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Early Breast Cancer Detection in Thermogram Images using AdaBoost Classifier and Fuzzy C-Means Clustering Algorithm

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Abstract

Background: In this paper we compare a highly accurate supervised to an unsupervised technique that uses breast thermal images with the aim of assisting physicians in early detection of breast cancer.

Methods: First, we segmented the images and determined the region of interest. Then, 23 features that included statistical, morphological, frequency domain, histogram and gray-level co-occurrence matrix based features were extracted from the segmented right and left breasts. To achieve the best features, feature selection methods such as minimum redundancy and maximum relevance, sequential forward selection, sequential backward selection, sequential floating forward selection, sequential floating backward selection, and genetic algorithm were used. Contrast, energy, Euler number, and kurtosis were marked as effective features.

Results: The selected features were evaluated by fuzzy C-means clustering as the unsupervised method and compared with the AdaBoost supervised classifier which has been previously studied. As reported, fuzzy C-means clustering with a mean accuracy of 75% can be suitable for unsupervised techniques.

Conclusion: Fuzzy C-means clustering can be a suitable unsupervised technique to determine suspicious areas in thermal images compared to AdaBoost as the supervised technique with a mean accuracy of 88%.

Keywords: Breast cancer, Breast thermography, Thermogram, Feature selection, Classification, TH

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Introduction

Breast cancer is the most common type of cancer among women. The important key for treatment is early detection; according to numerous pathological studies, more abnormalities are benign at the primary stages. In recent years, many studies and extensive research have been done to ascertain techniques for early detection of breast cancer that have higher precision and increased accuracy.[1,2] There are a number of techniques such as mammography, ultrasound and MRI in use for breast cancer diagnosis. Each has well-known advantages and disadvantages. Mammography is considered the gold standard for detection of breast cancer but still suffers from limited sensitivity, specificity, and among limitations as a screening tool. Ultrasound is used as an adjunctive tool in screening women with dense breasts along with mammography. The limitations of MRI are that it is not good at detection of ductal carcinoma *in situ*, slow, expensive, and fails to show all calcifications. However these modalities all suffer from one or more common disadvantages of radiation exposure, breast compression, only structural imaging, and limitations with breast density.[3-5] In order to remove the disadvantages of the current methods, infrared thermography can be used as a complementary method for detecting breast abnormalities with thermal images. Infrared thermography uses a highly sensitive infrared camera to obtain the image of the temperature distribution in the human body. This imaging technique due to the use of non-ionizing radiation (passive), non-contrast enhanced injection, lack of contact, and non-invasiveness is of value in many biological and medical applications compared or in combination with other imaging modalities. Temperature distribution patterns in thermography leads to the physiological interpretation of tissues (temperature change based on interaction patterns) which can reveal suspected areas of cancer tissue even when anatomical abnormalities on the tissue surface are not present and the tissue appears healthy.[6-9] Research on the temperature dynamic variations of the body surface after a cold stimulation to patients has been undertaken which may be advantageous for physicians, especially for early disease diagnosis. Stimulation of the sympathetic nervous system causes a constriction of the normal blood vessels in the breast. The blood vessels that supply a cancerous tumor will resist constriction or fail to constrict. Consequently, dynamic digital thermal subtraction gives us the possibility of isolating the vessels that supply nutrients to the tumor. This test ultimately raises the suspicion that a cancerous tumor may be present.[10] The current study is an effort to diagnose breast cancer by processing the information obtained from medical infrared imaging. Table 1 shows the related studies conducted in breast cancer detection using thermography techniques.[11-22]

This study compares a high accuracy supervised to an unsupervised technique to analyze breast thermal images with the aim to assist physicians with early detection of breast cancer. First, the images have been segmented and the region of interest (ROI) determined. Then, features that included statistical, morphological, frequency domain, histogram and gray-level co-occurrence matrix (GLCM) based features were extracted from the segmented right and left breasts.[23] In order to achieve the best features, feature selection methods were used. Contrast, energy, Euler number and kurtosis were marked as effective features. The selected features were evaluated by Fuzzy C-means (FCM) clustering as the unsupervised method and compared with the AdaBoost supervised classifier which has been previously studied.[23]

Materials and Methods

In this research, we used the native database to evaluate the performance of the proposed method. The thermography images were obtained by a Fanavaran Madoon Ghermez (FMG) Co., Ltd.[24] Infra-red camera (Thermoteknix VisIR 640, resolution: 480×640) from patients suspected to have breast cancer. Patients were referred to Imam Khomeini Hospital[25] by their physicians and designated TH1-TH5 dependent upon the cancer stage by an oncologist who observed all ethical

Table 1. Previously proposed methods of detecting breast cancer using thermogram images.

Study	Proposed approach
Williams et al.[11]	Showed the possibility of detecting breast cancer from increased temperature at breast tissue acquired by infrared thermography (temperature sensitivity was about 2°C in the image acquired during a few minutes).
Parisky et al.[12]	Four years of a clinical trial on 769 patients. The authors reported that infrared thermal imaging was a noninvasive, safe technique that could be very valuable in determination of the benign or malignant breast abnormalities when combined with mammography
Arora et al.[13] and Kennedy et al.[14]	Showed that the combination of thermotherapy and other diagnostic techniques could improve the accuracy of breast abnormality detection
Tang et al.[15]	A new criterion of breast cancer detection and method of its realization proposed as follows: 1) Surface temperature distribution of healthy breast usually exhibits a gentle variation which is background. 2) Localized surface temperature of a carcinomatous breast will increase on the basis of the above background which is LTI. 3) The carcinomatous possibility is proportional to the LTI maximum (amplitude) of the suspicious focus region. 4) The LTI amplitude can be measured through morphological signal processing.
Schaefer et al.[16]	The breast cancer analysis based on thermography using a series of statistical features extracted from the thermograms quantifying the bilateral differences between the left and right breast areas, coupled with a fuzzy rule-based classification system for diagnosis.
Acharya et al.[17]	Texture features are extracted from co-occurrence matrix and run length matrix. Subsequently, these features are fed to the Support Vector Machine (SVM) classifier for automatic classification of normal and malignant breast conditions.
Satoto et al.[18]	Wiener filter used to eliminate the noise. Using histogram equalization, image contrast improved. The last step of the preprocessing procedure uses region growing method. Then statistical features such as mean, standard deviation, entropy, skewness and kurtosis of the images extracted and finally the fuzzy algorithm is used for classification.
Kapoor et al.[19,20]	Background and additional areas of the image removed at first. Breast boundaries extracted using "canny" edge detection and gradient operator used to determine the boundary curves of the left and right breast. Lower bounds of breast determined using two elliptical curves, and the area under the curve has been eliminated. Then a separator for separating the right and left breasts have been used. In the feature extraction stage, the features of skewness, kurtosis, entropy and features based on co-occurrence matrix such as energy, homogeneity and correlation extracted. Finally the MLP neural network is used for classification of features.
Nicandro et al.[21]	Information such as the temperature difference between the left and right breasts, hot spots in the breast, the temperature difference between the hot spots, the center of the hot zone, features based on the histogram, patient age,… used to determine the suspected areas. To evaluate the performance. Naive Bayes classifier, hill climbing, iterative hill climbing, artificial neural networks, decision trees ID3 and C4.5 decision tree has been used. The iterative hill climbing algorithm had the best performance with the accuracy of 76.12% among all classifiers.
Dinsha et al.[22]	First, using CLAHF, the quality of thermal images improved and noise are eliminated using a non-linear filter. To achieve strong edges, Gaussian filter with weighting coefficients corresponding pixel intensities, has developed. The segmentation was performed using both k-means and FCM algorithms and features based on co-occurrence matrix separately. Finally, SVM & Bayesian classifiers used on feature space.

LTI: Localized temperature increases, CLAHF: Contrast limited adaptive histogram equalization, FCM: Fuzzy C-means, SVM: Support vector machine.

considerations. TH is a standard measure to analyze a thermovascular breast proposed in the 1980s. Physicians classify thermal images into 5 categories based on the combined vascular and temperature patterns across the two breasts.[26]

TH1: normal nonvascular

TH2: normal vascular

TH3: equivocal

TH4: abnormal

TH5: severely abnormal

For data acquisition, the patient was asked to place her hands on the head and five images from different angles (0°, ±45° and ±90°) were obtained (before ice test). Then the patient was asked to place her hands into the mixture of water and ice for about 20 min and again put the hands on the head to obtain five new other images from different angles (0°, ±45° and ±90°) (after ice test). Therefore, this database contains 670 images from 67 patients with different angles 0°, ±45°, and ±90° before and after the ice test until writing this paper. In this Paper we used just 3 image views of 0°, +45°, and +90° after the ice test for all 67 participants.[24]

The camera has been designed in a way to reduce/eliminate technical errors in the imaging process. For medical applications, a controlled environment helps to increase accuracy. The infrared camera should be placed at a certain distance from the patient. Some of pixels are considered as the foreground. Hence, there are parameters that can be completely useful and effective in a matter of testing/diagnosis or treatment, and instructions that should be observed during data collection procedures, as has been previously mentioned.[27]

Table 2 shows the distribution of patients according to cancer stage (standard level: TH) as assessed by an oncologist according to Gautherine et al.[26] for both right and left breasts.

The proposed method included four stages: 1) pre-processing and segmentation, 2) feature extraction, 3) feature selection, and 4) classification and TH labeling. Figure 1 shows the structure of the presented method.

Table 2. Distribution of the standard level separately labeled by the oncologist for both the right and left breasts.

TH	1	2	3	4	5
Right Breast	24	22	12	4	5
Left Breast	6	28	14	13	6

Pre-processing and segmentation

Pre-processing, especially in data driven studies, is a very important stage. In order to distinguish between normal and abnormal tissues, pre-processing and segmentation is performed in three stages: 1) regions of interest (ROIs) detection and thermal image enhancement, 2) breast tissue segmentation, and 3) detection of suspicious regions and image matrix normalization. Figure 2 shows the result of this section.[23]

Feature extraction

In the feature extraction stage, information from right and left breast images should be extracted in order to correctly distinguish between normal and abnormal tissues. The extracted features, which are the same as a previous paper,[25] are based on statistical features such as median,

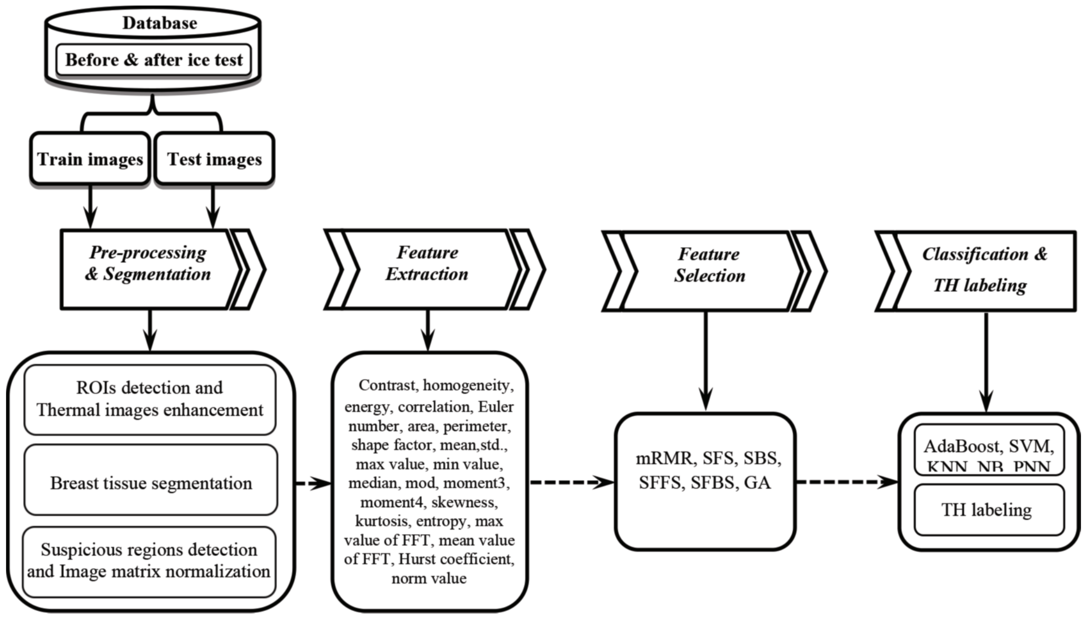

Figure 1. Proposed system architecture.

mode, skewness, kurtosis, central moment and entropy. They are also based on a histogram such as the mean, standard deviation, max value, min value and norm; based on GLCM such as contrast, homogeneity, energy and correlation; based on morphology of suspicious regions such as Euler number, area, perimeter, shape factor, Hurst coefficient, and frequency domain such as the max- and mean values of the fast Fourier transform.

Feature selection

Various information causes a high dimensionality feature matrix that reduces accuracy and increases computation burden. In order to obtain a more accurate selection and further reduction of the number of extracted features, we use different feature selection methods. In this paper, the minimal-redundancy and maximal-relevance (mRMR),[28] sequential forward selection (SFS),[29] sequential backward selection (SBS),[29] sequential floating forward selection (SFFS),[30] sequential floating backward selection (SFBS),[30] and genetic algorithm (GA)[31] were used and compared with each other.

Fuzzy clustering

Clustering is an unsupervised method and an automated process in which samples are divided into categories that contain similar members, termed clusters. The cluster is a collection of objects that are similar to each other and dissimilar with other objects in other clusters. The various

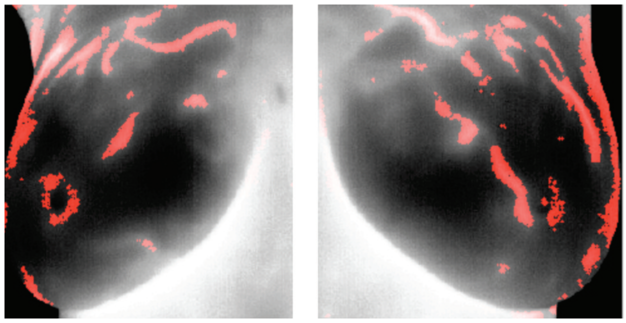

Figure 2. Region of interest.

criteria for similarity can be considered. For example, distance measure can be used for the clustering and the objects that are closer to each other are considered as one cluster. This is called distance based clustering. In Figure 3 the input samples on the left side are divided into four clusters on the right side. In this example, each input sample belongs to one of the clusters and there is no sample that belongs to more than one cluster.

In most clustering algorithms, a series of the primary representatives for input samples are supposed and then from the similarity of these input samples, the representatives can determine which sample belongs to which cluster. After this phase, new representatives are calculated for each cluster and again the examples are compared with these representatives to determine which samples belong to which cluster. This task is repeated until agent clusters do not change.[32]

Clustering is different from classification. In classification, the input samples are initially labeled by the supervisor. In clustering, the input

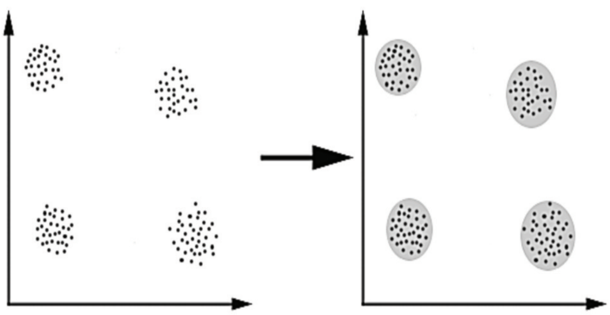

Figure 3. Clustering of input samples.[32]

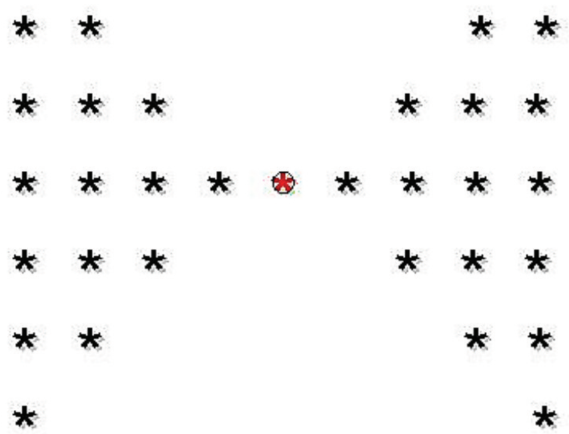

Figure 4. Fuzzy clustering.[34]

Table 3. The results of fuzzy C-means (FCM) applied to different angles of the images.

Feature Selectors	Breast	Accuracy (%) 0 degrees	45 degrees	90 degrees	Combination of 0, 45, and 90 degrees
mRMR	Left	73.13	73.73	73.73	71.34
	Right	74.33	71.94	72.54	73.73
SBS	Left	71.34	73.73	73.73	71.94
	Right	75.52	74.93	73.13	71.94
SFBS	Left	73.13	73.73	71.34	73.73
	Right	73.13	74.93	74.93	76.72
SFFS	Left	71.34	72.54	71.34	73.73
	Right	72.54	75.52	73.13	72.54
SFS	Left	74.33	71.94	71.34	73.73
	Right	72.54	74.93	73.13	72.54
GA	Left	73.73	74.33	73.73	71.94
	Right	73.73	75.52	77.31	75.52
Without feature selection	Left	73.13	73.73	72.54	72.54
	Right	73.73	71.94	72.54	73.73

mRMR: Minimal-redundancy and maximal-relevance; SBS: Sequential backward selection; SFBS: Sequential floating backward selection; SFFS: Sequential floating forward selection; SFS: Sequential forward selection; GA: Genetic algorithm

samples are not initially labeled. In clustering, similar samples are identified then labeled.

In other words, before data classification, clustering operations are carried out on the samples and then the cluster centers are calculated, one label is assigned to each cluster center, after which classification for all new input samples is performed.[33]

The purpose of clustering is to find clusters with similar objects in the input sample. The important question is how to determine that one clustering algorithm is good. It can be shown that no absolute standard exists for the best clustering, but this depends on the problem and the user has to decide whether the samples are properly clustered or not. However, different criteria for the well-being of a proposed clustering can guide the user to an appropriate clustering. One of the most important issues in clustering is the number of clusters. In some algorithms the number of

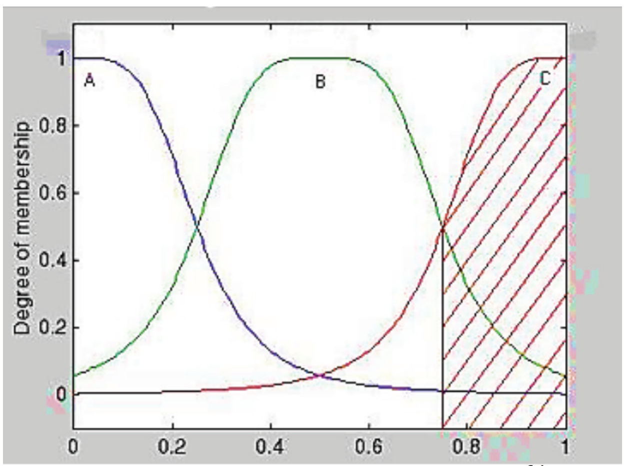

Figure 5. Fuzzy membership functions.[34]

Figure 6. One-dimensional distribution of input samples.[34]

Table 4. A comparison of the proposed method with previous supervised methods.

Methods		Accuracy (%)	Sensitivity (%)	Specificity (%)
Acharya et al.[36]		88.10	85.71	90.48
Ghayoumi Zadeh et al.[37]		-	93	97
Yaneli et al.[38]		78.56	-	-
Araujo et al.[39]		-	85.7	86.5
AdaBoost (previous supervised method)[23]	Right breast	88.03	91.3	95.9
	Left breast	85	89.7	92.5
Fuzzy C-means (FCM; present unsupervised method)	Right breast	77.31	88.2	93.1
	Left breast	74.33	87.3	91.6

clusters is specified, whereas in others the algorithm decides the number of clusters that the data should be divided amongst.

In order to better understand fuzzy clustering and different algorithms, it is necessary to start with the concept of fuzzy sets and their differences to become familiar with the classic collection. In the classic collection, a member either belongs to a reference set, set A, or not. For example, by considering the reference set of real numbers, 2.5 is not a member of the integer number while the number 2 is. In other words, membership of the number 2.5 to the set of integers is 0, whereas membership of the number 2 to this set is 1. In fact, one membership function can be defined for any set that the value of this function is 1 for the membership of this set and is 0 for the remainder. In the classic collections the value of this membership function is 0 or 1. Now, consider the set of old and young people. The question that arises here is whether a person at the age of 25 is related to this collection or not? Certainly this age cannot be considered a borderline age for young and older people. The reason, is that if age 35 can considered young, then 36, 37, and 38, etc. can be considered young, as well.

In fact, here, we are faced with the uncertainty concept. Uncertainty in everyday life is frequently observed, such as cold air, hot water, etc. All of the above examples are examples of fuzzy sets. The main difference between the classic sets and fuzzy sets is that in classic fuzzy sets, membership function in fuzzy sets is not just the value 0 or 1; rather, any value between 0 and 1 can be adapted. Now, consider the set of young and old people. if we consider the age of 25 as young, we can assign a membership value of 1 to age 25 and 0.8 to age 30, 0.75 to age 35, 0.1 to age 90. If the members of a given function only have 0 and 1 values, this set will be a classic set. For example the age of 50 will be entitled to receive 0.5 of a young and 0.5 of an old set which means a member of the reference set can belong to different membership values of fuzzy sets that have been defined on the reference set.[33]

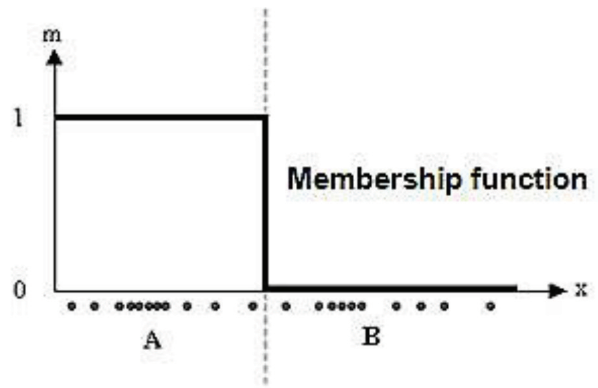

Figure 7. Classic clustering of input samples.[34]

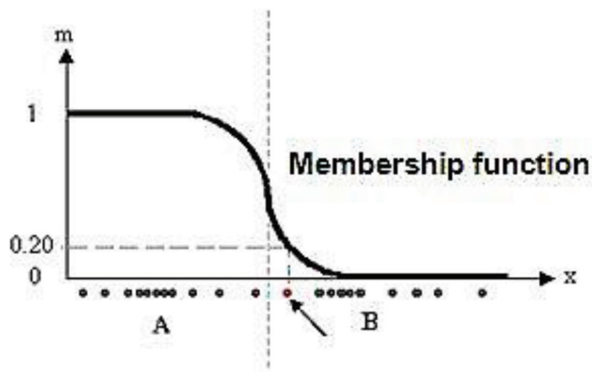

Figure 8. Fuzzy clustering of samples.[34]

In the classic clustering each input sample belongs to one and only one cluster and cannot be a member of two or more clusters. The main difference between classical and fuzzy clustering is that one sample can belong to more than one cluster. In Figure 4, if the input samples are as shown above, it is clear that the data can be divided into two clusters. However, the problem is that the sample determined in the middle can belong to both clusters. Therefore the researcher should decide where this sample belongs, either to the right cluster or the left. If we use fuzzy clustering, the given sample will belong to the right cluster with a membership value of 0.5 and with the same value to the left cluster. Another difference is that all right input samples (Figure 4) can belong to the left cluster with the very low membership value and the same is true for the left samples.[34]

Bhattacharya et al.[35] have used fuzzy clustering for the implementation of their algorithm based on the intensity of calcifications. It is supposed that the data can be clustered in 3 clusters (Figure 5).

Fuzzy C-means (FCM) clustering algorithm

Similar to the classic C-means algorithm, in this algorithm the number of clusters (c) have been previously determined. The objective function for this algorithm is defined as follows:

(1)

$$J=\sum_{i=1}^{c}\sum_{k=1}^{n}u_{ik}^{m}d_{ik}^{2}=\sum_{i=1}^{c}\sum_{k=1}^{n}u_{ik}^{m}||x_k-v_i||^2$$

In the above formula, m is a real number greater than 1. In most cases, 2 will be selected for m. X_k is the k^{th} sample and V_i is the representative or center of ith cluster. U_{ik}, shows the membership value of ith sample in the k^{th} cluster. || * || is the similarity (distance) index of the sample from the cluster center which can be any function that expresses the similarity of the sample with the cluster's center. By U_{ik}, a matrix can be defined by with c rows and n columns and its components can adopt any value between 0 to 1. If all the components of the U matrix are 0 or 1, then the algorithm will be similar to the classic C-means. Although the components of the U matrix can adopt any value between 0 to 1, the sum of the components in each column must be equal to 1,[34] and we have:

(2)

$$\sum_{i=1}^{c}u_{ik}=1,\ \ \forall\, k=1,\dots,n$$

The meaning of this condition is that the total membership of each sample to c clusters should be equal to 1. Using the above requirement and according to the minimum objective function, we have:

(3)

$$v_i=\frac{\sum_{k=1}^{n}u_{ik}^{m}x_k}{\sum_{k=1}^{n}u_{ik}^{m}}$$

(4)

$$u_{ik}=\frac{1}{\sum_{j=1}^{c}(\frac{d_{ik}}{d_{jk}})^{2/(m-1)}}$$

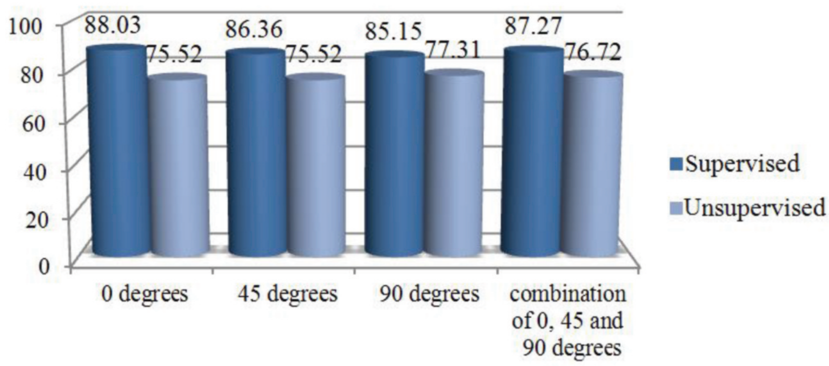

Figure 9. Comparison of different angles of both supervised and unsupervised algorithms in the right breast images.

Algorithm pseudo code:

1. Initialized c, m and U^0. Initial clusters guessed.
2. Cluster centers are calculated (vi are calculated).
3. Calculate the membership matrix from given clusters in step 2.
4. If $||U^{l+1}-U^l|| \leq \varepsilon$, the algorithm ends. Otherwise, again go to step 2.[34]

Figure 6 presents one-dimensional distribution of input samples for the expression of the fuzzy clustering.

If the classic C-means algorithm is used, data will be divided into two separate clusters where each cluster will only belong to one cluster. In other words, membership function of each sample will have a value of 0 or 1. Classic clustering results are shown in figure 7. This figure shows the membership function of cluster A. It is visible that input samples only belong to one of the clusters. In other words, matrix U is in binary form. If we use fuzzy clustering, we have figure 8. In this figure, the membership function is smoother and the boundary between the clusters is not specified with certainty. For example, a sample which is marked with arrows belongs to cluster A with the membership value of 0.2 and to cluster B with a value of 0.8. This algorithm, like other algorithms, has a number of advantages and disadvantages.[34]

Avantages of the FCM algorithm:

Always converges.
Unsupervised algorithm.

Limitations of the FCM algorithm:

High computation time.
Sensitive to the initial guess and may be stopped at a local minimum.
Sensitive to noise.

Results

In order to evaluate the performance of the proposed method, we used the native database.

In this way, all pre-processing, segmentation, feature extraction and feature selection was performed as before. In the final stage, the selected features were classified by FCM clustering algorithms. According to the TH set at 5 categories, in the FCM clustering algorithm, the number of classes sets as 5 which the membership value of each sample to each cluster was determined after implementation and execution of FCM. It could not be clearly revealed which cluster corresponded to which TH. In the proposed method, the maximum membership value of one given sample to each cluster was assigned. It should be determined to which TH this cluster belongs. As images were divided into 5 clusters, hence all the possible scenarios for a number of states equaled 5.

Therefore, after identification of cluster, one label was assigned to the sample related to this cluster. The accuracy of the algorithm was calculated by comparing this assigned label with the real label. Of note, we calculated the accuracy of the algorithm in each state. Finally, the average and maximum values were reported.

Table 3 shows the performance of the proposed

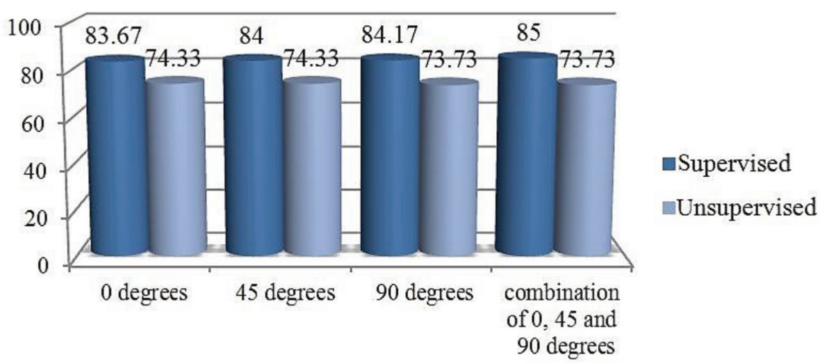

Figure 10. Comparison of different angles of both supervised and unsupervised algorithms in the left breast images.

method using unsupervised algorithms. A comparison of the two classifiers is shown in Figures 9 and 10. The best average values are carefully considered in each case.

As the above figures show, the supervised learning algorithms on the proposed approach showed better results than the unsupervised clustering algorithm. Clustering as an unsupervised algorithm had relatively good performance in the proposed method.

Table 4 shows a comparison of the results of the proposed method with other methods. The obtained results indicate high efficiency of the presented algorithm.

Discussion

In the proposed method, we used an imaging technique based on thermography to detect early changes that occurred in breast tissue and cancer cells. The thermography has been based on higher metabolic activity and blood flow surrounding the cancerous tissue rather than normal tissue. Infrared thermography is promising technology for breast cancer detection. This technology can be used as an imaging technique to improve the efficiency of detecting breast cancer and complement mammogram results. The advantages of thermal imaging compared to mammography are:[1-9]

1. Avoiding application of harmful, ionizing radiation.
2. The first symptoms of breast cancer detection based on mammography are diagnosed about 8 to 10 years later than thermography. Thus, according to the importance of time in cancer treatment and because 80% of tumors and abnormalities are still in the benign stage, the chance for treatment is increased by approximately 99%.
3. Thermography can lead to deletion of unnecessary biopsies. Studies show that 70% -80% of all biopsies performed after mammograms indicate no signs of cancer. Breast thermography has an accuracy of about 90%. According to research, thermography can increase the life expectancy rate. In addition, this is a passive method because it emits no ionizing radiation to the patient and is risk-free.

In this paper, we presented a high accuracy supervised and unsupervised technique that used breast thermal images with the aim to assist physicians in early detection of breast cancer. First, the segmented images and ROI were determined. Then, 23 features that included statistical, morphological, frequency domain, histogram and GLCM based features were extracted from the segmented right and left breasts. To achieve the best features, we used feature selection methods such as mRMR, SFS, SBS, SFFS, SFBS, and GA. Contrast, energy, Euler number, and kurtosis were marked as effective features. The selected features were evaluated by FCM clustering as the unsupervised method and compared with the AdaBoost supervised classifier, a previously studied technique. As reported, FCM clustering with a mean accuracy of approximately 75% can be a suitable unsupervised technique to determine suspicious areas in thermal images compared to AdaBoost as a supervised technique with a mean accuracy of approximately 88%.

Acknowledgments

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Conflict of interest

No conflict of interest is declared.

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