Median Filter Noise Reduction of Image and Backpropagation Neural Network Model for Cervical Cancer Classification

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Abstract. In this paper, we consider spatial operation median filter to reduce the noise in the cervical images yielded by colposcopy tool. The backpropagation neural network (BPNN) model is applied to the colposcopy images to classify cervical cancer. The classification process requires an image extraction by using a gray level co-occurrence matrix (GLCM) method to obtain image features that are used as inputs of BPNN model. The advantage of noise reduction is evaluated by comparing the performances of BPNN models with and without spatial operation median filter. The experimental result shows that the spatial operation median filter can improve the accuracy of the BPNN model for cervical cancer classification.

Keywords—spatial operation median filter, backpropagation neural network, cervical cancer classification, colposcopy.

1. Introduction

Cervical cancer is one type cancer that occurs in the woman's cervix, it begins with the appearance of abnormal cells (dysplasia). Cervical cancer grows very slowly and the development is very difficult to be detected. Most cases of cervical cancer detected in the hospital have advanced stages, so they are difficult to be treated. Early detection of cervical cancer is very important to prevent death from cervical cancer. Detection of cervical cancer can be performed by pap smear test.

Previous researches have applied soft computing approach to classify the stadium of cervical cancer using the pap smear data. One of which is the three stages method including Adaptive Fuzzy Moving K-means clustering, feature extracting and Fuzzy Min-Max neural network [1]. The other researches involve the radial basis neural network with adaptive fuzzy K-means clustering [2], Support Vector Machine (SVM) classifier, K-nearest neighbour and artificial neural network [3], and multilayer perceptron and bayes network [4].

Detection of cervical cancer can also be analyzed by using a colposcopy test. This test is done using a colposcopy tool by enlarging the image surface of the cervix to clarify the blood vessel image. The result of colposcopy test is in the form of digital image red green blue (rgb). The image quality is often poor due to the salt and pepper noise on the image. Image enhancement to reduce the noise can be done by a spatial operation median filter. This operation can also soften the image so the image has higher pixel density. Median filter has successfully denoised the mammography image of breast cancer [5]. The median filter has also been applied to remove the noise on the CT scan images of lung regions. Based on that enhanced image, the lung cancer detection is employed by Backpropagation Network [6].
We propose the median filter to reduce the noise on the colposcopy image and backpropagation neural network (BPNN) to classify the cervical cancer stadium. The BPNN model offers advantages, since it has adaptive learning capability to carry out activities based on the data given earlier. Backpropagation algorithm trains to obtain balance between the ability of the network to recognize input pattern used during training as well as to provide the correct response to the new similar input pattern [7]. The BPNN model has been successfully applied in many fields, such as in medical diagnosis [8-12], the stock price prediction [13], the design optimization [14], and the introduction of instrumental music notation numbers [15].

The cancer detection using digital image based on the soft computing approach requires feature extraction process. Those features are composed as input variables of the model. The values of the features are supposed to characterize the surface structure of the images. The gray level co-occurrence matrix (GLCM) is one method for feature extraction. Many researchers have worked to classify cervical cancer using the feature values obtained by GLCM extraction. They use various methods of soft computing and comparing approaches, such as multilayer perceptron and bayes network [4], SVM technique in machine learning method [16], nearest neighbour classifier, baye’s classifier, and ANN classifier [17], and fuzzy neural network [18].

In this study, two BPNN models are generated to classify the cervical cancer stadium. The first model is generated relied on colposcopy image proceed by spatial operation median filter. The second model is generated relied on the original colposcopy image. We compare the performance of both BPNN models.

2. Backpropagation Neural Network Model

The BPNN model is a class of multilayer perceptron neural network, learned by using backpropagation algorithm. The other class of multilayer perceptron neural network that used backpropagation algorithm is recurrent neural network. The backpropagation algorithm to train recurrent neural network has been effectively applied in time series forecasting [19].

The architecture of the BPNN model is composed of input layer, one or more hidden layers and output layer. Each layer involves a certain number of elements called neuron. We consider the BPNN model with single hidden layer. Let the input layer consists of \( p \) variables \( X_1, X_2, ..., X_p \) and one bias \( X_0 \). The hidden layer consists of \( m \) neurons \( Z_1, Z_2, ..., Z_m \) and one bias \( Z_0 \). The value of bias is ordinarily set as a unit number “one”. In this classification problem the output layer \( Y \) is set to have single neuron.

In the hidden layer and output layer, each neuron applies activation functions. The general formula of BPNN model is determined by the activation functions. We use a bipolar sigmoid

\[
y = f(x) = \frac{1 - e^{-x}}{1 + e^{-x}}, x \in R
\]  

(1)
as the activation function in the hidden layer, and a linear function

\[
y = f(x) = x, x \in R
\]  

(2)
as the activation function in the output layer. The BPNN model with the architecture in Figure 1 and the activation function (1) and (2) can be written in the following expression

\[
y = \sum_{j=1}^{m} w_j \left( \frac{1 - \exp(-v_{ij} + \sum_{i=1}^{p} v_{ij} x_i))}{1 + \exp(-v_{ij} + \sum_{i=1}^{p} v_{ij} x_i))} \right) + w_0 + \varepsilon
\]  

(3)

where \( y \) is dependent variable (output), \( x_i \) are independent variables (inputs), \( i = 0, 1, 2, ..., p \), \( v_{ij} \) are weights and \( v_{ij} \) are bias on hidden layer from input layer, while \( w_j \) are weights on output layer from hidden layer, \( w_0 \) is bias, and \( j = 1, 2, 3, ..., m \). \( \varepsilon \) is the model error. We train the BPNN model (3) to obtain the optimal weights \( v_{ij} \) and \( w_j \) using backpropagation algorithm. The architecture of the BPNN model is presented in Figure 1.
The optimal weights in equation are (3) are reached by minimizing the function

$$MSE = \frac{1}{n} \sum_{k=1}^{n} (y_k - t_k)^2$$

where $y_k$ is the $k$th output/predicted value, and $t_k$ is the associated actual observation/target (in this problem is cervical cancer condition), and $n$ is the number of observations.

3. Backpropagation Algorithm
Backpropagation algorithm is a supervised learning algorithm that is very popular algorithm in multilayer perceptrons neural network. This algorithm is relied on error correction learning by comparing the output and the target values [20]. Backpropagation algorithm includes three phases, namely feedforward, backpropagation, and weights adjustment.

The algorithm starts with initialize weights by a small random values. Then the algorithm follows the phase described below [21].

Phase I: Feedforward
Each input neuron ($X_i$, $i = 1, \ldots, p$) receives input signal $x_i$ and sends this signal to all neurons in the hidden layer. Each hidden neuron ($z_j$, $j = 1, 2, \ldots, m$) sums the weighted input signals $x_i$ and uses a specific activation function to calculate its output signal.
\[ z_j = f(z_{inj}) = f(v_{0j} + \sum_{i=1}^{p} v_{ij} x_i) \] \tag{5}

and sends this signal to the neuron in the output layer. In this study, we only consider single output neuron. Similarly, the output neuron \((y)\) sums the weighted input signals \(z_j\) and uses activation function to calculate its output signal

\[ y = f(y_{inj}) = f(w_0 + \sum_{j=1}^{m} w_j z_j) \] \tag{6}

**Phase II: Backpropagation**

The error information is computed by comparing the output and the corresponding target as follows

\[ \delta = (t - y) f'(y_{in}) \] \tag{7}

The output utilizes \(\delta\) to calculate the weights correction, which is used to update weights \((w_j)\) later

\[ \Delta w_j = \alpha \cdot \delta \cdot z_j \] \tag{8}

and

\[ \Delta w_0 = \alpha \cdot \delta \] \tag{9}

Each hidden neuron \((z_j, \; j = 1, 2, ..., m)\) uses delta input from the output layer, then uses it to calculate its error information term \((\delta_j)\)

\[ \delta_j = \delta_{inj} f'(z_{inj}) = (\delta w_j) f'(z_{inj}) \] \tag{10}

Then, \(\delta_j\) is used to calculate the weights correction term (to update weights \((v_{ij})\) in the layer below)

\[ \Delta v_{ij} = \alpha \cdot \delta_j \cdot x_i \] \tag{11}

and bias correction term

\[ \Delta v_0 = \alpha \cdot \delta_j \] \tag{12}

**Phase III: Update weights and bias**

The output neuron \((y)\) and each hidden neuron \((z_j, \; j = 1, 2, ..., m)\) update their weights in order to obtain new weights

\[ w_{jk}(\text{new}) = w_{jk}(\text{old}) + \Delta w_{jk} \] \tag{13}

\[ v_{ij}(\text{new}) = v_{ij}(\text{old}) + \Delta v_{ij} \] \tag{14}

The algorithm will stop when the error measure (typically uses MSE) less than error target or the epoch less than maximum epoch (the number of iterations). The error target and the maximum epoch are predetermined by the researcher. The backpropagation algorithm is learned by updating the weights to increase the accuracy.

4. **Spatial Operation Median filter**

Spatial operation also called the local operation is an image enhancement technique through a two-dimensional convolution kernel. This operation delivers an output image whose pixel intensity depends on the pixels around it [22]. The formula of spatial operation can be written as

\[ f_d(x, y) = O_{\text{spatial}} (f_i(x_i, y_i)) \; , \; (x, y) \in N(x, y) \] \tag{15}

where \(f_i(x_i, y_i)\) and \(f_d(x, y)\) are input and output images, respectively, and \(O_{\text{spatial}}\) is spatial operation. The neighborhood \(N\) is the set of pixels located around \((x, y)\). The spatial operation intends to reduce the noise rising in the image. The spatial operation can be employed by mean, median, and high-pass filtering methods. In this paper we concern on median filter.

Median filter works by exchanging the pixel in the input image with the pixel median and its neighbourhood according to the size of the specified kernel. The median filter provides a very good ability in noise reduction, especially in the salt-and-pepper form. On the same kernel size, it produces
less blurring than the mean filtering. The median filter uses the odd and small kernel-size in order to minimize blurring. We use a median filter with a kernel-size 3x3. The median filter processes a black and white colours image, so this operation can run only on a grey scale image. To apply this method, the original colour (rgb) image must be converted to the greyscale image.

5. Cervical Cancer Classification
Classification addressed in this study is to detect cervical cancer stadium based on colposcopy images drawn from the medical website www.gfmer.ch data set[23]. The images consist of 83 instances that are distributed as normal, cancer stadium I, cancer stadium II, cancer stadium III, and cancer stadium IV. We examine BPNN models for cervical cancer classifications using colposcopy images with and without pre-processing of spatial operation median filter. This operation aims to improve the image quality by softening and reducing noise in the image. The example of normal colposcopy images and the associated matrices before and after spatial operation median filter are presented in Figure 2.

![Figure 2](image1.png)

**Figure 2.** The grayscale colposcopy images and the associated pixel matrices of (a) the original image (b) the spatial operation median filter image

Figure 2 (a) displays the original colposcopy image that has a lot of salt and pepper noises. They appear as white patches which spread on the image. The noises are represented in the pixel values of the associated matrix that are greatly different from the surrounding values. In that image, the numbers 217, 53, 97, and 72 are pixel values that represent the noise appearances. Figure 2 (b) displays the colposcopy image with spatial operation median filter. We can observe that the associated matrix in figure 2 (b) has nearly the same pixel values. The differences among the pixel values in figure 2 (b) are smaller than those in figure 2 (a). This indicates that the image in figure 2 (b) has the higher pixel density than the image in figure 2 (a). Therefore, the image with median filter spatial operation appears smoother and cleaner compared to the original image.

To build the BPNN model, we begin the process by defining the inputs as the features of colposcopy images extracted by GLCM method. We define 13 features as inputs, namely energy, entropy, contrast, variance, correlation, inverse difference moment (IDM), sum average, sum entropy, sum variance, difference entropy, maximum probability, homogeneity, and dissimilarity [24]. Table 1 provides the maximum, minimum, average, and standard deviation values of each feature of the entire images with and without spatial operation.

| Table 1. Descriptive of image features |
|---------------------------------------|
| Feature            | Minimum | Maximum | Average | Standard Deviation |
| Energy             |         |         |         |                   |
| Entropy            |         |         |         |                   |
| Contrast           |         |         |         |                   |
| Variance           |         |         |         |                   |
| Correlation        |         |         |         |                   |
| Inverse Difference Moment (IDM) |         |         |         |                   |
| Sum Average        |         |         |         |                   |
| Sum Entropy        |         |         |         |                   |
| Sum Variance       |         |         |         |                   |
| Difference Entropy |         |         |         |                   |
| Maximum Probability|         |         |         |                   |
| Homogeneity        |         |         |         |                   |
| Dissimilarity      |         |         |         |                   |
The output variable only involves a single neuron which represents the cervical conditions. It is a categorical variable whose values are one for normal condition, two for cancer stadium I, three for cancer stadium II, four for cancer stadium III, and five for cancer stadium IV.

The BPNN models are evaluated by cross validation. We divide the data of 83 instances become 66 instances as training and 17 instances as testing data sets. The training set aims to build the model, and the testing set aims to evaluate the capability of the obtained model to predict the cervical cancer stadium based on the data that are not used in training process.

The backpropagation algorithm is employed to train the BPNN model for attaining best network architecture. It is a network with the number of hidden neuron that delivers the best performance both in training and testing sets. It is achieved by trial and error starting from a single hidden neuron, and continuing the training process by adding the number of hidden neurons until no significant improvement in the network performance. The performance of the model is addressed to the accuracy value, which is computed as follows

\[
\text{Accuracy} = \frac{\text{The number of correct classifications}}{\text{The number of observations}} \times 100\% \quad (16)
\]

In each architecture, the algorithm is exercised to achieve the optimal weights which are attained by minimizing the MSE (4). We do trial and error from a single hidden neuron until 13 hidden neurons. The results of the BPNN models with and without spatial operation in term of accuracy performances are presented in table 2. Table 2 demonstrates that the best architecture of BPNN models with and without median filter spatial operation are the models with respective number of hidden neurons 10 and 12. On the training data, both models reach the perfect performances, which are revealed from percentage of accuracy 100%. All 66 instances that consist of 21 normal, 14 stadium I, 14 stadium II, 10 stadium III, and 7 stadium IV are correctly classified. The experiment proves that reducing the noise by the spatial operation can increase the accuracy of the model, specifically on testing data. That assertion is supported by the result in table 2 that each BPNN model with median filter always performs better than each BPNN model without median filter in the same number of hidden neuron. Specifically, at the optimal number of hidden neuron, the spatial operation median filter can increase the accuracy from 82% (without spatial operation) to 88.24% (with spatial operation).

The results of the predicted classifications for each cervical condition on testing data are presented in table 3 and table 4.

### Table 2: Accuracy of BPNN models with and without spatial operation

| Input Variables | With Spatial Operation | Without Spatial Operation |
|-----------------|------------------------|--------------------------|
|                 | Max        | Min        | Average  | STDV | Max   | Min   | Average  | STDV |
| Energy          | 0.41       | 0.12       | 0.25     | 0.07  | 0.39  | 0.10  | 0.24     | 0.07  |
| Entropy         | 2.10       | 1.24       | 1.74     | 0.28  | 2.57  | 1.29  | 1.84     | 0.29  |
| Contrast        | 0.19       | 0.04       | 0.08     | 0.03  | 0.29  | 0.05  | 0.12     | 0.05  |
| Variance        | 37.25      | 6.33       | 20.96    | 7.53  | 37.24 | 6.39  | 20.87    | 7.37  |
| Correlation     | 0.99       | 0.93       | 0.96     | 0.02  | 0.99  | 0.85  | 0.95     | 0.03  |
| IDM             | 1.00       | 1.00       | 1.00     | 0.00  | 1.00  | 1.00  | 1.00     | 0.00  |
| Sum Average     | 12.10      | 4.79       | 8.74     | 1.67  | 12.11 | 4.81  | 8.72     | 1.64  |
| Sum Entropy     | 2.27       | 1.21       | 1.68     | 0.26  | 2.37  | 1.25  | 1.75     | 0.27  |
| Sum Variance    | 117.46     | 14.64      | 57.88    | 25.23 | 116.05 | 14.59 | 56.45    | 24.08 |
| Difference Entropy | 0.45     | 0.15       | 0.27     | 0.07  | 0.58  | 0.19  | 0.35     | 0.09  |
| Maximum probability | 0.57    | 0.19       | 0.37     | 0.10  | 0.55  | 0.17  | 0.36     | 0.10  |
| Homogenity      | 0.98       | 0.92       | 0.96     | 0.01  | 0.98  | 0.88  | 0.95     | 0.02  |
| Dissimilarity   | 0.16       | 0.03       | 0.08     | 0.03  | 0.25  | 0.05  | 0.11     | 0.04  |

*STDV = standard deviation
Table 2. The accuracy (%) of BPNN Model

| The number of hidden neuron | With spatial operation | Without spatial operation |
|-----------------------------|------------------------|--------------------------|
|                             | Training               | Testing                  | Training   | Testing     |
| 1                           | 27.27                  | 35.29                    | 44         | 29          |
| 2                           | 54.55                  | 58.82                    | 56         | 29          |
| 3                           | 54.55                  | 52.94                    | 77         | 23          |
| 4                           | 66.67                  | 64.71                    | 83         | 59          |
| 5                           | 60.61                  | 47.06                    | 85         | 41          |
| 6                           | 81.82                  | 64.71                    | 92         | 59          |
| 7                           | 90.91                  | 70.59                    | 95         | 41          |
| 8                           | 100                    | 64.71                    | 100        | 59          |
| 9                           | 100                    | 76.47                    | 94         | 53          |
| 10                          | 100                    | 88.24\textsuperscript{a} | 100        | 59          |
| 11                          | 100                    | 64.71                    | 100        | 53          |
| 12                          | 100                    | 88.24\textsuperscript{a} | 100        | 82\textsuperscript{a} |
| 13                          | 100                    | 76.47                    | 100        | 47          |
| 14                          | 100                    | 64.71                    | 100        | 29          |

\textsuperscript{a} The best BPNN model

Table 3. The predicted classifications of BPNN model with spatial operation on testing data

| Actual Diagnosis | The BPNN Classifications | Total |
|------------------|--------------------------|-------|
|                  | Normal | Std.I | Std.II | Std.III | Std.IV |
| Normal           | 4      | 3     | 2      | 3       | 5      | 17    |
| Std.I            | 3      | 1     | 1      |         |        |       |
| Std.II           | 2      | 1     |        |         |        |       |
| Std.III          | 3      |       |        |         |        |       |
| Std.IV           | 3      |       |        |         |        |       |
| Total            | 4      | 3     | 2      | 3       | 5      | 17    |

Table 4. The predicted classifications of BPNN model without spatial operation on testing data

| Actual Diagnosis | The BPNN Classifications | Total |
|------------------|--------------------------|-------|
|                  | Normal | Std.I | Std.II | Std.III | Std.IV |
| Normal           | 3      | 3     | 1      | 3       | 1      | 4     |
| Std.I            | 3      | 1     |        |         |        |       |
| Std.II           | 3      |       |        |         |        |       |
| Std.III          | 3      |       |        |         |        |       |
| Std.IV           | 1      | 2     | 3      |         |        |       |
| Total            | 3      | 3     | 4      | 5       | 2      | 17    |

Referring to table 3 and table 4, it can be perceived that two instances of stadium I and stadium II in BPNN with spatial operation are misclassified as stadium III, and the remaining instances are correctly classified. While three instances contain normal, stadium I and stadium IV in BPNN without spatial operation are misclassified.
If we focus only on the non cancerous and cancerous cervical conditions, we can evaluate the performance of BPNN model in term of specificity and sensitivity. There are four possibilities that can occur in the diagnosis, they are true positive (TP), true negative (TN), false positive (FP), and false negative (FN). The diagnosis refers to true positive if the diagnostic test of cancerous cervical condition leads to cancerous cervical condition. Similarly, the diagnosis refers to true negative if the diagnostic test of non cancerous cervical condition leads to non cancerous cervical condition. The diagnosis refers to false positive if non cancerous cervical condition is detected as cancerous cervical condition. Finally, the diagnosis refers to false negative if cancerous cervical condition is detected as non cancerous cervical condition. The following formulas define the specificity and sensitivity in terms of TP, TN, FN, and FP.

\[
\text{Sensitivity} = \frac{TP}{TP + FN} \times 100\%
\]

\[
\text{Specificity} = \frac{TN}{TN + FP} \times 100\%
\]

On the training data, all instances are well classified, so the FN and FP values are zero. Thus, the sensitivity and specificity values are 100% for both BPNN models. Table 5 shows the diagnosis results of cervical cancer on testing data which have been grouped in the TP, TN, FP, and FN values.

Table 5. The Diagnosis result of the BPNN Model on testing data

| Diagnose | With spatial | Without spatial |
|----------|--------------|-----------------|
| Cancer   | TP=13        | TP=13           |
|          | FP=0         | FP=0            |
| Non Cancer | FN=0       | FN=1            |
|          | TN=4         | TN=3            |

The sensitivity and specificity values are computed by using (17) and (18). The sensitivity and specificity values are both 100% for the BPNN model with spatial operation, 100% and 75% for the BPNN model without spatial operation, respectively. The BPNN model with spatial operation is as well as the one without spatial operation in terms of sensitivity, both reach 100%. This fact suggests that both types of colposcopy images can be used properly to detect the present of cancer cervical. The specificity value of the BPNN model with spatial operation performs better than that of the BPNN model without spatial operation median filter, means that the operation can increase the capability of the image to detect the absent of cancer cervical.

6. Conclusion

In this study, we propose the spatial median filter operation to enhance the quality of cervical colposcopy images, especially to reduce the noise of images in the salt-and-pepper form. The BPNN model is applied to the cervical colposcopy images with and without the spatial operation for classifying stadium of cervical cancer. We extract the colposcopy images by GLCM method obtain 13 parameter values. Those parameters are set as input variables of BPNN model. To evaluate which model is better we split the data as training and testing data set. The backpropagation algorithm is applied to train the model in order to obtain the weights of the model with the best performance. The performance of the model is evaluated by considering the sensitivity, the specificity, and the accuracy values. The result reveals that the BPNN model with the spatial operation median filter is more accurate than the BPNN model without spatial median filter operation.

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