# Fractal Feature Based Early Breast Abnormality Prediction

Anindita Roy[a*], Usha Rani Gogoi[a], Dipak Hrishi Das[b] and Mrinal Kanti Bhowmik[a]
[a]Department of Computer Science and Engineering, Tripura University (A Central University), Tripura (W), India.
[b]Department of Information Technology, Bir Bikram Memorial College, Tripura, India.
royanindita59@gmail.com[*], usgo130@gmail.com, dhdcse@gmail.com and mrinalkantibhowmik@tripurauniv.in

*Abstract*— **Breast cancer is associated with high mortality rates in women of both developing and under developed countries. Moreover, due to the poor medical facilities and lack of awareness, this mortality rate is higher in rural areas than that of the urban areas. Hence, to reduce this high mortality rate, the early detection of the breast diseases before the onset of the cancerous mass is very crucial. Among various breast imaging modalities, X-ray Mammography stands out to be the gold standard modality for Breast cancer detection. But vulnerability of women below 40 years towards radioactive exposure of X-ray mammography necessitates the concerned research community to explore avenues devoid of radioactive hazard as well as preferably non-invasive. Infrared Thermography (IRT) meeting such important requirements can be used as an adjunctive tool in breast abnormality detection of women of all age groups. Besides, due to its portability and cost effective nature, it can be used as a routine checkup tool for patients in remote areas and thus, can point out the subjects who requires urgent medical attention. To validate the predictability of both mammography and thermography in breast cancer detection, this paper develops a suspicious region based breast abnormality detection system. The paper investigates the efficacy of fractal features over the most widely used texture features in anomalous region based breast abnormality prediction from both mammograms and thermograms. We focus on fractal features in discriminating the abnormal and severe abnormal breast images from the normal and mild abnormal breast images by observing the difference in fractal dimension and lacunarity values. We investigated that the combination of fractal dimension and lacunarity features gives prediction accuracy of 95.94% on the mini-MIAS mammogram dataset of 128 images and 86.11% on a newly created DBT-TU-JU breast thermogram dataset of 36 abnormal images as compared to 79.31% and 78.94% using texture features, respectively. The experimental results reveal that the fractal features are more efficient in disease affected region based breast abnormality prediction from both mammograms and thermograms.**

*Keywords*— **Breast cancer, Infrared breast thermogram, Mammograms, Fractal dimension, Lacunarity.**

## I. Introduction

Breast cancer is one of the major causes of cancer related deaths in women [1]. Due to the lack of medical facilities for early detection in less developed countries or rural areas, the survival rates is very poor. Even though, X-ray mammography is considered as the gold standard screening modality for breast cancer, but it is incapable of detecting a mass until it attains a certain size [2]. Moreover, due to the radiation risk of mammography, it is not recommended for women whose ages are below 40 years [2]. These limitations of mammography necessitate the concerned research community to explore the feasibility of radiation-free, non-ionizing, portable and cost-effective infrared breast thermography (IBT) to be used as an adjunctive and routine checkup tool to improve the accuracy of breast abnormality prediction [1]. Moreover, due to its portability and non-ionizing nature, it can also be used for women in rural areas to pinpoint the patients that require urgent medical attention. Being a functional imaging modality, it detects the temperature distribution of the surface area. Due to angiogenesis, the temperature of the skin surface over the tumor is higher than the surrounding areas [3, 4], and therefore, the anomalous region is easily visible through an infrared camera.

Over the last decade, different fractal-based techniques have been used by authors in various fields of shape analysis such as in detection of breast abnormalities in mammograms or thermograms and in brain tumor detection from Magnetic Resonance Images. Zheng et al. [5] and Rangayyan et al. [6] had used fractal analysis for the detection of distorted sites in mammograms obtained before the detection of breast cancer in a screening program. They used the box-counting and ruler method for finding the fractal dimension. In 2010,Tavakol et al. [7] introduced the concept of using fractal geometry for the classification of breast thermograms as benign or malignant. They had shown that the benign masses have a dimension of approximately 1, while fractal dimensions of malignant masses are found to be beyond 1. Guo et al. had applied the concept of lacunarity along with fractal analysis to distinguish between mass and normal breast parenchyma of mammograms [8]. Filho et al. [9] used the Hurst coefficient and Lacunarity features for classifying the breast thermograms into normal and abnormal breasts. They found that the values of lacunarity were higher in abnormal breast thermograms compared to that of the normal one.

Our study investigates the abnormal findings of mammograms as well as the thermograms by analyzing the fractal features. The abnormalities, usually present in mammograms are circumscribed and spiculated masses, architectural distortion, asymmetry and calcifications [5], while in breast thermograms the abnormalities are generally represented by the presence of asymmetric thermal patterns in both breasts, presence of hotspots and vascularization in one or both breasts [2]. However, the presence of these abnormalities most of the time lead to the appearance of some textural differences between the both breasts. To obtain these

978-1-5386-2175-2/17/$31.00 ©2017 IEEE

textural difference between both breasts, the fractal features such as fractal dimension and lacunarity, well known for their effectiveness in analyzing the difference in textures have been used here. The fundamental principle of fractal is that a simple procedure undergoing infinitely many iterations becomes a complex process and fractals try to model this complex process by looking for a simple process underneath. These fractal patterns are quantitatively represented by two terms: Fractal dimension and lacunarity. Fractal dimension measures the space-filling capacity of a fractal pattern and lacunarity quantifies the way the space is occupied by the shape with respect to their gaps [10]. Besides, our study also compares the findings of the fractal features with some texture features which are already proved to be effective in literature [2, 11] for breast asymmetry analysis.

The contributions of the paper can be highlighted as:

a) Analysis of the fractal feature values for various types of breast abnormalities found in mammograms.

b) Prediction of breast abnormalities from breast thermograms of a newly developed database by using fractal features.

c) Comparison of the findings of fractal features with some efficient texture features.

## II. Methodology

Fractals are self-similar repetitive patterns that are more detailed in nature as the scale of observing window increases. The fractal dimension is measured by observing how the number of boxes deviates as the grid becomes finer by applying a box-counting algorithm. To determine the dimension of a fractal F, it is imagined that the fractal is laid on an equally spaced grid, and then the number of boxes required to cover the whole set is counted [12]. The deviation of the patterns as the scale size changes is studied using fractal dimension. Let F be any non-empty bounded subset of $R^n$ and let $N^\delta(F)$ be the minimum number of sets of diameter at most $\delta$ which can cover F. Then the fractal dimension is given by equation (1),

$$\dim_B(F) = \lim_{\delta \to 0} \frac{\log N^{\delta}(F)}{-\log(\delta)} \qquad (1)$$

Lacunarity is a measure that can describe the fractals with same fractal dimension but different appearance. It shows the probability of occurrence of gaps at each box size and finally computes the mean $m_1(r)$ and the variation from the mean $m_2(r)$ [10]. It is a measure of variance of the number of pixels present in a box normalized by the square of the mean for obtaining a single value as in equation (2),

$$\Lambda(r) = \frac{m_2(r)}{(m_1(r))^2} \qquad (2)$$

## III. Database Description

### A. Mini-MIAS Database

The mini-MIAS database is a reduced version of the original MIAS database developed by MIAS, where the images have been condensed to a 200-micron pixel edge and all the images are of size 1024 x 1024 [13]. The database has been arranged in pairs where each pair represents the left and right mammograms of a single patient. There are in total 208 normal and 114 abnormal (63 benign and 51 malignant) images. The types of abnormalities included in this database are: calcification, well-defined/circumscribed masses, spiculated masses, other ill-defined masses, architectural distortion and asymmetry.

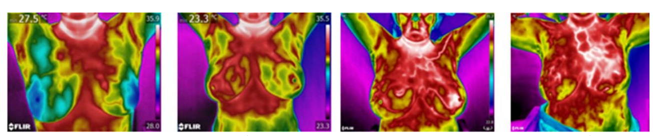
### B. DBT-TU-JU Breast Thermogram Database

The designing of the DBT-TU-JU breast thermogram database has been elaborately described in [4]. Currently, the database consists of 60 breast thermograms of both healthy and unhealthy patients. In addition, it includes findings of other breast screening modalities like mammography, fine needle aspiration cytology (FNAC), clinical observations. The abnormalities included in this database are: fibroadenoma, infection, breast cancer and others.

Some sample thermograms and mammograms of both of these databases are shown in Fig. 1 and Fig 2 respectively. The white regions present in the breast thermograms of Fig. 1 are the suspicious abnormal regions presence of whose implies the breast abnormality.

## IV. Experimental Results And Discussions

Results were obtained using both the mini-MIAS and DBT-TU-JU breast thermogram database. A dataset of 128 mammograms containing 26 malignant masses, 14 with



(a) (b) (c) (d)

Fig. 1. Sample Breast Thermograms with (a) Normal Breasts, (b) Asymmetric Thermal Patterns, (c) Benign Lump in left Breast & (d) Malignant Mass in left breast [4].

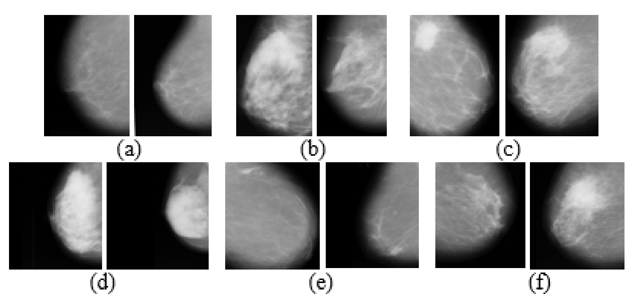


Fig. 2. Samples of mammograms with (a) Normal Breasts, (b) Architectural Distortion, (c) Malignant Mass, (d) Dense Breasts, (e) Benign Mass & (f) Left Right breast Asymmetry [13].

architectural distortions, 19 with dense breast, 20 with asymmetric patterns and 49 normal mammograms of the mini-MIAS database were randomly selected for the experimental purpose. Initially, the mammograms were enhanced by using histogram equalization followed by the extraction of the region of interest by using region growing segmentation method where the seed point was automatically selected based on the pixel with highest intensity value in the image. By applying the region growing method, it has been seen that in comparison to the segmentation results of anomalous mammograms, the normal mammograms result in very small ROIs. After extraction of anomalous regions, its fractal dimension and lacunarity were determined by using the box-counting and gliding box methods (equation 1 and 2), respectively. Due to the irregularity and heterogeneity present in the mammograms with malignant or benign masses and with other abnormalities, the fractal dimension and lacunarity values in almost all cases were found to be higher than the normal mammograms. Lacunarity shows minimum difference still combination of both lacunarity and fractal dimension helps to distinguish the images with same fractal dimension. The significance of fractal features in various breast abnormality prediction in mammograms is illustrated in Table I. The nonparametric Mann-Whitney-Wilcoxon test [14] with significance value of $p<0.01$ also proves the statistical significance of the fractal features. The test has been performed for each type of abnormality against the normal group. The null hypothesis Ho: states that the median of the fractal features of abnormal cases is equal to the median value obtained from the normal cases. It is observed that with $p<0.01$, MWW rejects the null hypothesis of equal medians at the default $p<0.01$ significance level for both features. Fig. 3(a) shows the average fractal dimension and lacunarity values of mammograms of normal breasts and with different breast abnormalities. The appearance of differential fractal dimension values between the various abnormalities signifies its efficiency in breast abnormality prediction from mammograms. The fractal feature analysis was also carried out for abnormality prediction from breast thermograms. Out

TABLE I P-VALUES OF FRACTAL DIMENSION AND LACUNARITY OF NORMAL BREASTS AND BREASTS WITH VARIOUS ABNORMALITIES.

| Type of Mammograms | Fractal Features | | P-value (Against Normal Group) | |
|---|---|---|---|---|
| | *Fractal Dimension* | *Lacunarity* | *Fractal Dimension* | *Lacunarity* |
| Normal | 1.121848 | 1.001977 | | |
| Malignant | 1.4035707 | 1.006415 | 0.0019 | 0.0023 |
| Benign Mass | 1.296796 | 1.001601 | 0.0029 | 0.0014 |
| Arch. Distortion | 1.53603 | 1.027642 | 0.00009 | 0.0018 |
| Dense Breast | 1.647121 | 1.05847 | 0.00009 | 0.0006 |
| Asymmetry | 1.343661 | 1.003416 | 0.0003 | 0.0034 |

of 60 breast thermograms, 24 are normal and 36 images were of abnormal cases. These 36 abnormal images comprised of 20 cases with either malignant or benign lumps (severe abnormal) and 16 cases with other breast problems (mild abnormal). In order to perform an anomalous region based breast abnormality prediction, only the abnormal breast thermograms with either asymmetric thermal patterns or suspicious hotspot areas had been considered. Initially, each abnormal breast thermogram was converted into gray scale image and then the unnecessary regions were discarded. Then seeded region growing segmentation technique was used to extract the region of interest i.e., the hotspot areas from the abnormal breast thermograms. From these extracted regions, the fractal dimension and lacunarity values were computed. Severe abnormal breast thermograms with benign or malignant lumps showed greater values of fractal features as depicted in Fig. 3(b). The average fractal feature value was higher in severe abnormal breast thermograms than in the mild abnormal breast thermograms having asymmetric thermal patterns. The statistical significance with significance value $p<0.01$ of the fractal features in case of thermograms has been shown in Table II. The Mann-Whitney-Wilcoxon test [14] has been performed for severe abnormal breast thermogram against the mild abnormal breast thermogram. The null hypothesis Ho: states that the median of the fractal features of severe abnormal cases is equal to the median value obtained from the mild abnormal cases. It is observed that with $p<0.01$, MWW rejects the null hypothesis of equal medians at the

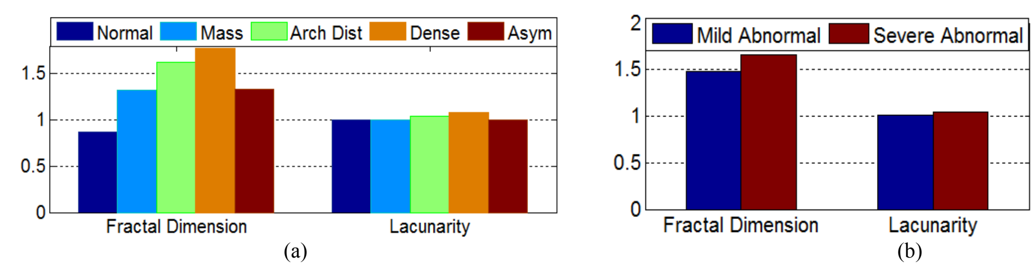



Fig. 3. Comparison of the values of Fractal Dimension and Lacunarity for (a) Normal mammograms and mammograms with various abnormalities, (b) Mild abnormal and severe abnormal thermograms.

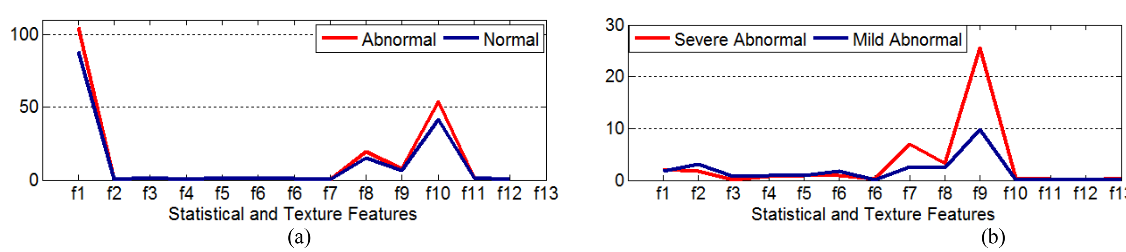



Fig. 4. Average of the texture features values obtained from (a) Normal and Abnormal Mammograms and (b) Mild Abnormal and severe abnormal breast thermograms.

TABLE II P-VALUES OF FRACTAL DIMENSION AND LACUNARITY OF MILD ABNORMAL AND SEVERE ABNORMAL BREAST THERMOGRAMS..

| Type of Thermograms | Fractal Features | | P-value (Against Mild Abnormal Group) | |
|---|---|---|---|---|
| | ***Fractal Dimension*** | ***Lacunarity*** | *Fractal Dimension* | *Lacunarity* |
| Mild Abnormal | 1.343725 | 1.0017 | | |
| Severe Abnormal | 1.627875 | 1.02935 | 0.0032 | 0.0043 |

default $p<0.01$ significance level for both features. To validate the findings of the fractal features in both mammograms and thermograms in breast abnormality prediction some texture features [2, 10] were computed and compared with the results of fractal features. The texture features computed here are: mean (f1), kurtosis (f2), skewness (f3), energy (f4), correlation (f5), homogeneity (f6), contrast (f7), sum of squares (f8), sum average (f9), sum variance (f10), sum entropy (f11), difference variance (f12), difference entropy (f13). For normal and abnormal mammograms and for thermograms with asymmetric thermal patterns (mild abnormal) and sharp hotspot areas (severe abnormal), it was observed that these texture features are effective for asymmetric analysis between both breasts. However, these features are not much effective for region of interest (hotspot areas in thermograms or mass, architectural distortions in mammograms) based abnormality prediction. The average of these thirteen features computed from normal and abnormal mammograms and mild abnormal and severe abnormal thermograms are plotted in Fig. 4(a) and 4(b) respectively which clearly demonstrates the inefficiency of texture features in region of interest based breast abnormality prediction. The analysis of fractal features is followed by the classification of mammograms and thermograms based on the values of the fractal dimension and lacunarity. Based on the rule-based classification, it was observed that the combination of fractal dimension and lacunarity can more significantly differentiate the abnormal mammograms from the normal mammograms in the experimental dataset than texture features. While combined, they provide a classification accuracy of 95.94% with 97.91% sensitivity and 92.3% specificity in case of mammograms and an accuracy of 87.5% with 85% sensitivity and 86.11% specificity in case of thermograms as shown in Fig. 5., thereby demonstrating their efficiency in both modalities as compared to the accuracy rates of texture features being 79.31% and 78.94% in mammograms and thermograms respectively.

## V. CONCLUSION

This paper presents the analysis of the efficiency of two fractal features: fractal dimension and lacunarity on breast mammograms and thermograms. Comparison of this result with the outcome of some other texture features conclude that for mass or other abnormality based abnormality prediction, the fractal features are more efficient than the texture features both in case of mammograms and thermograms.

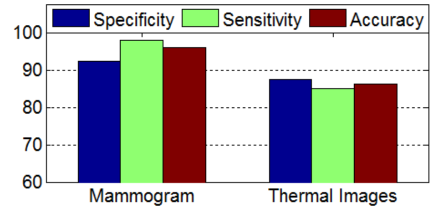


Fig. 5. Performance analysis of Fractal features in breast abnormality detection from mammograms and thermograms

## REFERENCES

[1] UR Gogoi, G. Majumdar, MK Bhowmik, AK Ghosh and D Bhattacharjee, "Breast abnormality detection through statistical feature analysis using infrared thermograms," *International Symposium on Advanced Computing and Communication (ISACC),* IEEE, pp. 258-265, 2015.

[2] UR Gogoi, MK Bhowmik, D Bhattacharjee, AK Ghosh and G Majumdar, "A Study and Analysis of Hybrid Intelligent Techniques for Breast Cancer Detection Using Breast Thermograms," *In Hybrid Soft Computing Approaches,* Springer India, pp. 329-359, 2016.

[3] M Araújo, RCF Lima, FS Magnani, RTN Silva and FGS Santos, "The use of a database as an auxiliar tool in thermographic diagnosis for early detection of breast diseases," *Proceedings of 12th Brazilian Congress of Thermal Sciences and Engineering*, Brazil, pp. 6, 2008.

[4] MK Bhowmik, UR Gogoi, K Das, AK Ghosh, D Bhattacharjee and G Majumdar, "Standardization of infrared breast thermogram acquisition protocols and abnormality analysis of breast thermograms," *Thermosense: Thermal Infrared Applications XXXVIII,* SPIE 9861, pp. 986115-1-18, 2016.

[5] L Zhen, AK Chan, "An artificial intelligent algorithm for tumor detection in screening mammogram," *IEEE transactions on medical imaging*, IEEE, pp. 559-567, 2001.

[6] RM Rangayyan, TM Nguyen, "Fractal analysis of contours of breast masses in mammograms," *Journal of Digital Imaging*, Springer, pp. 223–237, 2007.

[7] M Etehad Tavakol, C Lucas, S Sadri and E. YK Ng, "Analysis of breast thermography using fractal dimension to establish possible difference between malignant and benign patterns," *Journal of Healthcare Engineering*, Multi Science Publishing, pp. 27-44, 2010.

[8] Q Guo, J Shao and V F. Ruiz, "Characterization and classification of tumor lesions using computerized fractal-based texture analysis and support vector machines in digital mammograms," *International Journal of Computer Assisted Radiology and Surgery*, Springer, pp. 4-11, 2009.

[9] O T. da Silveira F., RC. Serrano, A Conci, R H. C. de Melo and R C. F. Lima, "On using lacunarity for diagnosis of breast diseases considering thermal images," *16th International Conference on Systems, Signals and Image Processing*, IEEE, pp. 1-4, 2009.

[10] JP Hovi, A Aharony, D Stauffer and BB Mandelbrot, "Gap independence and lacunarity in percolation clusters," *Physical review letters*, APS, pp. 877-880, 1996.

[11] H S Sheshadri, A Kandaswamy, "Breast Tissue Classification Using Statistical Feature Extraction Of Mammograms," *Medical Imaging and Information Sciences*, pp. 105-107, 2006.

[12] K Falconer, "Fractal geometry: mathematical foundations and applications", *John Wiley & Sons*, 2004.

[13] MIAS, The mini-MIAS database of mammograms. [Online]. Available: http://peipa.essex.ac.uk/info/mias.html. [Accessed: May 20, 2015].

[14] J C.F. De Winter and D Dodou, "Five-point Likert items: t test versus Mann-Whitney-Wilcoxon." *Practical Assessment, Research & Evaluation* 15.11 pp. 1-12, 2010.