Ultrasound Image Despeckling and detection of Breast Cancer using Deep CNN

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***Abstract*—Breast Cancer is a common type of cancer diagnosed and it is a leading cause of death amongst the female population worldwide. Ultrasound imaging is the preferred method used by hospitals for detection of breast cancer, due to the fact that it is much safer that other imaging modalities. However, Ultrasound images are contaminated with noise that is non-Gaussian and multiplicative referred to as speckles. Currently, medical technicians and physicians do diagnosis of breast cancer by manually inspecting the ultrasound images, which makes the process time consuming and costly. This may be considered as an issue which prevents the early detection of breast cancer. Hence, an early diagnosis of breast cancer can be beneficial in not only prescribing medical procedure that inhibits the cancer from spreading but also in minimizing the fatality rate. Due to the Speckles (noise) in ultrasound, automatic detection and diagnosis is an extremely difficult task. In this paper, a Convolutional Neural Network (CNN) has been proposed for Despeckling (Denoising) the ultrasound images and afterwards another CNN model is proposed for the classification of the ultrasound images into benign and malignant classes. The proposed models are tested on a Mendeley Breast Ultrasound dataset. Experimental results indicate that a classification accuracy of 99.89% is achieved through the proposed model and that the proposed model(s) outperform other methods in proposed in recent studies.**

Keywords—Image Despeckling, Ultrasound Noise Removal, Breast Cancer Classification, CNN

I. Introduction

Cancer is considered to be one of the most fatal ailments and a recent statistical study conducted in United States [1] has rated cancer as the second major cause of death. The cells of human body naturally age, die and get replaced by new cells. In some cases, the cells tend to grow abnormally and form a mass generally referred as tumor. The breast cancer tumors can be classified into two types; cancerous (malignant) and non-cancerous (benign). The non-cancerous tumors do not affect nearby organs and tissues, whereas the cancerous tumors are capable to spread out into various organs and tissues. The common organs for origination of cancer include breasts, lungs, skin, etc. A global statistical report of cancer affected cases from 185 countries has been presented by International Agency for Research [2]. It shows that among various types of cancers, female breast cancer is one of the commonly diagnosed cancers with 11.6% cases out of total observations and is also the leading cause of death in females. Hence, in order to reduce the mortality rate due to breast cancer, it is of prime importance to acquire an early and accurate diagnosis accompanied with immediate medical treatment.

The advances in medical imaging have aided in developing non-invasive imaging techniques for detection of various ailments. In [3], the authors have explained commonly used medical imaging schemes including Mammography (X-rays), Ultrasound (sonography), Magnetic Resonance Image (MRI), etc. Amongst the different available imaging techniques Ultrasound is the most widely used imaging modality for medical diagnostic purposes. Ultrasound is preferred over other techniques because it uses non-ionization based sound waves which are considered to be medically safe. The ultrasound transducer contains a piezoelectric crystal which sends pulses of sound waves and the echoes reflected from internal body tissues are utilized to generate an ultrasound image. Conventional ultrasound systems utilize sound frequencies ranging from 2 to 15 MHz. However, in a recent study relating to breast cancer biopsy procedures [4], the frequency range of 30 to 60 MHz has been used for better spatial resolution. A key consideration in using an ultrasound device is that overexposure and imprudent usage of device can cause tissue heating or create small pockets of gas. In contrast, exposure to ionization based medical imaging techniques (X-rays) can lead to more serious health concerns such as cancer, fainting, etc. Hence, Ultrasound imaging is preferable if it provides fair degree of clinical information. The health care providers are required to follow the principle of As Low As Reasonably Achievable (ALARA) in all types of medical diagnostic imaging modalities [5].

Ultrasound images tend to incorporate noise from various sources including the equipment used for acquisition and presence of different organs/tissues within the imagery area. The nature of noise in ultrasound images is non-Gaussian and multiplicative, usually referred as speckles [6]. Eliminating this type of noise is a relatively difficult task, as the intensity of noise varies with respect to the image intensity. The resolution and contrast of ultrasound image degrades seriously due to speckles, consequently making the medical diagnostic process difficult. Therefore, the despeckling of Ultrasound images holds a pivotal role and many research studies have been conducted in order to improve image quality either by decomposition schemes or noise by noise filtering algorithms.

The rest of the paper is organized as follows: Section II contains the literature review and section III explains the

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developing an ultrasound signal model and quality measurement parameters of ultrasound images. Section IV presents steps of proposed method for suppressing speckle noise, and classification of breast cancer ultrasound images. Section V includes the results for both real and simulated ultrasound images. Section VI presents the conclusion.

II. Literature Review

The inherent issue of speckles present in ultrasound images limits the accuracy of medical diagnosis. Hence, the filtering of speckles is of prime importance, and in recent years several studies have been undertaken to address this serious issue [7-8]. The techniques of despeckling can be divided into spatial domain and frequency domain. The traditional spatial domain linear filtering methods were proposed by Frost, Schur, Kuan, and Lee [9-10]. These filtering techniques tend to update the image pixel value by taking a weighted average of neighboring pixels, which reduces the speckles but also degrades the image quality. In [11], a modified spatial domain technique based on Anisotropic Diffusion Filters (ADF) with probabilistic memory mechanism has been presented that tends to minimize the issue of over-filtering. However, in this case the outcomes have a high dependency on parameter number of iterations. The frequency domain despeckling is based on wavelet transforms that converts the continuous-time signal into different frequency components (wavelets), essentially converting the speckles into additive noise and performing despeckling in the frequency domain [12]. The mother wavelet is used to generate the daughter wavelets by using a biased scaling coefficient. Various factors tend to put constraint on the performance of wavelet transforms including scaling, thresholding and artifacts generation due to the mother wavelet [13].

Non-local means (NLM) filtering techniques have been presented in [14] that consider a weighted averaging of window for evaluating the concerned pixel value. In this case, the degree of despeckling is improved but procedure is computationally expensive. In [15], a statistical model has been used in conjunction with NLM that performs despeckling based on statistical characteristics of speckles at the preprocessing stage. A fuzzy logic based approach is used in conjunction with NLM in [16] to eliminate the Rician noise but this technique is inefficient in preserving the edge details in image. A technique based on probabilistic NLM [17] has highlighted the defects of weight function used in traditional NLM [14], and has shown better despeckling performance. Techniques based on quantum inspired adaptive threshold functions are presented in [18] that dissociate the speckles by using a spectrum equalization procedure. In [19], a projection based despeckling method has been proposed by using the Orthogonal decomposition and creating overlapping segments to evaluate orthonormal vectors. The selection of orthonormal vectors is user dependent and it is the key parameter affecting despeckling performance of proposed scheme.

In the recent years, several machine learning based methodologies including the Convolutional Neural Networks (CNNs) have also been incorporated in medical image analysis [20-21]. These techniques tend to address various issues including the despeckling, segmentation, classification, quality assessment, etc. pertaining to ultrasound images with a higher degree of performance. The CNN models perform prediction for each pixel and the accuracy of prediction increases by utilizing the prior predicted values in next CNN model [22]. In [23], a conventional approach to use 2-D handheld ultrasound images of breast is presented, which tends be a time-consuming and operator dependent procedure. An automated whole breast ultrasound (ABUS) technique has been presented in [24] with capability to perform the whole breast scanning automatically, and showed improved accuracy in the breast cancer detection.

III. Ultrasound Image Model Literature Review

A generalized noisy image model can be described by,

$$I_{xy} = A_{xy}S_{xy} + G_{xy} \tag{1}$$

where I_{xy} and A_{xy} represent noise incorporated image and noise-free image respectively, S_{xy} and G_{xy} represent speckles and additive white Gaussian noise (AWGN) respectively, x and y represent the axial and lateral indices of image.

Speckles are the most dominant form of noise present in ultrasound images, hence the equation 1 can be simplified by eliminating the AWGN part.

$$I_{xy} = A_{xy}S_{xy} \tag{2}$$

The parameters including Resolution (α), Edge Detection (β), Signal-to-Noise Ratio (SNR), Mean Square Error (MSE), Correlation Coefficient (CC), Peak Signal-to-Noise Ratio ($PSNR$) are usually evaluated for assessment of the ultrasound image quality. α shall be low for better image resolution. β shall be closer to 1 to retain the sharpness details of edges. SNR, PSNR and CNR shall attain a high value for maximizing the actual signal value, whereas S-SNR shall attain a lower value. MSE is a measure of quality between the original and despeckled image. The Correlation Coefficient (CC) shall attain a value closer to 1, denoting a strong relationship between original and despeckled image. A detailed explanation of aforementioned parameters is provided in [3].

IV. Anticipated Method

The methodology adopted in this paper comprises of utilizing two CNN models in conjunction. The first CNN model performs despeckling, whereas the next CNN model performs classification of ultrasound images into two classes namely the benign and malignant. The performance assessment of proposed technique has been performed in comparison to various techniques available in literature including Random Forest, Support Vector Machine, Multilayer Perceptron and Naïve Bayes models.

A. Dataset Details

This paper uses the Mendeley Breast Ultrasound dataset [25] comprising of 250 images. There are 100 benign images and 150 malignant images. Fig. 1 displays samples of ultrasound benign images and malignant images. First column displays the benign images and the second column displays the malignant sample images. The images have a low resolution and are having a significant contamination of speckles. Hence, a CNN based technique will be formulated and applied on this dataset in order to perform despeckling and the effectiveness of proposed scheme will also be evaluated by observing the classification accuracy of devised scheme.

B. CNN for Despeckling

The objective of any despeckling scheme is to eliminate or minimize the adverse effects of noise, while preserving the key features. The deep learning based CNNs tend to learn

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features details from noisy image and perform an estimation of original image based on the extracted features information. CNNs have proven to be an effective tool for the image despeckling. In this work, a feed forward CNN is proposed while incorporating the Batch Normalization (BN) as well as the Rectifier Linear Unit (ReLU). The images of dataset have been denoised by employing a 20 layered CNN [26]. Speckles estimation is done by performing the residual mapping (R_{xy}) i.e. an accurate estimation of speckles $(R_{xy} \approx S_{xy})$. Afterwards, the estimation of original image is performed.

$$A_{xy} = \frac{I_{xy}}{R_{xy}} \quad (3)$$

$$L(\varphi) = \frac{1}{2} N \sum_{i=1}^{N} \| R(I_i; \varphi) - (I_i - A_i) \|_F^2 \quad (4)$$

The average MSE between residual image and estimated noise can be depicted in terms of a loss function (L). The deep net's training parameter (φ) can be learned by using the loss function. N is the set comprising of pairs of clean and noisy images. Enhancements in stabilizing the CNN training performance are achieved through BN. A CNN model of 20 layers is being using for denoising the ultrasound images before classification.

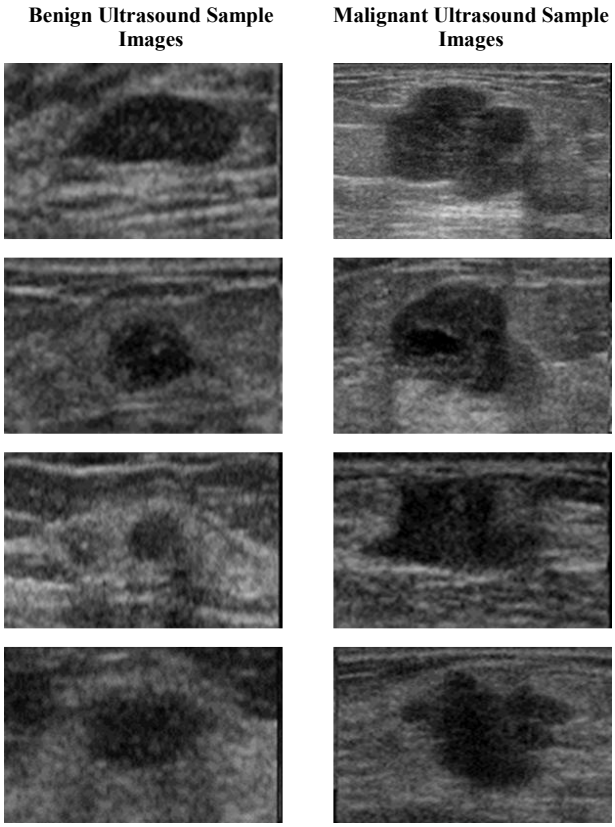

Fig. 1. Samples of Ultrasound Images. First column shows the benign and second column shows malignant samples

C. CNN for Classification

In this section, a CNN model has been proposed for the automatic classification of breast ultrasound images to either benign or malignant. The proposed model is composed of an Input Layer (IL) having a size of 28X28, two Hidden Convolutional Layers (HCLs) having a window size of 5X5, Pooling Layers (PLs) with 2X2 pooling capability and an Output Layer (OL). The HCLs have multiple features map and utilize variable weights. They are responsible for the extraction of various features from each portion of input image. In order to perform detection of same features at all the possible locations of the input image, all the units in a single features map must share the same set of weights and biases. Consequently, each features map tries to perform detection of different local features. The role of PLs is to present the information at output of HCLs in a condensed and simplified form. The fully connected OL is responsible for generating outcomes of the classification procedures.

The hierarchy of proposed model includes an IL (28X28 size), HCL-1 (20X24X24 size), PL-1 (20X12X12 size), HCL-2 (100x8x8 size), PL-2 (100X4X4 size) and OL respectively. Weights are updated by using an optimization scheme based on stochastic gradient descent, during the training phase [27].

$$W_k = W_{k-1} - \eta \frac{\partial E^m(W)}{\partial W} \quad (5)$$

where $E(W)$ is cost function, m is the sample size and η is the step size. In order to deal with issue of overfitting, a dropping out scheme has been used [28] which tends to ignore the randomly selected neurons while training. This technique leads to generalization of CNNs, by aiding in learning multiple internal representations. Furthermore, to counter the issue pertaining to overflow, a minor weight penalty is incorporated during training. The classification CNN model consists of 39 CNN layers including the input layer of size 100x100 ultrasound image while the output dense layer contains two classes either malignant or benign.

V. Expirimental Results

The experiments are performed using unprocessed as well as denoised ultrasound benign and malignant images. Table 1 contains the experimental results for the classification of the ultrasound breast cancer images into either benign or malignant. For both validation and testing, the experiments were performed on epochs sizes of 30, 60, 90, 120, 150, and 180. For unprocessed data, the best accuracy was achieved for the epoch size 180 with an accuracy of 84.02% same as the test validation accuracy achieved 100% as shown in Table 1. For processed data using CNN despeckling, accuracy increased to 88.00% for the same epoch size, which is almost 4% increase in accuracy. This is an excellent achieved and the accuracy results exceed those found in previous literature. The effect of despekling ultrasound images using neural networks is apparent in results.

TABLE I. Experimental results for classification of ultrasound Breast cancer images into Benign and Malignant

Data	**Test Validation Results**			**Testing Results**	
Results	**Epochs**	**Loss**	**Accuracy**	**Loss**	**Accuracy**
Unprocessed Data	30	0.2130	77.90%	3.3592	62.67%
	60	8.3e-6	100%	0.9682	69.33%
	90	1.1e-5	100%	1.0071	76.00%
	120	2.9e-5	100%	1.0247	80.10%
	150	6.2e-5	100%	0.8373	82.67%
	180	1.2e-4	**100%**	0.7413	**84.02%**
CNN Denoised Data	30	0.2130	88.75%	1.5486	66.67%
	60	8.3e-6	100%	0.6438	76.00%

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	90	1.1e-5	100%	0.6353	77.33%
	120	2.9e-5	100%	0.4850	82.67%
	150	6.2e-5	100%	0.4842	86.67%
	180	1.2e-4	**100%**	0.4629	**88.00%**

In Table 2, the justification for the use of CNN for despeckling ultrasound images of breast cancer is apparent. An experiment was performed for testing using five different classifiers; CNN, Support Vector Machines (SVM), Random Forest (RF), Multilayer Perceptron (MLP), and Naïve Bayes. Table 2 shows the classification accuracy of all five classifiers on both unprocessed data and CNN Denoised data. Note that since RF, SVM, MLP, and Naïve Bayes all require feature extraction; Discrete Wavelet Transform (DWT) is utilized for feature extraction for these classifiers. The CNN classifier achieved the best results for both unprocessed and CNN Denoised data with a classification accuracy of 84.02% and 88.00% respectively.

All results displayed in this paper indicate that the proposed CNN method for despeckling Ultrasound images along with the use of CNN as a classifier achieve results that exceed those reported in previous literature.

TABLE II. EXPERIMENTAL RESULTS FOR CLASSIFICATION OF ULTRASOUND BREAST CANCER IMAGES INTO BENIGN AND MALIGNANT

Classifier	Unprocessed Data	CNN Denoised Data
CNN	84.02%	88.00%
Random Forest	72.97%	81.20%
Support Vector Machine	64.75%	65.73%
Multilayer Perceptron	72.34%	74.46%
Naïve Bayes	61.70%	62.00%

VI. CONCLUSION

The early diagnosis of Breast Cancer and its classification is an extremely important task. With early diagnosis for any cancer including breast cancer, doctor may perform procedures and medication that might prove to be life saving for the patients. In this research paper, A CNN models has been proposed for the despeckling of the Breast Ultrasound Images and another CNN model is being proposed for classification of breast cancers into either benign or malignant. The proposed models were tested on the Mendeley Breast Ultrasound dataset. It has been observed that using CNN despeckler and the CNN classifier a 88.00% classification accuracy has been achieved which is higher in comparison to the accuracies of other schemes available in the literature. Future work will include identifying despeckling techniques that will work on various images with various distortions and developing deep learning architectures that will achieve the highest accuracy for any image quality. In addition, the segmentation of breast cancer will be investigated in future studies.

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