Machine Learning and Artificial Intelligence
J.-L. Kim (Ed.)

doi:10.3233/FAIA220426

Wavelet Pooling Scheme in the Convolution Neural Network (CNN) for Breast Cancer Detection

Ratapong ONJUN[a], Kittikorn SRIWICHAI[a], Narongdech DUNGKRATOKE[a] and Sayan KAENNAKHAM[a1]
[a] *School of Mathematics, Institute of Science, Suranaree University of Technology, Nakhon Ratchasima, 30000, Thailand*

Abstract. In this work, the wavelet transformation (WT) under the context of convolution neural network (CNN) is developed and applied for breast cancer detection. The main objective is to investigate the effectiveness of the WCNN pooling architecture when compared to other two famous pooling strategies; max and average pooling, particularly targeting at the features extraction and classifying the phases of breast cancer by avoiding the under and overfitting problems. It is discovered in this work that the combination of WT and CNN outperforms the traditional and typical CNNs (with 96.49% of accuracy 95.81% of precision, 96.73% of recall and 96.23% of F measure).

Keywords. Convolution neural network, wavelet transformation, breast cancer

1. Introduction

Convolutional neural networks (CNNs) are utilized in medicine to improve predictive precision. Radiomics features collected from non-invasive CT imaging of EGFR (epidermal growth factor receptor) gene mutations in lung lymphoma was recognized by a deep learning algorithm called Squeeze-and-Excitation (SE) Convolutional Neural Network (SE-CNN) [1]. A CNN namely ConvNet was employed in [2] to diagnose information for traditional Chinese medical treatment using tooth-marked tongue data. Another medical image processing analysis focusing on tumor identification has been studied in [3] using a Novel Machine-Learning-Based Hybrid CNN Model extraction of the primary tumor size. Recently, an CNN-based app was developed by [4] to classify the 5-year survival in patients with breast cancer (5YSPBC). Pooling is an important process embed in a CNN and is used to lower the resolution of feature maps to minimize processing time. Pooling layers are often employed in three different ways [5-6]; average pooling, max pooling, and pooling in a stochastic manner.

Apart from these choices, wavelet pooling has recently become attractive in the application of medical image analysis [7-8]. Wavelet analysis was used in [9] to assess heart sound signals using a modified frequency slice wavelet transform (MFSWT) algorithm. It was deployed as part of a few recent algorithms such as in Magnetic

[1] Corresponding Author, Sayan KAENNAKHAM, School of Mathematics, Institute of Science, Suranaree University of Technology, Nakhon Ratchasima, 30000, Thailand; E-mail: sayan_kk@g.sut.ac.th.

Resonance image reformation [10], X-rays images of human body parts [11], the advanced thermal exchange [12], and the Methodology digital pathology [13].

In this work, the effectiveness of pooling process based on wavelet transformation is explored. Breast cancer detection using the histopathological images were analyzed via. a CNN with different pooling schemes for the sake of comparison. All main components involved in the work are briefly provided as follows.

1.1. Convolutional Neural Network (CNN)

CNN process has 3 major's steps, 1) convolution layer 2) pooling layer, and 3) fully connected layer, which are briefly described as follows. Convolutional layer is the part that separates the feature of the image, such as border, colour, shape, etc., where CNN has a filter to inspect to separate the elements of the image and what we get will be something called a feature map. The convolution are classified as 2 types, narrow convolution and wide convolution. Narrow convolution is used in general convolution. The process is, if we convolution the $N \times N$- sized input with the $m \times m$ filter, we get a matrix of size $(N-m+1)\times(N-m+1)$. Wide Convolution is intended to prevent data loss at the edge of the input data. The process is, if we convolution the $N \times N$- sized input with the $m \times m$ filter, we get a matrix of size $(N+m-1)\times(N+m-1)$. After the convolution is performed, the activation function is calculated. Usually, an activation function ReLu activation function is mostly used. ReLU stands for Rectified Linear Unit for non-linear operation. The output is $f(x) = max(0, x)$.

1.2. The max and the average pooling schemes

In CNN, after the data has passed through the convolution layer, it is often sent to another layer known as a pooling layer. The function of the Pooling layer is to extract the most important parts of the data and increase the efficiency of processing faster. Max pooling reduces the dimensionality of images by reducing the number of pixels in the output from the previous convolutional layer. It is done by taking the selection of the maximum pixel value as the feature of the pooling region from the input matrix. Average pooling layer is performed to down-sampling the incoming data by moving an averaged filter on the incoming data in a particular region, getting the outgoing data as a single average.

1.3. The wavelet pooling scheme

In dealing with time series types of data, one of the most popular choices of tools is the wavelet transformation. The transformation is known to originally be crated from the well-known Fourier transform but it is also known to carry more convenient features. This is true particularly for structure isolation of periodic, finite, and constant signals. In the original formation of the wavelet, there are generally two types namely 'father wavelet' noted by $\varphi(t)$, and 'mother wavelet', noted by $\psi(t)$. Two main roles are performed by them; the father is the father one is responsible for the low-frequency parts which are expressed as approximate coefficients whereas the mother takes care of the high-frequency parts expressed as detailed coefficients. Wavelets under both kinds with $j = 1, 2, 3, ..., J$ in the J-level wavelet decomposition are defined as.

$$\varphi_{j,k}(t) = 2^{-\frac{j}{2}}\varphi(t - \frac{2^j k}{2^j}), \quad \psi_{j,k}(t) = 2^{-\frac{j}{2}}\psi(t - \frac{2^j k}{2^j}), \tag{1}$$

Together with the requirements, $\int \psi(t)dt = 0$ and $\int \varphi(t)dt = 1$, with the maximum scale is denoted by J. Regarding the structures of the wavelet, based on the type of data there are two structures: Continuous Wavelet Transformation (CWT) and Discrete Wavelet Transformation (DWT). In this study, the main focus is paid on DWT only. In DWT, the analysis uses a constant scaling step. The fixed scaling step $a_0 > 1$ and $a = a_0^j$ with discretized shifting step $\tau = ka_0^j\tau_0$ where $j,k = 0,1,2,m \in \mathbf{Z}$ .Then $\psi_{j,k}$, can be written as $\psi_{j,k} = a_0^{-\frac{j}{2}}\psi(a_0^{-j}(t - k\tau_0 a_0^j))$. For a given discrete time series $f(t)$, the inner product $< f, \psi_{j,k} >$ then gives the discrete wavelet transform

$$DWT(j,k) =< f, \psi_{j,k} >= \sum_{j,k \in Z} f(t) 2^{-\frac{j}{2}}\psi(2^{-j}t - k). \tag{2}$$

The time series has been redesigned as follows.

$$f(t) = \sum_{j,k \notin Z} DWT(j,k)\psi(t). \tag{3}$$

Among different versions and type of DWT, ith the limitation of the space, this study focuses only on the so-called Daubechies (db2).

2. Experiment setups

Two neural network architectures were created, convolutional neural network (CNN) and wavelet convolution neural network (WCNN), illustrated in Figure 1. In this figure, ‘Pooling Process’ indicates where the wavelet is implemented and the multiplying numbers above each block state the size and the number of filter.

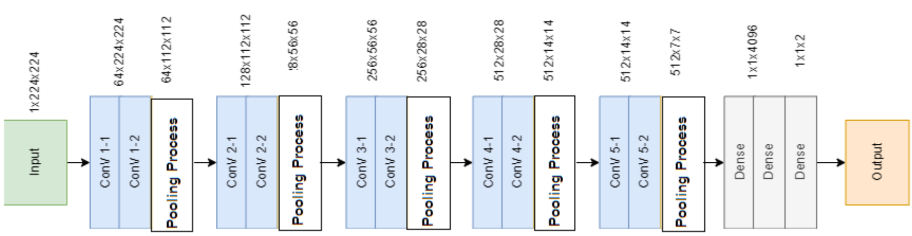

Figure 1. Typical architecture of a convolution neural network

2.1. The dataset

The dataset from Breast Cancer Histopathological Image (BreaKHis) [14] was used in the investigation. The dataset contains 7,909 microscopic images (2,480 images for benign breast tumors and 5,429 images for malignant breast tumors with various magnification, including 40x, 100x, 200x, and 400x). Each image is encoded in 700×460 pixels by PNG format, with 3-channel RGB, 8-bit depth in each channel, see Table 1. The examples of histopathological are shown in Figure 2. In our study, dataset is randomly divided into 80% training set and 20% testing set for each magnification factor. The down sampling method was used to convert the image size to 224×224 and convert all images to grayscale image.

Table 1. Details of dataset.

Classes	Magnification Factors				Total
	40x	100x	200x	400x	
Benign	652	644	623	588	2,480
Malignant	1,370	1,437	1,390	1,232	5,429

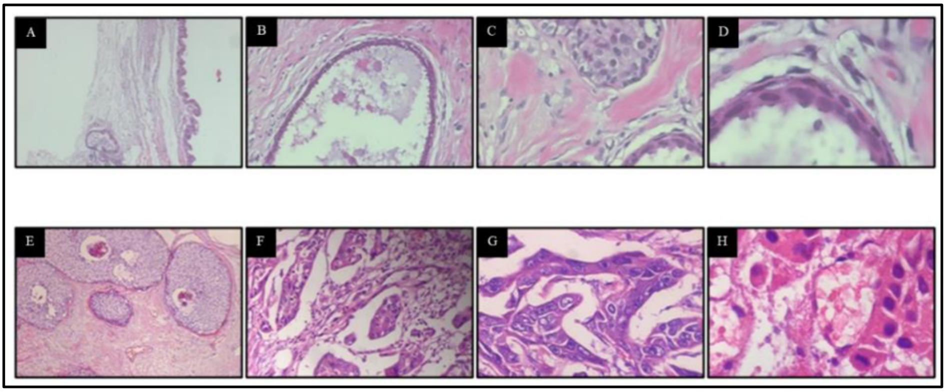

Figure 2. The example histopathological images of benign breast tumors and malignant breast tumors. (A) Benign (40x), (B) Benign (100x), (C) Benign (200x), (D) Benign (400x), (E) Malignant (40x), (F) Malignant(100x), (G) Malignant (200x) and (H) Malignant (400x).

2.2. The training setup

The entire neural network architecture is trained end-to-end by Adam optimization with a learning rate of 0.0007 and a batch size of 32 using the Categorical Cross entropy loss function. The networks are trained for 1000 epochs.

3. Main results and general discussion

Figure 3 shows that in the training process, WCNN had higher accuracy than CNN at all sizes of histopathological images. This figure has become clearer when the number of epochs reaches 600 and beyond. It strongly indicated that the more WCNN was trained, the more accurate the model became. Moreover, since it is clear that the gap between WCNN and CNN from 600 and 1000 was noticeable, there was no need to proceed beyond 1000 epochs.

Table 2 reveals that WCNN was more effective than CNN of all measurements for histopathological detection of breast cancer. WCNN was most effective at histopathological image size of 100x, achieving an accuracy of 85.22%, recall 96.60% and FMeasure 89.78% were the highest in this weaving. Nevertheless, the WCNN was found to have the highest precision using 400x histological image size. Therefore, in this experiment, WCNN outperforms CNN in all respects in terms of training accuracy, which is significantly greater than that of CNN at 600 training cycles. Apart from this, the table also showed that WCNN has high image efficiency in all measurements with peaks occurring when the histopathological image size is 100x.

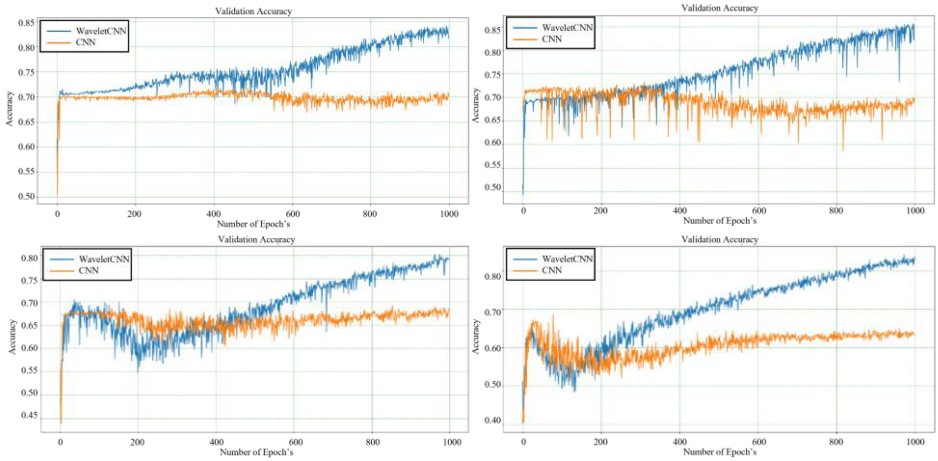

Figure 3. The accuracy curve of WCNN and CNN.

Table 2. The evaluation metrics computed from best result of WCNN in each magnification factor and compare the result to CNN.

Model	Magnification	Accuracy (%)	Precision (%)	Recall (%)	FMeasure (%)
CNN	40x	70.18	14.07	87.04	80.03
	100x	69.35	73.86	86.72	79.78
	200x	68.20	72.40	85.69	78.49
	400x	63.32	71.91	74.13	73.00
WCNN	40x	81.70	84.11	90.79	87.33
	100x	85.22	83.85	96.60	89.78
	200x	79.01	82.15	89.07	85.47
	400x	83.65	85.82	90.87	88.28

4. Conclusions

In this paper, we presented an efficient preprocessing step that was hoped to enhance the effectiveness of the typical convolution neural network with the wavelet transformation, so that it is called 'wavelet convolution neural network (WCNN)'. Breast cancer histopathological database (BreakHis) was used for improving detection of malignant lesions in breast mammograms. The proposed WCNN has been seen to produce reasonably satisfactory results (with accuracy 96.49%, precision 95.81%, recall 96.73%, and F measure 96.23%). The results point out that WCNN outperforms the other two well-known CNN architectures.

Acknowledgements

This work was supported by (i) Suranaree University of Technology (SUT), (ii) Thailand Science Research Innovation (TSRI), and (iii) National Science, Research and Innovation Fund (NSRF) (NRIIS number 160336).

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