

## A New Approach for Mammogram Image Classification Using Fractal Properties

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**Abstract:** *Accurate classification of images is essential for the analysis of mammograms in computer aided diagnosis of breast cancer. We propose a new approach to classify mammogram images based on fractal features. Given a mammogram image, we first eliminate all the artifacts and extract the salient features such as Fractal Dimension (FD) and Fractal Signature (FS). These features provide good descriptive values of the region. Second, a trainable multilayer feed forward neural network has been designed for the classification purposes and we compared the classification test results with K-Means. The result reveals that the proposed approach can classify with a good performance rate of 98%.*

**Keywords:** *Fractal Dimension, Fractal Signature, mammograms, self-similarity, classification.*

### 1. Introduction

Mammography associated with clinical breast examination and breast self examination are the only viable and efficient methods at present for mass screening to detect breast cancer. Breast cancer is the second most deadly form of cancer in women. It appears in women in the form of tumors [1]. The diagnosis of breast cancer in its early stage of development has become important in the prevention of breast cancer. To avoid a surgical procedure such as a biopsy at its initial stage, women widely depend on mammography. Mammography is the standard approach

for preliminary examination of breast cancer abnormalities [2]. This paper describes the application of fractals in breast cancer image classification. The Fractal concept developed by Mandelbrot provides an excellent explanation of the ruggedness of natural surfaces, and many other natural phenomena. It has been widely applied to many areas in science and engineering. L u n d a h i at al. [3] used the fractal concept to analyze X-ray medical images. The use of the fractal dimension to distinguish between malignant and benign cells is promising and could develop into a useful diagnostic tool in aiding the pathology. The rest of the paper is organized as follows. In Section 2 we present the related works. Section 3 briefly describes the proposed methodology. Section 4 discusses the classification approach and the results of the proposed methodology. Section 5 concludes the paper with future works.

## 2. Related works

Several researchers have introduced different approaches for classifying the mammogram images. A histogram intersection based image classification was proposed in [4]. Initially they used the bag-of-words model for image classification for capturing the texture information. A normalized histogram intersection with the K-nearest neighborhood classifier was applied. The classification accuracy depends on the normalization of the histogram. Reference [5] presents mammogram image classification based on rough set theory in conjunction with statistical feature extraction techniques. The features were derived from the gray level co-occurrence matrix, these features were normalized and the rough set dependency rules are generated from the attribute vector. The generated rules were passed to the classifier for the classification purpose. Classification of mammograms with benign, malignant and normal tissues using independent component was proposed by the authors in [6] with a classification accuracy of 97.3%. The face recognition methods such as AdaBost and Support vector machines for the analysis of digital mammograms was presented in [7]. The AdaBost classifier achieved 76% for all lesions and 90% for the masses. A fractal approach was proposed in [8] to model the mammographic parenchymal, ductal patterns and enhance the microcalcifications. The results proved that fractal modeling is an efficient approach for detection and classification of microcalcification in a computer aided diagnosis systems. A hybrid system [9] combines extracted features and human interpreted features from the mammogram, with the statistical classifier as other features in conjunction with GNN and achieved a classification rate of 91.3%. The simplest diagnosis of breast is to analyze the X-ray images. With the advancement in digital technology the radiologist could classify the tumors more accurately. Paper [10] is based on the following procedures. The first patch around tumors are manually extracted to segment the abnormal areas and the remaining of the image is considered as background. The image is filtered using Gabor wavelets and directional features are extracted at different orientation and frequencies. PCA were applied to reduce dimensions and finally the images were classified based on proximity support vector machines. The texture based classification is an important

global method for mammogram image classification. The study shows that rule based system has great importance in classification purposes. A rule based system for classification was proposed in [11]. In this paper, the texture component is extracted from segmented parts and the association rules are derived between various texture components from the segments of images and classified them based on intra and inter class dependencies. The result shows a classification accuracy of 89%. In [12] the authors applied different data mining techniques, neural networks and association rule mining for the classification purposes. The results show that the two methods perform classification accuracy above 70%. Reference [13] presents a new approach for the parenchymal pattern classification in which texture models are used to capture the mammography appearance within the area of the breast. Parenchymal density patterns are modeled as the statistical distribution of clustered, invariant filter responses in low dimensional space. Fractal can be used to classify and distinguish various types of cells. Shapes of fractal objects keep invariant under successive magnifying or shrinking the objects. Hence, fractal geometry can be applied to overcome the scale problem of texture. Fractal dimension can be defined in connection with real world data and can be measured. The curve, surface and volumes are complex objects for which ordinary measurements become limited because of their physical properties. Different techniques have been proposed to measure the degree of complexity by evaluating how fast the length, surface or volume increases with respect to smaller and smaller scales.

Based on the self-similarity of the geometric forms, one can find the power law describing the number of pieces “a” versus  $1/s$ , where “s” is the scale factor which characterizes the part “s” as copies of the whole, the exponent of this law is the Fractal Dimension (FD). The galaxies were classified using fractal dimension and Fractal Signature (FS) which gave a classification rate up to 95% [14]. The K-Means and Fuzzy C-Means algorithms are used for classification of remotely sensed images. In both methods it has been found that 98% classification rate could be achieved [15]. Different algorithms like Principal Component Analysis and Supervised Neural Network techniques exist for classification of images. Almost all of these procedures require apriori knowledge about how the input feature set is related to the images. The most commonly used algorithms for classification purpose are based on neural networks, like genetic algorithm, rule based classifier and fuzzy theory. In this work we have used the neural network approach for the classification of the digital mammogram images. The images considered in the present work are listed in the Digital Database for Screening Mammography [16] and MIAS [17]. Recently BIRADS (Breast Imaging Reporting and Data System) [18] is becoming the most common acceptable standard for mammography images. Based on the tissue density, they are classified into four categories. Fig. 1 shows a typical example of mammogram images with different BIRADS standards. Fig. 2 shows the different phases involved in the proposed method.

BIRADS I: the breast is almost entirely fatty.

BIRADS II: there is some fibroglandular tissue.

BIRADS III: the breast is heterogeneously dense.

BIRADS IV: the breast is extremely dense.

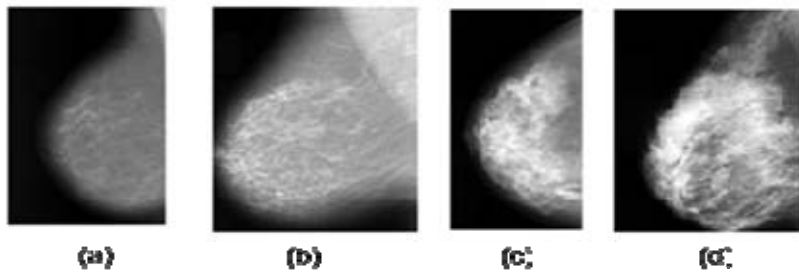


Fig. 1. Mammogram images of different BI-RADS I(a) to BI-RADS IV(d)

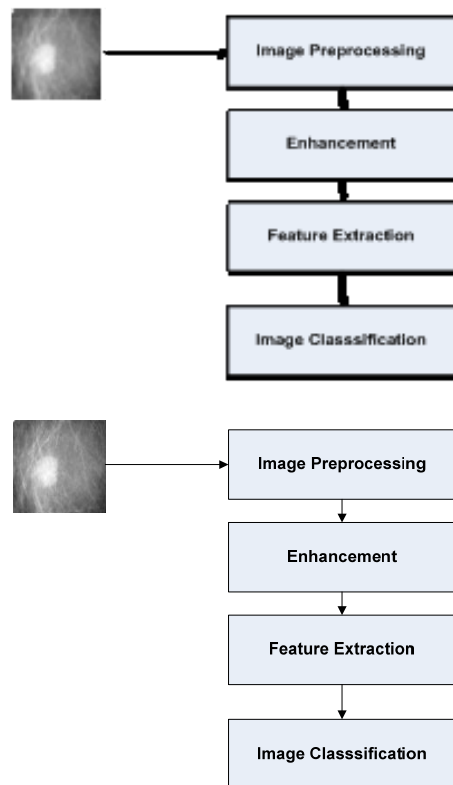


Fig. 2. Proposed system work flow

The medical images are always noisy and contain artifacts which are not relevant to the classification purpose. Pre-processing will enlarge the quality of the image. During this stage we applied a method based on the connected component labeling for removing many of the artifacts which are not relevant to the classification purpose. In this step the image is converted to binary format. The connected component labeling algorithm will select the largest region for segmentation and a map to the original image for reconstructing the image without an artifact. The ROI is selected for feature extraction from the enhanced image. The extracted features are then stored in a file and given as input for the training and classification phase.

### 3. Methodology

Fractals, introduced by Mandelbrot [19] have drawn great attention in the field of science and engineering. There are many definitions, according to Mandelbrot *A fractal is by definition a set for which the Hausdorff Besicovitch dimension strictly exceeds the Topological Dimension (DT)*. By definition [20] a space  $X$  is said to be finite-dimensional if there is some integer  $n$  such that for every open covering  $R$  of  $X$ , there is an open covering  $\zeta$  of  $X$  that refines  $R$  and has an order at most  $n + 1$ . The topological dimension of  $X$  is defined to be the smallest value of  $m$  for which this statement holds.

**Definition.** A set  $F$  is called a Fractal set if the following conditions are satisfied.

a) The global character of the set  $F$  is self-similar to the local characteristics of each sub-set, namely  $\zeta(F) \sim \zeta(fi)$ ,  $fi \supset F$ , where  $\zeta(.)$  stands for the characteristics of  $(.)$ .

b) The set  $F$  is infinitely separable, i.e.,

$$(1) \quad F = \{f_1^1, f_2^1, \dots, f_i^1, \dots, f_n^1\},$$

$$(2) \quad f_i^1 = \{f_1^2, f_2^2, \dots, f_i^2, \dots, f_n^2\},$$

$$\dots$$

$$(3) \quad f_k^m = \{f_1^{m+1}, f_2^{m+1}, \dots, f_k^{m+1}, \dots, f_n^{m+1}\}, m + 1 \rightarrow \infty.$$

A theoretical fractal object is self-similarity under all magnifications and the changes in properties with respect to changes in scale are limited. In the Euclidean space  $R^E$ , a real ratio  $r > 0$  determines a transformation called similarity, which transforms the point  $x = (X_1 \dots X_\delta \dots X_E)$  into the point

$$(4) \quad \tau(x) = ({}_r X_1, \dots, {}_r X_\delta, \dots, {}_r X_E),$$

and thus transforms a set  $S$  into the set  $\tau(S)$ . Many Fractal features can be extracted from an image. Fractal Dimension (FD) becomes the primary characteristics. The important concept of fractal dimension is a measure of non-linear growth, which reflects the degree of irregularities over multiple scales. It is very often non integer and is the basic measure of fractals. For  $D$ -dimensional objects the number of identical parts,  $N$  divided by a scale ratio  $\lambda$  can be calculated as  $N = 1/\lambda^D$ . The other dimensions apart from fractal dimensions are Topological dimension, Hausdorff dimension, Minkowski dimension and Lyapunow dimension. The topological dimension of a set  $P$  is an integer number which describes the dimension of a set required to divide  $P$  into more disconnected sets. The Hausdorff dimension is also known as Hausdorff-Besicovitch dimension. This method is useful where dimensionality of sets whose topological dimension do not give an accurate description of their topology. The alternative Fractal dimension can be calculated either in real or transform space. Different methods are used for estimating fractal dimension. Box-counting method, Variance method, Power spectrum method, Cube

counting method and Prism Counting method. Among them, the box counting approach is a simplification of Hausdorff dimension and is used in many image processing related areas.

The variance method is based on the scale dependence of the variance of fractional Brownian motion. In the variance method one divides the image surface into equal sized squared boxes and the variance is calculated for a particular box size. Fractal dimension is evaluated from the slope of the least square regression line that fits to the data point in the log-log plot of the variance. In the power spectrum method, every line height profiles that form the image are Fourier transformed and the power spectrum is evaluated and then all these power spectra are averaged. Fractal dimension is evaluated from the slope. Cube counting method [21] is derived directly from a definition of the box-counting fractal dimension. The algorithm is based on a cubic lattice with constant  $I$  superimposed on the  $z$ -expanded surface. Initially  $I$  is set at  $x/2$ , where  $x$  is the length of the edge of the surface, resulting in a lattice of  $2 \times 2 \times 2$  cubes.  $N(I)$  is the number of all cubes that contain at least one pixel of the image. The lattice constant  $I$  is then reduced by a factor of 2 and the process repeated until  $I$  is equal to the distance between two adjacent pixels. The slope of a plot  $\log(N(I))$  vs  $\log(1/I)$  is the fractal dimension. The prism counting method works as a grid of unit dimension  $I$  placed on the surface. This defines the location of the vertices of a number of triangles. When  $I = X/4$ , the surface is covered by 32 triangles of different areas inclined at various angles. The areas of all triangles are calculated and summed to obtain an approximation of the surface area  $S(I)$  to  $I$ . The grid size is then decreased by successive factors of 2 and the process continues until  $I$  corresponds to the distance between two adjacent pixel points. The slope corresponding to  $\log(S(I))$  vs  $\log(1/I)$  is the dimension. We applied the box-counting method for calculating the pixel wise fractal dimension of the image. The general formula for calculating the fractal dimension is given in the equation

$$(5) \quad D_b = -\lim_{l_b \rightarrow 0} \frac{\log N_b(l_b)}{\log l_b}$$

where  $N_b(l_b)$  is the number of boxes of size  $l_b$ , needed to completely cover the structure,  $D_b$  corresponds to the slope of the plot  $\log N_b(l_b)$  versus  $\log l_b$ . This dimension is sometimes called grid dimensioning, because of mathematical convenience the boxes are usually a part of a grid. One could define the box dimension where boxes are placed at any position and orientation, to minimize the number of boxes needed to cover the set. The choice may be made in the range of values of  $l_b$ . The smallest  $l_b$  value may be taken as ten times the smallest distance between points in the set, and the largest  $l_b$  value may be taken as ten times the maximum distance between points in the set divided by 10. One may exceed these limits and discard the extreme of the log-log plot where the slope tends to zero. The algorithm for calculating pixel wise fractal dimension is given in Algorithm 1.

**Algorithm 1.** Fractal dimension

Fractal Dimension	
<b>Input:</b>	Image <i>Img</i> of size [N*N] T and P = Window Size
<b>Output:</b>	Slope of the Image (FD)
1	<b>for</b> each pixel in an image <i>Img</i> ( <i>i</i> , <i>j</i> ) <b>do</b>
2	<b>for</b> $\epsilon = 1, 2, 3, \dots \epsilon_{\max}$ <b>do</b>
3	compute a window $T = 2\epsilon + 1$
4	compute $M_{\epsilon} = \max(T)$
5	compute $N_{\epsilon} = \min(T)$
6	compute $D_{\epsilon} = M_{\epsilon} - N_{\epsilon}$
7	<b>end for</b>
8	<b>end for</b>
9	<b>for</b> each pixel in an image <i>Img</i> ( <i>i</i> , <i>j</i> ) <b>do</b>
10	construct a window of suitable size P
11	<b>for</b> $\epsilon = 1, 2, 3, \dots \epsilon_{\max}$ <b>do</b>
12	$E_{\epsilon} = \text{avg}(D_{\epsilon})$
13	<b>end for</b>
14	Do a line fit of $(\log(R/\epsilon)), \log(((R/\epsilon)^3)E_{\epsilon})$
15	where R is a window of suitable size
16	<b>end for</b>

**Fractal Signature.** Fractals are used for model hierarchical structures in several areas of image processing. The changes in image properties with changes in scale have been investigated [22]. One of the important properties of a fractal object is the fractal surface area. For an image, the change of gray level surface needs to be measured on different scales. The change in a measured area with the changing scale is used as the Fractal Signature (FS) and these can be compared for classification. For a pure fractal gray level image, the area is computed as

$$(6) \quad A(\epsilon) = F \epsilon^{2-D},$$

where  $\epsilon$  is the resolution of the gray levels in the image,  $D$  is the fractal dimension and  $F$  is a constant. The surface area of the image is computed by the method suggested by Mandelbrot for curve measurement. The idea is to cover the gray level surface with a blanket having an upper surface  $u_{\epsilon}$  and lower surface  $l_{\epsilon}$ . For  $\epsilon=0$ , they are initialized to the gray level values of the image.

$$(7) \quad u_{\epsilon} = g(i, j) = l_{\epsilon},$$

where  $g(i, j)$  represents a gray level function. From  $\epsilon=1$  onwards,  $u_{\epsilon}$  is computed as the maximum of upper surface for  $u_{\epsilon-1}$  and  $l_{\epsilon}$  is computed as the minimum of the lower surface for  $l_{\epsilon-1}$ . They are given by equations:

$$(8) \quad u_{\epsilon}(i, j) = \max([u_{\epsilon-1}(i, j) + 1], \max_{|(m,n)-(i,j)| \leq 1} [u_{\epsilon-1}(m, n)]),$$

$$(9) \quad l_{\varepsilon}(i, j) = \min([l_{\varepsilon-1}(i, j) + 1], \min_{|(m,n)-(i,j)| \leq 1} [l_{\varepsilon-1}(m, n)]).$$

The image points  $(m, n)$  with distance less than one from  $(i, j)$  were taken to be four immediate neighbors of  $(i, j)$ . In computing  $u_{\varepsilon}$  and  $l_{\varepsilon}$  at different points, the four immediate neighbors are considered. The difference between the upper and lower surface for a scale gives the volume of the blanket for that scale. The volume is given by

$$(10) \quad V = \sum_{i,j} (u_{\varepsilon}(i, j) - l_{\varepsilon}(i, j)).$$

The surface area from which one can determine whether the surface is a fractal or not is computed as

$$(11) \quad A(\varepsilon) = [V_{\varepsilon} - V_{(\varepsilon-1)}] / 2\varepsilon.$$

The surface area gives a measure of the oscillations of the underlying surface for each scale [23]. If the image is a fractal, the plot of  $A(\varepsilon)$  versus  $\varepsilon$  on a log-log scale is almost a straight line. Variation of  $A(\varepsilon)$  with  $\varepsilon$  takes place based on the characteristics of an image. The slope  $S(\varepsilon)$  of  $A(\varepsilon)$  is defined as the fractal signature. Here the fractal signature is computed using features derived for 45 scales. The fractal signature for  $\varepsilon = 2, 3, \dots, 45$  was computed for different classes of images. The fractal signatures and their variation with area  $A(\varepsilon)$  are depicted in Figs 3 and 4. We can notice that fractal signatures vary in a similar manner for a particular type of images.

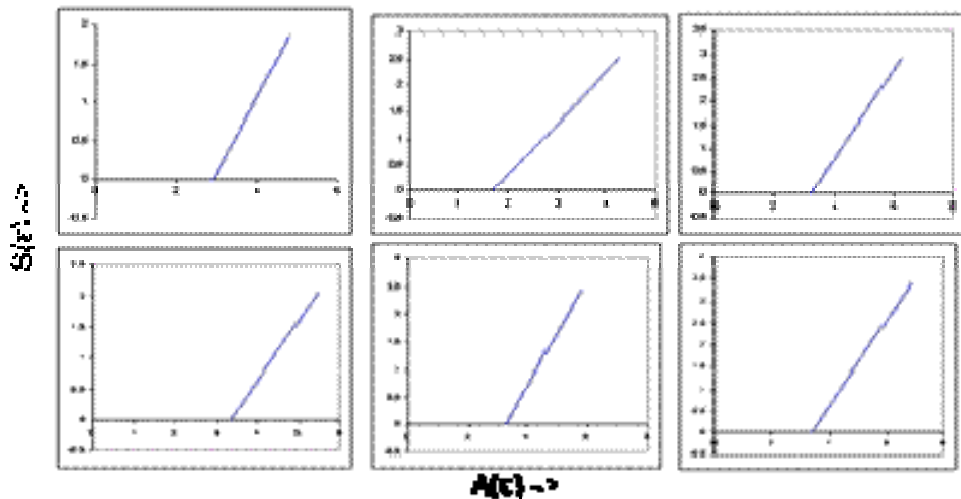


Fig. 3. Variation of fractal signature  $S(\varepsilon)$  with the area  $A(\varepsilon)$  for cancer images



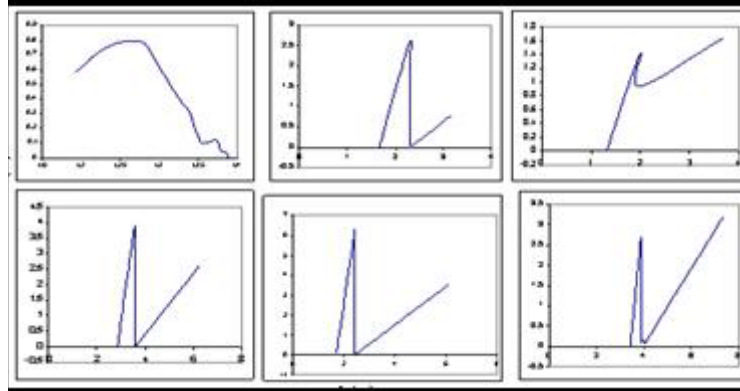


Fig. 4. Variation of fractal signature  $S(\epsilon)$  with the area  $A(\epsilon)$  for non cancer images

#### 4. Classification methods

Classification is the process of taking decisions that best matches the membership of the object. The task is a complex process that is influenced by many factors. The goal is to associate the appropriate class labels with the test image. These include statistical and structural methods. Non-parametric classifier, such as neural networks have become of great importance for image classification. These systems require a sufficient number of samples as pre-requisites for accurate classification. In our method these samples are taken from publicly available databases. Selecting suitable feature values of these samples is a critical step for successful image classification. Many potential feature values can be considered for the classification, which include texture, intensity gradients, signature information and contextual information. It is important to select only feature values which are most useful for the mammogram classification. Many approaches, such as fractal features, principle component analysis, wavelet transform can be used for extracting the features. The proposed method has been tested with a neural network classifier.

##### 4.1. Neural network methods

Any classification method [24] uses a set of features or parameters to characterize each object, here these features should be relevant to the task at hand. There are two phases of constructing a classifier [25]. First is the training phase, in which a training set is used to determine how the features are to be weighted and combined in order to classify the objects. Secondly, in the application phase, the weights obtained from the training set are applied to a set of new objects for classification. To obtain a better classification rating, a classifier based on neural networks was designed. The architecture of the network (Fig. 5) is a multi-layered one where the nodes in a layer are fully connected to the nodes in the next layer. The input layer contains the fractal feature values, such as fractal dimension and fractal signature. The hidden layer contains five nodes and the output layer has an output node. This

neural network is trained using the back propagation algorithm. The back propagation algorithm consists of two steps:

(i) A feed forward step in which the output of the nodes comparing the hidden layers and the output layer are computed. The output values are calculated as a linear combination of weight and node values of the previous layer [4]. This result is then operated on by the sigmoid function given by

$$(12) \quad R(s) = \left( \frac{1}{1 + e^{-s}} \right);$$

$$(13) \quad x_{j^{k+1}} = R\left(\sum W_{ij}^{(k+1)} x_j^{(k)}\right).$$

Here  $x_j^{(k)}$  is the value of the  $j$ -th node in the  $k$ -th layer and  $W_{ij}^{(k+1)}$  is the weight of the link connecting  $i$ -th node in  $k$ -th layer to  $j$ -th node in  $(k+1)$ -st layer.

(ii) A back-propagation step where the weights are updated backwards from the output layer to one or more hidden layers. The back-propagation step uses the steepest descent method to update the weights so that the error function  $\frac{1}{2} \sum (x_j^{(k)} - d_j)^2$  is minimized where  $d_j$  is the desired output class.

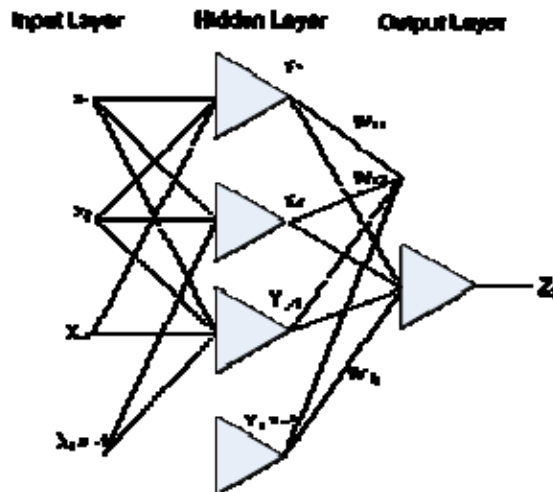


Fig. 5. Neural network architecture

#### 4.2. Unsupervised classification

Images were classified as cancerous or non cancerous by best fit into a cluster and are assigned to that cluster. The K-Means algorithms were used for the purpose. The algorithm uses random seeds, i.e., points with random mean values to form lines to separate the classes. Next, the points within the delineated areas are analyzed, and their mean values are calculated. The means form the new seeds from which a new series of lines can be formed to separate the classes. This process is done repeatedly. The advantage of this method is that it has the potential to model complex target functions with a small set of features. The clustering works based on the following equations:

$$(14) \quad D_{(i,k)} = \|(x_k - v_i)\|_2 \quad \text{for } i \leq c, k \leq N,$$

$$(15) \quad v_i^{(l)} = \frac{\sum_{j=1}^{N_i} x_j}{N_i},$$

$$(16) \quad \prod_{k=1}^n \max |v^{(l)} - v^{(l-1)}| \neq 0,$$

$D_{(i,k)}$  calculates the distances between each class,  $c$  is the number of clusters,  $N$  is the number of objects in the cluster and  $v$  determines the cluster center. The higher value of  $k$  results in smooth grouping. In our proposed system we choose the value of  $k$  as 3. The pseudo code for standard K-Means algorithm is given in Algorithm 2.

**Algorithm 2.** K-Means

1. Input  $\rightarrow$  Data set X
2. Output  $\rightarrow$  Partition Matrix
  - (a) For each iteration: compute the distances by (14)
  - (b) Select the points for a cluster with the minimal Distance ( $D$ ) belong to that cluster
  - (c) Calculate the cluster center by (15)
  - (d) Repeat above steps until by (16) is satisfied

## 5. Experiments and results

In this work about 316 mammogram images from MIAS and DDSM databases have been used for training and testing, out of which 40% of the data are used for the training part and 60% considered for the classification. Two different classifiers are used for the experiments: Neural Network and K-Means algorithm. Fig. 5 shows the neural network architecture for classification. In medical imaging, texture feature analysis has been widely used for classification purposes [26]. It is this important characteristic of an image which gives the radiologist a better understanding of the image. The texture shows its unique characteristics by its pixel values. There are many different approaches available for texture based classification. The proposed system calculates the fractal dimension and fractal signature values for the individual image. The extracted features are then input to the neural network for training and classification purposes. The region of interest was located manually from the given image. Table 1 shows the final procedure for calculating the signature value.

Table 1. Fractal signature extraction

Feature	Equation	Description
Fractal Signature	$A(\varepsilon) = [V\varepsilon - V_{(\varepsilon-1)}] / 2\varepsilon$	Fractal signature estimates the fractal dimension at resolution $\varepsilon$ by examining $A(\varepsilon)$ varies with changing $\varepsilon$

Figs 3 and 4 show how the surface area varies with respect to the size of the structuring element. The tested images were categorized into two groups: cancer and non-cancer images. In the region of interest, the obtained results vary in shape according to the image surface. The average values of the varying scale were considered as an individual signature value, which is given to the classification algorithm as an input. The fractal dimension could be obtained from the slope of fractional Brownian motion estimated by the least square linear regression. Fig. 6 gives the cluster maps of fractal dimension for the classification which show a set of sample images and their equivalent calculated FD. One can easily identify that the variation of image properties can influence the evaluation of dimension. Figs 7 and 8 give the FD and FS for cancer and non-cancer images respectively. In the classification phase an image of the extracted Fractal features are input to the neural network for training and labeling. Fig. 9 shows a set of random images from the collected images considered for classification. A comparative study of different classifying algorithms is the best to evaluate the accuracy of the proposed method. In this work we compared it with K-Means algorithm. Table 2 shows the comparison results of neural network with K-Means algorithm. The neural network approach has comparatively better classification accuracy compared to the unsupervised classifier.

Table 2. Comparison results

Algorithm	Classification Accuracy
K-Means	96%
Neural Networks	98%

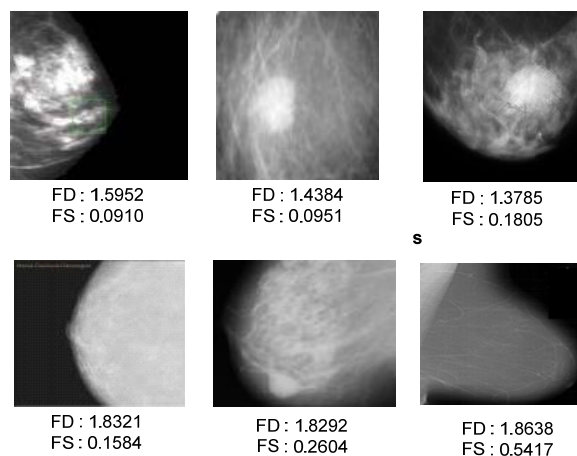


Fig. 7. FD and FS for cancer images

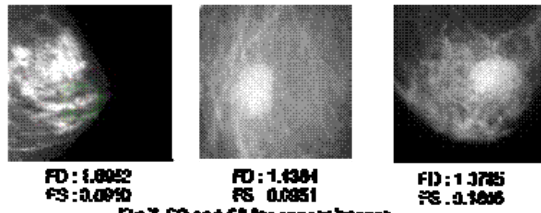


Fig.7. FD and FS for cancer images

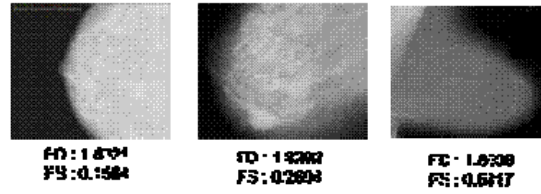


Fig. 8. FD and FS for non-cancer images

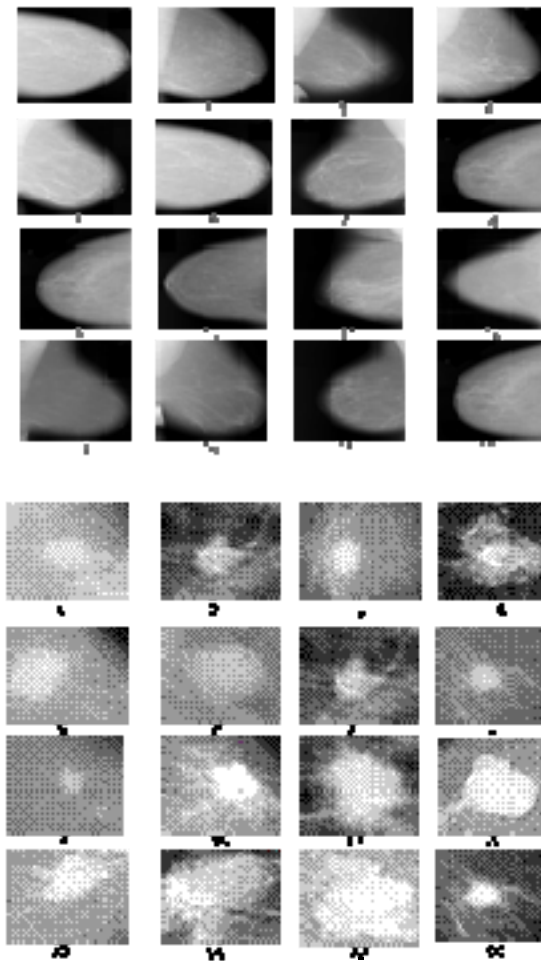


Fig. 9. Sample images for feature extractions

## 6. Conclusion

In this paper, we addressed the problem of classification using local Fractal features. The classification of breast cancer images is based on multi-layered back propagation algorithm. Fractal feature values such as Fractal Dimension and Fractal Signature are extracted for the classification purpose. The proposed methods of evaluating features are based upon pixel wise box counting and texture comparison. It is observed that using our proposed method has been observed to be far more perceptive than the traditional unsupervised learning algorithm. Using NN the classification rate was found to be 98%. The success of any image classification depends on many factors. The availability of good quality images, types of features extracted and more important – an experienced radiologist. In future we will consider other statistical models for feature extraction in order to improve the classification rate.

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## References

1. Kobatake, H., Murakami, H., Takeo, S., Nawano. Computerized Detection of Malignant Tumors on Digital Mammograms. – In: IEEE Tran. Medical Imaging, Vol. **18**, 1999, No 5, 369-378.
2. Zhou, X. Q., Huang, S. L., Lou. Authenticity and Integrity of Digital Mammography Images. – IEEE Trans on Medical Imaging, Vol. **20**, 2001, No 8, 784-791.
3. Lundahi, T., Wholey, S. M., Kay, R., Siffert. Fractional Brownian Motion: A Maximum Likelihood Estimator and Its Application to Image Texture. – In: IEEE Trans. Med. Imaging, Vol. **MI-5**, September 1986.
4. Erkang, C., Xianhua, L., Habin, P., Rakic, A. D. A., Maidment, V., Megalooikonomou. Mammographic Image Classification Using Histogram Intersection. – In: IEEE Proc. ISBI'10, 2010, 197-200.
5. Hassanien, E. A., M. H. Jafar Ali. Rough Set Approach for Classification of Breast Cancer Mammogram Images. – In: Int. Workshop on Fuzzy and App., 2003, 224-231.
6. Lúcio, F. A., C. S. C. Aristófanes, A. K. Barros. Diagnosis of Breast Cancer in Digital Mammograms Using Independent Component Analysis and Neural Networks. – LNCS, Vol. **3773**, 2005, 460-469.
7. Arod, T., Kurdziel, E. O. D., Sevre, D. A., Yuen. Pattern Recognition Techniques for Automatic Detection of Suspicious-Looking Anomalies in Mammograms. – Comput. Methods Prog. Biomed, 2005, 135-149.
8. Hui, Li, K. J. R., Liu, S.-C., B. L. O. Fractal Modeling and Segmentation for the Enhancement of Microcalcification in Digital Mammograms. – In: IEEE Trans. Med. Imaging, 1997, 785-798.
9. Zhang, P., Kumar, B., Verma. A Hybrid Classifier for Mass Classification with Different Kinds of Features in Mammography. – LNCS, Vol. **3614**, 2005.
10. Buciu, I., A. Gacsadi. Directional Features for Automatic Tumor Classification of Mammogram Images. – Biomedical Signal Processing and Control, 2011 (in Press).
11. Dua, S., S. Harpreet, H. W. Thompson. Associative Classification of Mammograms Using Weighted Rules. – Expert Syst. Appl., 2009, 9250-9259.
12. Antonie, M.-L., O. R. Ziane, A. Coman. Application of Data Mining Techniques for Medical Image Classification. – MDM/KDD, 2001, 94-101.

13. P e t r o u d i, S., T. K a d i r, M. B r a d y. Automatic Classification of Mammographic Parenchymal Patterns: A Statistical Approach. – In: IEEE Proc. EMBS, 2003, 798-801.
14. L e k s h m i, S., K. R e v a t h y, S. R. P r a b h a k a r a n N a y a r. Galaxy Classification Using Fractal Signature. – A&A, Vol. **405**, 2003, 1163-1167.
15. D o n, S., K. R e v a t h y. Classifying Remotely Sensed Data Using Fractal Features. – AIPR, USA, 2007, 262-266.
16. H e a t h, M., K. B o w y e r, D. K o p a n s, Jr. P. K e g e l m e y e r, R. M o o r e, K. C h a n g, S. M u n i s h k u m a r a n. Current Status of the Digital Database Screening Mammography. – In: Proceedings of the 4th IWDM, 1997, 457-460.
17. S u c k l i n g, J. et al. The Mammographic Image Analysis Society Digital Mammogram Database Exerpta Medica. – International Congress Series, Vol. **1069** 1994, 375-378.
18. American College of Radiology, Illustrated Breast Imaging Reporting and Data System BIRADS. Reston,VA, American College of Radiolog., 1993.
19. M a n d e l b r o t, B. B. The Fractal Geometry of Nature. San Francisco, CA, W. H. Freeman, 1982.
20. Y u a n, Y a n T a n g. Wavelet Theory Approach To Pattern Recognition. 2nd Edition. World Scientific.
21. D o u k e t i s, C., W. Z h o u h a n g, T. L. H a s l e t t, M. M o s k o v i t s. Fractal Character of Cold-Deposited Silver Films Determined by Low-Temperature Scanning Tunneling Microscopy. – Phys. Rev., Vol. **B51**, 1995, 11022-11031.
22. E s p i n a l, F., T. L. H u n b e r g e r, B. J a w e r t h, T. K u b o t a. Galaxy Classification Using Fractal Signature. – Opt. Eng., Vol. **37**, 1998, p. 166.
23. P e l e g, S., N. J. H a r t l e y, R. A v n i r d. Multiple Resolution Texture Analysis and Classification. – In: IEEE Trans. on Pattern Analysis and Machine Intelligence, Vol. **PAMI6**, 1984, 518-523.
24. Z h a n g, W., K. D o i, M. G i g e r, R. N i s h i k a w a, R. S c h m i d t. An Improved Shift-Invariant Artificial Neural Network for Computerized Detection of Clustered Microcalcification in Digital Mammograms. – Med. Phys., Vol. **23**, 1996, No 4, 595-601.
25. W h i t e, R. L. Object Classification in Astronomical Images. – In: Statistical Challenges in Modern Astronomy II. Springer, 1997.
26. K a r a h a l i o u, A., S. S k i a d o p o u l o s, I. B o n i a t i s, P. S a k e l l a r o p o u l o s, E. L i k a k i, G. P a n a y i o t a k i s, L. C o s t a r i d o u. Texture Analysis of Tissue Surrounding Microcalcifications on Mammograms for Breast Cancer Diagnosis. – The British Journal of Radiology, 2007, 684-656.