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Original Article

Diagnosis of Breast Cancer using a Combination of Genetic Algorithm and Artificial Neural Network in Medical Infrared Thermal Imaging

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Abstract

Introduction
This study is an effort to diagnose breast cancer by processing the quantitative and qualitative information obtained from medical infrared imaging. The medical infrared imaging is free from any harmful radiation and it is one of the best advantages of the proposed method. By analyzing this information, the best diagnostic parameters among the available parameters are selected and its sensitivity and precision in cancer diagnosis is improved by utilizing genetic algorithm and artificial neural network.
Materials and Methods
In this research, the necessary information is obtained from thermal imaging of 200 people, and 8 diagnostic parameters are extracted from these images by the research team. Then these 8 parameters are used as input of our proposed combinatorial model which is formed using artificial neural network and genetic algorithm.
Results
Our results have revealed that comparison of the breast areas; thermal pattern and kurtosis are the most important parameters in breast cancer diagnosis from proposed medical infrared imaging. The proposed combinatorial model with a 50% sensitivity, 75% specificity and, 70% accuracy shows good precision in cancer diagnosis.
Conclusion
The main goal of this article is to describe the capability of infrared imaging in preliminary diagnosis of breast cancer. This method is beneficial to patients with and without symptoms. The results indicate that the proposed combinatorial model produces optimum and efficacious parameters in comparison to other parameters and can improve the capability and power of globalizing the artificial neural network. This will help physicians in more accurate diagnosis of this type of cancer.

Keywords: Artificial Neural Network, Breast Cancer, Genetic Algorithm, Thermography

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1. Introduction

Early breast cancer detection, is one of the most important areas that researchers are working on, and it can increase the rate of diagnosis, cure and survival of the affected women [1]. Considering the high cost of treatment as well as the high prevalence of the disease among women, early diagnosis will be the most significant step in reducing the health and social complications of this disease. Breast cancer is the major cause of cancer-related mortality among women worldwide [2]. Early detection of cancer, especially breast cancer, will facilitate the treatment process. Cancer is ranked as the 3rd cause of death, in Iran. The number of breast cancer patients has risen in Iran in recent years and unfortunately more importantly, the average age of patients is 10 years less than the average age of women in western countries plus most patients are diagnosed at the end stage [3-5].

There are so many different methods to detect breast cancer, with different advantages and disadvantages; some of these methods are mentioned as follows:

Breast examination by a physician: In this exam, physicians inspect the breasts followed by a physical examination of the patient in different body positions. Physicians look for asymmetry, masses, lesions, skin changes and dimpling in the breasts. The physician will try to measure the size of the mass by his/her fingers [6].

Mammography: If the patient is older than 35 years, usually the physician will ask for mammography [7]. In mammography, the patient is exposed to X-ray and the breast is compressed using two parallel plates. Parallel-plate compression evens out the thickness of breast tissue to increase image quality by reducing the thickness of tissue penetrated by x-ray. Some women find this method annoying while some women find it painful. The mammograph must be checked and interpreted by a radiologist [8]. Also, because of some technical problems, the mammograph must be repeated that means more radiation exposure for the patients. Physicians are recommended to ask for a mammography test for women between 40 to 50 at adequate intervals [9-10] .

Ultrasound: since mammography can't penetrate dense and massive breast tissue of women under 35 years of age, ultrasound or sonography may be used to rule out breast cancer in this age group [11].

Haghighat-khah, et al, in 2005-2009 evaluated 225 women referred to breast clinics with breast masses. Medical history, physical exam, mammography and\or sonography and Pathology reports were recorded. Mammography and\or sonography results were compared with tissue diagnosis (gold standard). In this evidence-based study sensitivity and specificity of the mammography was 73% and 55.3% respectively, and false negative rates of mammography were 17.27%. Sensitivity and specificity of sonography was 69% and 50.7% respectively, and false negative rates were 17.68%. The sensitivity of sonography was significantly related to age, history of pregnancy, and breast feeding [12].

Thermography: Infrared imaging is one of the noninvasive imaging methods that are used as a diagnostic tool. The main idea of this method is based on infrared radiation of bodies with temperatures higher than absolute zero [13]. Thus, production of a patient's thermogram will show the temperature distribution in the patient's body. Due to the higher metabolic activity and angiogenesis surrounding the cancerous tissue, the cancerous parts have a higher temperature in comparison to normal tissue. Therefore, the cancerous tissue is highlighted and easily differentiated from normal tissue in a thermogram. Thermograms can give highly dynamic information about tumors. In this method in addition to normal tumors, very small tumors are also easily and very quickly detected. Tumors can be seen as a high temperature spot in thermograpic imaging [14-15]. In mammography it's a little different. Unless a tumor is smaller than a certain size, x-ray will pass through the tumor unaffected and it won't be observed in the mammograph. This qualifies infrared imaging as an effective diagnostic tool for early detection of breast cancer. Keyserlingk et al. [16] reported that the mean size of undetected tumors in infrared imaging is about 1.28 cm which is smaller than the 1.68 cm in mammography. Also thermography (infrared imaging) can detect tumors in patients' body around 8 to 10 years sooner than mammography [17-19].

The first use of infrared cameras was introduced in the 1960s, but unfortunately it wasn't effectively applied until the end of the 1990s [20]. Recent advances in infrared technology and image processing abilities have spurred renewed interest in the use of infrared breast imaging. Cancer diagnosis was one of the goals of this technology. In the beginning, an infrared image was taken from the breast area and the doctor would try to identify the cancer with the help of these images. Physicians classify the patients based on the results of these images [21]. Because of physicians' errors in checking and analyzing these images, the time-consuming nature of this process, and exhaustion of physicians, this technique is not applicable in populated areas. Another important parameter in breast cancer diagnosis in infrared imaging is asymmetry analysis but, because of the low quality of low resolution images that were captured with the first medical infrared imaging cameras, in the beginning of the use of infrared imaging, this parameter was not considered in breast cancer diagnosis. The second problem of the first studies done in this field was the low accuracy of the segmentation stage in the diagnosis of cancer [22]. Previously, high temperature spots in infrared images were detected by using intelligent software. But in this software, segmentation was done only based on segregation of all the high temperature spots of the infrared images. Although all of the high temperature spots of the image were extracted and it was the main problem of this system, and still the physicians were needed to identify the cancerous parts in the extracted high temperature points. In other words, the system was just separating all the system only separated all the high temperature sections [23]. In other works done previously, the infrared image was only analyzed based on the thermal features of the image pixels and that was the only feature that was used in breast cancer diagnosis. In other words, the thermal feature asymmetry of the pixels was used [24]. In this method, the cancerous parts of the breast were also extracted from the image. The difference between this method and previously explained methods was the higher processing load. In this method the color processing of the image was eliminated and the temperature of each pixel was considered in the segmentation, thus the classification results weren't accurate enough.

However, the first studies on thermal imaging techniques, were not interesting for the physicians, because of the low quality, and low resolution of the images taken by the first generation of the medical infrared imaging cameras. But, over the last few years, innovation and advances in medical infrared imaging, have spurred renewed interest among researchers and physicians in the use of infrared imaging in oncology and cancer diagnosis [25-26].

In order to detect the suspected malignant breast lesions, the researchers tried to extract the best diagnostic parameters from among the other parameters by use of quantitative and qualitative information from mammography. Also, they tried to improve the accuracy, sensitivity and diagnostic specification by using artificial neural network and genetic algorithm [27].

In the present study infrared imaging is used to create a database. Unlike the previous works, a combinatorial model consisting of genetic algorithm and artificial neural network is used to analyze the effect of the independent variables on dependent variables and highlight the best parameters in breast cancer diagnosis among other parameters [28-29]. Creating a neural network with meaningless and unimportant parameters, in the training section of the neural network, will reduce the globalization capability of the neural network and cause the neural network not to work effectively on test samples and result in a reduction of accuracy, diagnostic specificity as well as sensitivity of the system [30].

2. Materials and Methods

2.1. Active Beam Delivery System (ABDS)

In this study, MATLAB software is used for programming of artificial intelligence parts. The camera used in this work is a SDS D-series camera. The specifications of the camera are provided in Table 1.

Table 1.The specifications of the camera

Accuracy	±2 ºc
Thermal Sensitivity	0.1 ºc at 30 ºc
Detector Type	Uncoold microbolometer 160×120 pixels
Spatial Resolution	2.2 mrad
Spectral Range	8-14 µm

2.1. Database

The required information for this research was obtained by means of an experiment that was carried out at Hakim Sabzevari University in Sabzevar and with the cooperation of Sabzevar University of Medical Science [31]. This research was performed on the infrared images taken from 200 women aged between 18 to 35 . Among these women, 15 patients were found to have abnormal lesions in their breasts. The first step in data collection is to prepare infrared images from patients. The next step is to analyze these images and extract useful information for breast cancer diagnosis. To optimize the extracted features from these images, the artificial neural network and genetic algorithm are used together, to achieve the best results. The features extracted for the optimization stage are as follows:

1-Patient's Age 2- Mean 3- Differences among the Two Breasts 4- Variance 5- Skewness 6- Kurtosis 7- Entropy 8- Thermal Pattern of Breasts.

2.2. Image Processing

An example of the images transferred from camera to computer for analysis can be seen in Figure 1.

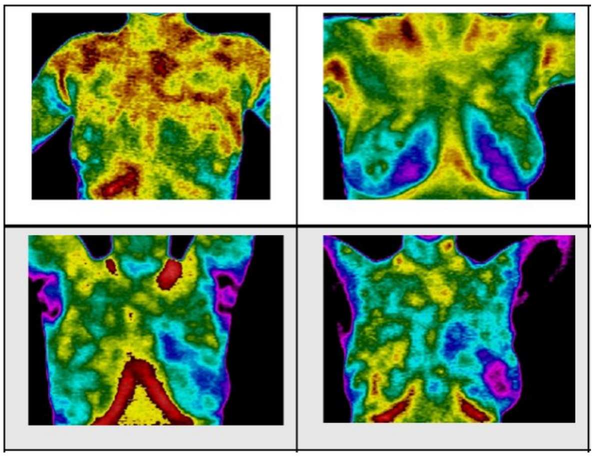

Figure 1. The primary image captured by infrared imaging camera

Detection of the breast area and its segregation in infrared images is the first step in this method. For this purpose gray- scale image is used. The flowchart of this step can be seen in Figure 2.

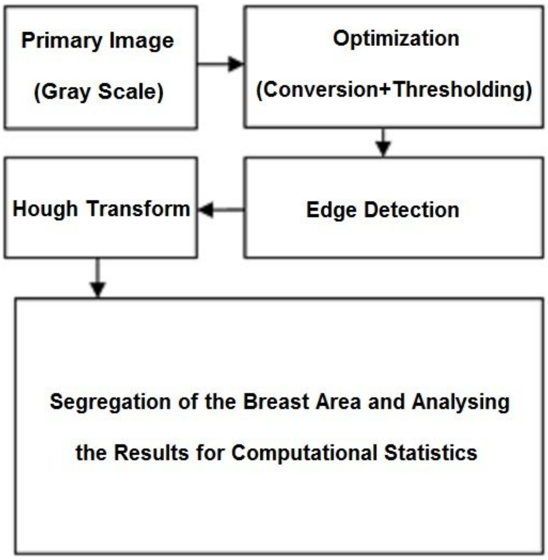

Figure 2. Flowchart and algorithm used for asymmetry analysis of breasts

The image intensity is directly linked to the thermal energy distribution of the correlated areas. The histogram will show the distribution intensity which describes the image's structure. Also, the histogram contains statistical information about the texture of the image. Mean, variance, kurtosis, skewness and entropy are five parameters that are calculated as follow [22]:

$$\text{Mean}\mu = \frac{1}{N}\sum_{j=1}^{N} P_j \qquad (1)$$

$$\text{Variance } \sigma = \text{——} \sum (p - \mu) \quad (2)$$

$$\text{Kurtosis} = -\sum \text{——} \quad (3)$$

$$\text{Skewness} = -\sum \text{——} \quad (4)$$

$$\text{Entropy} H(X) = \sum p \log p \quad (5)$$

In these equations intensity is shown by Pj, μ is the mean value and, Variance is shown by σ. Finally, the extracted parameters from equation 6 will enter the neural network.

$$\text{——————————} - 1 \quad (6)$$

2.3. Thermal Pattern

The procedure of this method is as follows:

1- At first, the breast area is detected and segregated from the original by use of a circular Hough transform [32].

2- Then the organs of the patient are segregated in the image by use of a Sobel edge detector operator [33].

3- The filter that is shown in equation 7, is passed through the whole image.

$$H(x,y) = \begin{cases} 1 \leftarrow \text{if} \begin{cases} R_{(\ ,\ )} > 100 \\ \text{and} \\ G_{(\ ,\ )} < 20 \\ \text{and} \\ B_{(\ ,\ )} < 20 \end{cases} \\ 0 \qquad\qquad \text{else} \end{cases} \quad (7)$$

$R_{(\ ,\ )}$, $G_{(\ ,\ )}$ and $B_{(\ ,\ )}$ are the intensity of red, green and blue pixels of the image, respectively.

4- The separated part of the image in the first stage is also passed through the filter.

5- The area of the artery of the neck which is located at the top of the image is calculated.

6- If nothing is detected in stage 4, then the breast is normal and not cancerous, otherwise the area of the output of stage 4 must be compared with the area of the artery region. If the detected area is bigger than the area of the artery, it will be identified as a cancerous region. Otherwise, it's not a cancerous region.

To identify the thermal pattern of cancerous cells in infrared imaging a coding system is defined. If the corresponding cells of studied pixel are cancerous, then the neural network output will equal 1, otherwise it equal zero.

The role of diagnostic parameters's coding is explained in Table 2. To increase the neural network convergence, the diagnostic parameters that play the role of input data for the neural network will pass through a normalization stage, before entering the neural network. Database normalization is the process of organizing the fields and tables of a relational database to minimize redundancy and dependency.

Table 2. Defined coding system for diagnostic parameters in neural network. Each code defines a unique value for each of the diagnostic parameters.

Age	age<20	F1=1
	20<age<25	F1=2
	25<age<30	F1=3
	30<age	F1=4
Differences Between Breast	differences <5	F2=1
	5< differences <10	F2=2
	10< differences<20	F2=3
	20< differences	F2=4
Thermal Pattern	NO	F3=1
	YES	F3=2
Mean	mean <0.5	F4=1
	0.5< mean <1	F4=2
	1< mean	F4=3
Variance	variance <0.5	F5=1
	0.5< variance <1	F5=2
	1< variance	F5=3
Skewness	skewness <0.5	F6=1
	0.5< skewness <1	F6=2
	1< skewness	F6=3
Kurtosis	kurtosis <1	F7=1
	1< kurtosis <5	F7=2
	5< kurtosis <10	F7=3
	10< kurtosis	F7=4
Entropy	entropy <0.1	F8=1
	0.1< entropy <0.5	F8=2
	0.5< entropy	F8=3

Normalization usually involves dividing large tables into smaller (and less redundant) tables and defining relationships between them. The objective is to isolate data so that additions, deletions, and modifications of a field can be made in just one table and then propagated through the rest of the database via the defined relationships. Values F1 to F4 correspond to the weights of each diagnostic parameter that serves as an input to the neural network.

2.4. Artificial Neural Network

Neural networks, as trainable systems, are able to learn from previous experiences and the environment, as well as improve their behavior while being trained. The most important point in neural networks, is training. With training, network parameters such as weight and bias are adjusted. In other words, the network is trained by the input data and will produce an output commensurate in regards to the input data. In this research, a 3 layer Feed–Forward neural network with a sigmoidal activation function (logsig) in the middle layer and linear function in the input layer, is used. For the input layer of the neural network, 8 neurons are selected (the number of neurons in the input layer is selected based on the fault percentage of the network output). For the middle layer of the neural network 6 neurons are selected to form the best structure [34]. Choosing the correct number of neurons in the middle layer of the network is very important, because it will reduce the time of the neural network's training process and keep the network in learning system. The result of the mammography will produce appropriate output for the neural network. The neural network model is shown in Figure 3.

The neural network specifications are shown in Table 3.

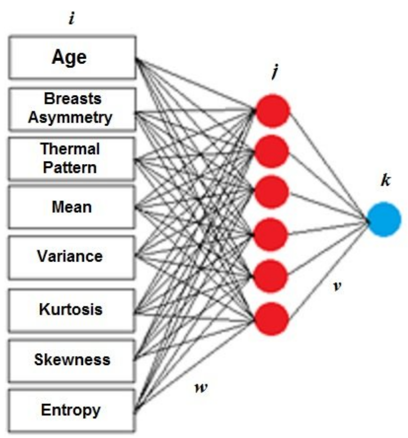

Figure 3. Chosen parameters for neural network input

Table 3. Neural network specifications

number of input layer neurons	8
number of hidden layers	1
Number of output layer neurons	1
number of hidden layer neurons	6
Activation function	logsig
Type of network training	Back propagation
Mean square error	0.01
Learning rate	0.1
Iteration	500

Accuracy, plus the rate of convergence of a neural network model are shown in Figure 4.

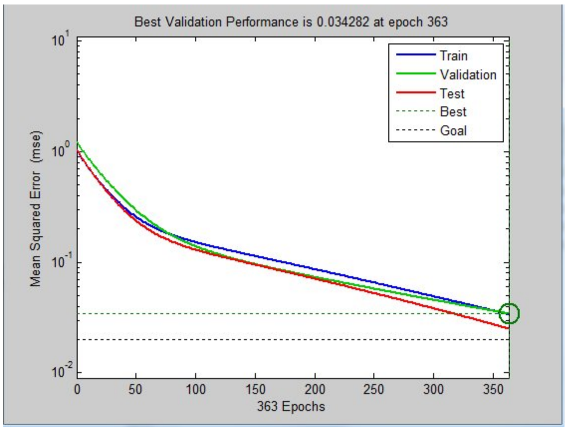

Figure 4. Diagram showing the results of data training and testing of neural network.

2.5. Optimization

The aim of optimization is to choose the optimal values of a group of parameters by considering some roles and conditions. In this research study, a combination of genetic algorithm and artificial neural network was used for choosing the optimal values of the specific parameters [35]. Figure 5 shows a block diagram of the simulated system in this study.

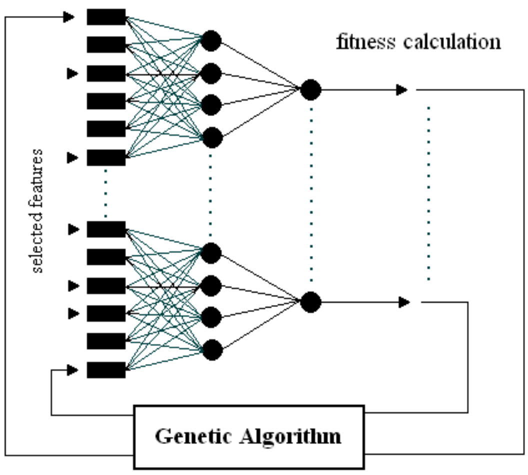

Figure 5. A back-propagation combinatorial model of the genetic algorithm and artificial neural network.

At first, a binary matrix vector with a length of the parameters, number (8 parameters) was accidentally created. Each element of this vector corresponds to specific diagnostic parameters in the neural network. For example, if the output equals 1, then the corresponding diagnostic parameter will be selected but, if the output is zero, the corresponding Diagnostic parameter will not be selected. The selected values for genetic algorithm can be seen in table 4.

Table 4. The genetic algorithm structure specification

Number of Generations	80
Number of Population	40
Crossover Probability	0.8
Mutation Probability	0.1

One of the evaluation criteria of diagnostic screening tests is sensitivity. Sensitivity is defined as a ratio of patients' number, that have been properly classified, to the total number of tested patients [36-37]. In this research, the diagnostic sensitivity and the diagnostic specification have been used in a trained neural network to calculate the evaluation function. The evaluation function is shown in equation 8[27]. In this equation, TP is the number of true positive, TN true negative, FP false positive, and FN false negative.

Fitness=—————— (8)

Reaching the parameters' optimal value is the stopping condition of genetic algorithm.

2.6. Model Evaluation

In order to check the performance of the proposed model, 50 samples from the database were selected and used to train the neural network. The factors that determine the merit of the combinatorial model are shown in Table 5 and 6 [27].

Table 5. Merit factors of the combinatorial model

		Non-cancerous	Cancerous
Mammography Results	Real Non-cancerous Breast Condition	TN True Negative	FP False Positive
	Real Cancerous Breast Condition	FN False Negative	TP True Positive

Table 6. Defined merit factors' equations

Sensitivity	$SEN = \frac{TP}{B} \times 100$
Specificity	$SPE = \frac{TN}{A} \times 100$
Accuracy	$ACC = \frac{TP + TN}{A + B}$

B and A are the actual number of people with and without cancer, respectively.

3. Results

The best results obtained from the combinatorial model are shown in Table 7 and 8. The simulation results indicate that our proposed combinatorial model can extract the best 3 parameters out of the 8 diagnostic parameters. A careful look at the selected parameters will confirm the performance of the proposed model. For example, the selected parameter B7, which is related to Kurtosis, necessarily has a higher accuracy, because it has a higher degree in computational statics in comparison to the mean and variance. Also difference between the two breast areas is an other one of the diagnostic methods for asymmetry detection.

Table 7. The best obtained results from the selected parameters in proposed combinatorial model (neural network-genetic algorithm)

B1	B2	B3	B4	B5	B6	B7	B8
0	1	1	0	0	0	1	0

B1 to B8 represent age, differences between breast, thermal pattern, mean, variance, skewness, kurtosis and entropy parameters, respectively.

Table 8. The results of the model's merit

%SEN	%SPE	%ACC
50	75	70

The effect of each parameter in cancer diagnosis after 50 iteration of combinatorial models is shown in Figure 6.

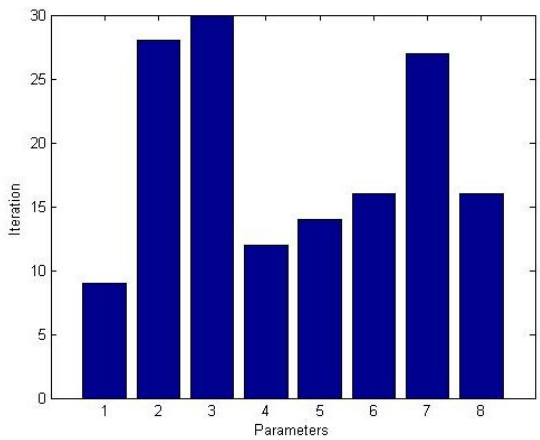

Figure 6. The effect of each parameter in cancer diagnosis.

4. Discussion

Breast cancer is one of the most common cancers among women worldwide. If breast cancer is detected early, it can be easily cured; therefore there is a crucial need for early screening and breast cancer detection, before reaching advanced levels of cancer. On the other hand, researches have shown that if detected earlier (tumor size less than 10mm), the breast cancer patient has an 85% chance of cure as opposed to 10% if the cancer is detected late[18]. Other research also shows evidence that early detection is vital in saving lives [38]. For women aged 25 to 40, an every 3 year examination [39] of the breasts are suggested. It is better if this examination is done with non-invasive, non-harmful and radiation-free methods to reduce the damages to minimum. Sometimes because of a lack of familiarity and an indiscrimination of disease by physicians, treatment is being started very late, and this has serious consequences and causes irreversible harm to the patient [40]. Previously, researchers have tried to introduce an intelligent system to classify different patterns of cancers using a mathematical model. But until now, they haven't found an accurate model for the classification of every cancers' pattern, and they are still trying to improve the previous methods. In the proposed method of this research, thermal imaging is used to improve the accuracy of diagnosis and classification.

5. Conclusion

Thermal imaging has so many advantages, for example lower cost in comparison to other diagnostic methods, being non-invasive, no direct contact with the patient's body, no radiation and determining the mass properties. By using the proposed combinatorial model that consists of back propagation neural network and genetic algorithm; the best diagnostic factors are separated from other factors. In order to do this, all of the diagnostic specifications are inserted to the combinatorial model, and the system will select and extract the diagnostic parameters. One of the reasons for using the neural networks is its ability to simulate the non-linear functions. But to simulate the effect of the dependent variables on independent variables the genetic algorithm is used. We have 8 diagnostic parameters in this system. To get the best results from an intelligent system and diagnose the breast cancer effectively and without the help of physicians, we have to reduce the diagnostic information to minimum, and only use the kind of information that has the least processing volume. For this purpose infrared images are used in this research. In other words, the information processing volume must be as low as possible to reduce the process's time and errors, and prevent the system from diagnostic errors. However, from a human point of view, 8 parameters are very low and can be processed easily, but when we are using an intelligent system and want to train the system by using a large number of patients from a database, it's not so easy any more. The results of the combinatorial model with 50% sensitivity, 75% specificity and 70% accuracy show proper precision in cancer diagnosis.

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