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OPTIMIZATION OF FUZZY MODEL USING SINGULAR VALUE DECOMPOSITION AND ITS APPLICATION FOR DIAGNOSING CERVICAL CANCER

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Abstract

Cervical cancer is known as a deadly disease for women. Over the past 30 years, the mortality rate of cervical cancer has dropped by more than 50% due to the increased use of Pap smear tests. Therefore, early detection and diagnosis are very important to know the possibility of cervical cancer. The purpose of this research is to establish a Takagi-Sugeno-Kang (TSK) fuzzy model using singular value decomposition method and to apply the model for diagnosing cervical cancer where the data were taken from four extractions of colposcopy images. Singular decomposition method was used to determine the parameters of fuzzy rules of the TSK fuzzy model. The results show that the

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one order TSK fuzzy model gives better accuracy, sensitivity, and specification than Mamdani fuzzy model for training data. On the other hand, for testing data, Mamdani fuzzy model gives better accuracy, sensitivity, and specification than one order TSK fuzzy model. Furthermore, TSK fuzzy model gives better sensitivity than Mamdani fuzzy model.

1. Introduction

Cervical or cervix is a part of female reproductive system. Cervical cancer affects the cervix inside the pelvis. The disease is caused by HPV (human papilloma virus). Cervical cancer is a deadly disease for women in both developed and developing countries. According to the American Cancer Society [3], the mortality rate of cervical cancer has dropped by more than 50% for the last 30 years. The main reason for this change is an increase in the use of Pap smear tests. This test is a step to early detection. Therefore, early detection of cervical cancer needs to be done in order for it to be given a proper treatment or medication. This makes many researchers conduct research on early detection of cervical cancer with a variety of models.

Myers et al. [20] constructed a model of the natural history of HPV and cervical cancer using a Markov model. Then, Goldie et al. [10] developed a model of the natural history of HPV and cervical cancer by adding vaccine HPV-16/18. In addition, Lee and Tameru [15] constructed models of the development of human papilloma virus (HPV) to cervical cancer. Miller et al. [19] established a model of early detection to increase the prognostic value of 18 F-FDG PET using a simple visual analysis of the characteristics of the tumor in patients with cervical cancer. Kivuti-Bitok et al. [12] constructed a dynamic model for the diagnosis of cervical cancer. Praba and Priya [21] compared classification techniques *k*-NN classifier, Bayesian classifier and ANN classifier for the diagnosis of Pap smear. The results indicate that the algorithm (artificial neural network) provides a high performance in the set of reduced images with a high accuracy and produces excellent classification for Pap smear.

Su et al. [29] used a two-stage cascade classification system for an automatic detection of cervical cancer cells. The results show that the level of overall accuracy of the method is 95.805%. Research on early detection of cervical cancer also used a variety of data, such as Talukdar et al. [31] who diagnosed cervical cancer using fuzzy *C*-means algorithm clustering from the image of Pap smear results. Mahanta et al. [17] tried to change the image of Pap smear results to be of type red green blue (RGB) for classifying cervical cancer. In the following year, Mahanta et al. [18] used structure based segmentation and shape analysis of Pap smear images for diagnosing cervical cancer. Then, Rose and Allwin [24] identified abnormal cervix that leads to cancer using fuzzy *C*-mean algorithm on cervical ultrasound image. Liang et al. [16] used colposcopy image sequence with support vector machine (SVM) classifier to automatically identify abnormal cervical regions.

Yushaila [34] classified cervical cancer stage using fuzzy model of extracting colposcopy images. Researches with fuzzy model keep being conducted, for example, Kuzhali et al. [14] who predicted the risk of cervical cancer using fuzzy rough set. Quteishat et al. [23] used systems based on fuzzy min-max (FMM), neural network (NN) and adaptive fuzzy moving *K*-means (AFMKM) for classifying cervical cells. Hernández et al. [11] built an expert system to aid the diagnosis of cervical cancer in the atypical glandular cells using fuzzy logic and image interpretation cytology. Al-Batah et al. [2] identified cervical cancer using the multiple adaptive neuro fuzzy inference system (MANFIS) with automatic feature extraction algorithm.

Fadhilah [7] classified cervical cancer with a combination of Mamdani fuzzy model and stepwise regression for input selection of the extracted image colposcopy. Qi et al. [22] applied the fuzzy rule-building expert systems (FuRES) and fuzzy optimal associative memory (FOAM) for the diagnosis of cervical carcinoma.

In improving the accuracy of diagnosis, several researchers also process the preliminary data with a variety of methods. Korchiyne et al. [13] classified the CT images and MRI SCAN using fractals and combined with grey level co-occurrence matrix (GLCM) method. This method can improve the clinical diagnostic tests for osteoporosis pathologies. A'yun and Abadi [1] performed an operating point on mammogram images to optimize the diagnosis of breast cancer using a fuzzy system. Ashok and Aruna [4] applied the feature selection methods for the diagnosis of cervical cancer by SVM classifier. Selection of images is achieved by using mutual information (MI), sequential forward search (SFS), sequential floating forward search (SFFS) and random subset feature selection (RSFS) methods.

Athinarayanan and Srinath [5] developed an automated cancer detection with image processing in which the segmentation and extraction of the image texture are effective using SVM. Sukumar and Gnanamurthy [30] proposed a method of automatic detection and diagnosis of cervical cancer using Pap smear images. In their method, preprocessing and feature extraction used GLCM and nuclei region segmentation while the classification used adaptive neuro fuzzy inference system. Researchers continually improve the diagnosis of cervical cancer by a variety of methods. In this paper, we constructed a TSK fuzzy model for diagnosis of cervical cancer by extracting data from colposcopy images.

2. Method

In this research, we used 90 data of extraction of cervical colposcopy images. These data were taken from [6, 25, 27] which were then divided into two parts, namely 80 as training data and 10 as the testing data. The steps of the research are shown in Figure 1.

Image extraction

The process of extracting the image is one of the processes that are important in pattern recognition. In image extraction process, we used gray level co-occurrence matrix (GLCM). According to Gadkari [8], GLCM method is one method that is quite effective in doing classification because it can provide detailed information about an image in terms of texture. In the extraction process using GLCM, the image will be converted into gray scale so that for each pixel in the image region, there is only one value of gray.

The statistical characteristics can be extracted from GLCM method. In this research, there were four extractions of entropy difference, mean, correlation, sum average used as input for the fuzzy model. One example of the extraction process for one of the cervical colposcopy images is shown in Figure 2.

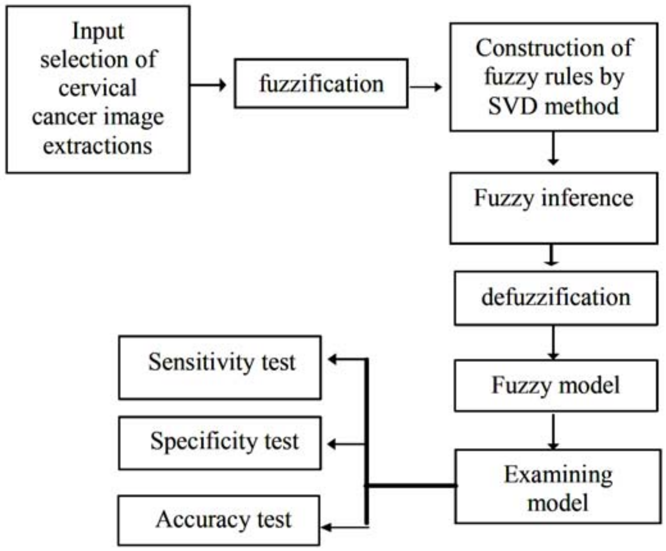

Figure 1. Diagram of research flow.

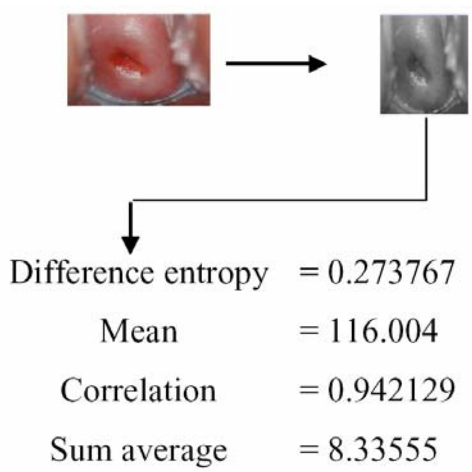

Figure 2. Changing the format into the image of gray and extraction results.

Fuzzy model

The construction of fuzzy model consists of four steps, namely fuzzification, determining fuzzy rules, construction fuzzy inference, and defuzzification. In this research, we used Mamdani and TSK inference systems for establishing the fuzzy model [32]. The *i*th fuzzy rule of TSK model can be written as follows:

$$R^i: \text{If } x_1 \text{ is } A_{i1} \text{ and....and } x_n \text{ is } A_{in}, \text{ then } y_i = b_{i0} + b_{i1}x_1 + \cdots + b_{in}x_n, \quad (1)$$

where $i = 1, 2, ..., L$ and L is the number of fuzzy rules, A_{ij} is a fuzzy set on *j*th input and *i*th fuzzy rule, y_i is consequent of *i*th fuzzy rule, b_{ij} is a real parameter to be determined. Then, the output of TSK fuzzy model with singleton fuzzifier, product inference machine and center overage defuzzifier can be written as follows [32]:

$$y = \sum_{i=1}^{L} w_i(b_{i0} + b_{i1}x_1 + \cdots + b_{in}x_n), \quad (2)$$

where $w_i = \dfrac{\mu_{i1}(x_1)\mu_{i2}(x_2)\cdots\mu_{in}(x_n)}{\sum_{i=1}^{L}\mu_{i1}(x_1)\mu_{i2}(x_2)\cdots\mu_{in}(x_n)}$ and $\mu_{ij}(x_j) = \mu_{A_{ij}}(x_j)$.

Singular value decomposition

The parameters of consequent on fuzzy rules (1) can be formed into a matrix. According to Scheick [26], singular value decomposition of the matrix *A* with size $m \times n$ is

$$A = USV^T, \quad (3)$$

where $U_{m\times m}$ and $V_{n\times n}$ are unitary matrices and $S_{m\times n}$ is a diagonal matrix where the diagonal entries $s_{ii} = \sigma_i$ are the singular values of *A*, $i = 1, 2, ..., r$, $\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_r \geq 0$. Then, it will be constructed model (2) that minimizes the objective function *J* [33] with

$$J = \sum_{k=1}^{N} (d(k) - y(k))^2 = (d - Xb)^T (d - Xb), \tag{4}$$

where $d(k)$ is the real output of kth data $= [d(1) d(2) \cdots d(N)]^T$, and $y(k)$ is the output model of TSK of kth data. Then, X is a matrix of size $N \times L(n+1)$, where N is the number of data, n is the number of input and L is the number of rules, $b = [b_1\ b_2 \cdots b_m]^T$ is a matrix of consequent parameters (1) with size $m = L(n+1) \times 1$.

Function J on (4) will reach minimum if $d - Xb = 0$ or $Xb = d$, where X is in the form

$$X = \begin{bmatrix} w_1(1) & w_1(1)x_1(1) & \cdots & w_1(1)x_n(1) & \cdots & w_L(1) & \cdots & w_L(1)x_n(1) \\ w_1(2) & w_1(2)x_1(2) & \cdots & w_1(2)x_n(2) & \cdots & w_L(2) & \cdots & w_L(2)x_n(2) \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ w_1(N) & w_1(N)x_1(N) & \cdots & w_1(N)x_n(N) & \cdots & w_L(N) & \cdots & w_L(N)x_n(N) \end{bmatrix}. \tag{5}$$

Then, we applied equation (3) to get the singular value decomposition of matrix X. The optimal solution of linear equation system $Xb = d$ with $X = USV^T$ [9] is

$$\hat{b} = \sum_{i=1}^{r} \sigma_i^{-1} < d, \quad u_i > v_i = \sum_{i=1}^{r} \frac{u_i^T d}{\sigma_i} v_i, \tag{6}$$

where r is the number of nonzero nonsingular values, $U = [u_1, ..., u_N]$, and $V = [v_1, ..., v_{(n+1)L}]$. Thus, b_i can be estimated by the entries of matrix $\hat{b}$.

Accuration test

The values of defuzzification of the model and the real values of the data can be compared between training and testing data to get accuracy rate, sensitivity rate, and specification rate. The formulas for the accuracy, sensitivity, and specification level [28] are as follows:

1 True positive (TP) is when patients have the disease and the result of classification states too.

2 False positive (FP) is when patients do not have the disease but the result of classification states that they have the disease.

3 True negative (TN) is when patients do not have the disease and the result of classification states that they do not have the disease.

4 False negative (FN) is when patients have the disease but the result of classification states that they do not have the disease.

$$\text{accuracy} = \frac{\text{the number of the correct data}}{\text{the amount of entirely data}} \times 100\%,$$

$$\text{sensitivity} = \frac{\text{the number of } TP}{\text{the number of } (TP + FN)} \times 100\%,$$

$$\text{specification} = \frac{\text{the number of } TN}{\text{the number of } (TN + FP)} \times 100\%.$$

3. Results

Colposcopy image extraction process produces four image properties. The four properties are difference entropy, correlation, mean and sum average. Furthermore, these properties are used as input in forming a fuzzy model for diagnosing cervical cancer. In this research, we used Mamdani and TSK fuzzy model.

Mamdani fuzzy model

The steps to construct Mamdani fuzzy model are done as follows:

1. Fuzzification

In this step, first, we defined the universal set for each input. Then, we defined the fuzzy sets in the universal set. In this research, we defined nine fuzzy sets with Gaussian membership function in each input. Then, we defined five fuzzy sets for output with triangular membership functions where the centers of the fuzzy sets were 0, 1, 2, 3 and 4. The fuzzy sets with centers 0, 1, 2, 3 and 4 were used to identify normal phase, stage 1, stage 2, stage 3 and stage 4 of cervical cancer, respectively.

The universal sets for the four inputs are $D = [0.19\ 0.62]$ for *difference entropy*, $C = [0.86\ 0.99]$ for *correlation*, $M = [52\ 185]$ for *mean*, and $S = [4.3\ 12.6]$ for sum average.

The fuzzy sets on the difference entropy (D) input are defined using membership functions as follows:

$$\mu_{D_1}(x) = f(x,\ 0.0228,\ 0.19) = e^{-\frac{(x-0.19)^2}{2(0.0228)^2}},$$

$$\mu_{D_2}(x) = f(x,\ 0.02284,\ 0.243) = e^{-\frac{(x-0.243)^2}{2(0.02284)^2}},$$

$$\mu_{D_3}(x) = f(x,\ 0.02285,\ 0.297) = e^{-\frac{(x-0.297)^2}{2(0.02285)^2}},$$

$$\mu_{D_4}(x) = f(x,\ 0.0228,\ 0.3513) = e^{-\frac{(x-0.3513)^2}{2(0.02281)^2}},$$

$$\mu_{D_5}(x) = f(x,\ 0.02284,\ 0.405) = e^{-\frac{(x-0.405)^2}{2(0.0228)^2}},$$

$$\mu_{D_6}(x) = f(x,\ 0.0228,\ 0.4587) = e^{-\frac{(x-0.4587)^2}{2(0.02284)^2}},$$

$$\mu_{D_7}(x) = f(x,\ 0.0228,\ 0.5125) = e^{-\frac{(x-0.5125)^2}{2(0.02281)^2}},$$

$$\mu_{D_8}(x) = f(x,\ 0.02284,\ 0.5662) = e^{-\frac{(x-0.5662)^2}{2(0.02284)^2}},$$

$$\mu_{D_9}(x) = f(x,\ 0.02285,\ 0.62) = e^{-\frac{(x-0.62)^2}{2(0.02285)^2}}.$$

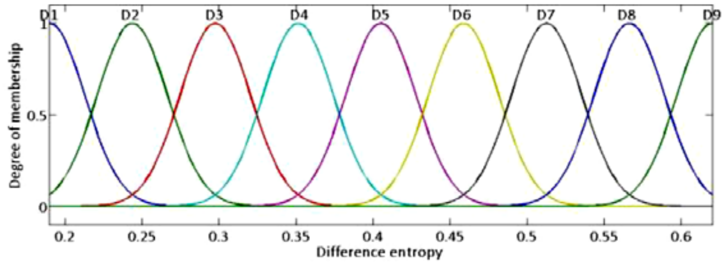

Figure 3. Membership functions of fuzzy sets on the difference entropy input.

Membership functions of fuzzy sets on the correlation (C) input are defined as follows:

$$\mu_{C_1}(x) = f(x, 0.00688, 0.86) = e^{-\frac{(x-0.86)^2}{2(0.0068)^2}},$$

$$\mu_{C_2}(x) = f(x, 0.006918, 0.8762) = e^{-\frac{(x-0.8762)^2}{2(0.006918)^2}},$$

$$\mu_{C_3}(x) = f(x, 0.006884, 0.8925) = e^{-\frac{(x-0.8925)^2}{2(0.006884)^2}},$$

$$\mu_{C_4}(x) = f(x, 0.006918, 0.9087) = e^{-\frac{(x-0.9087)^2}{2(0.006918)^2}},$$

$$\mu_{C_5}(x) = f(x, 0.006897, 0.925) = e^{-\frac{(x-0.9087)^2}{2(0.006918)^2}},$$

$$\mu_{C_6}(x) = f(x, 0.006884, 0.9413) = e^{-\frac{(x-0.9413)^2}{2(0.006884)^2}},$$

$$\mu_{C_7}(x) = f(x, 0.006918, 0.9575) = e^{-\frac{(x-0.9575)^2}{2(0.006918)^2}},$$

$$\mu_{C_8}(x) = f(x,\ 0.006884,\ 0.9738) = e^{-\frac{(x-0.9738)^2}{2(0.006884)^2}},$$

$$\mu_{C_9}(x) = f(x,\ 0.006803,\ 0.99) = e^{-\frac{(x-0.99)^2}{2(0.006803)^2}}.$$

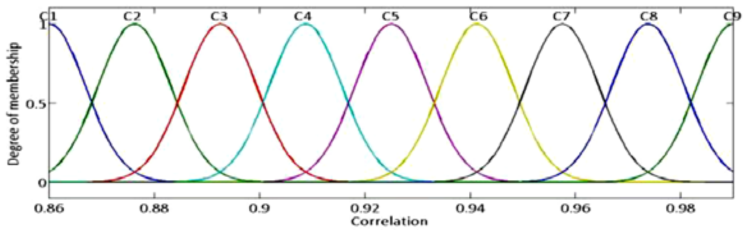

Figure 4. Membership functions of fuzzy sets on the correlation input.

Membership functions of fuzzy sets on the mean (M) input are defined as follows:

$$\mu_{M_1}(x) = f(x,\ 7.062,\ 52) = e^{-\frac{(x-0.52)^2}{2(7.062)^2}},$$

$$\mu_{M_2}(x) = f(x,\ 7.058,\ 68.63) = e^{-\frac{(x-68.63)^2}{2(7.058)^2}},$$

$$\mu_{M_3}(x) = f(x,\ 7.069,\ 85.25) = e^{-\frac{(x-85.25)^2}{2(7.069)^2}},$$

$$\mu_{M_4}(x) = f(x,\ 7.051,\ 101.9) = e^{-\frac{(x-101.9)^2}{2(7.051)^2}},$$

$$\mu_{M_5}(x) = f(x,\ 7.049,\ 118.5) = e^{-\frac{(x-118.5)^2}{2(7.049)^2}},$$

$$\mu_{M_6}(x) = f(x,\ 7.088,\ 135.1) = e^{-\frac{(x-135.1)^2}{2(7.088)^2}},$$

$$\mu_{M_7}(x) = f(x,\ 7.054,\ 151.8) = e^{-\frac{(x-151.8)^2}{2(7.054)^2}},$$

$$\mu_{M_8}(x) = f(x,\ 7.049,\ 168.4) = e^{-\frac{(x-168.4)^2}{2(7.049)^2}},$$

$$\mu_{M_9}(x) = f(x,\ 7.049,\ 185) = e^{-\frac{(x-185)^2}{2(7.049)^2}}.$$

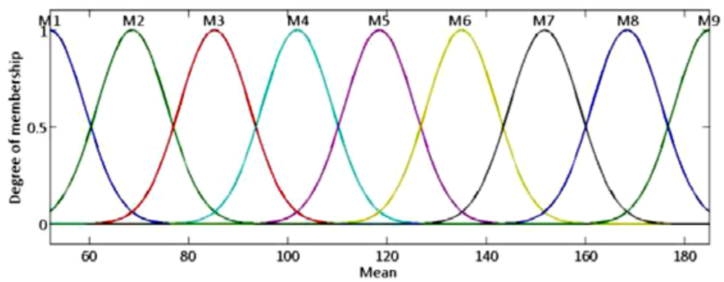

Figure 5. Membership functions of fuzzy sets on the mean input.

Membership functions of fuzzy sets on the sum average (S) input are defined as follows:

$$\mu_{S_1}(x) = f(x,\ 0.4408,\ 4.3) = e^{-\frac{(x-4.3)^2}{2(0.4408)^2}},$$

$$\mu_{S_2}(x) = f(x,\ 0.4404,\ 5.338) = e^{-\frac{(x-5.338)^2}{2(0.4404)^2}},$$

$$\mu_{S_3}(x) = f(x,\ 0.4404,\ 6.375) = e^{-\frac{(x-6.375)^2}{2(0.4408)^2}},$$

$$\mu_{S_4}(x) = f(x,\ 0.4408,\ 7.412) = e^{-\frac{(x-7.412)^2}{2(0.4408)^2}},$$

$$\mu_{S_5}(x) = f(x,\ 0.4408,\ 8.45) = e^{-\frac{(x-8.45)^2}{2(0.4408)^2}},$$

$$\mu_{S_6}(x) = f(x,\ 0.4423,\ 9.488) = e^{-\frac{(x-9.488)^2}{2(0.4423)^2}},$$

$$\mu_{S_7}(x) = f(x,\ 0.4379,\ 10.53) = e^{-\frac{(x-10.53)^2}{2(0.4379)^2}},$$

$$\mu_{S_8}(x) = f(x,\ 0.4412,\ 11.56) = e^{-\frac{(x-11.56)^2}{2(0.4412)^2}},$$

$$\mu_{S_9}(x) = f(x,\ 0.4416,\ 12.6) = e^{-\frac{(x-12.6)^2}{2(0.4416)^2}}.$$

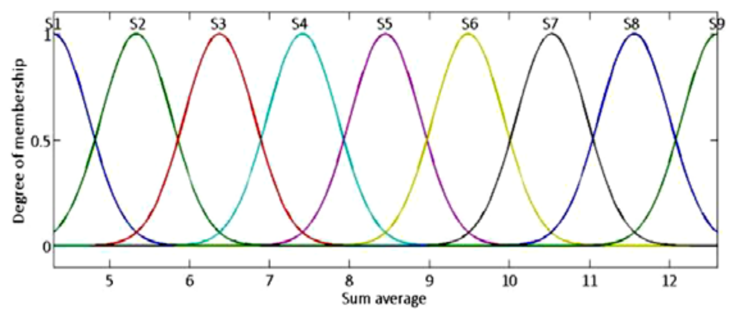

Figure 6. Membership functions of fuzzy sets on the sum average input.

Furthermore, the fuzzy sets defined in output are shown in Figure 7.

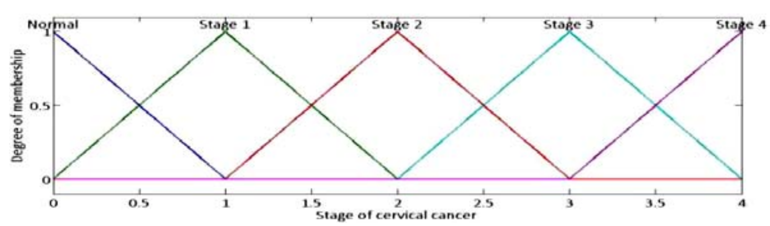

Figure 7. Membership functions of fuzzy sets defined on output.

2. Fuzzy rules

The fuzzy rules were developed from the 80 training data and by using fuzzy sets shown in Figures 3 to 7, then we obtained 74 rules as follows:

Rule (1) If difference entropy is D_4 and correlation is C_6 and mean is M_8 and sum average is S_8, then stage 1.

Rule (2) If difference entropy is D_5 and correlation is C_5 and mean is M_8 and sum average is S_8, then stage 1.

Rule (3) If difference entropy is D_5 and correlation is C_7 and mean is M_9 and sum average is S_9, then stage 1.

Rule (4) If difference entropy is D_4 and correlation is C_7 and mean is M_8 and sum average is S_8, then stage 1.

$\vdots$

Rule (74) If difference entropy is D_3 and correlation is C_7 and mean is M_3 and sum average is S_3, then stage 4.

3. Fuzzy inference and defuzzification

In this research, we used product Mamdani fuzzy inference and the defuzzification was done by using singleton fuzzifier, and center overage defuzzifier with the formula as follows:

$$y(x_1, ..., x_n) = \sum_{i=1}^{L} \frac{y_i \mu_{i1}(x_1)\mu_{i2}(x_2)\cdots\mu_{in}(x_n)}{\sum_{i=1}^{L} \mu_{i1}(x_1)\mu_{i2}(x_2)\cdots\mu_{in}(x_n)},$$

where $\mu_{ij}(x_j) = \mu_{A_{ij}}(x_j)$ and y_i is the center of fuzzy set on the consequent of ith fuzzy rule.

One order TSK fuzzy model

The one order TSK fuzzy model was developed through the following steps:

1. Fuzzification

Fuzzification process for input is analog with the process of fuzzification built by Mamdani fuzzy inference.

2. Fuzzy rules

The difference between Mamdani and TSK fuzzy rule is on the consequent of the rule. The consequent of TSK fuzzy rule is the linear combination of inputs. Based on the training data, there were 74 rules obtained by Mamdani fuzzy model. Then, the fuzzy rules for one order TSK fuzzy model are in the form below:

Rule (1) If difference entropy is D_4 and correlation is C_6 and mean is M_8 and sum average is S_8, then $y_1 = b_1 + b_2 *$ Diff. Entropy $+ b_3 *$ Mean $+ b_4 *$ Correlation $+ b_5 *$ Sum Average.

Rule (2) If difference entropy is D_5 and correlation is C_5 and mean is M_8 and sum average is S_8, then $y_2 = b_6 + b_7 *$ Diff. Entropy $+ b_8 *$ Mean $+ b_9 *$ Correlation $+ b_{10} *$ Sum Average.

$\vdots$

Rule (74) If difference entropy is D_3 and correlation is C_7 and mean is M_3 and sum average is S_3, then $y_{74} = b_{366} + b_{367} *$ Diff. Entropy $+ b_{368} *$ Mean $+ b_{369} *$ Correlation $+ b_{370} *$ Sum Average.

Based on the resulted fuzzy rules, the consequent coefficient of fuzzy rule will be obtained by constructing matrix *X*. Since the number of training data used to build the rules was 80 with 4 variables and there were 74 rules, then the size of matrix *X* is $80 \times [(4 + 1) \times 74] = 80 \times 370.$ Finally, we obtained matrix *X* for TSK model as follows:

$$X = \begin{bmatrix} 0.9256 & 0.3407 & \cdots & 0.0000 \\ 0.0006 & 0.0002 & \cdots & 0.0000 \\ \vdots & \vdots & \vdots & \vdots \\ 0.0000 & 0.0000 & \cdots & 0.0000 \end{bmatrix}. \tag{7}$$

Furthermore, matrix X is factorized by singular value decomposition method. Based on equation (7), we applied equation (3) to get singular values of matrix X as shown in Figure 8.

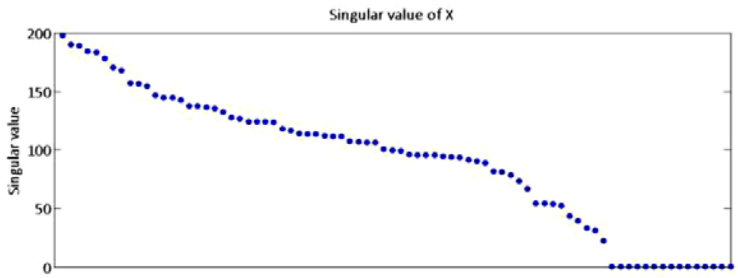

Figure 8. Singular values of X.

Using equation (6) and choosing all nonzero singular values, we obtained the consequent coefficient of TSK rule in the matrix form $b = [0\ 0\ 0.0058\ 0\ 0.0004 \cdots 0.0019]^T$. Then, the obtained rules are as follows:

Rule (1) If difference entropy is D_4 and correlation is C_6 and mean is M_8 and sum average is S_8, then $y_1 = 0 + 0 *$ Diff. Entropy $+ 0{,}0058 *$ Mean $+ 0 *$ Correlation $+ 0{,}0004 *$ Sum Average.

Rule (2) If difference entropy is D_5 and correlation is C_5 and mean is M_8 and sum average is S_8, then $y_2 = 0 + 0 *$ Diff. Entropy $+ 0{,}006 *$ Mean $+ 0 *$ Correlation $+ 0{,}0004 *$ Sum Average.

Rule (3) If difference entropy is D_5 and correlation is C_7 and mean is M_9 and sum average is S_9, then $y_3 = 0 + 0 *$Diff. Entropy $+ 0{,}0054 *$ Mean $+ 0 *$ Correlation $+ 0{,}0004 *$ Sum Average.

Rule (4) If difference entropy is D_4 and correlation is C_7 and mean is M_8 and sum average is S_8, then $y_4 = 0{,}003 + 0{,}002 *$ Diff. Entropy $+ 0{,}0054 *$ Mean $+ 0{,}003 *$ Correlation $+ 0{,}004 *$ Sum Average.

$\vdots$

Rule (74) If difference entropy is D_3 and correlation is C_7 and mean is M_3 and sum average is S_3, then $y_{74} = 0 - 0{,}0001 *$ Diff. Entropy $- 0{,}026 *$ Mean $- 0{,}0002 *$ Correlation $+ 0{,}0019 *$ Sum Average.

3. Fuzzy inference and defuzzification

We used product Mamdani fuzzy inference, while the defuzzification was done by using (2).

4. Discussion

In building TSK fuzzy model, several singular values should be selected to achieve a high level of accuracy. The results for accuracy, sensitivity and specification from Mamdani and TSK fuzzy model are shown in Table 1.

Table 1. Accuracy, sensitivity and specification from Mamdani and TSK fuzzy model

Fuzzy model	Select singular value	Data					
		Training data			Testing data		
		Accuracy	Sensitivity	Specification	Accuracy	Sensitivity	Specification
Mamdani model		93.75%	96.42%	100%	100%	100%	100%
Zero order TSK model	74	93.75%	100%	92.30%	20%	100%	0%
	73	93.75%	100%	92.30%	20%	100%	0%
	72	90%	100%	92.30%	50%	100%	0%
	71	90%	100%	92.30%	50%	100%	0%
	70	90%	100%	92.30%	50%	100%	0%
	69	90%	100%	92.30%	60%	100%	0%
	67	85%	100%	88.46%	60%	100%	0%
	65	82.50%	100%	80.76%	70%	100%	50%
One order TSK model	80	100%	100%	100%	60%	100%	50%
	79	96.25%	100%	92.30%	60%	100%	50%
	75	93.75%	100%	88.46%	70%	100%	50%
	74	93.70%	100%	88.46%	70%	100%	50%
	73	92.50%	100%	88.46%	80%	100%	50%
	72	92.50%	100%	88.46%	80%	100%	50%
	71	90%	98.14%	84.61%	80%	100%	50%
	70	88.75%	98.14%	80.76%	80%	100%	50%
	69	87.50%	98.14%	80.76%	80%	100%	50%
	67	83.75%	98.14%	80.76%	60%	100%	50%
	65	83.75%	98.14%	80.76%	70%	100%	50%

Based on Table 1, for selecting 80 singular values, one order TSK fuzzy model has the highest level (100%) of accuracy, sensitivity and specification on the training data. However, for the testing data, the accuracy, sensitivity and specification of that model are 60%, 100% and 50%, respectively. Furthermore, Mamdani fuzzy model has accuracy, sensitivity and specification of 100% for the testing data. For the training data, the one order TSK fuzzy model with 80 singular values has a higher level of accuracy, sensitivity and specification than the Mamdani and zero order TSK fuzzy models. For the testing data, Mamdani fuzzy model gives the highest accuracy, sensitivity and specification than zero and one order TSK fuzzy models.

5. Conclusion

This research established the zero and one order TSK fuzzy models with a singular value decomposition method. The model was compared to Mamdani fuzzy model to diagnose cervical cancer. It is found that the TSK model has capability to detect cervical cancer because the sensitivity level reaches 100% on the training and testing data. However, Mamdani fuzzy model has the capability to diagnose normal because the specification values for training and testing data reach 100%.

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