

Breast Cancer Classification using a Hybrid Model of Fuzzy and Neural Network

Dhoriva Urwatul Wutsqa, Agus Maman Abadi, and Nurhayadi

Abstract—In this study, breast cancer has been successfully classified by using a hybrid model of fuzzy and neural network. For this purpose, we propose two-hybrid models namely fuzzy neural network (fuzzy NN) and fuzzy radial basis function neural network (fuzzy RBFNN). The backpropagation algorithm is employed to estimate the weights of the fuzzy NN model. The K-Means clustering and singular value decomposition are developed to estimate the parameters of the fuzzy RBFNN. The benign and malignant breast tissues data drawn from Wisconsin Breast Cancer Database (WBCD) and Wisconsin Diagnostic Breast Cancer (WDBC) are used in the classification. The variables in the data sets are the features from the digitized images of fine needle aspiration (FNA) biopsy of the breast. The result shows that both models deliver high accuracies on WBCD and WDBC data sets. However, the fuzzy NN shows slightly better performance than the fuzzy RBFNN.

Index Terms—Breast cancer classification, WBCD, WDBC, fuzzy NN, fuzzy RBFNN

I. INTRODUCTION

BREAST cancer is the second most common cancer in the world after lung cancer. Early detection of breast cancer plays an important role in anticipating the spread of cancer to other parts of the body. Detection of breast cancer can be done in various ways, including mammography, clinical history, physical examination, and biopsy. Fine-needle aspiration (FNA) is a biopsy method that uses a small needle to take fluid, cells or a small part of tissues to be analyzed under a microscope. The University of Wisconsin Hospital has published the data sets drawn from the digitized FNA samples, e.g. Wisconsin Breast Cancer Database (WBCD) and Wisconsin Diagnostic Breast Cancer (WDBC). The differences between these two data sets are in the extracted features obtained from the images as variables that represent benign or malignant breast cancer.

Recently, studies on breast cancer classification using WBCD and WDBC data sets have been developed by applying computational intelligence. By utilizing this kind

of data sets, many researchers have been interested in using neural network (NN) approach as a detection tool, including NN [1]-[3], and NN using Island-based training method [4], the combination of adaptive resonance theory neural network and genetic algorithm [5]. Moreover, Mu & Nandi [6] have developed support vector machine (SVM) and SOM-RBFNN for breast cancer detection based on WDBC data sets.

Several attempts to develop a tool for breast cancer classification based on soft computing are still in progress. The combination of many soft computing methods is becoming a challenging issue for researchers to improve the performance of the method. In this study, we propose a hybrid model of fuzzy and NN approach, which is an integration of fuzzy logic and NN as a tool for classifying breast cancer. The integration of the two methods provides the benefits in a way that it combines the management of cognitive uncertainty and learning, adaptation, fault-tolerance, parallelism, and generalization [7]. Basically, the hybrid model of fuzzy and NN has the same learning system as that of NN. The fundamental difference between the two approaches lies in the values of input, weight, or output, i.e.: fuzzy numbers instead of crisp values.

So far, the two popular types of NN are feedforward neural network (FNN) and radial basis neural network (RBFNN). The FNN is a multilayer perceptron NN with a back-propagation algorithm that involves supervised learning to estimate the weights of the networks. Meanwhile, RBFNN is a specific NN with radial basis activation function, which involves unsupervised and supervised learning to estimate the parameters of radial basis function and the weights of the network, respectively. Many researchers have demonstrated the superiority of FNN and RBFNN in predicting and classifying problems. Some examples include designing the FNN method for COVID-19 cases [8], long-term software fault [9], money laundering prediction [10], shorted-turns faults in electrical machine diagnosis [11], gastric cancer [12], and breast cancer classification [13],[14], and cervical cancer classification [15]. On the other hand, the RBFNN has been reported to be used in the classification of thyroid disease [16], screening of thalassemia [17], and detection of lung cancer [18].

The hybrid fuzzy-NN models based on the FNN and RBFNN models are simply denoted as fuzzy NN and fuzzy RBFNN, respectively. There are various types of fuzzy NN and fuzzy RBFNN, depending on which area the fuzzification process will be performed. Fuzzification can be done on all input, weight, and output neurons, or only on one of them, or a combination of two neurons. The fuzzification using level sets of the fuzzy number on

Manuscript received November 06, 2021; revised April 04, 2022. This work was supported in part by Directorate of Research and Community Service, Ministry of Research, Technology, and Higher Education of the Republic of Indonesia for the financial support under the grant No. 02/Penel./P. Fundamental/ UN.34.21/2017.

Dhoriva Urwatul Wutsqa is a professor of the Statistics Department, Universitas Negeri Yogyakarta, Indonesia, (corresponding author, e-mail: dhoriva_uw@uny.ac.id).

Agus Maman Abadi is a professor of the Mathematics Department, Universitas Negeri Yogyakarta, Indonesia (e-mail: agusmaman@uny.ac.id).

Nurhayadi is an associate professor of the Mathematics Education Department, Tadulako University, Indonesia, (e-mail: nurhayadi@gmail.com).

all neurons has been proposed [19]. The fuzzy number can be designed using membership functions such as trapezoidal, which is combined with a maximum operator on the input as a structure of fuzzy NN [20] and Gaussian on fuzzy RBFNN [21]. Mitra & Basak [22] employ fuzzy c-means as a clustering method in RBFNN and fuzzification on input and output data.

In this study, we propose fuzzy NN and fuzzy RBFNN methods where the fuzzifications are applied in the input variables. We define fuzzy number differently compared to previous studies. Here, fuzzification is employed by using triangle membership function without involving a maximum operator, so all membership functions are included as inputs. Each input is transformed into a fuzzy membership function so that the number of the network inputs becomes larger as it is multiplied with the number of fuzzy membership functions involved in the model. The developed fuzzy NN and fuzzy RBFNN are then utilized to classify breast cancer based on WBCD and WDBC input data sets.

II. MATERIAL AND METHODS

A. Data Sets

In this study, we examined two data sets provided by Wisconsin Breast Cancer Database (WBCD) and Wisconsin Diagnostic Breast Cancer (WDBC) obtained from the University of Wisconsin Hospitals, Madison [23],[24]. These data are the results of breast biopsy using fine needle aspiration (FNA) tests from patients at the University of Wisconsin Hospital. The data of breast FNA have been classified as benign and malignant. These features are obtained from the digitized images of the FNA of WBCD and WDBC data sets.

The information of WBCD consists of 9 features, i.e. clump thickness, uniformity of cell size, uniformity of cell shape, marginal adhesion, single epithelial cell size, bare nuclei, bland chromatin, normal nucleoli, and mitoses. The values are ranged from 1 to 10 where 1 and 10 represent the closest values to benign and malignant, respectively. The WDBC data sets include 10 features, namely radius, texture, perimeter, area, compactness, smoothness, concavity, concave points, symmetry, and fractal dimension.

B. Fuzzy Membership

A fuzzy set is a generalization of a classic set to handle non-exact information that is found in real world problems. It is developed by Zadeh in 1965. The membership of an element in a fuzzy set is represented by a degree of membership function with the range over a unit interval of [0,1]. Fuzzy logic has been an interesting study in many literatures. The fuzzy logic has been applied in detection of inter-turn fault in power transformers [25], prediction of the flood alarm [26], and analytical hierarchy process [27].

There are several membership functions that can be used in the fuzzification process, including the triangle, trapezium, and Gaussian membership function. In this study, we focus on a triangle membership function of

$$\mu(x) = \begin{cases} 0 & ; \quad x \leq a \text{ and } x > c \\ \frac{(x-a)}{(b-a)} & ; \quad a < x \leq b \\ \frac{(c-x)}{(c-b)} & ; \quad b < x \leq c \end{cases} \quad (1)$$

The values of a , b , and c are determined by relying on the minimum and maximum values of the variable.

C. Fuzzy NN

In this study, a fuzzy NN is defined as an NN model with input in the form of a fuzzy number (1). The fuzzy NN architecture is based upon the NN architecture by adding one more layer i.e.: the fuzzy input, after the crisp input. The network architecture of the fuzzy NN model is shown in Fig. 1.

The variables $x_1, x_2, \dots, x_j, \dots, x_p$ are p crisp neurons in the input layer. Those variables are converted to fuzzy numbers as the functions $\mu_{1.1}(x_1), \mu_{2.1}(x_1), \dots, \mu_{l.j}(x_j), \dots, \mu_{q.p}(x_p)$, which will be processed as fuzzy inputs. The activation function in the hidden layer is a logistic sigmoid function and in the output layer is an identity function. The y variable is a single neuron in the output layer. Then, the fuzzy NN model can be written as

$$y = \sum_{k=1}^r v_k f_k + v_0 + \varepsilon, \quad (2)$$

where

$$f_k = \frac{1}{1 + \exp\left(-\left(w_{0k} + \sum_{l=1}^q \sum_{j=1}^p \mu_{l.j}(x_j) w_{l.jk}\right)\right)},$$

w_{0k} is a bias and $w_{l.jk}$ is a weight on the hidden layer from the input layer, while v_0 is a bias and v_k is a weight on the output layer from the hidden layer, and ε is the model error.

The bias and weight estimations of the model (2) are employed by using the backpropagation algorithm. The algorithm is modified from Fauset [28] by substituting the crisp input to be fuzzy input.

The steps of the backpropagation algorithm are as follows.

Step 0. Initializing weights.

Step 1. While stopping condition is false, do Steps 2–9.

Step 2. For each training pair, do Steps 3-8.

Feedforward:

Step 3. Each fuzzy input unit ($\mu_{l.j}(x_j)$, $j = 1, 2, \dots, p$; $l = 1, 2, \dots, q$) gets input signal $\mu_{l.j}(x_j)$ and sends this signal to all hidden units.

Step 4. Each hidden unit (Z_k , $k = 1, \dots, r$) sums its weighted input signals,

$$z_in_k = w_{0k} + \sum_{l=1}^q \sum_{j=1}^p \mu_{l.j}(x_j) w_{l.jk}$$

Compute the activate sigmoid function to obtain its output signal:

$$z_k = f_k(z_in_k)$$

and send the signal to output unit.

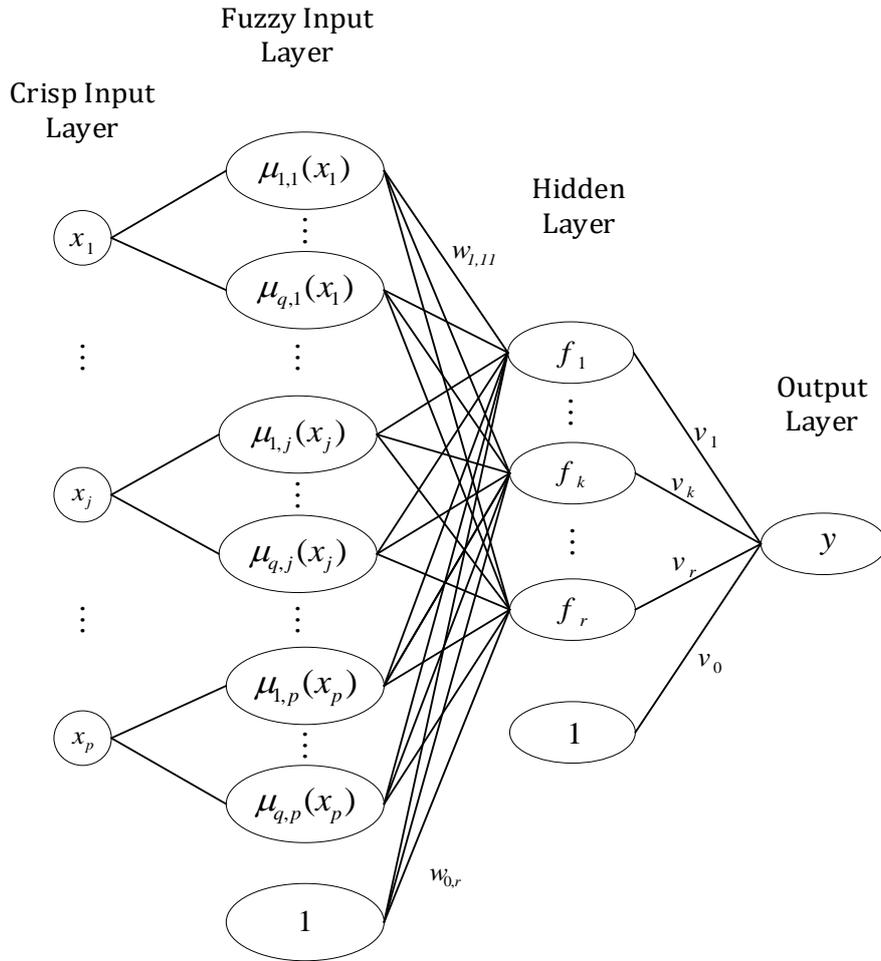


Fig. 1. Fuzzy NN architecture

Step 5. The output sums its weighted input signals

$$y_{in} = v_0 + \sum_{k=1}^r z_j v_k.$$

The activation function in the output layer is identity, so the computed activation of the output signal is

$$y = v_0 + \sum_{k=1}^r z_j v_k.$$

Backpropagation of error:

Step 6. The output unit (y) gets a target pattern corresponding to the input training pattern. Compute its error information term,

$$\delta = (t - y)f'(y_{in}).$$

Compute its weight correction term to update v_k later,

$$\Delta v_k = \alpha \delta z_k,$$

and its bias correction term to update v_0 later, i.e.:

$$\Delta v_0 = \alpha \delta.$$

Step 7. Each hidden unit ($Z_k, k = 1, 2, \dots, r$) gets the delta input from output unit of

$$\delta_{in_k} = \delta v_k,$$

and multiplies by derivative of its activation function to calculate its error information term of

$$\delta_k = \delta_{in_k} f'(z_{in_k}).$$

Compute its weight correction term to update $w_{l,jk}$, i.e.:

$$\Delta w_{l,jk} = \alpha \delta_k \mu_{l,j}(x_j),$$

and compute its bias correction term to update w_{0k} ,

$$\Delta w_{0k} = \alpha \delta_k.$$

Update weights and biases:

Step 8. The output updates its bias and weights ($k = 0, 1, 2, \dots, r$), i.e.:

$$v_k(new) = v_k(old) + \Delta v_k.$$

Each hidden unit Z_k updates its bias and weights ($j = 1, 2, \dots, p; l = 1, 2, \dots, q$)

$$w_{0k}(new) = w_{0k}(old) + \Delta w_{0k}$$

$$w_{l,jk}(new) = w_{l,jk}(old) + \Delta w_{l,jk}.$$

Step 9. Test Stopping Condition.

D. Fuzzy Radial Basis Function NN

The term of RBFNN corresponds to a specific activation function that belongs to the kernel function denoted as radial basis function (RBF). The RBF is a monotonic function, which is characterized by two parameters, i.e.: center and width. Similar to fuzzy NN, the fuzzy RBFNN architecture consists of four layers, the crisp input layer, fuzzy input layer, hidden layer, and output layer. The main difference is in the activation functions of the hidden layer, which are denoted as the RBF $\varphi_1, \varphi_2, \dots, \varphi_k, \dots, \varphi_r$. The weights and bias are only set between the hidden and the output layers.

The activation function in the fuzzy RBFNN model is a Gaussian function of the fuzzy number (1), hence the model is expressed as

$$y = \sum_{k=1}^r v_k \varphi_k[\boldsymbol{\mu}(\mathbf{x})] + v_0 + \varepsilon. \quad (3)$$

The k -th Gaussian function $\varphi_k[\boldsymbol{\mu}(\mathbf{x})]$ is

$$\begin{aligned} \varphi_k[\boldsymbol{\mu}(\mathbf{x})] &= \exp\left\|\frac{\varphi_k[\boldsymbol{\mu}(\mathbf{x})] - \mathbf{C}_k}{R_k}\right\| \\ &= \exp\left(-\sum_{j=1}^p \sum_{l=1}^q \frac{(\mu_{l,j}(x_j) - c_{k(l,j)})^2}{R_k^2}\right) \end{aligned}$$

where R_k is the maximum distance in the k -th cluster, $\mathbf{C}_k = (c_{k(l,j)})$ is k -th cluster center vector of l -th fuzzy input and j -th variable, and $\boldsymbol{\mu}(\mathbf{x})$ is the fuzzy input vector, and ε is the model error.

The learning process of fuzzy RBFNN follows the steps in the RBFNN model, which involves unsupervised and supervised learning. In this study, the first learning is performed by using K-mean clustering method and the second one is performed by singular value decomposition (SVD).

The K-means is a classical and widely used clustering method. In the K-means method, the objects are assigned to the clusters having the nearest centroids. The K-means clustering is implemented on fuzzy input vector $\boldsymbol{\mu}(\mathbf{x})$ to estimate the parameters of Gaussian function \mathbf{C}_k and R_k . The distance of the objects $\boldsymbol{\mu}(\mathbf{x})$ to the centroids \mathbf{C}_k is calculated using the Euclidian distance, i.e.:

$$D(\boldsymbol{\mu}(\mathbf{x}), \mathbf{C}_k) = \sqrt{\sum_{j=1}^p \sum_{l=1}^q (\mu_{l,j}(x_j) - c_{k(l,j)})^2}. \quad (4)$$

The process of the algorithm follows these steps:

- 1) Distribute the objects randomly to the initial K clusters and select the K initial cluster centroids.
- 2) Through the list of the objects, allocate an object to the cluster whose centroid is the closest.
- 3) Compute the centroids of the cluster with the new arrangement.
- 4) Repeat the reallocation of the object to the new cluster until no more movement is necessary.

The determination of the weights in the fuzzy RBFNN model (3) corresponds to the solution of the linear system y with respect to the variable $\varphi_k[\boldsymbol{\mu}(\mathbf{x})]$, $k = 1, 2, \dots, r$. The SVD method is one of the recommended methods for solving systems of linear equations based on matrix singular values. The SVD method has been effectively shown to

reduce fuzzy rule base [29], and to determine the consequent parameters of fuzzy rule [30].

Dealing with the determination of the weight in (3), we need to define the SVD of the matrix Φ . This is the factorization of the matrix Φ into the product of three matrices such that

$$\Phi_{n \times (r+1)} = \mathbf{U}_{n \times n} \boldsymbol{\Sigma}_{n \times (r+1)} \mathbf{V}_{(r+1) \times (r+1)}^T, \quad (5)$$

where n is the number of observations, r is the number of clusters, and Φ is the matrix of Gaussian functions and unit constant. Matrix $\boldsymbol{\Sigma}$ is the diagonal matrix of singular values of the matrix Φ , that is

$$\boldsymbol{\Sigma} = \begin{bmatrix} \sigma_1 & 0 & \dots & 0 \\ 0 & \sigma_2 & \dots & 0 \\ \vdots & \vdots & \dots & \vdots \\ 0 & 0 & \dots & \sigma_{r+1} \\ \vdots & \vdots & \dots & \vdots \\ 0 & 0 & \dots & 0 \end{bmatrix}_{n \times (r+1)} \quad (6)$$

where $\sigma_1 \geq \sigma_2 \geq \sigma_3 \geq \dots \geq \sigma_r > \sigma_{r+1} > 0$. The matrices \mathbf{U} and \mathbf{V} are defined as

$$\mathbf{U} = [\mathbf{u}_1 \quad \mathbf{u}_2 \quad \dots \quad \mathbf{u}_n],$$

where

$$\mathbf{u}_1 = \begin{bmatrix} u_{11} \\ u_{21} \\ \vdots \\ u_{n1} \end{bmatrix}, \mathbf{u}_2 = \begin{bmatrix} u_{12} \\ u_{22} \\ \vdots \\ u_{n2} \end{bmatrix}, \mathbf{u}_n = \begin{bmatrix} u_{1n} \\ u_{2n} \\ \vdots \\ u_{nn} \end{bmatrix},$$

and

$$\mathbf{V}^T = [\mathbf{v}_1 \quad \mathbf{v}_2 \quad \dots \quad \mathbf{v}_{(r+1)}],$$

where

$$\mathbf{v}_1 = \begin{bmatrix} v_{11} \\ v_{21} \\ \vdots \\ v_{(r+1)1} \end{bmatrix}, \mathbf{v}_2 = \begin{bmatrix} v_{12} \\ v_{22} \\ \vdots \\ v_{(r+1)2} \end{bmatrix}, \mathbf{v}_{(r+1)} = \begin{bmatrix} v_{1(r+1)} \\ v_{2(r+1)} \\ \vdots \\ v_{(r+1)(r+1)} \end{bmatrix}.$$

The weights of the fuzzy RBFNN-SVD are calculated using this expression

$$\hat{\mathbf{v}} = \sum_{k=1}^{r^*} \frac{\mathbf{u}_k^T \mathbf{t}}{\sigma_k} \mathbf{v}_k, \quad (7)$$

where $\hat{\mathbf{v}}$ is a weight vector of fuzzy RBFNN-SVD, \mathbf{t} is an output (target) vector, \mathbf{u}_k is a k -th column of matrix \mathbf{U} , σ_k is a k -th singular value of matrix Φ , with $\sigma_k > 0$, \mathbf{v}_k is a k -th column of matrix \mathbf{V}^T , and r^* is the number of positive singular values.

E. The Breast Cancer Classification Procedure

The models used for breast cancer classification are fuzzy NN and fuzzy RBFNN. The difference of the steps to build both models lies in the learning process. The procedures to build fuzzy NN and fuzzy RBFNN for breast cancer classifications involve the following steps.

Step 1. Define the input and output variables.

In this study, we investigate the modeling of WBCD and WDBC data sets. So, the input variables are the 9 and 10 features of FNA for the WBCD and WDBC, respectively. The output variable only involves a single variable, i.e. a diagnosis of breast cancer whose values are 0 for benign (tumor) and 1 for malignant (cancer).

Step 2. Set training and testing data.

The input-output data sets of WBCD and WDBC are divided into two data sets, namely training and testing data sets. The training data set is used to build the model, while the testing data set is used to evaluate the ability of the model to be generalized towards new data.

Step 3. Fuzzification of input variables.

The fuzzification step deals with the process to change the input variable in the crisp into the fuzzy number form. We set three triangle membership functions (1).

Step 4. Learning process.

The fuzzy NN only involves one learning process, which is intended to find the weights between the fuzzy input and hidden layers, and the weights between the hidden and output layers. This can be achieved using the backpropagation algorithm. The fuzzy RBFNN includes K-means clustering to estimate the parameter of the Gaussian function, namely mean and maximum distance. Since each Gaussian function activates each hidden neuron, so the number of hidden neurons equals the number of clusters. The weights between the hidden and output layers are calculated using the SVD method.

Step 5. Calculate the accuracy of the model

The performance of the model is measured by the accuracy of the model to diagnose the breast FNA condition. The accuracy is expressed as the percentage of the number of correct diagnoses based on the entire data.

III. RESULTS AND DISCUSSION

The breast cancer data sets of WBCD and WDBC are used in this experiment, in which each dataset contains 100 benign and 100 malignant cases. The features of the digitized FNA of WBCD and WDBC are treated as input variables, and the condition of breast cancer is used as the output. We utilize a triangle as a membership function with three fuzzy sets. The three triangle membership functions are illustrated in Fig. 2.

The values of parameters a , b , and c for each membership function and each variable are presented in Tables 1 and 2 for WBCD and WDBC, respectively.

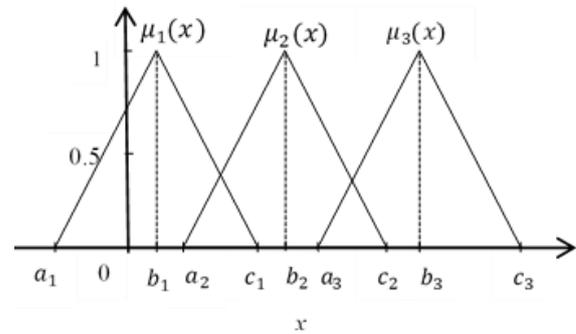


Fig. 2. Triangle fuzzy membership function

TABLE I
PARAMETER VALUES OF THE MEMBERSHIP FUNCTION OF WBCD DATA

Variables	$\mu_1(x)$			$\mu_2(x)$			$\mu_3(x)$		
	a_1	b_1	c_1	a_2	b_2	c_2	a_3	b_3	c_3
Clump Thickness	-2.6	1	4.6	1.9	5.5	9.1	6.4	10	13.6
Uniformity of Cell Size	-2.6	1	4.6	1.9	5.5	9.1	6.4	10	13.6
Uniformity of Cell Shape	-2.6	1	4.6	1.9	5.5	9.1	6.4	10	13.6
Marginal Adhesion	-2.6	1	4.6	1.9	5.5	9.1	6.4	10	13.6
Single Epithelial Cell Size	-2.6	1	4.6	1.9	5.5	9.1	6.4	10	13.6
Bare Nuclei	-2.6	1	4.6	1.9	5.5	9.1	6.4	10	13.6
Bland Chromatin	-2.6	1	4.6	1.9	5.5	9.1	6.4	10	13.6
Normal Nucleoli	-2.6	1	4.6	1.9	5.5	9.1	6.4	10	13.6
Mitoses	-2.6	1	4.6	1.9	5.5	9.1	6.4	10	13.6

TABLE II
PARAMETER VALUES OF THE MEMBERSHIP FUNCTION OF WDBC DATA

Variable	$\mu_1(x)$			$\mu_2(x)$			$\mu_3(x)$		
	a_1	b_1	c_1	a_2	b_2	c_2	a_3	b_3	c_3
Radius	-1.06	8.20	17.45	10.51	19.76	29.02	22.08	31.33	40.58
Texture	1.01	9.71	18.41	11.89	20.58	29.29	22.76	31.46	40.16
Perimeter	-11.05	51.71	114.50	67.44	130.10	192.90	145.80	208.60	271.40
Area	-1038.	201.9	1442.0	512.6	1750	2991	2060	3301	4542
Smoothness	-0.05	0.00	0.06	0.02	0.07	0.13	0.09	0.14	0.20
Compactness	-0.09	0.02	0.13	0.05	0.15	0.26	0.18	0.28	0.39
Concavity	-0.16	0.00	0.16	0.04	0.21	0.37	0.25	0.41	0.57
Concave Points	-0.07	0.00	0.08	0.02	0.10	0.17	0.12	0.19	0.27
Symmetry	0.04	0.12	0.19	0.14	0.21	0.29	0.23	0.30	0.38

Table 1 clearly shows that all membership functions of WBCD data have the same parameter values since all variables have the same minimum and maximum values. However, each variable has a different fuzzy number, depending on its crisp number. The architectures of the fuzzy NN and fuzzy RBFNN models involve, respectively, 9 and 10 crisp input variables for WBCD and WDBC, 27 and 30 fuzzy input variables for WBCD and WDBC, and a single output neuron. The number of hidden neurons has been determined by trial and error until the models give the highest accuracy.

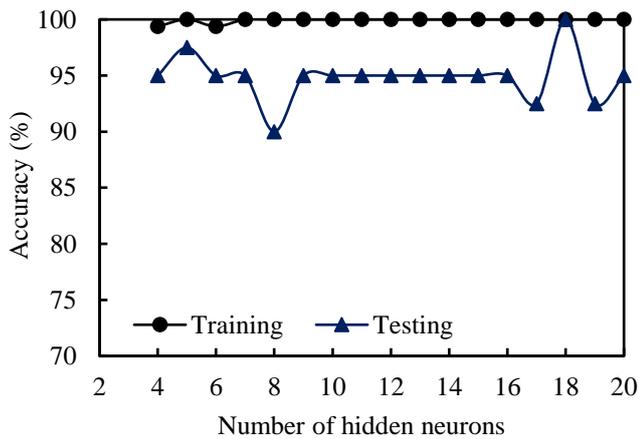
The composition of training and testing data are 80% and 20%, respectively. The architectures of both models are learned by modifying the number of the hidden neuron of the training data. The experiments run the learning process from 4 to 20 hidden neurons. The trends of the accuracies of the fuzzy NN and fuzzy RBFNN of the experiments are displayed in Fig. 3. The accuracy of the fuzzy NN model on the training data has reached 100% in the small number of hidden neurons and tends to remain constant. In the testing data, it tends to fluctuate as the number of hidden neurons increases.

Accuracies on the training data in the fuzzy RBFNN tend to fluctuate. Upon the testing data for WBCD, the accuracy of fuzzy RBFNN becomes constant once it reaches its peak

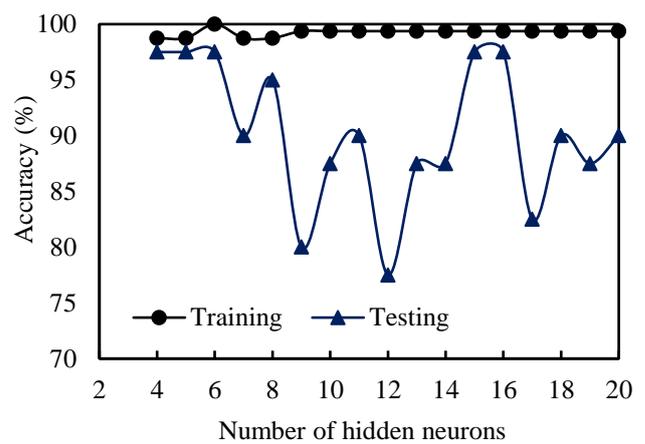
at 100%. For WDBC, it also becomes constant when it reaches 90% accuracy following increasing number of hidden neurons. These empirical evidences suggest no specific association pattern exists between accuracy and the number of hidden neurons. Thus, the experiments were done in various settings of hidden neurons number.

The best models are determined by considering the accuracy of the models on both training and testing data. The classification accuracies yielded by best models on WBCD and WDBC data are listed in Table 3. The results in Table 3 demonstrate that both models perform well. However, the classification accuracy of the fuzzy NN model is slightly better than that of the fuzzy RBFNN. On the WBCD data, the fuzzy NN model achieves 100% accuracy for both training and testing data.

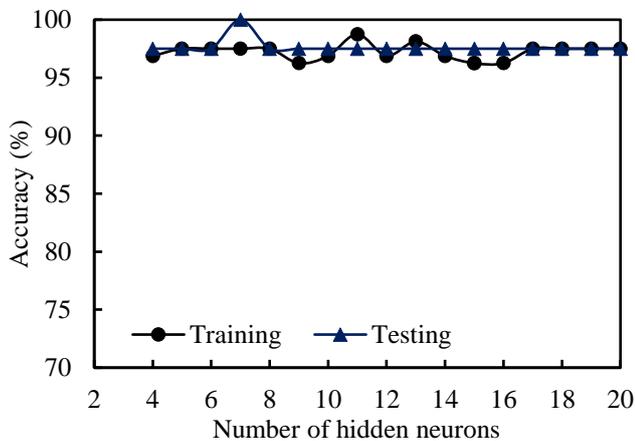
If the number of the hidden neurons is being considered, we cannot come to the conclusion about which model is more efficient. This is because the fuzzy NN reaches 18 hidden neurons on WBCD data and 6 hidden neurons on WDBC to give the best accuracy. On the other hand, the fuzzy RBFNN reaches 7 hidden neurons on WBCD but 17 hidden neurons on WDBC, indicating that there is no certain pattern of which model is more efficient. Nevertheless, on the fuzzy NN learning, backpropagation method can indeed attain a very small error rate on the training data.



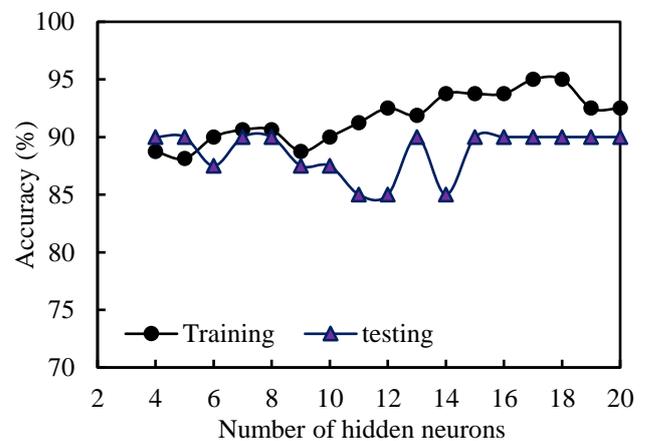
(a)



(b)



(c)



(d)

Fig. 3. The accuracy trends of (a) Fuzzy NN on WBCD, (b) Fuzzy NN on WDBC, (c) Fuzzy RBFNN on WBCD, and (d) Fuzzy RBFNN on WDBC

This can be seen from the results of fuzzy NN on both WBCD and WDBC data sets, which yield no misclassification data.

Studies using WBCD and WDBC data have been done via various methods. Performance comparison of the fuzzy NN and fuzzy RBFNN models (average accuracy on training and testing data) with previous studies is presented in Table 4. All the models listed in Table 4 are based on the soft computing approach. Table 4 demonstrates that the fuzzy NN is a very competitive model since it surpasses almost all other models on WBCD and WDBC. The fuzzy

RBFNN still reveals a good alternative model. It has higher performance than the previously reported results of [2], [31]-[33] on WBCD data. Although it underperforms compared to other models on WDBC, it yields a high accuracy of 92.5%. The results of the whole models deliver high performance both on the WBCD and WDBC data with an accuracy of more than 90% or even 100%. These results suggest that the variables considered in breast cancer classification supplied by WBCD and WDBC are a suitable tool to predict benign and malignant breast conditions

TABLE III
THE ACCURACY (%) OF BREAST CANCER CLASSIFICATION

	Fuzzy NN			Fuzzy RBFNN		
	Training	Testing	Number of hidden neurons	Training	Testing	Number of hidden neurons
WBCD	100	100	18	97.50	100	7
WDBC	100	97.50	6	95	90	17

TABLE IV
COMPARISON OF PERFORMANCE OF FUZZY NN AND FUZZY RBFNN MODEL WITH OTHER STUDIES

Data Set	Model [Reference]	Accuracy (%)
WBCD	Feedforward Neural Network (FNN)[2]	95.30
	Artificial Neural Network (ANN)[3]	99.80
	Neural network- differential evolution algorithm (NN-DEV) [4]	99.97
	Hybrid cascade forward neural network with Elman neural network (HCFNN-ERNN) [31]	97.94
	Rough sets and backpropagation neural network (RSBPNN) [32]	98.60
	Principal component Analysis-Support Vector Machine (PCA-SVM) [33]	97.19
	Fuzzy NN	100
Fuzzy RBFNN	98.75	
WDBC	ANN [3]	99.47
	FNN [2]	96.60
	Self-organizing mapping (SOM) RBF [6]	97.10
	One-pass generalized classifier neural network (OGCNN) 10-fold cross-validation [34]	93.50
	K-means-SVM [35]	97.38
	Nested ensemble classifier (NEC) [36]	98.07
	Fuzzy NN	98.75
	Fuzzy RBFNN	92.50

IV. CONCLUSION

The fuzzy NN and fuzzy RBFNN have been proposed by modifying the crisp inputs to be fuzzy inputs using triangle membership function. The learning algorithm follows the method implemented in the underlying NN model, but it is operated on fuzzy inputs instead of crisp inputs. The experimental result demonstrates that both models perform effectively as classification tools on WBCD and WDBC data sets, but the fuzzy NN slightly outperforms fuzzy RBFNN. This result also suggests that all the variables

corresponding to WBCD and WDBC data sets published by Wisconsin University are the proper predictors for breast cancer classification. Both models show that the classification accuracies on training and testing data sets are almost similar. This reveals the benefits of the models, which deals with the generalization capability to classify new observation.

REFERENCES

- [1] M. Borkar, K. Deulkar, and A. Garg, "Prediction of breast cancer using artificial neural networks," *International Journal of Engineering Research & Technology*, vol.4, no. 09, pp. 475-477, 2015.
- [2] G. I. Salama, M. B. Abdelhalim, and M. A. Zeid, "Breast cancer diagnosis on three different datasets using multi-classifiers," *International Journal of Computer and Information Technology*, vol. 1, no. 1, pp. 36-43, 2012.
- [3] M. H. Alshayegi, H. Ellethy, S. Abed, and R. Gupta, "Computer aided detection of breast cancer on the Wisconsin dataset: An artificial neural networks approach," *Biomedical Signal Processing and Control*, vol. 71, 2022.
- [4] H. T. T. Thein and K. M. M. Tun, "An approach for breast cancer diagnosis classification using neural network," *Advanced Computing: An International Journal*, vol. 6, no. 1, pp. 1-11, 2015.
- [5] Punitha, C. P. Sumathi, and T. Santhanam, "A combination of genetic algorithm and ART neural network for breast cancer diagnosis," *Asian Journal of Inform Technology*, vol. 6, no. 1, pp. 112-117, 2007.
- [6] T. Mu and A. K. Nandi, "Breast cancer detection from FNA using SVM with different parameter tuning systems and SOM-RBF classifier," *Journal of The Franklin Institute*, vol. 344, no. 3-4, pp. 285-311, 2007.
- [7] R. Fuller, *Neural fuzzy systems*. Abo Academy University, 1995.
- [8] T. Toharudin, R. S. Pontoh, R. E. Caraka, S. Zahroh, A. Akbar, B. Pardamean, and R. C. Chen, "Indonesia in facing new normal: an evidence hybrid forecasting of COVID-19 cases using MLP, NNAR and ELM," *Engineering Letters*, vol. 29, no. 2, pp. 749-758, 2021.
- [9] M. Begum, Md. S. B. Hafiz, Md. J. Islam, and M. J. Hossain, "Long-term software fault prediction with robust prediction interval analysis via refined artificial neural network (RANN) approach," *Engineering Letters*, vol. 29, no. 3, pp. 1158-1171, 2021.
- [10] J. K. Alhassan and N. E. Yusuf, "A cascaded artificial neural network and K-medoids method for money laundering detection in financial organizations," *Lecture Notes in Engineering and Computer Science: Proceedings of the World Congress on Engineering 2021, 7-9 July, 2021, London, U.K.*, pp. 113-117.
- [11] O. A. IMORU, F. V. Nelwamondo, A. A. Jimoh, and T. Marwala, "Diagnosis of shorted-turns faults in electrical machine using neural network," *Lecture Notes in Engineering and Computer Science: Proceedings of the World Congress on Engineering and Computer Science 2018, 23-25 October, 2018, San Francisco, USA.*, pp. 303-307.

- [12] M. A. Aslam, C. Xue, M. Liu, K. Wang, and D. Cui, "Classification and Prediction of Gastric Cancer from Saliva Diagnosis using Artificial Neural Network," *Engineering Letters*, vol. 29, no. 1, pp. 10-24, 2021.
- [13] I. Saritas, "Prediction of breast cancer using artificial neural networks," *Journal of Medical Systems*, vol. 36, no. 5, pp. 2901-2907, 2012.
- [14] B. S. Kumash, K. Verma, and A. S. Thoke, "Adaptive gradient descent backpropagation for classification of breast tumors in ultrasound imaging," in *Proc. of the Int. Conf. on Information and Communication Technologies (Elsevier)*, 2015, pp. 1601-1609.
- [15] D. U. Wutsqa and M. Marwah, "Median filter noise reduction of image and backpropagation neural network model for cervical cancer classification," *Journal of Physic: Conference Series*, vol. 855, 2017.
- [16] R. Erol, S. N. Ogulata, C. Sahin, and Z. N. Alparslan, "A radial basis function neural network (RBFNN) approach for structural classification of thyroid disease," *Journal of Medical Systems*, vol. 32, no. 3, pp. 215-220, 2008.
- [17] G. L. Masala, B. Golosio, R. Cutzu, and R. Pola, "A two layer classifier based on radial basis function for the screening of thalassemia," *Computers in Biology and Medicine*, vol. 43, no. 11, pp. 1724-1731, 2013.
- [18] A. M. Abadi, D. U. Wutsqa, and L. R. Pamungkas, "Detection of lung cancer using radiograph images enhancement and radial basis function classifier," in *Proc. of the 10th Int. Congress on Image and Signal Processing, BioMedical Engineering and Informatics, IEEE, 2017, Shanghai*.
- [19] N. Y. Pehlivan and A. Apaydin, "Fuzzy radial basis function network for fuzzy regression with fuzzy input and fuzzy output," *Complex & Intelligent Systems*, vol. 2, no.1, pp. 61-73, 2016.
- [20] D. U. Wutsqa and P. S. Rahmada, "Point operation to enhance the performance of fuzzy neural network model for breast cancer classification," *Journal of Engineering and Applied Sciences*, vol. 12, no. 17, pp. 4405-4410, 2017.
- [21] Z. Chao and H-J. Kim, "Slice interpolation of medical images using enhanced fuzzy radial basis function neural networks," *Computers in Biology and Medicine*, vol. 110, pp. 66-78, 2019.
- [22] S. Mitra and J. Basak, "A fuzzy radial basis function network," *Neural Computing & Applications*, vol. 10, no. 3, pp. 244-252, 2001.
- [23] W. H. Wolberg and O. L. Mangasarian, Breast Cancer Wisconsin (Original) Data Set, 1992. [https://archive.ics.uci.edu/ml/datasets/Breast+Cancer+Wisconsin+\(Original\)](https://archive.ics.uci.edu/ml/datasets/Breast+Cancer+Wisconsin+(Original)), 1992, Accessed 20 Jan 2017.
- [24] W. H. Wolberg, W. Nick, and O. L. Mangasarian, Breast Cancer Wisconsin (Diagnostic) Data Set, 1992. [https://archive.ics.uci.edu/ml/datasets/Breast+Cancer+Wisconsin+\(Diagnostic\)](https://archive.ics.uci.edu/ml/datasets/Breast+Cancer+Wisconsin+(Diagnostic)). Accessed 20 Jan 2017.
- [25] J. K. Arthur, J. O. Akoto, D. A. Narkah, O-N.K. Dokyi, and E. Tumasi, "Detection of inter-turn fault in power transformers using fuzzy logic," *Lecture Notes in Engineering and Computer Science: Proceedings of the World Congress on Engineering 2021, 7-9 July, 2021, London, U.K.*, pp. 169-174.
- [26] K. Waraha, D. Bakhm, and P. Suebsan, "Applications of fuzzy soft sets to the flood alarm model in Northern Thailand," *Engineering Letters*, vol. 29, no. 3, pp. 1020-1025, 2021.
- [27] T-K-L. Nguyen, Q-M. Le, and T-H-D. Vu, "Fuzzy analytical hierarchy process approach of attracting investment capital into industrial parks in Hai Duong Province, Vietnam," *Engineering Letters*, vol. 29, no. 3, pp. 1083-1088, 2021.
- [28] L. Fausett, *Fundamentals of Neural Networks: Architecture, Algorithms, and Applications*. New Jersey, NJ: Prentice Hall, 1994.
- [29] Y. Yam, P. Baranyi, and C. T. Yang, "Reduction of fuzzy rule base via singular value decomposition," *IEEE Transactions Fuzzy Systems*, vol. 7, no. 2, pp.120-132, 1999.
- [30] A. M. Abadi and D. U. Wutsqa, "Neuro fuzzy model with singular value decomposition for forecasting the number of train passengers in Yogyakarta," in *Proc. of 11th Int. Conf. on Fuzzy Systems and Knowledge Discovery, IEEE, 2014, Xiamen*, pp. 178-182.
- [31] M. Sh. Alkhasawneh, "Hybrid cascade forward neural network with Elman neural network for disease prediction," *Arab. J. Sci. Eng.*, pp. 1-12, 2019.
- [32] K.B. Nahato, K.N. Harichandran, and K. Arputharaj, "Knowledge mining from clinical datasets using rough sets and backpropagation neural network," *Comput. Math. Methods Med.*, pp. 1-13, 2015.
- [33] W. Wu and S. Faisal, "A data-driven principal component analysis-support vector machine approach for breast cancer diagnosis: Comparison and application," *Trans. Inst. Meas. Control*, vol. 42, no. 7, pp. 1301-1312, 2020.
- [34] A. K. Naik, V. Kuppili, and D. R. Edla, "Efficient feature selection using one-pass generalized classifier neural network and binary bat algorithm with a novel fitness function," *Soft Comput.*, vol. 24, no. 6, pp. 4575-4587, 2020.
- [35] B. Zheng, S. W. Yoon, and S. S. Lam, "Breast cancer diagnosis based on feature extraction using a hybrid of K-means and support vector machine algorithms," *Expert. Syst.*, vol. 41, no. 4, pp.1476-1482, 2014.
- [36] M. Abdar, M. Zomorodi-Moghadam, X. Zhou, R. Gururajan, X. Tao, P.D. Barua, and R. Gururajan, "A new nested ensemble technique for automated diagnosis of breast cancer," *Pattern Recogn. Lett.*, vol. 132, pp. 123-131, 2020.