancer disease.Breast cancer is the leading cause of death among women. Around 8% of women are diagnosed with Breast cancer (BC), after lung cancer it is the second popular cause of death in world. BC is characterized by the mutation of genes, constant pain, changes in size, color(redness), skin texture of breasts.Hematoxylin and eosin (H&E) stained breast tissue samples from biopsies are observed under microscopes for primary diagnosis of breast cancer. Several types of research have been done on early detection of breast cancer to start treatment and increase the chance of survival. Today, Machine Learning (ML) techniques are being broadly used in the breast cancer classification problem. They provide high classification accuracy and effective diagnostic capabilities.Deep-learning (DL) methods in artificial intelligence (AI) play a dominant role as high-performance classifiers in the detection of the disease using ultrasonic images. Given many new DL models have been being developed for this purpose, the objective of this study is to investigate the fine tuning of pretrained convolutional neural networks (CNNs) for the classification of BC using ultrasonic images. If fine-tuned pre-trained CNNs can provide equivalent or better classification results than other more sophisticated CNNs, then the deployment of AI-based tools for detecting BC using ultrasonic data can be more rapid and cost-effective.

Keywords: Breast cancer (BC), Deep learning, Convolutional neural networks (CNNs), ultrasonic images.

I INTRODUCTION

The breast cancer (BC) is a common and fatal disease among women throughout the world. BC is the third highest fatal disease among different cancer types, such as lung, liver, and brain. World Health Organization (WHO) reported the breast cancer as the most common cancer amongst women globally. It is also the highest ranked type of cancer cause the death among women in the world. In Malaysia, Breast cancer has the highest rate of cancer deaths, around 25%, and it is the commonest cancer among women. Breast Cancer is causedby multifactorial and involves family history, obesity, hormones, radiation therapy, and even reproductive factors. Every year, one million women are newly diagnosed with breast cancer, according to the report half of them would die, because it’s usually late when doctors detect the cancer. [2,3]It’s also caused by a typo or mutation in a single cell, which can be shut down by the system or causes a reckless cell division. If the problem is not fixed after a few months, masses are formed from cells containing wrong instructions. Usually, breast cancer can be easily detected if specific symptoms appear. However, many women who are suffering from breast cancer have no symptoms. Hence, regular breast cancer screening is very important for early detection and it aids treatment because the prognosis is very important for long-termsurvival. Since early detection, diagnosis, and treatment of cancer can reduce the risk of death, it plays a significant role in saving the life of the patient. Any delay in detection of cancer in early stages leads to disease progression and complication of treatment therefore long waiting time prior to

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diagnosis of breast cancer and starting the treatment process is of prognostic concern. In addition, the number of new BC patients is expected to increase by 70% in the next 20 years. Therefore early, and precise diagnosis plays a pivotal role to improve the prognosis and increase the survival rate of patients with BC from 30 to 50%. In general, breast tumor has two types, benign and malignant. Benign is a noninvasive (non-cancerous) while malignant is an invasive (cancerous) type of tumor. Both tumors have further subtypes that need to be diagnosed individually because each may lead to different prognosis and treatment plans. Proper diagnosis requires accurate identification of each subcategory of BC, also called BC multi-classification. Medical imaging modalities are more commonly adopted and effective for BC detection than any other testing method.[1]In Fig 1.1 well-known medical imaging modalities for BC diagnosis is done through ultrasonic and the other methods are mammography (breast X-ray images), ultrasound (US) imaging or sonograms, magnetic resonance imaging (MRI), computed tomography (CT) and Histopathology (HP) image. Medical imaging is usually performed manually by one or more expert doctors (radiologist, sinologist, or pathologist).

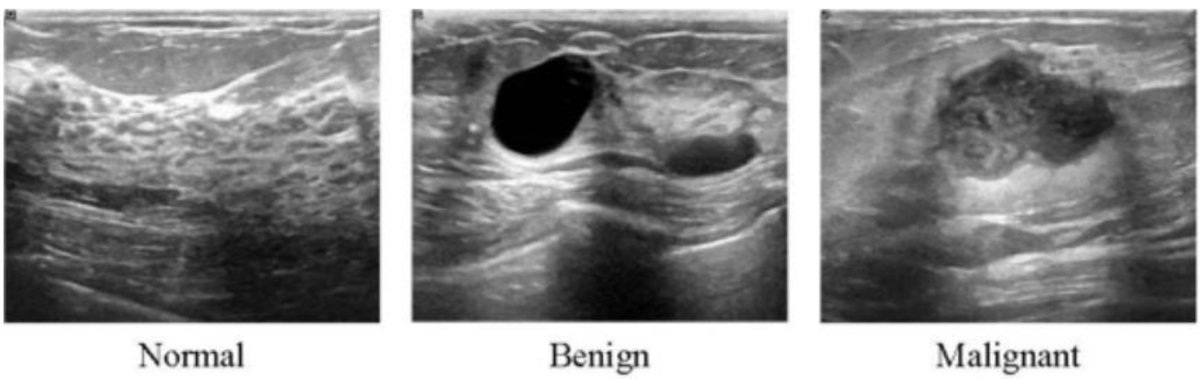

Fig 1.1 Samples of original Ultrasound breast images dataset

Medical images and artificial intelligence (AI) have been found useful for rapid assessment to provide treatment for cancer patients. Therefore, the design and deployment of AI tools for image classification of BC in a short period of time with limited data have been an urgent need. Radiologists have recently found that deep learning (DL) developed in AI, which was able to detect BC using ultrasonic and ML algorithms could be useful for identifying breast abnormalities. Recently, several articles have been published to solve BC classification, segmentation, registration, detection, or grading problems by using traditional machine learning (ML) approaches (e.g., support vector machine, Naïve Bayes, and decision tree) or by using state of-the-art artificial neural network (ANN)-based approaches [e.g., shallow neural networks (SNNs) and deep neural networks (DNNs)]. A SNN is based on a single hidden layer between input and output layers, whereas DNNs mostly consist of two or more than two hidden layers along with input and output layers. The [4] reviewed publications related to traditional ML approaches using hand-engineered features (HEFs) for the analysis of cancer images, including BC images. The authors discussed and analyzed different medical imaging modalities, image pre-processing tasks, and image detection, segmentation, and feature extraction techniques. Finally, traditional ML-based studies were evaluated with future direction. In [4,5,6] authors focused on the detection of common forms of cancer, such as breast, lung, prostate, and skin, using multimodalities, such as X-ray, US, and CT. The authors analyzed traditional ML techniques adopted for each cancer detection, segmentation, and classification. In addition, the use of various imaging modalities for cancer detection was discussed and compared. Finally, future directions were suggested for new researchers. However, previous review studies mainly focused on traditional ML approaches by using imaging

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modalities usually for binary classification. Conversely, recent review studies have emphasized on ANNs using multimodalities for BC analysis. They analyzed various types of ANN adopted for BC analysis by using multimodalities, such as Mg, US, MRI, and thermal imaging.

Three pretrained convolutional neural networks(CNNs), which are AlexNet, GoogleNet, and SqueezeNet, were selected and fine-tuned without data augmentation to carry out 2-class and 3-class classification tasks .Therefore this is study attempted to investigate the potential of the parameter adjustments in the transfer learning of three popular pretrained CNNs: AlexNet, GoogLeNet, and SqueezeNet, which are known to have least prediction and training iteration times among other pretrained CNNs reported from the ImageNet Large-Scale Visual Recognition Challenge [8,9]If these fine-tuned networks can achieve desired performance in the classification of BCusing ultrasonic images by a configuration in such a way to highly perform the task, then the contribution of the findings to the BC would be significant. This is because it can facilitate the urgent need for rapidly deploying AI tools to assist clinicians in making optimal clinical decisions by saving time, resources, and technical efforts in developing models that may result in the same or lower performance.

II LITRATURE REVIEW

2.1 Deep learning approach using CNN

Oliveiraet al [10] presented an image classification based on virtual content especially microscopic images from histopathological sections, is challenging task, facing issues such as usually large amount of inter intra class variability, depressed the ability the presence of rich geometrical structure due to structural monological diversity, and complex textures. Fig 2.1 shows typical complex textures found in histopathological images deep learning explores the possibility of learning features directly from input data avoiding hand crafted features the key call update features the key concept of deep learning is to discover multiple levels of representation aiming the higher-level features represent more abstract semantics of the data. As a particular deep learning technique CNN have achieved success in image classification problem including medical image analysis. In summary a CNN consist of multiple trainable stages stacked on top of each other followed by supervised classifier and set of arrays named future maps represents both input and output of each stage.

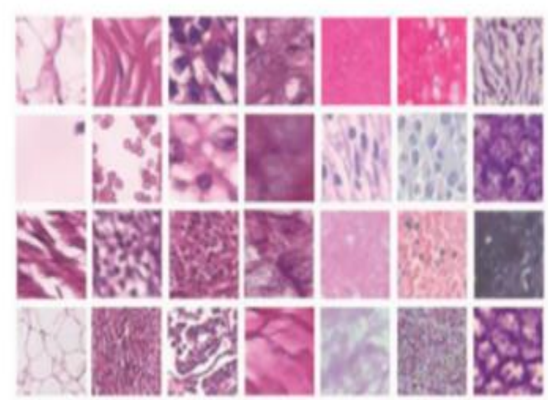

Fig 2.1 Examples of real textures present in histopathological images

There are three main types of layers used to build CNN architectures they are conventional layer,pooling layer and fully connected layer. Normally a full CNN architecture is obtained by staking several of these layers. In a CNN the key computation is the convention of afeature detector with an input signal.Conventional layer computes the output of neuros connected to local regions in the input, each one computing a dot product between their weights and the region they are connected to in the input volume. The set of weights which are convolved with the input is filter or kernel.Every filter is a small spatially (width and height) but extends through the full debt of the input volume.

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2.2Histopathology and deep learning based breast cancer image analysis

Histopathology is a technique applied for cancer diagnosis and prognostication for many decades where Pathologists analyze tissue cells under different microscopic standards. However, the pathologist's chance to come to one final decision is rare since the assessment is subjective and hence frequent use of this method become tiresome and not repeatable. In addition, issues related to slide preparation, variations in scanning across sites and staining, and biological variance among patients made the histopathological based breast cancer analysis very challenging.Debeleeet al[15]have applied the histopathological method for breast cancer image analysis using deep convolutional neural networks as a supervised classificationmethod.They adopted three deep convolutional neural network architectures (AlexNet, GoogleNet, and ResNet) in their study to classify the 260 images into four classes (normal, benign, in-situ and invasive). The original image dataset distribution for the four classes were 51 for normal, 74 for benign, 68 for In-situ and 67 for Invasive. The classification was made patch-wise and image-wise, but the performance of image-wise classification better than patch wise for all three CNN models.They have adopted two deep convolutional neural network models (Inception-V3 and Inception ResNetV2) to classify the BreaKHis histology image dataset into binary classes (Benign and Malignant) and multi-classes. The multi-class is imposed because of malignant subtypes that include ductal carcinoma (DC), lobular carcinoma (LC), mucinous carcinoma (MC), and papillary carcinoma (PC). In their experimental analysis, they found that histopathological based image classification using the two selected DCNN models were superior compared to the existing methods. And they proved that Inception-ResNet-V2 is the most performing DCNN architecture for diagnosing breast cancer using histopathological images

III METHODOLOGY

Pretrained CNNs and training parameters for transfer learning

Ultrasound scan is mostly used for examination and early detection of breast cancer. Moreover, it is safe in comparison to other radiology imaging techniques. Breast Ultrasound dataset can be used to train machine learning models which can classify, detect, and segment early signs of masses or micro-calcification in breast cancer. Researchers with interest in classification, detection, and segmentation of breast cancer can utilize this data of breast ultrasound images, combine it with other datasets, and analyze them for further insights. The data is comprehensive, containing breast cancer states (normal, benign, and malignant).Three pretrainedCNNs [11,12,13]are used like AlexNet, GoogLeNet and SqueezeNet were selected in this study. The reason for selecting these CNNs was that these three models require the least training time among other pretrained CNNs. The architectures and specification of training parameters for transfer learning of AlexNet, GoogLeNet, and SqueezeNet are described as follows.Basic properties of the three networks in terms of depth, size, numbers of parameters, and input image size are given in Table 3.1

Network	Depth	Size (MB)	Parameters(millions)	Input image size
AlexNet	8	277	61.0	227 X 227
GoogLeNet	22	27	7.0	224 X 224
SqueezeNet	18	5.2	1.24	227 X 227

Table 3.1 Basic properties of three convolutional neural networks

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Table 3.2The three classes of breast cases and the number of images in each case

Case	Number of images
Benign	487
Malignant	210
Normal	133
Total	780

Three pretrained CNNs [11,12,13] are used like AlexNet, GoogLeNet and SqueezeNet were selected in this study. The reason for selecting these CNNs was that these three models require the least training time among other pretrained CNNs. The architectures and specification of training parameters for transfer learning of AlexNet, GoogLeNet, and SqueezeNet are described.The data collected at baseline include breast ultrasound images among women in ages between 25 to 75 years old. The number of patients is 600 female patients. The dataset consists of 780 images with an average image size of 500×500 pixels. The images are categorized into three classes, which are normal, benign, and malignant. The number of images in each class is shown in Table 3.2. The data samples are illustrated in Fig. 3.1. Samples of original images and the images after preprocessing are shown in fig.3.2. Furthermore, each image has its own ground truth (mask image) as shown in fig. 3.3.

Fig 3.1 Samples of original Ultrasound breast images dataset (Original images that are scanned by the LOGIQ E9 ultrasound system).

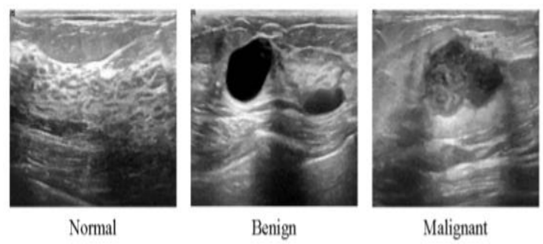

Fig 3.2 Samples of Ultrasound breast images dataset after refining.

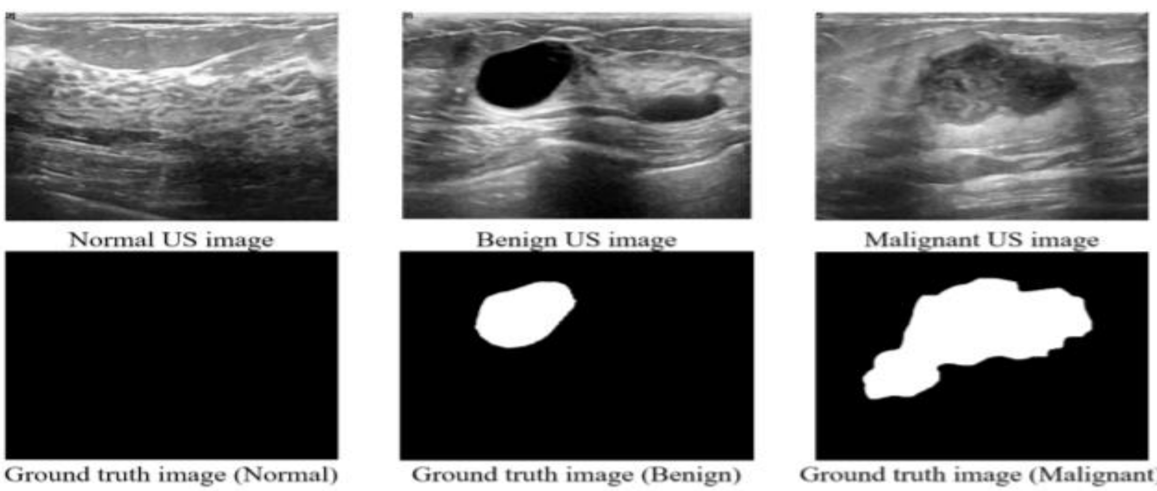

Fig 3.3 Samples of Ultrasound breast images and Ground Truth Images

These images were used for evaluating the performance of the CNNs are accuracy, sensitivity, specificity, precision, F1 score, and area under a receiver operating characteristic curve (AUC).

The sensitivity (*SEN*) is defined as the percentage of breastcancerin patients who are correctly identified as having the cancer and expressed as

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SEN=$\frac{TP}{P}$X 100 =$\frac{TP}{TP+FN}$ X 100 (1)

where *TP* is called true positive, denoting the number of breast cancer patients who are correctly identified as having the cancer, *FN* false negative, denoting the number of breast cancer patients who are misclassified as having no cancer, and *P* the total number of breast cancer patients.

The specificity (*SPE*) is defined as the percentage of non-breast cancer subjects who are correctly classified as having non cancer patients:

SPE=$\frac{TN}{N}$ X 100 =$\frac{TN}{TN+FP}$ X 100 (2)

where *TN* is called true negative and denotes the number of non-breast cancer subjects who are correctly identified as having non cancer patients, *FP* false positive, denoting the number of non-breast cancer subjects who are misclassified as having the infection, and *N* the total number of non-breast cancer.

The accuracy (*ACC*) of the classification is defined as

ACC=$\frac{TP}{TN+P}$ X 100 (3)

The precision (*PRE*) is also known as the percentage of positive predictive value and defined as:

PRE=$\frac{TP}{TP+FP}$ X 100 (4)

The F1 score is defined as the harmonic mean of precision and sensitivity:

F1=$\frac{2TP}{2TP+FP+FN}$ (5)

The receiver operating characteristic (ROC) is a probability curve created by plotting the TP rate against the FP rate at various threshold settings, and the AUC represents the measure of performance of a classifier. The higher the AUC is, the better the model at distinguishing between breast cancer and non-breast cancer cases. For a perfect classifier, AUC = 1, and an AUC = 0.5 indicates a classifier that randomly assigns observations to classes. The AUC is calculated using the trapezoidal integration to estimate the area under the ROC curve.

IV Results and Observations

The results obtained from the transfer learning of the fine-tuned AlexNet, GoogLeNet, and SqueezeNet illustrate the high accomplishment of the pretrained models for the classification of breast cancer. Due to the database updates over time and the public availability of other data collections, it is impossible to carry out exact comparisons of the results reported many other works. Comparisons with baseline works using the same datasets which strongly suggest that the fine-tuned pretrained networks achieved better performance than several other base-line methods in terms of classification accuracy, and partitions of training and testing data.

Table 4.1 Classification of the results of three CNNs

CNN	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F_1 score	AUC
90% Trainingand 10 % testing						
AlexNet	97.59 ±0.60	95.45±4.55	97.76±0.37	98.55±2.51	0.969±0.014	0.998±0.004
GoogLeNet	96.09 ±2.30	96.97 ±2.62	96.02±2.28	98.48 ±2.62	0.977 ±0.023	0.999 ±0.004
SqueezeNet	97.47 ±1.31	98.47 ±2.62	97.7 ±1.30	094.20 ±2.51	0.963 ±0.026	0.999 ±0.009
50% Training and 50 % testing						

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AlexNet	97.59 ±0.60	95.45±4.55	97.76±0.37	98.55±2.51	0.969±0.014	0.998±0.004
GoogLeNet	96.09 ±2.30	96.97 ±2.62	96.02±2.28	98.48 ±2.62	0.977 ±0.023	0.999 ±0.004
SqueezeNet	97.47 ±1.31	98.47 ±2.62	97.7 ±1.30	094.20 ±2.51	0.963 ±0.026	0.999 ±0.009

Table 4.1 shows the classification results obtained from the transfer learning of AlexNet, GoogLeNet, and SqueezeNet, using images with two different training and testing data ratios. The 3 pretrained CNNs achieved very high accuracy, sensitivity, specificity, precision, F1 score, and AUC in all cases. Particularly, GoogLeNet and SqueezeNet had almost 100% accuracy with 80% training and 20% testing data. The AUCs were almost perfect in all cases for all three CNNs.

V CONCLUSION

Breast ultrasound images can produce great results in classification, detection, and segmentation of breast cancer when combined with machine learning. AsAlexNet, GoogleNet, and SqueezeNet require the least training time among pretrained DL models, but with suitable selection of training parameters, excellent classification results can be achieved without data augmentation by these networks. The findings contribute to the urgent need for harnessing the pandemic by facilitating the deployment of AI tools that are fully automated and readily available in the public domain for rapid implementation.

In comparison with other recently developed DL models, the three pretrained CNNs achieved very high classification results in terms of accuracy, sensitivity, specificity, precision, F1 score, and area under the receiver-operating-characteristic curve.

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