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On the Wavelet Convolution Neural Networks for Ultra-Sound Based Breast Cancer Detection

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Abstract. Breast cancer is one of the deadliest types of cancer, and it comes in a wide variety of forms, resulting in a wide variety of detection methods. Several deep learning techniques have been applied to decrease unnecessary biopsies and lessen the burden on radiologists. One of the most popular architectures for this task is the Convolutional Neural Networks (CNNs). This paper aims to explore the integration of convolutional neural networks (CNN) and wavelet transform (WT) to identify the optimal combination and architecture of these methods for efficient detection of breast cancer in ultrasound images. To accomplish this task, the wavelet convolutional neural network (WCNN) structures are proposed and trained for the mission of screening breast cancer abnormalities embedded in ultrasound type of images. Compared with other two popular networks, ResNet50 and MobileNetV2, it has been found that the proposed WCNN has produced a satisfactory solution, with an accuracy of 98.24 %, precision of 97.29%, recall of 100%, and F measure of 98.24%.

Keywords. Convolution neural network, Wavelet transformation, Breast cancer.

1. Introduction

Breast cancer remains a paramount global concern for women, being the most widespread cancer among them and resulting in countless deaths. Numerous factors can lead to its development, and alarmingly, almost a million cases remain unidentified each year. Many women face barriers in accessing diagnostic tools, causing late detections, delayed treatments, and exacerbated symptoms. Thankfully, a variety of screening methods like mammograms, needle breast biopsies, breast ultrasound (BUS), and MRI are available. Incorporating machine learning into these diagnostic processes offers a promising avenue for earlier and more accurate detection, enhancing the potential for successful treatment outcomes. [1].

Over the past decades, a large number of machine learning tools have been proposed, developed, and applied for this task. Yassi et al. [2] proposed a Fuzzy system combined

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with optimization for distinguishing breast cancer types in 2014. Amrane et al. [3] compared Naive Bayes and k-nearest neighbor classifiers in 2018, with KNN achieving 97.51% accuracy. Deep learning, like Convolutional Neural Networks (CNNs), has also made strides. Haq et al. [4] used Relief and Autoencoder PCA for feature selection, achieving 99.91% accuracy. Nawaz et al. [5] achieved 95.4% accuracy using DenseNet CNNs on histopathological images. Onjun et al. [6] enhanced CNNs with wavelet transformation, reaching 96.49% accuracy. Sriwichai et al. [7] proposed WT-CNN hybrids for improved breast cancer detection. T. Saba et al. [8] obtained 92.8% accuracy with CNNs on breast ultrasound images (only mention a few).

While many well-documented studies have been highlighted, it's worth noting that ultrasound images have not been extensively addressed by CNN-based deep learning to the best of our understanding. Additionally, the CNN can benefit from integration with other robust mathematical techniques to enhance its efficiency. To address this deficiency, our research emphasizes the use of wavelet transformation in tandem with CNN to identify breast cancer in ultrasound images.

2. Mathematical components

As noted earlier, the objective of this study is to integrate two primary components: the traditional neural network (CNN) and the wavelet transformation. In this section, we provide a concise overview of these two elements.

2.1. Convolution Neural Networks (CNN)

A typical CNN comprises input, output, and hidden layers, divided into convolution, pooling, and fully connected (FC) stages. The convolution layer identifies correlations between larger input images and lighter counterparts. Meanwhile, the pooling layer reduces computational load and the network's sensitivity to variations, aiding subsequent pattern recognition. It replaces input blocks with singular values, either through peak aggregation or averaging. The FC layer synthesizes information for final decisions. Various CNN architectures exist, differing in layer structure and count.

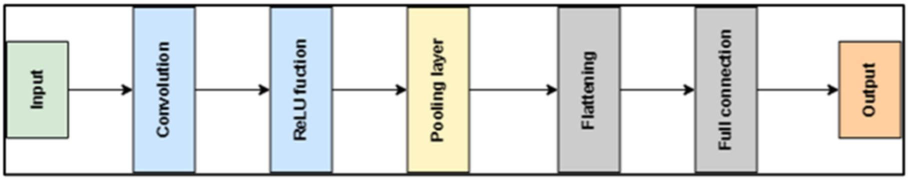


Figure 1. Typical architecture of a convolution neural network.

2.2. Heading Wavelet transformation (WT)

Wavelet Transformation is a mathematical technique used for analyzing intricate signal systems, which include different signals. It primarily works by transitioning signals from the time domain to the frequency domain. There are two main kinds of wavelet transformations: Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT). In this study, we employ DWT. Through this transformation, a signal is depicted as a combination of low-frequency signals, where wavelet coefficients act as their respective magnitudes. These coefficients are computed using low-pass and high-pass filters to derive the low-frequency and high-frequency components. Specifically, for a time-dependent signal, the low-frequency component signal at a certain resolution level and position is calculated using Eq. (1).

$$A_j(k) = \sum_{l=0}^{n} h(l) A_{j-1}(k + 2^j l) \tag{1}$$

Where h(l) is a low-pass filter, and the high-frequency component signal at j- level resolution at the k- position (i.e. $D_j(k)$) can be calculated from the difference between the two low-pass component signals at next to each other as in Eq. (2)

$$D_j(k) = A_{j-1}(k) - A_j(k) \tag{2}$$

Therefore, we can deduce that the desired $x(k)$ signal is produced by combining the high-frequency and low-frequency component signals as described below.

$$x(k) = A_n(k) + \sum_{j-1}^{n} D_j(k) \tag{3}$$

Where n denotes the resolution level and we chose seven varieties of DWT, specifically Daubechies namely Daubechies (db2).

3. Experiment preparation

3.1. Data preparation

A subset of ultrasound from Ultrasound Breast Images for Breast Cancer (UBIBC) is used to train and evaluate the proposed approach. UBIBC consists of 9,016 images as 8,116 training set, 900 testing set detailed in Table 1. The examples of ultrasound used in the work shown in the Figure 2. The preprocessing phase involves resizing the ultrasound images to meet the specifications of the suggested pretrained models. All models require images of dimensions 224×224×3. Every image is presented in a 700×460 pixel resolution, saved in PNG format, and has a 3-channel RGB with an 8-bit depth per channel.

Table 1. Details of Ultrasound Breast Images for Breast Cancer (UBIBC).

Type of dataset	Classes	Total
Training set	Benign	4,074
	Malignant	4,042
Testing set	Benign	500
	Malignant	400

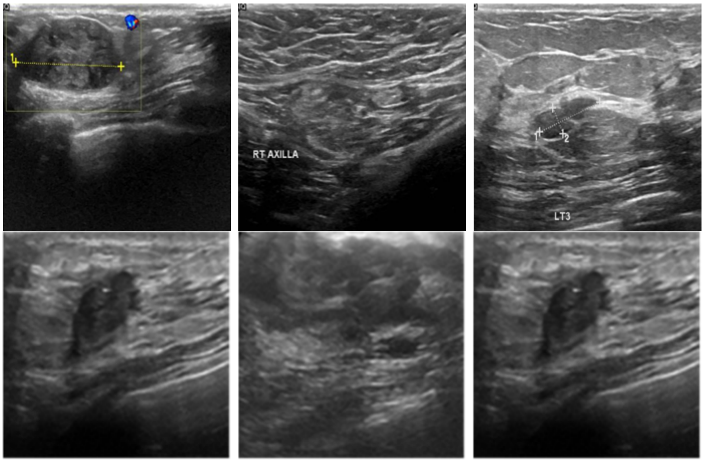


Figure 2. The example ultrasound images of benign (top) and malignant (bottom).

3.2. Experiment Design

In our research, we utilized the Python3 programming language for our experiments. We developed a neural network model by integrating wavelet transformation with a convolutional neural network, termed as wavelet convolution neural network (WCNN). Figure 3 presents the comprehensive layout of this model.

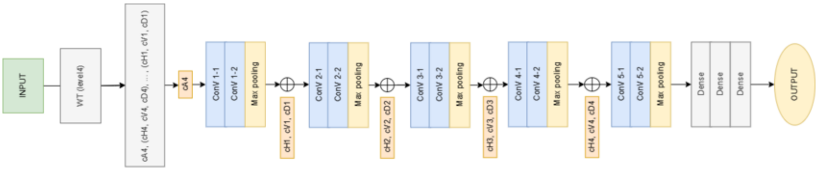


Figure 3. The detailed structure of WCNN.

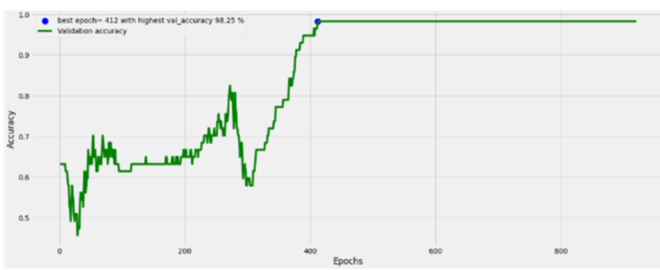
Every neural network design is processed using Adamax Optimization from start to finish. We initiate with a learning rate of 0.01, followed by decay steps set at 10,000 and a decay rate of 0.9. The batch size chosen is 32, and the Categorical Cross entropy loss serves as the loss function. These neural network structures underwent training from the ground up for a total of 1000 epochs.

3.3. Evaluation metrics

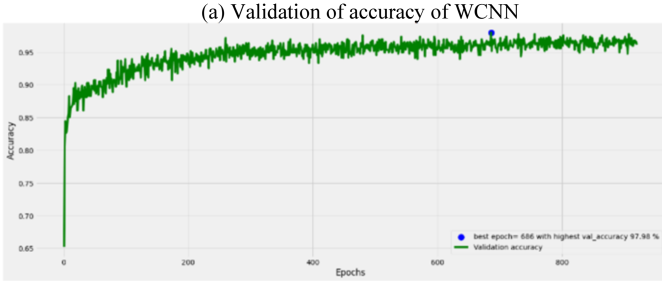
In machine learning, the confusion matrix is a widely embraced tool for evaluating classification model performance. It tallies correct and incorrect outcomes, gauging the model against real data. Accuracy, precision, recall, and F1-score are prevalent metrics. Moreover, in medical contexts, the receiver operating characteristic curve (ROC) holds significance. Thus, in our study's final phase, we compared WCNN, ResNet50, and MobileNetV2 using accuracy, precision, recall, F1-score, and the ROC curve.

4. Experiments and results

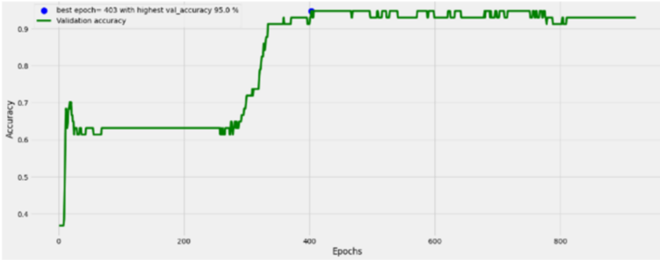
The proposed model (WCNN model) and the other two neural networks, ResNet50 and MobileNetV2, were evaluated using UBIBC images. The three CNN architectures were trained on 8,116 UBIBC images and tested on 900 UBIBC images. In the training process of the three neural network architectures, a total of 1000 epochs were conducted. After completing the training process, WCNN achieved the highest accuracy of 98.25% in epoch 412, as shown in Figure 4(a). The best accuracy for ResNet50 and MobileNetV2 was 97.98% in epoch 686 and 95.00% in epoch 403, as shown in Figures 4(b) and 4(c), respectively. Importantly, WCNN's accuracy displayed greater consistency compared to the other models, an essential characteristic in the field of diagnostics. Figure 5 showcases the ROC curve for all models, with WCNN being the frontrunner in accuracy. Its 99.21% area under the ROC curve (AUC) further underscores WCNN's dominance in breast cancer detection compared to the other models. Additionally, the system's effectiveness in accurately identifying benign and malignant cases through random selection is emphasized. Their performance metrics are presented in Table 2. Notably, the WCNN model demonstrated outstanding classification capabilities, achieving impressive metrics: accuracy (98.24%), precision (97.29%), recall (100%), and F1-score (98.24%). In comparison, the ResNet50 model posted a solid performance with an accuracy of 95.61%, precision of 95.77%, recall of 97.14%, and F1-score of 96.45%. The MobileNetV2 model also exhibited commendable results with an accuracy of 93.86%, precision of 93.15%, recall of 97.14%, and F1-score of 95.10%. Significantly, WCNN outperformed both ResNet50 and MobileNetV2 in various metrics.



(a) Validation of accuracy of WCNN



(b) Validation of accuracy of ResNet50



(c) Validation of accuracy of MobileNetV2

Figure 4. Validation of accuracy of all models.

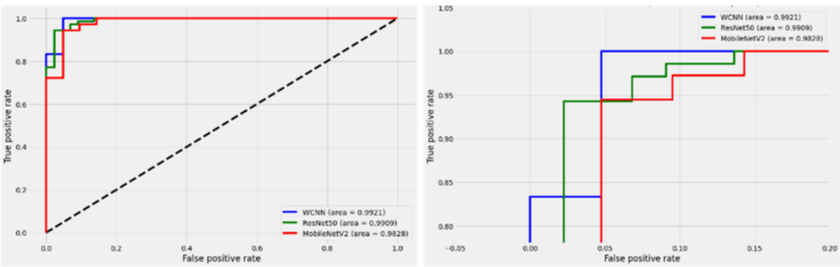


Figure 5. ROC curve of all models, with an inset zooming in on the top-left portion for more detail.

Table 2. The evaluation metrics computed from best result of WCNN, ResNet50 and MobileNetV2.

Model	Accuracy (%)	Precision (%)	Recall (%)	F-Measure (%)
WCNN	**98.24**	**97.29**	**100**	**98.24**
ResNet50	95.61	95.77	97.14	96.45
MobileNetV2	93.86	93.15	97.14	95.10

5. Conclusions

By considering the desirable features provided by the wavelet transformation (WT), this work attempts to improve the performance of the convolutional neural network (CNN) for detecting breast cancer using an ultrasound dataset. This new combination is named a ‘wavelet neural network (WCNN)’. For the sake of comparison, two other popular architectures, ResNet50 and MobileNetV2, are parallelly executed on the same dataset. It has been found in this work that WCNN has produced a satisfactory solution, with an accuracy of 98.24 %, precision of 97.29%, recall of 100%, and F measure of 98.24%. With this promising aspect of the new architecture, it is truly worth investing further as to what extent this will work for more complex problems and it is set as our future work.

Acknowledgements

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