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# Point Operation to Enhance the Performance of Fuzzy Neural Network Model for Breast Cancer Classification

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**Abstract:** Stadium of breast cancer can be detected by using mammographic images. The accuracy is strongly influenced by the image quality. In this study, we propose a point operation of intensity adjustment to enhance the quality of the images. We implement the Fuzzy Neural Network (FNN) Model for breast cancer classification based on the enhaced mammographic images. Then, the images are extracted by using Gray Level Co-occurrence Matrix (GLCM) method to obtain the parameter values of the images. The fuzzification of the parameter values is required to generate the inputs of the FNN Model which are in the form of fuzzy numbers instead of classic numbers. We compare the performances of the FNN models with and without the point operation. The results demonstrate that on the training data both FNN models deliver satisfied performance with no misclassified data. While on the testing data, the FNN Model with point operation outperforms the FNN model without point operation. This result suggests a strong effectiveness of the mammographic images preprocessing point operation to increase the accuracy of the FNN Model to classify breast cancer.

**Key words:** Point operation, Fuzzy Neural Network (FNN), breast cancer, mammographic images, models, GLCM

## INTRODUCTION

Breast cancer is the growth of cells in breast tissue which is abnormal, continuous, uncontrolled and unlimited. Breast cancer detection corresponds to the classification problem. The previous studies focus not only on the medical approach but also on the soft computing approach. Several works use data features of Wisconsin breast cancer dataset. They are computed from a digitized image of a Fine Needle Aspirate (FNA) of a breast mass to classify breast cancer into benign or malignant. The related researches include general regression neural network, Multilayer Perceptrons (MLP) and probabilistic neural network (Kiyani and Yildirim, 2004), SVM tuning systems with different parameters and SOM-RBF classifier (Mu and Nandi, 2007), fuzzy C-means clustering RBF (Al-Daoud, 2010) and neuro-fuzzy system (Keles and Keles, 2013).

Classification of breast cancer can also be employed by using mammography. Mammography is the process of human breast examination using low-dose X-rays. The result of mammography is in the form of digital image grayscale. The extraction of digital image is needed to obtain the parameter values of the image by using the Gray Level Co-occurrence Matrix (GLCM) method (Zadeh *et al*., 2013). The values are expected to represent the condition of breast cancer and they can be considered as variables that can classify the breast cancer. Many researchers are interested in drawing on those parameter values as breast cancer classification tool by soft computing approach. They utilize them through a combination of artificial neural network and genetic algorithm (Zadeh *et al*., 2013; Nirouei and GITI, 2007; Thein and Tun, 2015) and a meta-cognitive RBF network and its projection based learning algorithm (Babu and Suresh, 2013).

The accuracy of the model used in the classification breast cancer is strongly determined by the quality of the mammographic image. The image intensity is one characteristic that represents the image quality which is often found improper. We propose intensity adjustment point operation to improve the intensity of mammographic image. Researches deal with point operation utilization for cancer detection are still infrequent. The result using fuzzy approach (Ayun and Abadi, 2016) delivers the effectiveness of the point operation in improving the model accuracy.

The studies of the classification of the breast cancer stadium are still underway by various methods, one of which is the Fuzzy Neural Network (FNN). The FNN model has a network architecture designed to process fuzzy data (Park and Han, 2000). The FNN Model offers advantages, since in which the fuzzy logic provides an inference mechanism under cognitive

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uncertainty while computational neural networks offer exciting advantages such as learning, adaptation, fault-tolerance, parallelism and generalization (Fuller, 1995). The application of the FNN Model has been carried out for various purposes such as for thyroid and breast cancer diagnosis (Senol and Yildirim, 2009) for speech recognition system (Kumar *et al*., 2011) and for polysurgery visits estimation (Rahmadiani and Anggraeni, 2012).

In this study, the FNN Model is examined to classify breast cancer stadium using mammographic images where the preprocessing data is performed using point operation of intensity adjustment. Then, we compare the performances of the FNN Model combined with point operation intensity adjustment and the one without point operation intensity adjustment. The result shows that the FNN Model with point operation intensity adjustment provides better performance than simply using the original mammographic image.

## MATERIALS AND METHODS

**Fuzzy Neural Network Model:** In this study, we first present a brief description of basic concept of fuzzy, including fuzzy set, member function, fuzzy number and fuzzy operator.

**Basic concept of fuzzy number:** A fuzzy set is introduced by Zadeh *et al.* (2013) as a means to represent and manipulate uncertain data that it is vague (Fuller, 1995). If X is a collection of objects denoted by x, then fuzzy set A in X is a set of sequential pairs:

$$A = \{(x, \mu_A(x)|x \in X)\} \tag{1}$$

where, $\mu_A(x)$ is a degree of membership of x in A, it is a function that maps X into the interval (0, 1). Fuzzy number can simply be defined as fuzzy set in real number set R. More precisely, A is called a fuzzy number if A is normal and convex (Klir *et al*., 1997). Two classes of fuzzy number that frequently used in practice are triangular and trapezoidal fuzzy numbers. We deliberate only trapezoidal fuzzy number through this study. A fuzzy set A in R has trapezoidal membership function:

$$\mu(x) = \begin{cases} 0 & \text{if} \quad x<a \text{ or } x>d \\ \dfrac{x-a}{b-a} & \text{if} \quad a \leq x<b \\ 1 & \text{if} \quad b \leq x \leq c \\ \dfrac{d-x}{d-c} & \text{if} \quad c<x \leq d \end{cases} \tag{2}$$

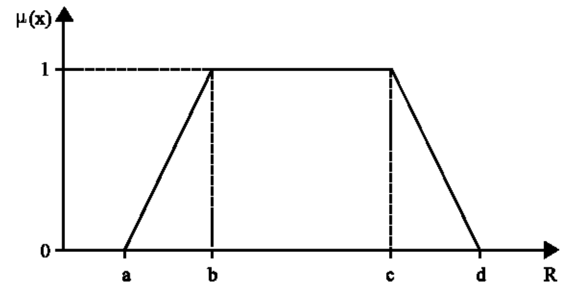


Fig. 1: Trapezoidal fuzzy number

It is called trapezoidal fuzzy number. The trapezoidal function is presented in Fig. 1. To fuzzify the crisp number, we need to combine and modify two fuzzy sets using fuzzy operator. There exist three basic fuzzy operators, involving AND OR and NOT. Here, we utilize AND operator which is defined as:

$$\mu_{A \cup B} = \max(\mu_A(x), \mu_B(x)) \tag{3}$$

**Fuzzy Neural Network Model:** The FNN Model is a hybrid model combining fuzzy logic and neural network. The FNN Model preserves the network architecture and learning ability and simply fuzzify the crisp network parts. The class of FNN Model depends on which parts of the network are substituted by fuzzy number. Accordingly, the fuzzification can be in the inputs, connection weights or outputs (Fuller, 1995). In classification problem, the output contains categorical data, it does not require fuzzyfication. Therefore, we consider the class of FNN Model by substituting the crisp inputs with fuzzy numbers.

Let $X_1, X_2, ..., X_p$ are fuzzy input variables and Y is a single crisp output variable. Hence, the architecture of the FNN model with single hidden layer can be displayed as in Fig. 2. We set a standard sigmoid function:

$$f(x) = \frac{1}{1+e^{-\sigma x}}, x, s \in R \tag{4}$$

As the activation function in the hidden layer and a linear function:

$$f(x) = \sigma x, x, \sigma \in R \tag{5}$$

As the activation function in the output layer. The FNN Model with the architecture in Fig. 2 and the activation function Eq. 4 and 5 can be written in the following expression:

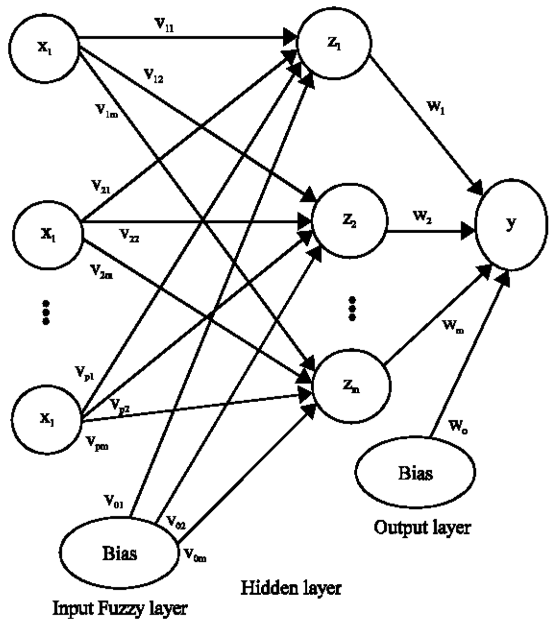


Fig. 2: The architecture of the FNN Model with single hidden layer

$$y = \sum_{j=1}^{m} w_j \left(1 + \exp\left(-v_{0j} + \sum_{i=1}^{p} x_i v_{ij}\right)\right)^{-1} + w_0 + \varepsilon \qquad (6)$$

Where:

- $y$ = Dependent variable (output) are independent variables (inputs), $i = 0, 1, 2, ..., p$
- $v_{0j}$ = Bias
- $v_{ij}$ = Weights on hidden layer from input layer
- $w_j$ = Weights on output layer from hidden layer is bias $j = 1, 2, 3, ..., m$
- $\varepsilon$ = Model error

We train the FNN Model (Eq. 6) to obtain the optimal weights $v_{ij}$ and $w_j$ and bias $v_{0j}$ and $w_0$ using backpropagation algorithm (Kusumadewi and Hartati, 2010). The optimal weights are reached by minimizing the function:

$$E = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \qquad (7)$$

Where:

- $y_i$ = The ith actual observation/target (in this problem breast cancer condition)
- $y_i$ = The associated predicted value
- $n$ = The number of observations

**Point operation intensity adjustment:** Point operation is an image processing that can only be done on a single pixel and is also known as a point wise operation. This operation accesses the pixel at a given location, modifies it by linear or non-linear operations and places the new pixel value at the corresponding location in the new image (Munir, 2004). This operation is repeated for the entire pixels in the image. Mathematically, point operation is expressed as:

$$f_B(x, y) = O_{point}(f_A(x, y)) \qquad (8)$$

Where:

- $f_A(x, y)$ and $f_B(x, y)$ = Input image and output image, respectively
- $O_{point}$ = Point operation

The point operation is employed by modifying the histogram of the input image to be adequate to the expected characteristics. A histogram of an image is a graph that shows a frequency distribution of pixel intensity values of an image.

The point operation consists of an intensity a geometric or a combination of both adjustments. We focus on the intensity adjustment throughout this study. Intensity adjustment runs by linear mapping of intensity values in the underlying histogram to ones in the new histogram.

## RESULTS AND DISCUSSION

**Breast cancer classification:** The combination FNN-point operation method is examined using breast mammographic images taken via website Mammographic Image Analysis Society (MIAS) database. The data consist of 120 instances that are distributed as normal, benign and malignant. We study the FNN Model relied on two image types involving image with and without data preprocessing of point operation. The data preprocessing of point operation aims to enhance the quality of the mammographic image. This method adjusts the intensity of the image that can be figured out from the histogram of the pixel frequency distribution. Figure 3 and 4 show the examples of the mammographic images before and after point operations, respectively.

The histogram in Fig. 3 indicates that the image has a low pixel at the intensity below 40 and above 225 and Fig. 4 reveals that it has a higher pixel at the entire intensity values range from 0 until 255.

In order to define the input of the FNN Model, the images are extracted using Gray Level Co-occurrence Matrix (GLCM). This process leads to obtain the parameters values that used as input variables. We derive 13 parameters of the images, namely contrast, correlation, energy, homogeneity, entropy, variance, Inverse Difference Moment (IDM), sum average, sum entropy, sum variance, difference entropy, maximum probability

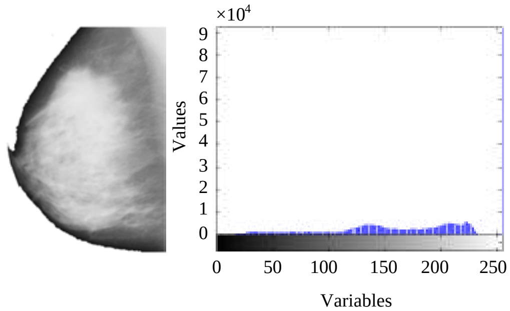


Fig. 3: The mammographic image and the associated histogram before the implementation of point operation

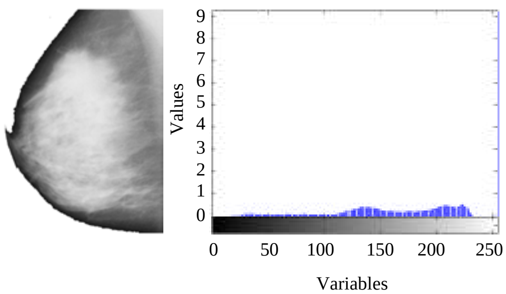


Fig. 4: The mammographic image and the associated histogram after the implementation of point operation

Table 1: Descriptive of parameters used for training FNN

| | Without point operation | | With point operation | |
|---|---|---|---|---|
| Input variables | Max. | Min. | Max. | Min. |
| Contrast | 0.22 | 0.11 | 0.24 | 0.15 |
| Correlation | 0.99 | 0.95 | 0.99 | 0.95 |
| Energy | 0.61 | 0.19 | 0.72 | 0.18 |
| Homogeneity | 0.98 | 0.96 | 0.98 | 0.95 |
| Entropy | 2.09 | 1.04 | 2.19 | 0.82 |
| Variance | 57.05 | 30.73 | 58.12 | 29.28 |
| IDM | 1.00 | 1.00 | 1.00 | 1.00 |
| Sum average | 14.92 | 10.53 | 15.06 | 10.07 |
| Sum entropy | 2.00 | 0.99 | 2.07 | 0.78 |
| Sum variance | 200.50 | 89.94 | 210.50 | 82.58 |
| Difference entropy | 0.33 | 0.18 | 0.38 | 0.20 |
| Maximum probability | 0.78 | 0.29 | 0.85 | 0.26 |
| Dissimilarity | 0.10 | 0.05 | 0.13 | 0.06 |

and dissimilarity (Haralick *et al*., 1973). Table 1 provides the maximum and minimum values of each variable of images data set with and without point operation. Those values are important for defining the universal sets on the fuzzification process.

Based on the values listed in Table 1, the fuzzy membership functions (Eq. 2) are generated for all parameters. Here, we generate 9 fuzzy sets for each parameter and use Eq. 3 to determine the fuzzy inputs. An output/target variable is a single neuron whose values consist of exactly three neurons due to the number of breast cancer classifications. They are one for normal condition, two for benign and three for malignant. We have the architecture consisting of an input layer with 13 neurons a hidden layer with 1 until 10 neurons and an output layer with a single neuron.

To build the FNN model we split the data become training and testing data set to evaluate the performance of the FNN Model. Out of 120 instances, 96 instances have been exercised for training and 24 instances have been exercised for testing purposes.

The models are evaluated in term of three performances, namely specificity, sensitivity and accuracy, both for training and testing data. The concepts relates to several terms those are True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). If the diagnostic test of a patient who actually having disease is also having disease, the result of diagnostic is denoted as true positive. Similarly, if the diagnostic test of a patient who actually having no disease shows having no disease as well, the test result is true negative. On the contrary, if the diagnostic test of a patient who actually having no disease is suggested having disease, the result of diagnostic is denoted as false positive. If the diagnostic test of a patient who actually having disease shows having no disease, the test result is false negative. The specificity and sensitivity are expressed in terms of TP, TN, FN and FP as follows:

$$\text{Sensitivity} = \frac{TP}{TP + FN} \times 100\% \tag{8}$$

$$\text{Sensitivity} = \frac{TN}{TN + FP} \times 100\% \tag{9}$$

The accuracy is simply defined as:

$$\text{Accuracy} = \frac{\text{The number of correct of classifications}}{\text{The number of observations}} \times 100\%$$

The back propagation algorithm is proceed to obtain the number of hidden neuron that gives the optimal model by considering the performances on training and testing data set. The accuracy for the FNN models with and without point operations are presented in Table 2 and 3 shows that best FNN models with and without point operations lead to the models with 6 hidden neurons. The algorithm can provide appropriate performances on training set which are indicated from the results of the best FNN models with no misclassification. The distributions of normal, benign and malignant breasts are 32 instances each and all are correctly classified.

The experiment result also shows that the point operation can significantly improve the accuracy of the

Table 2: The accuracy (%) of FNN model

| The number of hidden neuron | With point operation | | Without point operation | |
|---|---|---|---|---|
| | Training | Testing | Training | Testing |
| 1 | 48.90 | 37.50 | 43.75 | 25.00 |
| 2 | 62.50 | 50.00 | 72.92 | 20.83 |
| 3 | 82.29 | 58.33 | 84.38 | 25.00 |
| 4 | 93.75 | 58.33 | 91.67 | 37.50 |
| 5 | 96.88 | 70.83 | 96.88 | 29.17 |
| 6* | 100.00 | 79.17 | 100.00 | 54.17 |
| 7 | 100.00 | 70.83 | 100.00 | 25.00 |
| 8 | 100.00 | 75.00 | 100.00 | 29.17 |
| 9 | 100.00 | 70.83 | 100.00 | 25.00 |
| 10 | 100.00 | 70.83 | 100.00 | 20.83 |

Table 3: The distribution of classifications on testing data

| Actual diagnosis | The FNN classifications | | | |
|---|---|---|---|---|
| | Normal | Benign | Malignant | Total |
| **With point operation** | | | | |
| Normal | 8 | | | 8 |
| Benign | 1 | 5 | 2 | 8 |
| Malignant | 1 | 1 | 6 | 8 |
| Total | 10 | 6 | 8 | 24 |
| **Without point operation** | | | | |
| Normal | 1 | 4 | 3 | 8 |
| Benign | 1 | 5 | 2 | 8 |
| Malignant | 1 | | 7 | 8 |
| Total | 3 | 9 | 12 | 24 |

Table 4: The performance of the FNN model

| Diagnose | With point operation | | Without point operation | |
|---|---|---|---|---|
| | Present | Absent | Present | Absent |
| **Training data set** | | | | |
| Positive | TP = 64 | FP = 0 | TP = 64 | FP = 0 |
| Negative | FN = 0 | TN = 32 | FN = 0 | TN = 32 |
| **Testing data set** | | | | |
| Positive | TP = 14 | FP = 0 | TP = 14 | FP = 7 |
| Negative | FN = 2 | TN = 8 | FN = 2 | TN = 1 |

model. It can be perceived on testing data results, specifically from the accuracy of the best model that increases from 54.17% (without point operation) to 79.17% (with point operation) and generally from the accuracy of the models with point operation that are always higher than the accuracy of the models without point operation for every hidden neuron amount. The distributions of the actual and predicted classifications are given in Table 3. It can be seen that the FNN with point operation delivers satisfied result where all normal instances are well classified. On the contrary, the FNN without point operation only yields one normal instance that is correctly classified. For benign instance, the FNN with point operation performs well as the FNN without point operation. For the malignant instance, the FNN without point operation is slightly performs better than the FNN with point operation.

The performances of FNN Model in terms of sensitivity and specificity are calculated by using Eq. 8 and 9 and the TP, TN, FP and FN values are summarized in Table 4. The yielded sensitivity and specificity values on training data set are all 100% or no misclassified for both FNN Model. However, on the testing data set their values are 87.5 and 100% for the FNN Model with point operation, 87.5 and 12.5% for the FNN Model without point operation.

It is surprising that the FNN Model with point operation works well as the one without point operation in term of sensitivity, it means that the intensity enhancement cannot increase the capability of the images to detect the present of the disease of the patient. The specificity value 100% suggests that the intensity enhance by point operation of mammographic images can be used properly to detect the absent of the disease of patient and the specificity value 12.5% of the original mammographic images suggests the opposite result. These results subscribe to the results of fuzzy approach to the same problem (Ayun and Abadi, 2015). The sensitivity of fuzzy models (Ayun and Abadi, 2015) with and without point operation perform properly whose values are 93.75 and 87.5%, respectively. While the specificity values are 87.5 and 37.5%, respectively.

## CONCLUSION

In this study, the hybrid method of the FNN Model and point operation intensity adjustment has been applied to classify the breast condition of normal, benign and malignant using mammographic images. The initial inputs are defined as the parameters values extracted from the images by GLCM method, consisting of 13 parameters. The trapezoidal membership function is deliberated to fuzzify crisp input variables. The result reveals that the point operation intensity adjustment to mammographic images can work effectively in improving the accuracy of the FFN Model, specifically in detecting the absent of the disease of the patient.

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