

A Review of the Automatic Methods of Cancer Detection in Terms of Accuracy, Speed, Error and the Number of Properties (Case Study: Breast Cancer)

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Abstract: The purpose of this study is are view of the automatic methods of cancer detection in terms of accuracy, speed, error and the number of properties and we have selected the breast cancer as the subject of the case study. The data used in this academic study area courtesy of the UCI in California. This database is called the wisconsin breast cancer datasets and includes 699 data units divided into benign and malignant classes. Ten properties wereassigned to each datum. Four types of algorithms are used in this study, namely, classification algorithms, vector machine algorithms, neural networks algorithms and data mining algorithms. Each category was evaluated separately and the best method in each category was identified in terms of accuracy, speed, error and the number of properties.

Key words: Automatic methods of cancer detection, breast cancer, classification algorithms, vector machine algorithms, neural network algorithms, data mining algorithms

INTRODUCTION

Breast cancer is a common type of cancer. According to the calculations of the US National Cancer Institute one of every eight women may be afflicted with cancer throughout of her life [<http://www.bcaction.org/Pages/GetInformed/Top10Myths.html>]. Generally, this disease is a result ofthe convergence of some risk factors that cause the disease. The breast cancer is a cancer with high mortality rate among women such that it is the most common cause of death in the female community.

Timely detection of breast cancer (maximum 5 year after the first cancer cell division) increases the chance of the patient survival from 56% to over 86%. So, it seems essential to have a precise and reliable system for timely diagnosis of benign or malignant breast tumors. In or country, the breast cancer ranks second after lung cancer and ranks first among female cancers and is responsible for a fifth of the women's deaths caused by cancer (Anderson *et al.*, 2006). Traditionally, this type of cancer is diagnosed by biopsy via surgery and this method is the most accurate one among the existing methods but, it is an expensive and invasive procedure and raises emotional and psychological concerns and anxiety for the patient (Mangasarian *et al.*, 1995). However, because of biological similarity between benign and malignant patterns, the diagnostic specificity is not reasonable yet and differentiating between benign and malignant through

mammography is highly dependent on the radiologist's skill. But, it is not always possible to find a skilled radiologist for the interpretation of mammography images; therefore, there is a strong urge to have an experienced radiologistat hand because, it is the only way that one may raise the bar for both diagnostic sensitivity and specificity at the same time. But, since access to a qualified radiologist for interpretation of the images is not possible in all parts of Iran andeven in the case of availability there is the possibility of human errors, therefore designing a computer model as a rapid and cost effective and easily available diagnostic method could be in order. Clearly if the mass is correctly diagnosed as benign, there is no need for surgery and that will dismissmany concerns imposed on the patient as a result of such operations (Krishnaiah *et al.*, 2013; Rumelhart *et al.*, 1986; Ahmed *et al.*, 2013). In this study, the researcher intends to choose the best model by comparing various techniques.

Introduction to algorithms: Identification via Support Vector Machine (SVM) In 1965, the Russian researcher Vladimir Prikcame up with the idea of minimizing the risk and it was a very important step in the design of classifiers. The SVM is a binary classifier that separates two classes using a linear border or super plane so that the maximum margin of the super plane may result. Maximizing the margin of the super plane will result in

maximum separation between the classes. The training points that are closest to the maximum super plane margin are called support vectors. Only these vectors (points) are used to determine the boundary between the classes. In this method, the boundary line between the two classes can be calculated in a way that:

All instances of class +1 are on one side of the border and all instances of class -1 are on the other side of the border. The decision boundary must be such that the distance between the closest training instances of both classes in the direction perpendicular to the decision making boundary is maximized as much as possible. The general form of decision making border line can be written as Eq. 1:

$$Wx+b = 0 \quad (1)$$

Where:

- X = The point on the decision making border line
- W = The ann-dimensional vector perpendicular to the decision making border line the distance from the origin to the decision making border line
- Wx = Indicates the internal multiplication of the two vectors w, x (Zheng *et al.*, 2014)

K-means algorithm: In the clustering technique is a famous data mining method in which an automatic process is used to classify samples in a given data space into distinct categories based on their characteristics and each category is called a cluster. Therefore, the cluster is a collection of objects that contains objects with the highest similarity together and they have the lowest level of similarity to the objects in other clusters. A number of criteria may be used to define the similarity including the parameter of distance, i.e., nodes that have the minimum distance with one another are grouped in one cluster and such clustering method is called distance-based clustering (Chen *et al.*, 2011).

Thereafter, some useful information may be extracted by checking and comparing the data in each cluster. K-means is one of the well-known clustering algorithms. This algorithm is one of the cluster-center based algorithms with the following order of execution (Han and Kamber, 2006). Obtaining points as the clusters' centers at random attributing each data sample to a cluster such that the data sample has the lowest distance to the center of the cluster. In the standard presentation of the algorithm, first some points are randomly selected corresponding to the number of the required clusters (K). Then, the data are assigned to one of the clusters based on the level of proximity (similarity) and thus, new clusters are generated. The same procedure can be repeated and

each time by averaging the data, new centers can be calculated for the data and the data can be assigned to new clusters again. This process continues until the clusters do not change anymore. Usually, the condition for algorithm termination and its convergence criterion is the lack of change in the existing clusters, achieving a predetermined number of iterations or the expiration of the deadline.

The precise choice of the initial cluster centers highly influences the convergence of this algorithm and the optimal final clusters. These centers must be selected carefully and should be located at appropriate distances relative to each other.

Imperialist Competitive Algorithm (ICA): The evolutionary algorithms are a subset of the evolutionary calculations that belong to the branch of artificial intelligence and include algorithms wherein the search takes place from several points in the problem space. These algorithms are based on random search and exemplify natural biological evolution and work on potential answers that have superior characteristics and are capable of providing a better approximation of the optimal answer.

The ICA algorithm, like other evolutionary optimization methods, starts out with an initial population. In this algorithm, each data point is called a country. Countries are divided into two categories: colony and imperialist. Each imperialist country, depending on the extent of its power, dominates several colony countries and controls them. This algorithm is based on the colonial competition and absorption policy. In the provision of this algorithm, such policy is implemented via movement of an empire's colonies in accordance with a specific relationship (Ke *et al.*, 2010; Samoui and Bessassi, 2013).

Neural network algorithm: The neural network design has two main aspects of architecture and learning algorithm. The target neural network has a Multilayer Perceptron (MLP) structure with a better performance in comparison with other methods. MLP structure is a standard combination of inputs, linear and nonlinear neural units and outputs. The output of all processing units of each layer is fed to all of the processing units of the next layer as input. The input layer processing units are all linear but in the hidden layers, especially in the output layer, nonlinear neurons with hyperbolic or sigmoid tangent function or any other possible continuous and derivable nonlinear function can be used.

Neural networks have this ability to learn from the past, experience and environment and improve their behavior during learning. MLP neural network's learning method uses a supervised learning method for training. In the supervised learning method, a set of paired data called training samples are defined as $A = (X_i, t_i)$ wherein X_i is the input and t_i is the desired network output corresponding to the input. After feeding the X_i input to the neural network, the actual output of Y_i network is compared to t_i and the learning error is calculated and used later to set the parameters of the network in such a way that if the next time the same X_i input is fed to the network, the network output approximates closer. The learning algorithm used in the MLP neural network is the post-error-propagation learning algorithm.

There are two computational paths in the above algorithm. The departure path in which the stimulating functions act on each neuron and the return path in which the sensitivity vectors (error vectors) are returned back to the first layer. Finally, the information obtained from the above two paths is used to set up the network's weight matrices and Bias vectors of MLP network. In order to stop the repetition of the post-error-propagation algorithm, we can use the Mean Squared Error (MSE) in the form of Eq. 2:

$$MSE = \sum_{i=1}^Q \frac{(t_i - aL(P_i))^2}{Q} \quad (2)$$

The important point in the neural network is the sound choice of the weights and if necessary, the network's bias quantities. The method of weights selection is called learning algorithm training and a significant part of the network differences with one another lies in the method by which the parameters are set up (Mahapatra *et al.*, 2012; Kuruvilla and Gunavathi, 2014; Amato *et al.*, 2013; Khan *et al.*, 2013).

Classification methods: Four classification algorithms were used for this study, namely, perceptron artificial neural network method, Kohonen, fuzzy Artmap and tree classification.

Artificial neural network classification: The artificial neural network concept was adopted from the human nervous system. These networks classify input patterns based on two unsupervised and supervised methods. In the unsupervised method, the output patterns are not introduced and the system itself classifies them on the

basis of the similarity of the input patterns. But in the supervised method, the input is fed to the system and the difference between the desired output and the output of the network is used to change and adapt the weights. The training phase is the precursor of the classification phase in which the network carries out the training process by changing and adjusting the linking weights between the layers. In this study, we have used the perceptron, Kohonen and fuzzy Artmap artificial neural networks (Kohonen, 2001).

Perceptron artificial neural network: The perceptron neural network is the first applied network in the artificial neural network history and a symbol of supervised pre-fed neural network and its design consists of one input layer, at least one hidden layer and an output layer. Each layer is made up of nonlinear processing units called neurons (the nerves) and the connections between neurons in the successive layers carry the associated weights.

The connections are directional and are only in the forward direction. The method of learning in the supervised algorithm is the post-error-propagation method. In this method, the network weight is adjusted according to the gradient technique. So, that after the desired output value is compared with the actual network output, the network searches for the maximum descending gradient and in the next iterations, the network parameters can be set up based on the guideline of the descending error gradient. The parameters' set up is repeated throughout this process until the amount of network error reaches an acceptable value (Bishop, 1995).

Kohonen neural network: The Kohonen network is dual-layer network with unsupervised training. The Kohonen network is a self-organizing network that learns a mapping of samples introduced for learning (Kohonen, 2001). The structure of a Kohonen network (similar to a single-layer Perceptron network) has one input layer and some output neurons. Kohonen Network training with n inputs and m outputs is described as follows:

- First, the initial values of the network weights are selected at random
- The training samples are introduced to the network
- The following values are calculated for each of the output layer neurons

$$d_{min} = \min \left\{ d_i = \sum_{i=1}^n (X_i - W_{ij})^2, j=1, \dots, n \right\} \quad (3)$$

The winning output neuron is identified and the weights are correct by using a neighborhood function:

$$W_{ij}(l+1) = W_{ij}(l) + \eta(l)N(l)(X_i - W_{ij}(l)) \quad (4)$$

Where:

$\eta(t)$ = The training parameter

$N(t)$ = The neighborhood function

- The value of t is added.
- The algorithm is repeated from step 2

The number of iterations can be considered fixed or the iterations continue until the network is trained, i.e., the weight values change slightly. After the network was trained, it is necessary to introduce the samples to the network. The output of the network is based on the closest distance. Among the output neurons, the winner (of the network output) is the neuron that has the least euclidean distance with the input sample. The output of the Kohonen map is the topological mapping corresponding to the network input.

Fuzzy art map artificial neural network: This network was introduced in 1992 by Hansen *et al.* (2000). Fuzzy Artmap is a supervised network that combines two fuzzy Art networks: ART_a and ART_b. In the following, the parameters of these two networks are defined. These two networks connect to each other by a series of connections between the F₂ layers of the two networks that are called map fields abbreviated as Fab. Each of these connections has a weight W_{ij} with a value between 0 and 1. The Map Field has two parameters β_{ab} and ρ_{ab} and the output vector X^{ab}. The input vector into ART_a is converted into vector A under the supplemental coding. In the training phase of the fuzzy Artmap network, the input pattern vector into the ART a network and the desired output (B) associated with the input pattern A are presented to the ART_b network. ART_b, the care parameter ρ_v is set to 1 to distinguish the desired output vectors. After the presentation of the vectors B and A, the ART_a and ART_b networks enter the resonance phase. At this stage, another care criteria defined according to the Eq. 3 is calculated to assess whether the winning neuron in ART_a is associated with the desired output vector in ART_b:

$$\frac{|y^b \wedge W_j^{ab}|}{y^b} \supseteq \rho_{ab} \quad (5)$$

Where:

y^b = The output vector in ART_b (pattern in F₂^b)

J = The subscript of the winner neuron in F₂^b

w_j^{ab} = The weights of Map Field connections with the Jth neuron in jth the care parameter in map field

If the above criterion is not met, the care parameter in ART_a is increased a certain amount until the fuzzy artmap network selects another winning neuron. The vector A will be entered into the network again and the process will be repeated until the care criterion is satisfied. At this time, the weights of the Map Field connections are updated according to the following Eq. 6:

$$W_j^{ab} = \beta_{ab} X^{ab} + (1 - \beta_{ab}) W_j^{ab} \quad (6)$$

The initial value of the ρ_a is set by the basic care parameter $\bar{\rho}_a$. After updating the weights, the basic care parameter in ART_a is set to this initial value again. After completion of the training phase, parameters ρ_a and β_a are initialized to a zero value. The Map Field output vector is defined as follows:

$$X^{ab} = W_j^{ab} \quad (7)$$

So that J is the subscript of the winning neuron in F₂^b. This equation shows that the Map Field assigns a classifying number to each neuron in the F₂^b layer.

Tree classification: In the IDRISI software, the tree classification is based on the algorithm (Kumar *et al.*, 2013). In practice, this algorithm selects an attribute (such as the reflective band) by iteration, divides the samples that can be split into two groups and minimizes the difference within each subgroup while maximizing the difference between the groups. The tree classification progresses by consecutive breakdown of the data within new middle nodes containing more homogeneous subsets of the training pixels. A newly created middle node in a situation that the training pixel has only one class or one class predominates the pixels, may generate a leaf. When there is not any middle nodes left for splitting, the final tree classification rules take shape. The IDRISI Software makes use of 3 splitting algorithms: entropy, gain ratio and Gini.

Data mining

The processing models described in this research are as follows: Neural networks, Bayesian network, K-nearest neighbor, C5.0 tree and CART tree. This section presents

a brief introduction of these models (Bellaachia and Guven, 2006). Suppose you have a series of data in the set S. The C4.5 algorithm works as such: if all the items in S are for a collection or S is sufficiently small, a leaf with maximum collection in S is added to the tree. Otherwise, a test is selected based on a single distribution with one or two outputs. This experiment as the root of a tree is considered as a test by placing each of the outputs.

The S set is divided into S1, S2, etc., subsets based on the corresponding output. This process is applied to all subsets. In 1997, The C 4.5 algorithm was replaced with a business system entitled 5/c5.0. The applied changes resulted in remarkable capabilities that include:

- Variation of the boosting process which is a collection of classifiers that will be considered the final classification at a later stage. The boosting process usually achieves significant prediction accuracy
- New data types, irrelevant values, cost of incorrectly classified variables and the methods used to pre-filter the domain
- Set of the chaotic rules when a class is classified, all the relevant rules are pin pointed and voted there to. This enhances the interpretation of the set of rules. Moreover, it increases the precision of their prediction rate

The decision tree and the set of rules have progressed in an ascending fashion. The rate of climbing increases through segmentation. C 5.0 can run on multi-processor computers as well. The CART decision tree is a binary recursive segmentation method. The data are randomly selected. Throwing away is not necessary and not recommended. The trees grow to their maximum size without the use of the stop law. Then the regressive pruning phase back to the root commences (part by part isolation).

The next study which to be pruned is the part that has the lowest performance relative to the whole in the training data tree (it should be pointed out that more than one section can be removed at any stage). This process creates trees that are fixed under any order of arrangement. In fact, the CART algorithm mechanism is intended to generate not one but a consecutive collection of pruned trees which are all optimal candidate trees. The right size trees is identified and selected by evaluating the performance of each tree in the pruning stage (Caneda *et al.*, 2014).

Rote is one of the easiest and almost insignificant classifications which saves all the conducted training data. It runs the classification operation only when the

test exactly matches a training example. A clear objection to this method is that a lot of test data will not be classified because they do not exactly match with any of the recorded training data. A more advanced method in this regard is the k-nearest neighbor method. According to this algorithm, a group is pinpointed with k samples in the training dataset that are closest to the test data and the desired tag is selected based on the superiority of a specific class in its neighborhood (Salama *et al.*, 2012). Based on the given dataset, each belongs to a class. Each of these classes has a vector. Our goal is to create a rule to assign each of the samples to a class in the future.

This is carried out only through the vectors intended for the variables. Many ways have been introduced to create such rules. One of the most important methods is Bayes method. This algorithm is important for many reasons. This algorithm can be made very easily because it does not require complex iterative parameters. This means the algorithm can be used in some cases that there is a high volume of data. Neural networks are new systems and computational methods for machine learning and display of knowledge. Also, its ultimate goal is the application of gained knowledge to predict output response of the complex systems (Delen *et al.*, 2005; Messadi *et al.*, 2014).

The main idea of this kind of network is (partly) inspired by biological nervous system functions. The key element of this idea is the formation of new structures for the information processing system. This system consists of many interconnected processing elements called neurons. They collaborate together to solve a problem and pass on the information through synapses. In these networks, if a cell is damaged, the rest of the cells may compensate for the lack of it and also contribute to its reconstruction.

MATERIALS AND METHODS

Introduction of data: The data used in this academic study are a courtesy of the UCI in California. The title of this database is The Wisconsin Breast Cancer datasets and includes 699 data items. The data are divided into two benign and malignant classes. Ten properties were attributed to each datum. These properties are presented in the Table 1. The data properties were chosen with an eye to medical considerations. The thickness of malignant cells's masses is usually classified in single-layer groups while the cancer cells are usually placed in multi-layered groups. There are various sizes and apparent abnormal shapes of the cancer cells. This is why, these parameters are useful in diagnosis and detection of cancerous and

Table 1: Introduction of the data and the properties

Domain	Attribute	ID
1-10	Sample code number	1
10-1	Clump thickness	2
10-1	Uniformity of cell size	3
10-1	Uniformity of cell shape	4
10-1	Marginal adhesion	5
10-1	Single epithelial cell size	6
10-1	Bare nuclei	7
10-1	Bland chromatin	8
10-1	Normal nucleoli	9
10-1	Mitose	10
2 for benign and 4 malignant classes	Class	11

non-cancerous cells. With regard to the rate of cell adhesion, normal and healthy cells usually get close to each other while the cancer cells do not show such solidarity among them. As a result, lowered adherence also can be used to detect cancer cells. With regard to the single biological cell size, its size may vary as we explained earlier. Biological cells that grow big can be considered as cancer cells. A bare nucleus is in fact a nucleus without any cytoplasm surrounding it. Usually, these nuclei are observed in malignant tumors. In fact, chromatin is the expression of non-uniform nuclear material that is observed in malignant cancer cells. In the cancer cells, chromatin is observed as follows. Typical nuclei with tiny structures have been observed in healthy tissues. In cancer cells, the nuclei gradually swell and their number increase over time. Mitosis is a part of the nucleus that generates two identical daughter cells during prophase. Cell division takes place during this process. The pathologists can estimate the amount of cancer by counting the mitoses.

Preprocessing: Data preprocessing is the first step in performing the task. According to the information that the database put in our disposal, there are 16 forgotten data in its 7th column. To fix this problem, a data histogram was plotted to be used in the preprocessing. Because the properties are disconnected, the mod was used for the forgotten data. Other values except 10 are very few versus the value of 1. Only one-fourth of the data have attained the value of 10. That's why, the forgotten values are shown with the value of 1. The outlying data are the next problem that will be dealt with during the statistical tasks. Of course, the data used in this study had been previously checked by the related center and the outlying data have been removed from them. In other words, the database has presented the users with neat data. However, some processes were carried out to ensure there are no outlying data around.

Selection of the properties: One of the most important steps that can greatly help the processing to get better results is selecting the right features. If these properties are not selected correctly, there is a high potential for synergy. Synergy means trouble at the prediction stage. The large number of features can drastically increase the number of calculations in the event that it does not appreciably change the authenticity. So, a good choice of the right properties can increase the processing efficiency.

To do this, the property correlation matrix was calculated. Since, the correlation threshold of 0.95 was selected, no property correlation was observed. Therefore, all of the properties can be used in the prediction process. We used the random selection procedure to do justice to the training data sample selection and testing and to eliminate the dependence of the training on a particular order of data. The highlight of performance assessment of the models presented in this research is this same point that the evaluation results are not dependent on the particular order of data and each model that runs using a random selection from the dataset, 70% are allocated to training and 30% to testing. So, the results are not dependent on a particular order of the data.

RESULTS AND DISCUSSION

To carry out the modeling based on the artificial neural network, first we fed the data (dataset) to the Excel software. The dataset is randomly (MATLAB Software's Rand function) divided into two parts: training (learning) dataset and testing dataset. In order to do this, about 30% of the data was used for validation and testing and 70% of the data was used for training. Then by scripting and the use of existing neural network Toolbox in MATLAB software (Neural network tool), we selected the data (input and output variables) and determined the type of network (Feed-forward back prop), type of training function (trainlm), number of layers, number of neurons, type of transfer function (tansig), function error (mse) and so on, as well as the number of iterations (epoch), maximum error, time, weight, etc and next we found out the best option by trial and error (Fig. 1 and 2). With regard to computation time, SMV method drastically reduces the training by reducing the number of input properties. The computation time is also compared to the main SVM algorithm in Fig. 2 which depicts the importance of the choice and extraction of the property.

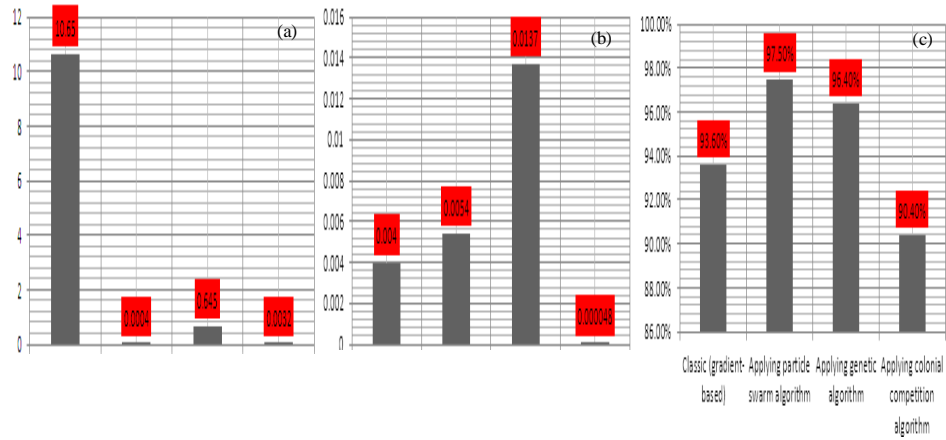


Fig. 1: Comparing the results obtained from simulation after applying three optimizing algorithms; a) CPU time; b) Error; c) Accuracy

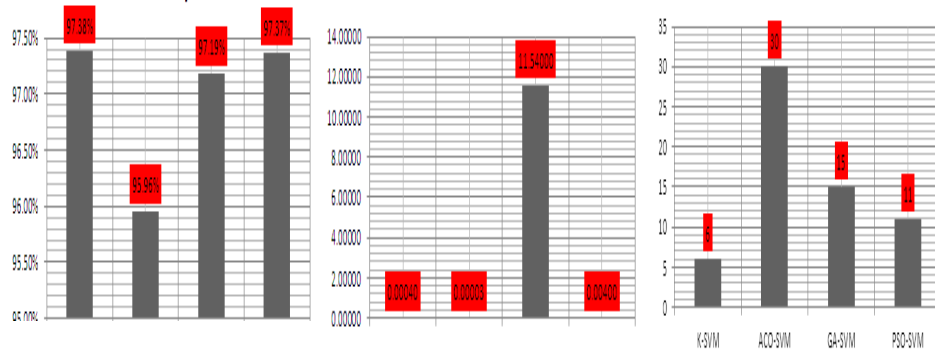


Fig. 2: Comparing the results of some of SVM algorithms: a) Accuracy; b) CPU time; c) Feature v space dimension

According to the final results, their recommended k-SVM procedure is more accurate than SVM for the diagnosis of benign and malignant tumors and the new input structures and patterns with the membership of new patterns based on the main data. The results of the classification using methods such as artificial neural network (Perceptron neural networks, Kohonen and fuzzy Artmap) and the tree classification are presented in the figure. According to the figure, the tree classification method with three branching techniques (gain ratio, entropy and Gini) has obtained the average total accuracy of 90 and Kappa coefficient 0.88, respectively while the eural network methodshad an accuracy of 92 and the Kappa coefficient of 0.90, respectively (except the Kohonen method).

Thus, the neural networks classification methods (with the average total accuracy of 2 and the average Kappa coefficient of 2%) were more accurate than the tree

classification method (with three branching methods) for the series of data used in the study. In addition when the different methods of the neural network were analyzed, it was clear that the fuzzy Artmap neural network method was more accurate than Perceptron and Kohonen methods (with the total accuracy enhancement of 2 and 22% and the Kappa coefficient enhancement of 3 and 24%). Finally, it can be said that there was no significant difference among the three branching methods employed in this study (Fig. 3).

According to the Fig. 4, clearly the Bayesian network has predicted the classes more accurately and can be used with more confidence for predictions. Also, its distribution authenticity is much less than other models. But these cases are quite the reverse in the neural network, i.e., its distribution is much more and its mean authenticity is lower than all other models.

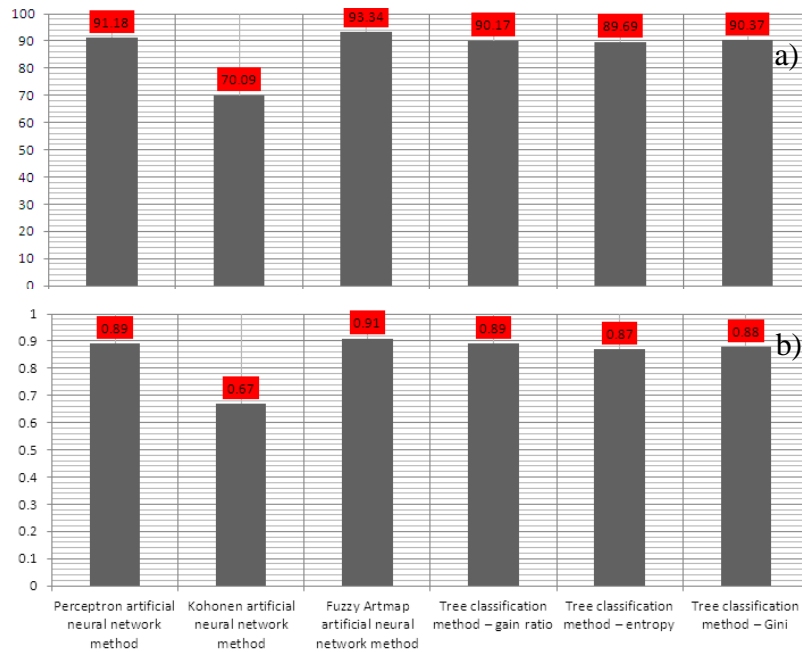


Fig. 3: Evaluation of the classification accuracy; a) Accuracy; b) Kappa coefficient

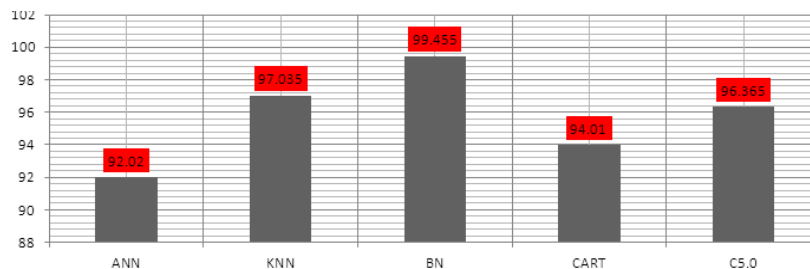


Fig. 4: Statistical information of the authenticity of the models after the evaluation

CONCLUSION

In the case of diagnosis by SVM from the K-SVM algorithm based on the properties it can be competitively compared with any of the old data mining methods of cancer detection. In the property extraction phase, the older methods are not used for extracting useful information. Properties with below 50% accuracy may not be appropriate for classification purposes. No single property is highly effective for mass classification applications. The properties must be combined to achieve a better performance. After evaluating each property individually, it is advisable to check a combination of these properties. Both geometry and texture properties are useful for detection of mass. The selection of a classification property that may be able to improve the accuracy will prove useful. In the case of diagnosis by

neural network, the algorithm based on gradient that considers the Levenberg-Marquardt algorithm and post-error-propagation method. One of its disadvantages is late convergence and stopping at optimal local points, as well as the optimal choice of number of layers, the number of neurons in each layer and the type of stimulation function of each neuron in the data with high complexity which is not a simple task. Therefore, the smart optimization algorithms such as mass particles algorithm, genetic algorithm, imperialist competitive algorithm, etc., that we used three types of them for network modeling in this study. The results showed that the imperialist competitive method is significantly capable of correct determination of neural network weights for its training and error elimination.

With regard to classification methods, all pixels could correctly identify the agricultural lands. The high

classification accuracy of agricultural lands classes may be a result of its distinctive spectroscopic characteristics in comparison with other types of coating. When different methods of artificial neural networks were analyzed, it was clear that the fuzzy Artmap artificial neural network provides more accurate results relative to perceptron and Kohonen artificial neural networks (with an overall accuracy enhancement of 2 and 22% and the Kappa coefficient enhancement of 3 and 24%).

In this research, the fuzzy Artmap artificial neural network had the highest classification accuracy. In the case of data mining techniques, it is clear in accordance with that the Bayesian network predicted the classes more accurately in and can be used with more confidence in the predictions. Moreover, its distribution authenticity is much less than other models. But, these cases are quite reversed in the neural network, i.e., its distribution authenticity is much more and its average accuracy is much lower than the other models. Among all models created by different training and testing data, only the neural network models were unable to provide a prediction in some cases. That is, they presented some data without any comments thereto.

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