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Fuzzy Neural Network with Intensity Adjustment and Median Filter for Classifying Cervical Cancer

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Abstract

In this paper, we develop a fuzzy neural network model for classifying cervical cancer. A fuzzy neural network is a specific feed forward neural network which processes fuzzy variables. The fuzzy neural network model gives benefits, since the fuzzy logic accommodates cognitive uncertainty, and neural network allows learning and generalization. The cervical cancer is classified using colposcopy images. We also propose image preprocessing of intensity adjustment and median filter to enhance the contrast and to shrink the noise of the image. The parameters extracted from the image by the grey level co-occurrence matrix method are designed as the original inputs of the fuzzy neural network model. These inputs are in crisp forms, so they require to be changed in fuzzy forms. In this study, we use trapezoidal fuzzy number and OR operation. The fuzzy neural network is implemented to the original colposcopy images, to the colposcopy images with the intensity adjustment, with the median filter, and with the combination of both. The results demonstrate that the fuzzy neural network models have the same performance to all types of images on training data and deliver the best performance on the images with the combination of intensity adjustment and median filter on testing data.

Keywords**:** ***fuzzy neural network, intensity adjustment, median filter, cervical cancer, classification***

1 Introduction

Cervical cancer is one of the most common cancers in Indonesia. Both new cases and the number of deaths from cervical cancer have increased annually. The numbers of new cases of cervical cancer for four consecutive years are 296 cases, 300 cases, 348 cases and 356 cases, while the numbers of deaths due to cancer for four consecutive years are 36 cases, 35 cases, 42 cases and 65 cases [1]. Early detection is very important to decrease the risk of death caused by cervical cancer.

Pap smear test is a test that is considered quite effective to early detect cervical cancer. If the Pap smear test shows abnormal cervical cells and significant cell changes occur, then the person will be advised to undergo colposcopy tests. Colposcopy test is done by using a colposcopy tool that works by enlarging the image of the cervix surface so that the vein image will be perceived more clearly. Then, the physician can classify the stadium of cervical cancer using that cervix surface image produced by colposcopy.

Colposcopy result is in the form of digital images. The image produced in the acquisition process may be distorted due to the environmental or the equipment condition. Low contrast and noise are distortion phenomena that play important role in image interpretation and feature extraction, which consequently influence the classification accuracy. In this regard, the image preprocessing to increase the contrast and to reduce the noise becomes a challenging research. In this study, we offer an intensity adjustment to increase the contrast and a median filter to reduce the noise of the cervical image. The uses of those methods have been proved to be effective to improve the quality of the various image and to increase the classification accuracy.

Cancer diagnostic corresponds to the classification process. Therefore, many researchers have given great attention to develop cancer diagnostic systems using soft computation approach by exploiting digital images. Methods which are included in soft computing are a neural network (NN), a fuzzy logic, and a probabilistic reasoning. Some researchers attempt to combine NN and fuzzy logic, such as fuzzy neural network model. It is characterized by the fuzzy numbers which are defined on the NN components: inputs, weights, or outputs. It takes the advantages of the NN capabilities in the learning process, fault tolerance, and generalization. A fuzzy logic can be used to anticipate the uncertainty that occurs in the elements of the NN.

In this study, the fuzzy neural network model is applied as an intelligent system for classifying cervical cancer. It processes the colposcopy images to produce the cervical cancer classification. To increase the performance of the fuzzy neural network model, the quality of the colposcopy images is improved by image preprocessing using a combination of intensity of adjustment and the median filter.

To highlight the capability of the fuzzy neural network and the combination of intensity adjustment and the median filter, we compare the classification accuracy of the fuzzy neural network on the images preprocessed separately by intensity adjustment and median filter, and on the original images.

2 Related Work

Recently, studies on cancer detection, specifically on cervical cancer detection have been developed based on soft computing. Fuzzy logic and neural network are soft computations widely preferred as medical diagnostic tools for cervical cancer classification. The previous studies use NN multilayer perceptron [2], hybrid multilayer perceptron (HMLP) network [3][4] expert system with fuzzy logical [5][6], and radial basis function neural network [7] for cervical cancer classifications.

Overall, those researches use neural network and fuzzy separately. However, a fuzzy neural network which is a combination of fuzzy logic and neural network can be useful for solving the classification problem, including cervical cancer classification. It has been proved that it is effectively used to analyze other areas. The fuzzy neural network model has been employed for various intentions, such as for thyroid and breast cancer diagnosis [8][9], speech recognition system [10], fault detection [11], weather forecasting [12], batik classification [13], and hepatobiliary disorders diagnosis [14].

Most researchers on cervical classification use Pap smear test results. This test cannot diagnose the stadium of cervical cancer. Colposcopy image of cervical can be used by the physician to determine the stadium of cervical cancer. A neural network approach has been applied to classify five stadiums of cervical cancer using colposcopy images [15]. This work also employs a median filter to colposcopy images to improve the image quality with respect to noise and salt removing. The medial filter is also applied to MR images [16], breast cancer images [17], and lung images [18] [19]. Another problem that possibly occurs in the image is a low contrast image. The intensity adjustment is one method that can enhance the contrast. The results of [9] [20] [21] demonstrate that intensity adjustment can enhance the qualities of the images and work effectively to increase the classification accuracy.

The computational research using colposcopy images is still uncommon. In this study, we aim to develop a soft computing method for cervical cancer stadium classification using colposcopy images. The method is based on fuzzy neural network model with the design adopted from [9]. In this model, the fuzzification is implemented only in the input. The fuzzification process includes two steps, those are changing crisp inputs to fuzzy inputs, then employing a fuzzy operator OR. This design is a new approach to cervical cancer classification since it just has been applied to breast cancer classification [9]. In addition, we also propose the image enhancement using the combination of intensity adjustment and median filtering. This process aims to improve the quality of the image, and accordingly, the classification accuracy will increase.

3 Methodology

In this section, we describe the concepts and the proposed methods for classifying cervical cancer stadiums. It includes the concepts of fuzzy set, fuzzy neural network model, and the image preprocessing methods in the form of intensity adjustment and median filter.

3.1 Fuzzy Set

A fuzzy set has a working system as the human brain's way to process uncertain information. Unlike the classical set that each element has membership value 0 or 1, the fuzzy set allows each element to have real number in the interval [0, 1] as the membership value which represent the degree of memberships. In this study, the membership function is represented by the trapezium curve. A fuzzy number is easily denoted as a fuzzy set in real number set. The trapezoidal fuzzy number is expressed as

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

Operators on fuzzy set are designed based on the operators on classic set. Basic operators on fuzzy set are introduced by Zadeh including AND, OR, and NOT. In this research, we use OR operator [22]

$$\mu_{A \cup B}(x) = max\left(\mu_A(x), \mu_B(x)\right) \tag{2}$$

3.2 Fuzzy Neural Network

A fuzzy neural network is one kind of fusion of neural network and fuzzy logic. It deals with fuzzification of the conventional neural network. The fuzzification could be defined in the inputs, weights, or output neurons [23]. In this research, the fuzzification is defined only in the inputs using trapezoidal fuzzy membership function and OR operator. The conventional neural network with one hidden layer involves three layers: an input layer, a hidden layer, and an output layer. The proposed fuzzy neural network with one hidden layer involves five layers since it needs two steps to modify the crisp inputs to fuzzy inputs. The first step is changing the crisp inputs to fuzzy membership functions, the second step is applying OR fuzzy operator to the defined fuzzy inputs.

Let the variables $x_1, x_2, ..., x_j, ..., x_p$ as p crisp neurons in the input layer and functions $\mu_{11}(x_1), \mu_{21}(x_1), ..., \mu_{lj}(x_j), ..., \mu_{qp}(x_p)$ as q fuzzy numbers of p crisp inputs. Let A_l as a fuzzy set corresponds to l^{th} fuzzy number. Then, we employ the operator (2) to A_l on x_j such that

$$\mu_{\bigcup A_l}(x_j) = max\left(A_1(x_j), A_2(x_j), ..., A_q(x_j)\right) = max\left(\mu_{1j}(x_j), \mu_{2j}(x_j), ..., \mu_{qj}(x_j)\right) \tag{3}$$

For simplicity, equation (3) is written as $\mu_{max}(x_j)$. Let the variables z_k and y are a hidden neuron and an output neuron, respectively. Based on the formulated definitions, the structure of the fuzzy neural network is presented in Figure 1.

The fuzzy neural network model uses the standard sigmoid function in the hidden layer

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

and the identities function

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

in the output layer. When the function (4) is applied on the fuzzy input $\mu_{max}(x_j)$ and the function (5) on the hidden neuron z_k, we get a fuzzy neural network model

$$y = \sum_{k=1}^{r} v_k \left(1 + exp\left(-w_{0k} + \sum_{j=1}^{p} \mu_{max}(x_j) w_{jk}\right)\right)^{-1} + v_0 + \varepsilon \tag{6}$$

where w_{0k} is a bias and w_{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.

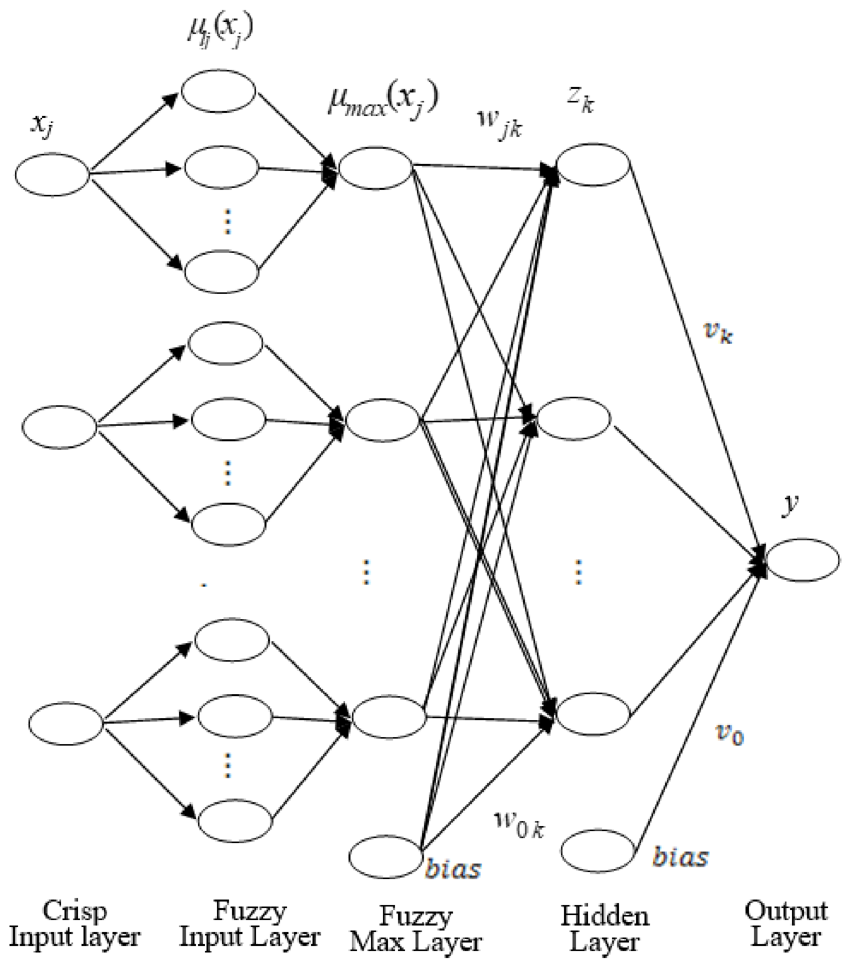


Fig. 1: A fuzzy neural network structure

3.3 Intensity Adjustment

The specific character of the images can be described from the pixel intensity values. The distribution of the pixel intensity values is presented in a histogram. Intensity adjustment is an image processing that aims to modify the intensity in the histogram to the new one. The effect of intensity adjustment depends on the defined mapping. In this study, the intensity adjustment is defined using a linear mapping of intensity values. The effect of the linear mapping is the change of the brightness and the contrast of the images and the associated histogram. In this study, the intensity adjustment produces brighter and more contrast images. Besides that, it changes the histogram to have a wider range.

3.4 Median Filter

A median filter is a quite popular image enhancement to reduce salt and noise and can maintain the edge. It is included in the spatial operation technique. The spatial operation changes the pixel value based on its neighborhood. Through the median filter, the extremely pixel value is substituted with the median of the grey level neighborhood of the value, where all pixel values in the neighborhood are ordered and the median is determined beforehand [24]. The median filter also has a capability to reduce blurring. It uses the odd and small kernel-size to minimize blurring. On the same kernel size, it produces less blurring than linear smoothing filter. We use a median filter with a kernel-size 3x3.

4 The Proposed Method

The fuzzy neural network modeling for disease classification in this study is related to the problem of determining the cervical cancer stadium using colposcopy images. The proposed method consists of three main steps: preprocessing the image, extracting the images to obtain measurable parameters, and constructing the fuzzy neural network model. The method is described in detail as follow.

Step 1. Preprocessing the image

The data used in this research are cervical colposcopy images. The images are in rgb type, so they need to be transformed into grey scale images. Then, the images are preprocessed using an intensity adjustment, a median filter, and a combination of intensity adjustment and median filter to improve the quality of the contrast and to reduce the salt and noise.

Step 2. Extracting the image

To get the information from the images, we perform a feature extraction to the grey scale colposcopy images, it is a process to get the unique characteristics that distinguish an object from another object. In this study, the feature extraction is performed to get the information related to the matrix of occurrence intensity. It is done by using a gray level co-occurrence matrix (GLCM) method. The information produced by the extraction process is the quantitative-valued parameters that are used as crisp inputs of the fuzzy neural network model.

Step 3. Constructing a fuzzy neural network model

In this step, we need to define the inputs of the model. The crisp inputs is the parameters yielded by GLCM extracting process. The fuzzy inputs are fuzzy numbers of the crisp inputs which are calculated using trapezoidal membership function and

OR operator as described in Section 3.1. The output is a single variable representing the cervical cancer stadiums. Before the learning process is done, the data are divided into two parts: training and testing data sets. Then, we perform the back propagation algorithm as the learning method [25]. The learning process is performed on training data set to construct the fuzzy neural network model (6), or specifically to estimate the weights between the fuzzy input layer and the hidden layer and the weights between the hidden layer and the output layer.

After following those three steps, then the performance of the obtained model is evaluated with regard to its accuracy in predicting the cervical cancer stadium. The best model is selected by considering the accuracy of the model to classify the cervical cancer stadium both on training and testing data.

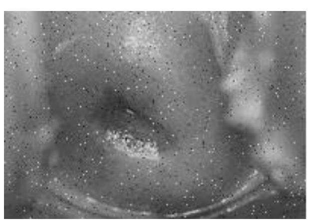
5 Results, Analysis, and Discussions

The fuzzy neural network model has been examined on the data set of 83 colposcopy images, which is available in the medical website www.gfmer.ch. The images have been classified into five cervical conditions: normal, stadium 1, stadium 2, stadium 3, and stadium 4. To obtain the fuzzy neural network model with a high accuracy, we performed a training-testing process. The training process intends to build the fuzzy neural network model. The testing process intends to evaluate how well the obtained model to predict the outside data. This relates to the generalizability of the model. The 83 images were split into 66 images for training and 17 images for testing. The distributions of the images based on five cervical conditions on training and testing data sets are given in Table 1.

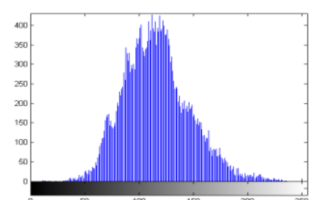
Table 1: The distribution of colposcopy images

Cervical Condition	The number of images	
	Training data	Testing data
Normal	21	4
Stadium 1	14	4
Stadium 2	14	3
Stadium 3	10	3
Stadium 4	7	3

In this study, we compare the performances of the fuzzy neural network models for classifying cervical cancer on the images with no preprocessing, with the intensity adjustment, with the median filter and with the combination of intensity adjustment and median filter preprocessing. The intensity adjustment affects the contrast and the grey level histogram, while the median filter affects the noise and the pixel matrix. We illustrated those effects on the image of the normal cervix. Figure 2 depicts (a) the original image, (b) the associated pixel matrix, and (c) the histogram. The image has a low contrast and has noise and salt. The low contrast is described by the histogram which has a narrow range. The salt and noise are expressed by the pixel matrix in which some values are extremely different from the nearby values, such as 66 and 70. Figure 3 depicts (a) the images with intensity adjustment, (b) the associated pixel matrix, and (c) the associated histogram. The yielded image demonstrates the suitable contrast. The implication of the intensity adjustment also can be observed from the histogram whose pixel intensity values are distributed uniformly from 0 to 255. This process does not eliminate the noise and salt, even they look clearer. This case was demonstrated in the pixel intensity values of the original image whose values 66 and 70 decreased to 37 and 42. Figure 4 depicts (a) the image with the median filter, (b) the associated pixel matrix, and (c) the associated histogram. The noise and salt from the original image are removed. This implies that the pixel matrix delivers almost the same values without any extreme value. Moreover, the contrast image is not improved, which can be seen in the associated histogram which fairly remains the same as in the original one. Figure 5 depicts (a) the image with the combination of intensity adjustment and median filter, (b) the associated pixel matrix, and (c) the associated histogram. The resulted image is clean from salt and noise and has a proper contrast. The pixel matrix has similar values with the pixel matrix of images with median filter operation. Furthermore, the histogram has also similar range to the histogram of images with intensity adjustment.

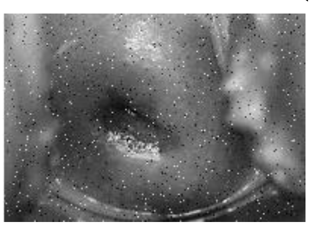


142	144	146	149	70
139	140	147	155	159
138	139	146	153	157
139	139	147	154	158
66	158	150	157	161

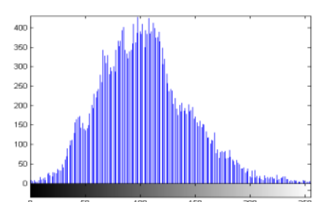


(a) (b) (c)

Fig. 2: (a) The original cervical image (b) the pixel matrix
(c) the pixel intensity histogram



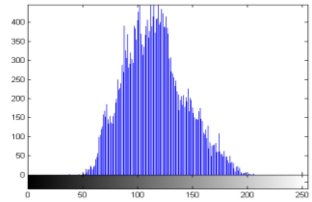
138	141	144	148	42
134	136	145	156	161
133	134	144	153	158
134	134	145	154	160
37	160	149	158	164



(a) (b) (c)

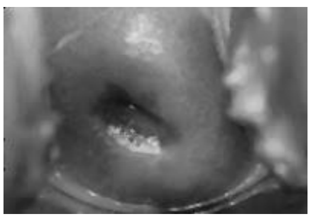
Fig. 3: (a) The intensity adjustment cervical image (b) the pixel matrix
(c) the intensity histogram

142	144	146	149	155
140	142	146	149	157
139	139	147	154	158
139	139	150	154	158
143	144	151	157	161

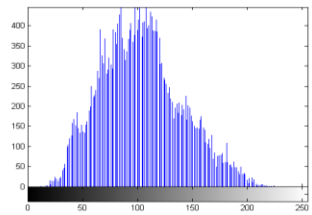


(a) (b) (c)

Fig. 4: (a) The median filter cervical image (b) the pixel matrix (c) the pixel intensity histogram



138	141	144	148	156
136	138	144	148	158
134	134	145	154	160
134	134	149	154	160
140	141	150	158	164



(a) (b) (c)

Fig. 5: (a) The combination of intensity adjustment and the median filter cervical image (b) the pixel matrix (c) the pixel intensity histogram

The first step after image preprocessing is image extraction with the gray level co-occurrence matrix (GLCM) method. The image features resulted from extraction are used as crisp inputs. The features defined in this research are referred to [26], which consist of 11 features, such as contrast, correlation, energy, homogeneity, entropy, the sum of squares, inverse, sum variance, difference entropy, maximum probability, and dissimilarity. The inputs which are in crisp form are required to be converted into fuzzy form. The fuzzification in this study uses the membership function of the trapezium curve (1) with three fuzzy numbers. From the three fuzzy numbers, we select one fuzzy number with the OR (2) operator as the fuzzy input variable. The output of the fuzzy neural network model involves a single neuron whose values consist of five categories: category 1 for normal, category 2 for stadium 2, category 3 for stadium 3, category 4 for stadium 4, and category 5 for stadium 4 cervix. Now, we can build a fuzzy neural network model with 11 inputs and a single output. The number of hidden neurons is determined by trial and error until the fuzzy neural network achieves the best performance. The experiments results are given in Table 2.

Table 2: The classification accuracies of fuzzy neural networks

The number of hidden Neuron	Model 1		Model 2		Model 3		Model 4	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
1	46.97	47.06	48.49	35.29	30.30	29.41	51.52	17.65
2	50.00	35.29	69.70	52.94	69.70	52.94	69.70	47.06
3	80.30	58.82	69.70	64.71	66.67	41.18	86.36	52.94
4	98.49	64.71	100.00	58.82	87.88	58.82	95.45	58.82
5	100	64.71	100	52.94	98.49	58.82	98.49	64.71
6	100	52.94	100	70.59	100	52.94	100	64.71
7	100	64.71	100	64.71	100	76.47	100	58.82
8	100	64.71	100	64.71	100	70.59	100	70.59
9	100	76.47	100	82.35	100	64.71	100	70.59
10	100	64.71	100	70.59	100	82.35	100	88.24
11	100	70.59	100	58.82	100	64.71	100	64.71
12	100	76.47	100	64.71	100	70.59	100	70.59
13	100	76.47	100	58.82	100	70.59	100	70.59
14	100	64.71	100	70.59	100	58.82	100	64.71
15	100	58.82	100	64.71	100	58.82	100	76.47

Model 1 is a fuzzy neural network on the original images
Model 2 is a fuzzy neural network on intensity adjustment images
Model 3 is a fuzzy neural network on median filter images
Model 4 is a fuzzy neural network on the combination of intensity adjustment and median images

The results in Table 2 show that the best fuzzy neural network models on the original and the intensity adjustment images are obtained at nine hidden neurons, while the model with median filter and the model with the combination of both approaches are obtained at 10 hidden neurons. These results show that the fuzzy neural network models for all four types of images have the same accuracy level, with no misclassified data. Those performances agree with the results of [9] [15], which also reach accuracy 100%. Theoretically, the back propagation algorithm can approximate any function with the desired degree of accuracy. This characteristic allows the accuracy having a high possibility to reach 100%.

Model performance is important deals with its generalization ability. Table 2. also shows that the combination of intensity adjustment and the median filter has the highest positive effect on the generalization ability with accuracy 88.24 % on testing data, while the intensity adjustment and the median filter have the same effect on the fuzzy neural network model accuracy on the testing data. Although the Model 2 and the Model 3 deliver the same accuracy, the colposcopy images resulted by the intensity adjustment and the median filter process are totally different. Therefore, their distributions of the misclassification data are different. The misclassified data in Model 2 are as follows: a normal cervix is misclassified as a cervix stadium 1, a cervix stadium 1 is misclassified as a normal cervix, and a cervix stadium 3 is misclassified as a cervix stadium 2. The misclassified data in Model 3 are as follows: two cervixes stadium 3 are misclassified as a cervix stadium 1 and cervix stadium 2, and a cervix stadium 4 is misclassified as a cervix stadium 1.

The results on testing data show that the image preprocessing can increase the generalization ability of the fuzzy NN model. These tendencies are consistent with the results of [9] [20] [21] regarding the advantage of the intensity adjustment and consistent with the results of [15] regarding the advantage of the median filter. The most effective method is the combination of intensity adjustment and median filter. It provides the same accuracy as the back propagation NN method [15] which only uses the median filter as in Model 3. Thus, adding a fuzzy input layer in the NN model does not guarantee the better result. But theoretically, the fuzzy input is more reasonable since the attribute yielded by the GLCM method differs vaguely the cervical cancer stadium.

The result on testing data also shows that after the model reaches the highest accuracy, it tends to have lower accuracy on the model structure with more hidden neurons. A more complex model is not always followed by the capability of the model for generality to out sample data. Generally, it can be stated that increasing the image contrast with an intensity adjustment and eliminating noise with a median filter are effective to improve the accuracy of a fuzzy neural network model for classification of cervical cancer.

6 Conclusion

A fuzzy neural network model is built for classifying cervical cancer using colposcopy images. The preprocessing images of intensity adjustment and median filter have been operated to enhance the contrast and reduce the noise. The physician has classified the colposcopy image database into normal, cancer stadium 1, stadium 2, stadium 3, stadium 4 cervixes. The crisp inputs are generated from the parameters extracted by the GLCM method. The fuzzy inputs are calculated using trapezoidal membership function and OR operator. The fuzzy neural network model is evaluated on the images with no preprocessing, with an intensity adjustment, a median filter, and a combination of both preprocesses. The proposed fuzzy neural network model shows remarkable performances on the training data for four types of data, which are indicated from the result with no misclassified data. The fuzzy neural network model together with the combination of intensity adjustment and median filter can reach the highest performance in term of generality capability to classify cervical cancer stadiums.

The inputs fuzzification process in fuzzy NN has various types. We can change the fuzzy membership function, the operator, and also the number of fuzzy numbers. The accuracy of the model depends on those chooses. It is still an interesting problem for further research to design more effective fuzzification process.

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