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Construction of fuzzy radial basis function neural network model for diagnosing prostate cancer

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ABSTRACT

In this paper, we propose a construction of fuzzy radial basis function neural network model for diagnosing prostate cancer. A fuzzy radial basis function neural network (fuzzy RBFNN) is a hybrid model of logical fuzzy and neural network. The fuzzy membership function of the fuzzy RBFNN model input is developed using the triangle function. The fuzzy C-means method is applied to estimate the center and the width parameters of the radial basis function. The weight estimation is performed by various ways to gain the most accurate model. A singular value decomposition (SVD) is exploited to address this process. As a comparison, we perform other ways including back propagation and global ridge regression. The study also promotes image preprocessing using high frequency emphasis filter (HFEF) and histogram equalization (HE) to enhance the quality of the prostate radiograph. The features of the textural image are extracted using the gray level co-occurrence matrix (GLCM) and gray level run length matrix (GLRLM). The experiment results of fuzzy RBFNN are compared to those of RBFNN model. Generally, the performances of fuzzy RBFNN surpass the RBFNN in all accuracy calculation. In addition, the fuzzy RBFNN-SVD demonstrates the most accurate model for prostate cancer diagnosis.

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1. INTRODUCTION

Prostate cancer is a disease that often occurs in adult men. The occurrence is commonly found at the age of 60 years or more, and is rarely found at the age 40 years or younger [1]. Prostate cancer is one of the common types of cancer in men in Indonesia. It is on the sixth rank of the diseases after breast cancer, lung cancer, colon cancer, cervical cancer, and liver cancer. According to the data and information center [2] the prevalence of prostate cancer in Indonesia in 2013 is estimated at 0.2% or as many as 25,012 people. The soft computing approaches related to the diagnosis of prostate cancer have been carried out by applying artificial neural [3], [4] and neuro-fuzzy system [5]-[7].

The development of soft computing such as neural networks (NN), fuzzy, and their combination for cancer diagnosis tool is still interesting for many researchers. Fuzzy radial basis function neural network (RBFNN) is a class of the hybrid model of fuzzy and NN. The fuzzy RBFNN is a potential method that could be used as a prostate diagnosis. It has been applied to various problems [8]-[10]. The fuzzy RBFNN can be

defined in different ways regarding the fuzzification process and the parameter estimation of the RBFNN. The fuzzification process on fuzzy RBFNN model is similar to that on a hybrid of fuzzy and back propagation neural network (fuzzy NN) model. Fuzzifications on fuzzy RBFNN using α-level sets and fuzzy α - cut interval have been proposed respectively by [11] and [8]. To fuzzify the inputs of fuzzy NN, Wutsqa and Rahmada [12] implement a combination of fuzzy membership function and OR operator, while Senol and Yildrim [13] implement a fuzzy membership function and the fuzzy rule. The fuzzy membership function to handle the uncertainty data is widely used in many mathematical problems, shuch as linear programming [14] and operation research [15].

The weights of RBFNN can be estimated by the least square method. However, this method is not suitable for the highly correlated input variables. Orr [16] suggests the global ridge regression (GRR) method to carry out that problem. Even GRR provides a global optimum solution that will be appropriate only for the small number of inputs. Back propagation (BP) is another alternative method used by Pehlivan and Apaydin [11]. BP has a limitation. It produces a local optimum solution. In this study, the singular value decomposition (SVD) is applied as the weight estimation in fuzzy RBFNN. It can be used to solve the linear system. The SVD theorem relates to the eigenvalues and singular values. SVD has an advantage corresponding to the global optimum solution. It is an efficient method since it involves a noniterative calculation. Numerous studies have addressed the benefit of choosing SVD to solve the linear system [17]-[20].

Another issue about the prostate cancer diagnosis is the variables considered as the influence variables of the prostate condition. The works [3]-[7] use prostate-specific antigen (PSA) level in blood, age, and prostate volume (PV) of patients as the inputs of the model. Except for those inputs, Stephan *et al.* [4] also use ultrasonic prostate images as an input variable. Studies that used prostate images to detect the prostate cancer are very limited, even though it is prospective as a clinical evidence for prostate cancer diagnosis. A quantitative information of the prostate radiograph can be attained by retaining texture feature extraction. There exist four texture types, i.e. statistical texture, structural texture, model based texture, and transform based texture. Each type is differentiated from the object and the method of measurement. We focus on the statistical texture with gray level co-occurrence matrix (GLCM) and gray level run length matrix (GLRLM) methods. Statistical texture features can be obtained using statistical approaches from the higher order of pixel grey values of images [21]. Haralick *et al.* [22] have developed the statistical measurements of the image using the GLCM method. GLCM method has been frequently used as an image extraction method [23]-[27]. GLRLM has also been applied by [21] and [27].

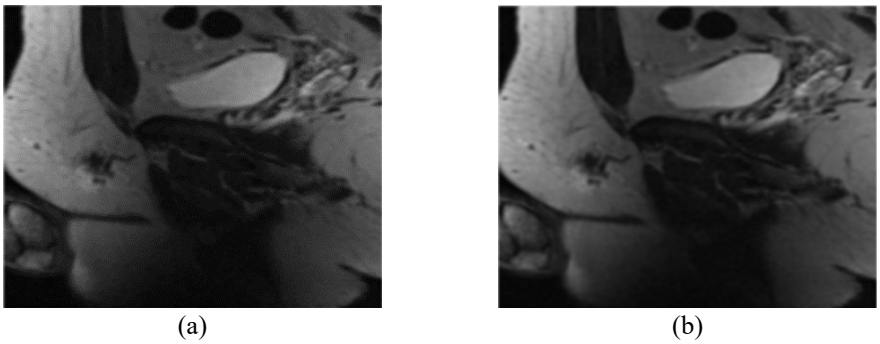
In this study, we propose a fuzzy RBFNN model using SVD weight estimation for prostate classification. The variables of the fuzzy RBFNN model are the features extracted from the prostate radiograph by using GLCM and GLRLM methods. Image preprocessing using high-frequency emphasis filter and histogram equalization (HE) are applied to enhance the quality of the prostate radiograph. The fuzzification is proceeded only in the inputs using fuzzy membership function. To highlight the superiority of the proposed methods, the results are compared with those obtained by GRR and BP methods. They are also compared with those yielded by the RBFNN method with all weight estimation methods.

2. RESEARCH METHOD

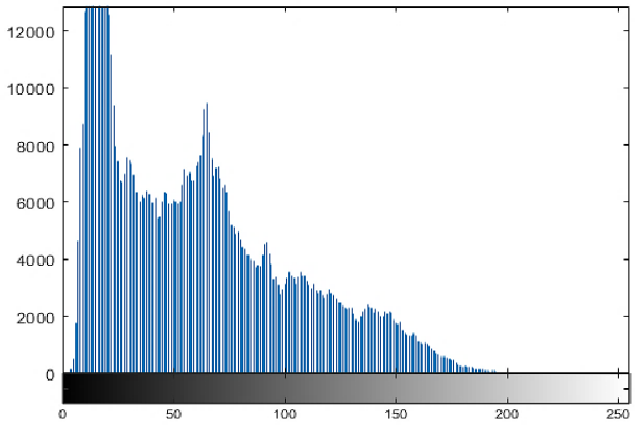
2.1. Image preprocessing

Image preprocessing is performed to change the red green blue (RGB) image into a grayscale image or a binary image. We propose the high-frequency emphasis filter (HFEF) to sharpen the image and histogram equalization to enhance the brightness of the image. High-frequency emphasis filter (HFEF) is an image preprocessing in the frequency domain. The HFEF method still produces the image with low contrast and low brightness and has the narrow histogram of intensity. The histogram equalization yields the higher contrast and brighter image, and histogram with intensity level uniformly distributed [28]. Abadi *et al*. [29] have demonstrated the effectiveness of the HFEF and histogram equalization to improve the quality of an image and increase the accuracy of the RBFNN model to detect lung cancer.

Figure 1 (a) exhibits the example of the prostate radiograph. The grayscale image is presented in Figure 1 (b) and its histogram is presented in Figure 1 (c). The high frequency emphasis filter (HFEF) is implemented to the grayscale image and the result is presented in Figure 2 (a) and its histogram is presented in Figure 2 (b). The resulted image is still improper. After the process of histogram equalization (HE), the image is brighter and has a higher contrast, as shown in Figure 3 (a). Its histogram is in Figure 3 (b), and its intensity values are uniformly distributed.



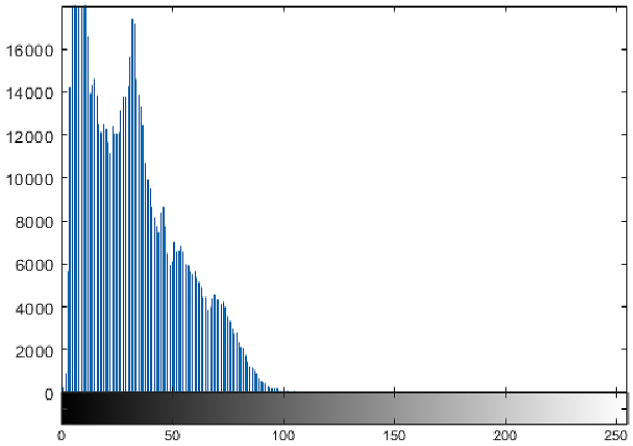
(a) (b)



(c)

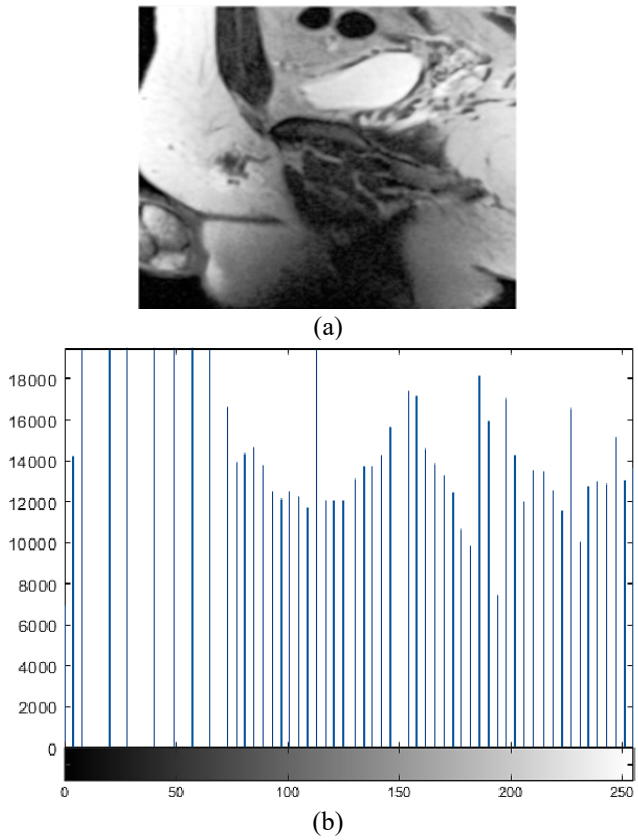
Figure 1. (a) Original RGB image, (b) Grayscale image, (c) Histogram of grayscale image

(a)



(b)

Figure 2. (a) Grayscale image after HFEF, (b) Histogram of HFEF image



(a)

(b)

Figure 3. (a) Grayscale image after HFEF and HE, (b) Histogram of HFEF and HE image

2.2. Feature extraction

Each image can be transformed to a matrix of pixels which value is called grey level. Textural feature extraction is done to obtain the characteristics of the images from the pixel matrix. There are many approaches to extract the feature of the images. In this research, we propose two second order statistical approaches. They are the gray level co-occurrence matrix (GLCM) and gray level run length matrix (GLRLM). A gray level co-occurrence matrix is defined as a two-dimensional histogram of gray levels for a pair of pixels, which are separated by a fixed spatial relationship. While in the GLRLM approach, the gray level runs are characterized by the gray tone of the run and the length and the direction of the run. The GLCM extraction involves ten features which are derived from [22]. They are contrast, prominence cluster, cluster shade, energy, entropy, homogeneity, sum average, difference entropy, inverse difference moment normalized (IDN), and inverse measure of correlation. The GLRLM extraction involves six features consisting of the short run emphasis (SRE), long run emphasis (LRE), run percentage (RP), run length non-uniformity (RLN), low gray level run emphasis (LGRE), and high gray level run emphasis (HGRE) [30].

2.3. Fuzzy radial basis function neural network (RBFNN)

Fuzzy RBFNN is a class of hybrid model of fuzzy logic and neural network. The fuzzy term corresponds to the fuzzy variable that could be defined in the input, weight, and output. The fuzzification process is needed to change the crisp number into the fuzzy number. In this research, the fuzzification is performed only in the input variable. We utilize triangular membership functions to change the crisp input into the fuzzy input. The architecture of fuzzy RBFNN is constructed by adding the architecture of RBFNN with one layer, namely fuzzy input layer. Thus, the fuzzy RBFNN architecture consists of four layers: a crisp input layer, fuzzy input layer, hidden layer, and output layer. Let $x_1\ x_2, \ldots, x_n$, are the p crisp input variables, $\mu_{1,1}(x_1)$, …, $\mu_{q,1}(x_1)$, …, $\mu_{1,p}(x_n)$,…, $\mu_{q,p}(x_n)$ are the p x q fuzzy input variables, q is the number of fuzzy memberships, $\phi_1, \phi_2, \ldots, \phi_m$are the m hidden neurons, and y is the output neuron. Then, the architecture of fuzzy RBFNN with single output neuron is presented in Figure 4.

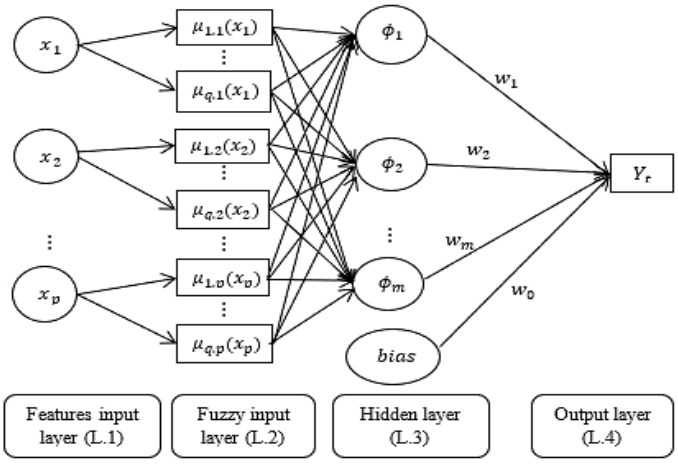


Figure 4. Architecture of fuzzy RBFNN model [9]

Fuzzy RBFNN model includes two activation functions: a radial basis function in the hidden layer and linear function in the output layer. The most popular radial basis function is the Gaussian function. This function is effective for classification [31]. The output of the fuzzy RBFNN model with Gaussian and linear functions can be expressed in the formula (1).

$$Y_t = \sum_{j=1}^{m} w_j \, \phi_j(\mu(X)) + w_0 \quad (1)$$

where w_j, $j = 1, 2, ..., m$ and w_0 are weights and bias between the hidden layer and output layer. The Gaussian function on *j*th hidden neuron ϕ_j is defined on the fuzzy input vector $\mu(X)$ as;

$$\phi_j(\mu(X)) = exp\left(\frac{(\mu(X)-c_j)^T(\mu(X)-c_j)}{r_j^2}\right) \quad (2)$$

where

$$\mu(X) = [\mu_{1,1}(x_1), \ldots, \mu_{q,1}(x_1), \ldots, \mu_{1,p}(x_p), \ldots, \mu_{q,p}(x_p)]^T$$

is a fuzzy input vector, and

$$c_j = [c_{11}, \ldots, c_{q1,} \ldots, c_{1p}, \ldots, c_{qp}]$$

is a *j*th cluster center vector, and r_j is the maximum distance in the *j*th cluster.

The learning process of fuzzy RBFNN is the same as the RBFNN. It contains unsupervised and supervised learning. The unsupervised learning intends to estimate the Gaussian parameters cluster center vector c_j and maximum distance in the *j*th cluster r_j. We propose fuzzy C-means clustering (FCM) method as unsupervised learning. The FCM groups each object to all clusters represented by the degree of membership function. The procedure of fuzzy C-means method is addressed to the procedure of Zimmermann [32]. The steps are as follows [32], [33].

- Fix the number of clusters (m), $2 \le m < n$, where n is the number of objects. Determine s, $1 < s < \infty$ and the termination criteria (ε).
- Initialize the C partition matrix $U^{(0)}$

$$U^{(0)} = \begin{bmatrix} \mu_{11} & \mu_{12} & \cdots & \mu_{1n} \\ \mu_{21} & \mu_{22} & \cdots & \mu_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \mu_{c1} & \mu_{c2} & \cdots & \mu_{cn} \end{bmatrix}$$

- Calculate the C *cluster* centers *p*-dimensional vector $\mathbf{v}_j = (v_{j1}, v_{j2}, \ldots, v_{jp})$ for *j*th cluster center

$$v_{ji} = \frac{\sum_{k=1}^{n}(\mu_{jk})^s x_{ki}}{\sum_{k=1}^{n}(\mu_{jk})^s}, \; i = 1, 2, \ldots, p$$

– Update $U^{(t)}$ and calculate the membership of $U^{(t+1)}$ by following the steps.
For $k = 1$ to n, calculate the Euclidian distance between object observation x_j and cluster center v_j

$$d_{sk} = \| \boldsymbol{x}_k - \boldsymbol{v}_j \|$$

and set $I_k = \{s | 1 \le j \le c, d_{jk} = || \mathbf{x}_k - \mathbf{v}_j || = 0\}$ and $\bar{I}_k = \{1, 2, ..., c\} - I_k$
Calculate a new membership matrix U of kth object and jth cluster as;

$$\text{If } I_k = \phi \ , \ \mu_{jk} = \frac{1}{\sum_{g=1}^{c} \left(\frac{d_{jk}}{dg_k} \right)^{2/(s-1)}}$$

else $\mu_{jk} = 0$ for all $j \in \bar{I}_k$ and $\sum_{j \in I_k} \mu_{jk} = 1$.

Next k.

– Calculate the difference of $U^{(t)}$ and $U^{(t+1)}$ in term of the proper matrix norm, if $\| U^{(t)} - U^{(t+1)} \| < \varepsilon$, stop. Otherwise, set $t = t + 1$ and repeat from step 3 to step 5.

The supervised learning intends to estimate the weights w_j and bias w_0. The optimal weights are estimated by minimizing

$$SSE = \sum_{k=1}^{n} (y_k - \hat{y}_k)^2 \quad (3)$$

where n is the number of training data, $\hat{y}_k$ is the predicted value of the output variable, y_k is the target or the actual value of the output variable.

The function that must be estimated in the output layer is a linear function, so SVD is an appropriate choice. The singular value decomposition (SVD) method is performed on the matrix φ which elements are Gaussian function $\phi_j(\mu(X))$.

The matrix $\phi(\mu(X)) = \begin{pmatrix} \phi_1(\mu(X))_1 & \phi_2(\mu(X))_1 & \cdots & \phi_m(\mu(X))_1 & 1 \\ \phi_1(\mu(X))_2 & \phi_2(\mu(X))_2 & \ldots & \phi_m(\mu(X))_2 & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \phi_1(\mu(X))_n & \phi_2(\mu(X))_n & \cdots & \phi_m(\mu(X))_n & 1 \end{pmatrix}$ is decomposed to become the product of three matrices

$$\phi(\mu(X))_{nx(m+1)} = UDV^T \quad (4)$$

where $U = [u_1, u_2, ..., u_n]_{nxn}$, $u_k \ (k = 1, 2, ..., n)$ is a column vector, $V = [v_1, v_2, \ldots, v_{m+1}]_{(m+1)x(m+1)}$, $v_j (j = 1, 2, \ldots, m+1)$ is column vector, the matrix $D_{nx(m+1)}$ is a matrix whose the diagonal entries is the singular values of matrix $\phi(\mu(X))$. Then, the singular values satisfy $\sigma_1 \ge \sigma_2 \ge \ldots \ge \sigma_s \ge 0$. Furthermore, the weight vector $\hat{w} = [\hat{w}_1, \hat{w}_2, \ldots, \hat{w}_m, \hat{w}_0]^T$ of the fuzzy RBFNN model can be obtained as follows;

$$\hat{w} = \sum_{i=1}^{r} \frac{u_i^T d}{\sigma_i} v_i \quad (5)$$

where d is a vector of target, and r is the number of positive singular values.

As a comparison, we also employ the back propagation (BP) algorithm and global ridge regression (GRR) method as supervised learning. The BP algorithm is very famous as a learning method in the neural network model and very effective to estimate the parameters both in linear and nonlinear function. It implements gradient descent method to minimize the sum squared error (SSE). The BP algorithm trains the network by following the three main steps: the feed forward of the input training pattern, the back propagation of the associated error, and the adjustment of the weights [34]. The GRR method estimates the weight by adding a positive regulation parameter ($\lambda > 0$) to the sum square error [16]. The λ value is selected by minimizing the generalized cross-validation (GCV) [35].

2.4. Procedure of fuzzy RBFNN to diagnose prostate cancer

The proposed method includes the image preprocessing, textural feature extraction, the fuzzification, and fuzzy RBFNN optimization. The procedure starts from the image preprocessing using HFEF and histogram equalization to get a suitable image for classification. The textural feature extraction

using GLCM and GLRLM are performed to take the features of the prostate radiographs. This step produces the crisp inputs of fuzzy RBFNN. Then, the crisp inputs are fuzzified using a triangle membership function. The data are divided into training and testing sets. The fuzzy RBFNN model is constructed using the training data, and it is evaluated in term of its generalization capability using testing data.

Now, the construction of fuzzy RBFNN model is implemented to the fuzzy inputs using FCM for unsupervised learning and SVD method for supervised learning. In this step, we need to set the number of fuzzy membership functions, clusters, and positive singular values to obtain the optimal fuzzy RBFNN model. To determine the optimal model, we consider the accuracy of the model both on training and testing data. The overall procedure of constructing fuzzy RBFNN to classify prostate cancer is presented in Figure 5.

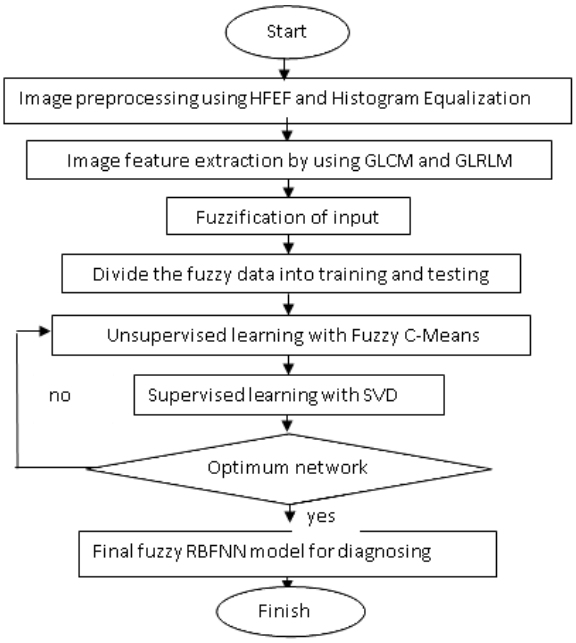


Figure 5. Construction procedure of fuzzy RBFNN to diagnose prostate cancer

3. RESULTS AND ANALYSIS

The experimental data are drawn from the website [36]-[42]. The data consist of 100 prostate radiographs which have been classified into normal, benign, and malignant. Before doing the analysis, the quality of the prostate image is improved by using the HEEF and histogram equalizer. The crisp inputs of fuzzy RBFNN are the features extracted using GLCM and GLRLM methods. The architecture of fuzzy RBRNN includes 10 crisp input variables for the GLCM method and 6 input variables for GLRLM method. The fuzzy inputs are the fuzzy membership values which contain three triangle membership functions. The mathematical formula of the triangle membership functions is shown in (6).

$$\mu(x) = \begin{cases} 0, \ x < a, and x > c \\ \frac{x-a}{b-a}, \quad a < x \leq b \\ \frac{c-x}{c-b}, \quad b < x \leq c \end{cases} \tag{6}$$

The values of a,b,c are set relied on the minimum and maximum values of the variable. The number of fuzzy inputs becomes 30 and 18 fuzzy inputs for the features extracted using GLCM and GLRLM, respectively. The output of the fuzzy RBFNN is the diagnosis of prostate cancer. It is categorized as 1 for normal, 2 for benign, and 3 for malignant.

The data are split into 80% training sample and 20% testing sample. The optimum fuzzy RBFNN model is obtained by changing the number of clusters. This process leads to changing of the cluster center and maximum distance values, and automatically changing the Gaussian function values. The SVD method is applied to the matrix of Gaussian functions to estimate the weights. The optimal number of clusters corresponds to the fuzzy RBFNN model with the highest accuracy both on training and testing data. The results of the optimal fuzzy RBFNN models using GLCM and GLRLM methods are presented in Table 1 and Table 2.

Table 1. Accuracy of the fuzzy RBFNN-SVD with GLCM

The number of clusters	Accuracy (%)		The number of clusters	Accuracy (%)	
	Training	Testing		Training	Testing
3	57.5	60	17	75	65
4	61.25	60	18	75	75
5	62.5	60	19	73.75	60
6	62.5	60	20	75	65
7	70	80	21	80	70
8	66.25	65	22	78.75	75
9	70	80	23	80	70
10	70	80	24	77.5	75
11	71.25	70	25	78.75	70
12	71.25	70	26	80	75
13	70	75	27	78.75	65
14	70	70	28	80	70
15	71.25	75	29	80	60
16	72.5	75	30*	81.25	80

Table 2. Accuracy of Fuzzy RBFNN-SVD Model with GLRLM

The number of clusters	Accuracy (%)		The number of clusters	Accuracy (%)	
	Training	Testing		Training	Testing
3	57.5	60	17	80	70
4	62.5	60	18	77.5	70
5	61.25	65	19	83.75	70
6	61.25	75	20	85	60
7	62.5	65	21	85	60
8	65	70	22	82.5	65
9	65	70	23	83.75	70
10	66.25	70	24	82.5	60
11	67.5	75	25	82.5	65
12	81.25	60	26	83.75	75
13	72.5	70	27	82.5	65
14	80	65	28	83.75	65
15	80	50	29 *	87.5	75
16	83.75	65	30	86.25	75

Table 1 and Table 2 demonstrate that the percentage accuracy of the fuzzy RBFNN-SVD fluctuate both on training and testing data, and the accuracy increase on training data is not always followed by the accuracy increase on testing data. The highest accuracies on training and testing data are achieved at the number of cluster 30 and 29 for the features extracted using GLCM and GLRLM methods, respectively. On the training data, the accuracy of fuzzy RBFNN with GLRLM which attains 87.5% is higher than GLCM which attains 81.25%. On testing data, however, the accuracy of fuzzy RBFNN with GLCM which attains 85% is higher than GLRLM which attains 75%. The best fuzzy RBFNN-SVD-GLCM has an architecture with ten crisp input neurons, thirteen fuzzy input neurons, thirty hidden neurons, and a single output. The best fuzzy RBFNN-SVD-GLRLM has an architecture with six crisp input neurons, eighteen fuzzy input neurons, twenty-nine hidden neurons, and a single output neuron.

In this study, we compare the results of the fuzzy RBFNN-SVD to fuzzy RBFNN with different weight estimation methods, the back propagation (BP) and global ridge regression (GRR). We also compare the fuzzy RBFNN-SVD to RBFNN with SVD, BP, and GR weight estimation methods. Three performances are considered to compare the models. Except the accuracy, we also evaluate the model performance based on the sensitivity and specificity values. The sensitivity represents the percentage of the number of patients with the disease which is correctly diagnosed over the number of all patients with the disease. The specificity represents the percentage of the number of patients with no disease which is correctly diagnosed over the number of all patients with the no disease. Table 3 provides the comparison of the model performances considered in this research in terms of accuracy, sensitivity, specificity. It demonstrates that the accuracy and the sensitivity of the models tend to outperform in the data extracted by using GLCM than GLRLM. The SVD weights estimation deliberates the higher accuracy and specificity values than GR and BP methods both in the fuzzy RBFNN and RBFNN. The GR and BP methods can hardly diagnose the normal prostate since mostly their specificity values are zero. If we compare all models, the fuzzy RBFNN-SVD delivers the best performance in terms of accuracy. Specifically, the fuzzy RBFNN-SVD gives the best performance in the three criteria of accuracy, sensitivity, and specificity in the GLCM features and in the criteria of accuracy and specificity in the GLRLM features. Thus, we can conclude that the fuzzy RBFNN-SVD is an effective model to diagnose prostate cancer.

Table 3. The performance (%) of diagnosis results

Model	data	GLCM			GLRLM		
		accuracy	sensitivity	specificity	accuracy	sensitivity	specificity
RBFNN-GR	training	66.25	96.74	22.22	58.75	100	0
	testing	70	100	0	60	100	0
RBFNN-BP	training	62.5	100	0	58.75	100	0
	testing	60	100	0	58.75	100	0
RBFNN-SVD	training	80	100	61.11	77.5	96.74	50
	testing	75	86.67	0	70	100	40
Fuzzy RBFNN-GR	training	72.5	93.38	27.78	81.25	100	66.67
	testing	75	100	0	70	100	20
Fuzzy RBFNN-BP	training	63.75	100	0	63.75	100	0
	testing	65	100	0	60	100	0
Fuzzy RBFNN-SVD	training	82.5	100	64.7	87.5	98.41	82.35
	testing	80	100	50	75	75	75
Fuzzy Mamdani	training	68.75	98.41	23.53	71.25	100	11.76
	testing	70	100	0	70	100	0
Elman NN	training	63.75	100	0	58.75	100	0
	testing	70	100	0	50	100	0

4. CONCLUSION

A new structure fuzzy RBFNN-SVD has been explored to diagnose prostate cancer using radiograph image using two texture feature extractions of GLCM and GRLCM methods. In this study, we also employ the image enhancement high frequency emphasis filter (HFEF) and histogram equalization to sharpen the image and improve the contrast of the image. The proposed method is compared to fuzzy RBFNN model with different weight estimation methods – back propagation and global ridge regression, and to RBFNN model with three different weight estimation methods as in fuzzy RBFNN. The experimental results show that on training data, the proposed method on the feature extracted using GLRLM is more accurate than other existing methods which has 87.5% accuracy. But, on testing data, the most accurate model is the fuzzy RBFNN-SVD implemented in the features yielded by GLCM extraction which has 80% accuracy**.**

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