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ORIGINAL ARTICLE

Detection of Breast Cancer using Statistical Features

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ABSTRACT
Breast cancer is the major cause of deaths among women. The foremost widespread technique used for the detection of carcinoma is the diagnostic procedure. Determination of abnormalities could be a terribly tough task. Malignant and benign are the two types of cancer having various form or size and according to experts and specialists this can be seen through mammogram. The mammogram images had been obtained from Digital Database for Screening Mammogram is employed for conducting experiment. In this paper, an algorithm based on fuzzy inference system and image processing associated with segmentation based on statistical features is developed for the classification of benign and malignant state of breast cancer by comparing parameters such as accuracy, sensitivity and specificity which shows our proposed approach is better than the other classifications and the calculated percentage is valid for accuracy, sensitivity and specificity are 94%, 94% and 93% respectively.
Keywords: Breast Cancer, Carcinoma, Mammogram masses, Weight function, Digital Database for Screening Mammogram (DDSM).

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INTRODUCTION

The breast cancer is believed to be one in all most farreaching causes of death among ladies and second highest reason for deaths among humans[1]. It has been foreseen that each single minute a woman is interpreted with carcinoma and every 13 minutes a woman expires due to disease[2]. Many techniques and methods had been introduced for early detection and diagnosis of carcinoma such as Biopsy, Mammography, Fine Needle Aspiration, Magnetic Resonance Imaging but the mammography is the most widespread method for early prognosis of disease[3]. The target of mammography is an early prognosis of carcinoma, particularly through espial of masses and micro calcification [4]. According to the report by Breast Imaging Reporting and Data System (BIRADS) [5], malignant masses are irregular in shape whereas benign masses are oval or spherical. Medical experts classified masses as malignant or benign throughout identification stage[6]. Medical experts read mammograms and check out to spot the abnormalities present within the breast mass [7-8]. It has been predicted that ten to thirty percent of women interpret with carcinoma have false negative mammograms[9-10]. Nearly false negative mammograms are contributed to physician radiologist failure to spot the carcinoma at associate degree early stage due to lack of knowledge or experience or misinterpretation [11]. According to the medical purpose of view, reading and interpretation, mammograms are the terribly complicated factor [12-13]. In recent years, computer aided identification way are accustomed guide physicians in early diagnosis and detection of carcinoma [14]. Computer aided diagnostic methods guided to hurry up the diagnostic method planned for varied diseases such as diagnosis of various cancers classification, inclusive of breast and lung cancer [15].

Medical experts can diagnose and detect carcinoma at an early stage using computer aided diagnostic tools, which use computer technologies to determine abnormalities present in mammograms such as masses and calcification [16]. With the help of those results, medical experts can diagnose and detect carcinoma at an early stage. Computer-aided techniques are used for pre-processing and analysis of images as supporting or second reading the primary stage of the computer aided diagnostic tool is to capability to work out abnormalities in breast and therefore the second stage is to diagnose the abnormalities found in masses identified in first stage [17-19]. The most vital step before implementing two stages of computer- aided diagnostic tool is pre-processing stage should occur that issegmentation of breast part from the whole background [20-22]. Mammogram image analysis may aid radiologists in the early identification and diagnosis of carcinoma tumors, as well as the diagnosis of therapy [23]. Although many studies have utilized a variety of strategies to categorize malignant and benign masses, only a few methods are capable of categorizing the breast mass area into malignant and benign masses. This may be done by imposing certain limits as well as using a variety of characteristics. Although by employing a large amount of features does not create reasonable classification rate but also make the carcinomatumor classification additional complicated. The form characteristics of masses have been introduced for classifying breast masses as malignant mass or benign mass with the employment of shape properties. Most of the recent works done on mammography are almost based on mammography's bar chart and it has been found that histogram based on the mammograms are not much effective for classifying the breast masses. This is due to the fact that histograms based on mammograms pattern changes mainly due to noise and over intensification of mammogram images. Thus, in this research, there has been developed an algorithm rooted upon the fuzzy inference system as well as image processing associated with segmentation based on statistical features for classification of benign and malignant state of breast cancer with higher accuracy.

MTAERIAL AND METHODS

The section illustrate about the hybrid system in which the combination of fuzzy inference system and image processing technique is used. Segmentation technique is used in image processing for extracting feature from mammograms. In the hybrid system, we also use machine learning in which random forest classifier algorithm is used. In Figure 1, the first step is made fuzzy inference system in which six statistical input variables i.e. Area, mean, entropy, grey threshold stage, standard deviation, variance are used. The inputs are useful for predicting the status of mammogram breast. After choosing the variables, the first step is to determine the fuzzy set and its corresponding ranges. Fuzzy rule based permits specialists know-how to bear in mind statistical parameters of mammogram after which based totally at the policies developed gives a unique decision. After the completion of fuzzy system, we made graphical user interface for the designed fuzzy system in which segmentation technique is used. To enhance more accuracy of the system, we also used random forest Classifier.

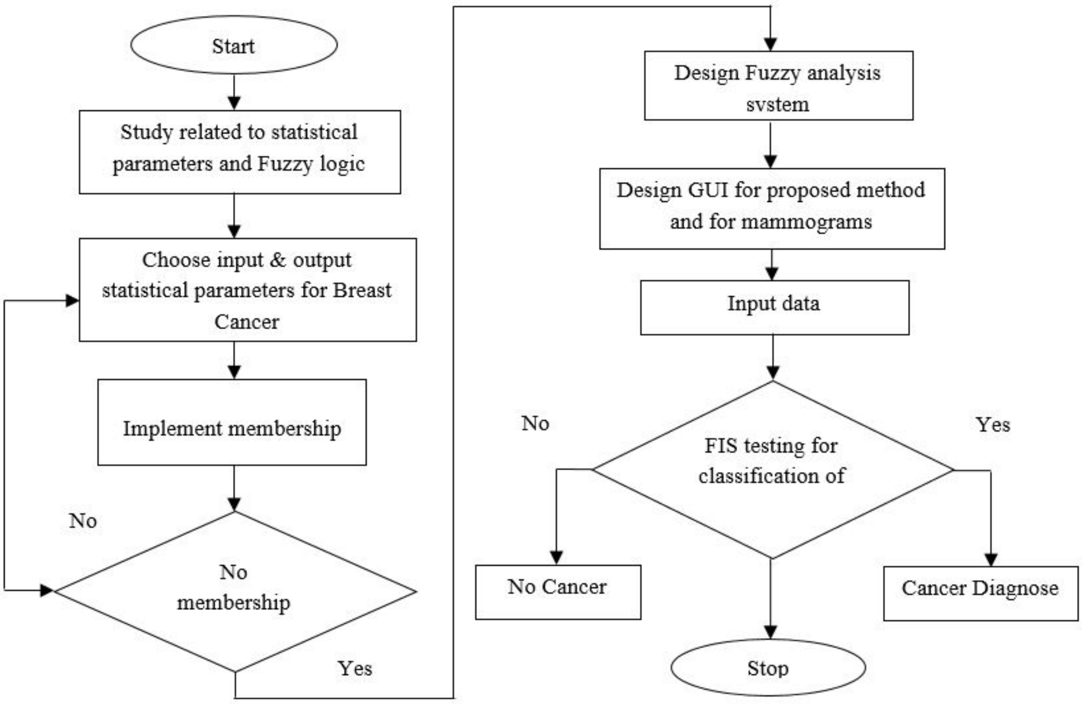


Figure:1 Method for Implementation of Proposed System

Dataset:
The proposed machine became execute by the use of "MATLAB 2016b" on "home windows 7 (64bit). The collection of data changed into arranged by means of branch of pathologist. The data set used in experiments contains 150 mammogram is of size 1024x1024 pixels, 200 micron. For classifying the mammogram as normal and abnormal Fuzzy System and image segmentation were used and the samples were collected from the different hospitals of Jalandhar (Punjab) and also from DDSM.

Input Variables:
Figure 2 shows six input variables as mentioned in methodology which is the first step to determine the fuzzy set and its corresponding ranges.

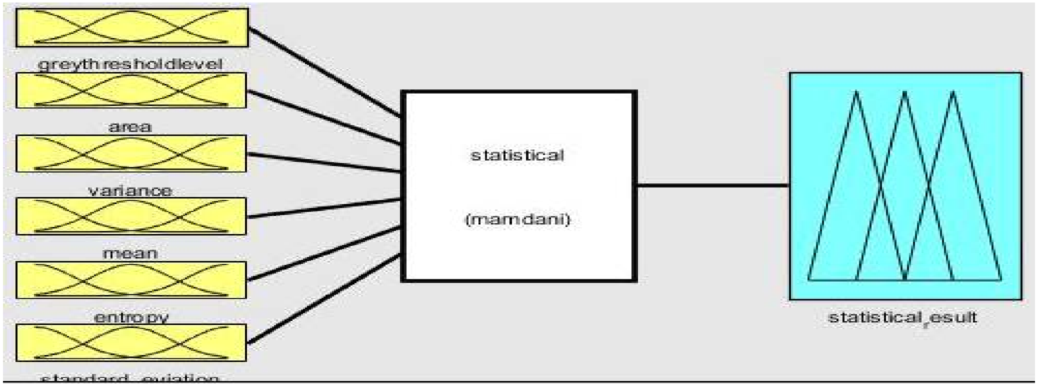
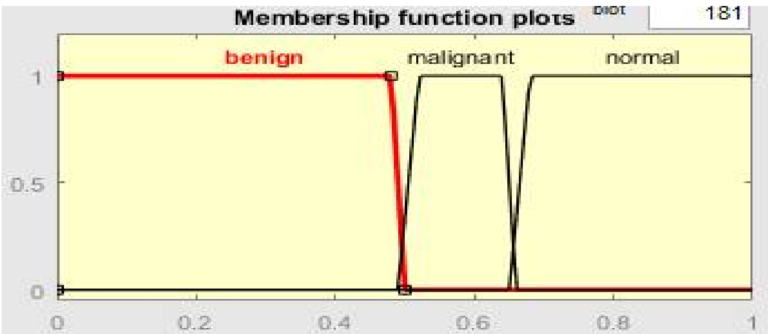
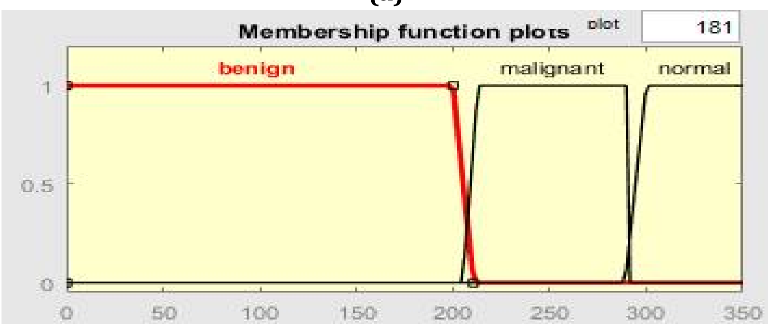


Figure: 2 Fuzzy Inference System for Breast Cancer Diagnosis

Membership Function:
Figure 3(a) and Figure 3 (b) shows membership function of the input variables i.e. mean and area. This is the second process after making input variables. Shapes of all the membership functions are associated with each input and output variables. In fuzzy system, we choose trapezoidal membership functions 'trapmf' which gives most accurate results.



(a)



(b)

Figure: 3 Illustrates (a)Mean Membership Functions (b) Area Membership Functions

Rule Editor:
The pattern's input is referred to as the "fact list," and it may be changed using the rule editor. The rule editor is a large editable text field for displaying and creating rules [21]. The rules of are shown in Figure 3.4. 729 criteria for grey threshold level, area, variance, mean, entropy, and standard deviation from fis 1. The rule editor is shown in Figure 4.
The formula for creating the rules is as follows:
Rules = M^i
M = Membership function
i = Input Parameters

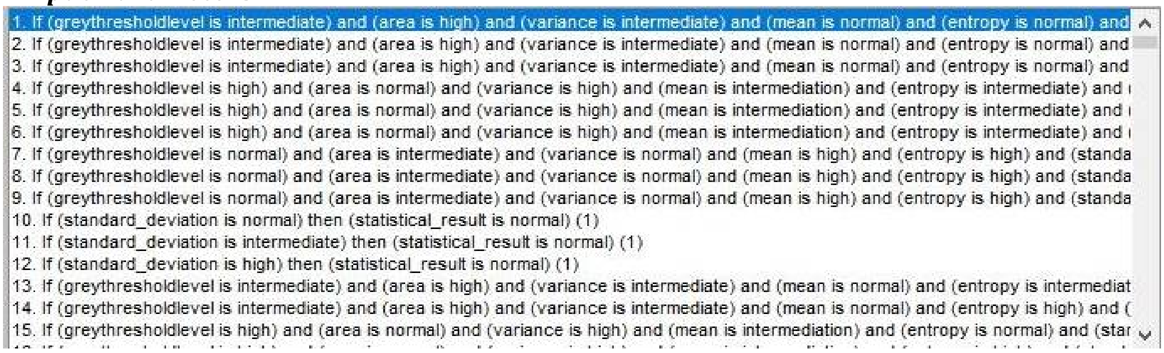


Figure: 4 Rule Editor

Fuzzification and Defuzzification:
Fuzzification and Defuzzification is the base of fuzzy inference system. Fuzzification is the process of converting the crisp input which means ‘0 or 1’ into a fuzzified output i.e. ‘0.1, 0.2 and so on’ and Defuzzification is the opposite method of fuzzification which converts fuzzified value into a crisp value.

RESULTS AND DISCUSSION
Rule Viewer:
The fuzzy inference systems is being investigated with the help of a rule viewer. The output of this evaluation as a result verification indication, such as the appearance of the unit membership function. The entire fuzzy inference method's information is revealed through the rule viewer. Menu bar and status line are personal items in accumulation. While framing, the exact input value may be entered in the text box located in the bottom right corner. In the bottom right corner, there is a text area where we may enter a specific input value. A rule viewer for the anticipated structure is shown in Figure 5. It displays the outcome of the whole fuzzy system. The result on the left plane (near the crest) is more than "180" (Value of Defuzzified), indicating moderate cancer risk.

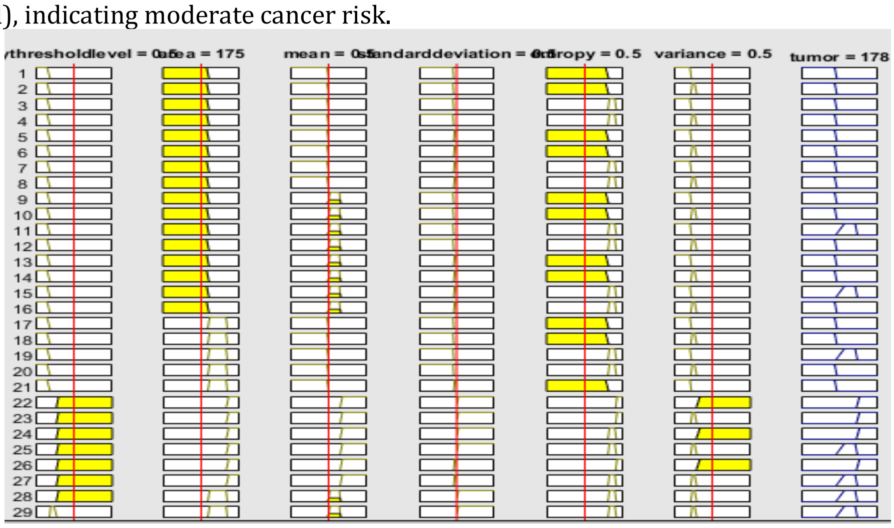


Figure:5 Rule Viewer

Surface Viewer:
To determine the degree to which any one output is dependent on one or both of the inputs. The surface viewer is used to spawn and construct an output surface plot for the fuzzy inference system (FIS). The surface plot of a tumor between two parameters, 'area and mean,' is shown in Figure 6. Input and output are shown by the blue and yellow hues, respectively.

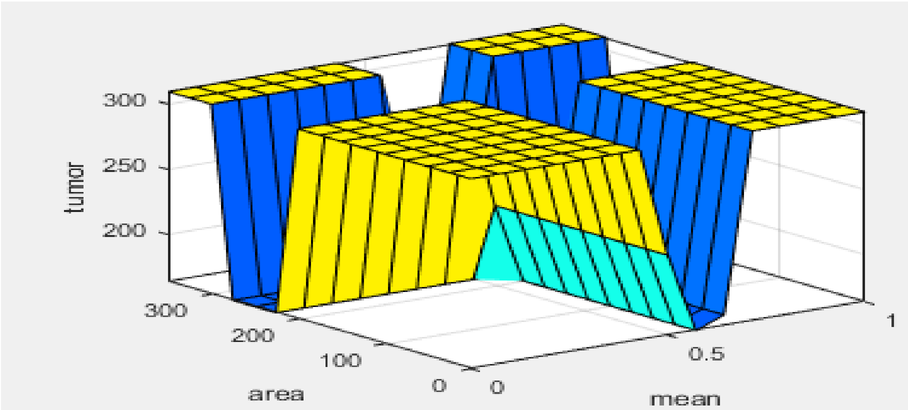


Figure:6 Surface Viewer

Steps for extracting features:

Mammography is currently the most popular technology used for screening of breast cancer. The various steps for extracting features are pre-processing image which converts it into gray scale, segmentation, texture based on feature extraction followed by classifying into benign and malignant tumor are shown in Figure 7.

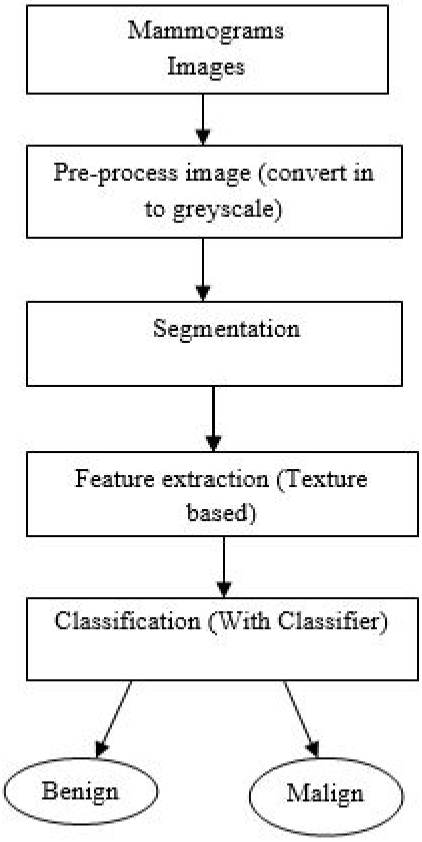
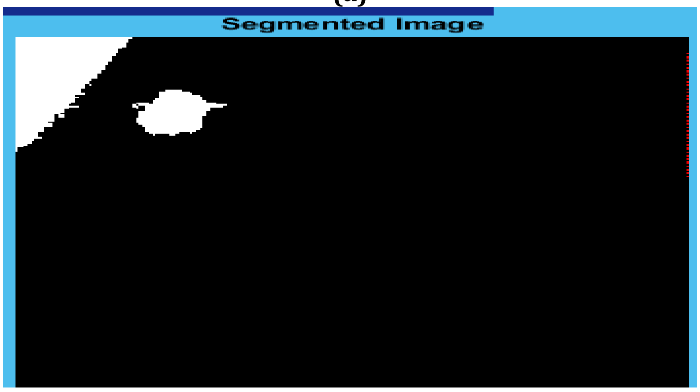


Figure: 7 Steps for extracting features

Segmentation of Mammograms Image:

Segmentation is a technique which separates an image into characteristic properties such as texture, gray threshold level, color, contrast and brightness. The different image segmentation techniques are prewitt operator, sobel operator, Robert operator and canny operator. The purpose of this procedure is to detect the affected area and further classifying into benign or malignant tumor. Figure 8(a) show the pre-process image which converts it into gray scale image.

(a)



(b)

Figure: 8 Illustrates (a) Pre-Process Image (b) Segmented Image

After, pre-process and gray scale, with the help of segmentation algorithm segmentation the abnormal part from the image in Figure 8(b).

Feature Extraction:

The extraction of texture feature has proven a useful technique in detecting normal and abnormal breast tissues using mammograms. This will give typical and atypical region with masses, micro variance, standard deviation, smoothness, energy, contrast entropy, homogeneity, Kurtosis, accuracy, percussion, correlation, Skewness, sensitivity, specificity. In Figure 9, these result verify the texture of the images and useful for finding the validate result of carcinoma.

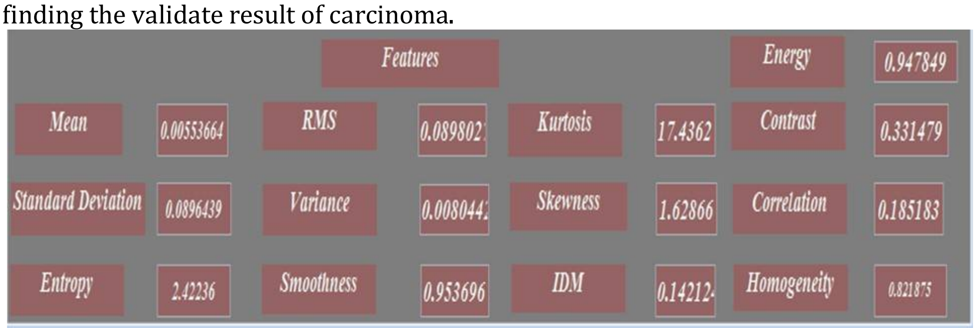


Figure: 9 Feature extraction result

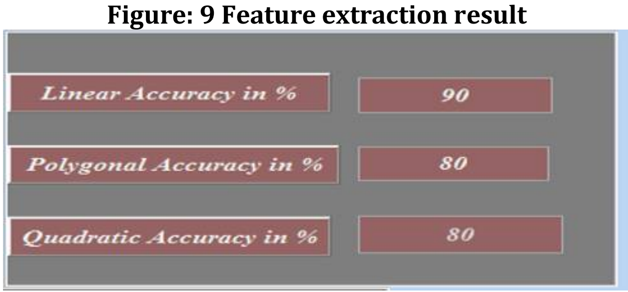


Figure: 10 System Accuracy

Tumor can be seen differently during benign stage such as circular, regular and smooth boundaries whereas malignant stage gives more irregular shapes. Figure 10 shows the system accuracy and Figure 11 explains the mammogram images on how the techniques and classifiers used for identifying normal, benign and malignant tumor. This whole system is implemented by MATLAB program where the front user interface GUI is designed in a user friendly way. Thus figure 11 shows the full system visualization with final outcome. Figure 12 depicts the result with the types.

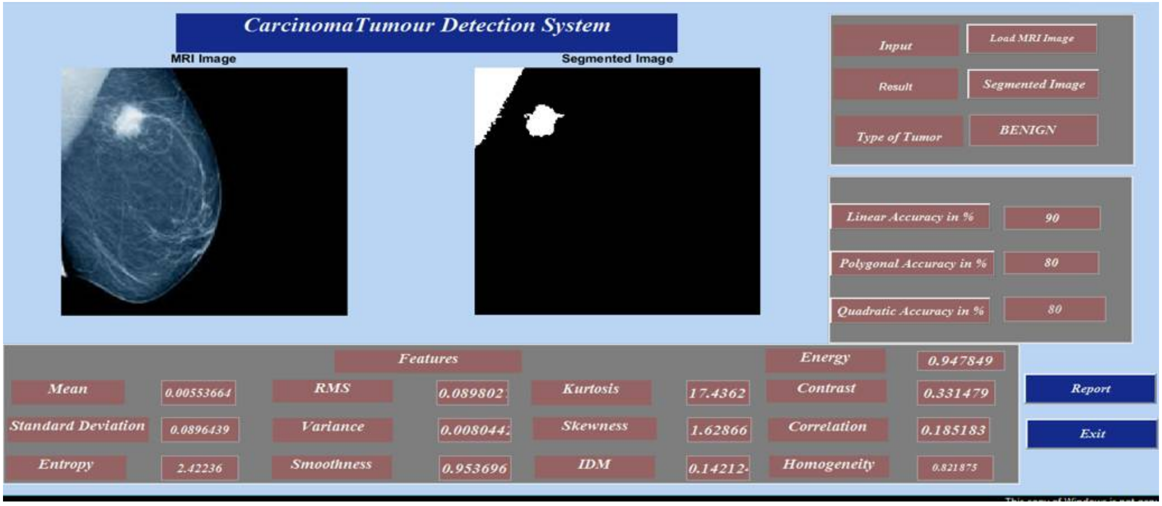


Figure: 11 Final Result

After meeting with doctors/experts and survey of literature six parameters are selected which are: Area, Variance, Grey threshold level, Mean, Entropy and Standard deviation as shown in table 1.

Figure: 12 Result with the types

Table: 1 Statistical Features of Extracted Mass

Features	Formula
Mean	$\mu=\frac{1}{M*N}\sum_{i=1}^{M}\sum_{j=1}^{N} x_{ij}$
Area	n= number of pixels
Standard Deviation	$\sqrt{\frac{\sum_{a=1}^{M}\sum_{b=1}^{N}\{Ii(a,b)-\mu^2\}}{M*N}}$
Variance	$\sigma^2=\left(\frac{1}{M*N}\sum_{i=1}^{M}\sum_{j=1}^{N} x_{ij}^2\right)-\mu^2$
Grey level threshold	$\sigma^2(t)=w_0(t)\sigma_0^2+w_1(t)\sigma_1^2$
Entropy	$\frac{1}{M*N}\sum_{a=1}^{M}\sum_{b=1}^{N} Ii(a,b)(-In\, Ii(a,b))$

Table: 2 Experimental Results for Breast Masses

S. No.	Grey threshold level	Area	Mean	Standard deviation	Entropy	Variance
Benign masses						
B1	0.1412	2.45E+04	0.4179	0.4932	0.9805	0.2433
B2	0.1686	2.30E+04	0.3441	0.4751	0.9287	0.2257
B3	0.1451	2.13E+04	0.3443	0.4751	0.9289	0.2258
B4	0.1647	2.79E+04	0.4341	0.4956	0.9874	0.2457
B5	0.1608	2.80E+04	0.4221	0.4939	0.9824	0.2439
Malignant masses						
M1	0.2	2.99E+04	0.3758	0.4843	0.955	0.2346
M2	0.2275	2.53E+04	0.2697	0.4438	0.841	0.1969
M3	0.1922	2.51E+04	0.3151	0.4646	0.899	0.2158
M4	0.1804	3.33E+04	0.355	0.4785	0.9384	0.229
M5	0.1725	2.45E+04	0.3143	0.4643	0.8981	0.2155
Normal masses						
N1	0.2275	4.60E+04	0.7712	0.42	0.7758	0.1764
N2	0.2235	4.64E+04	0.7156	0.4511	0.8614	0.2035
N3	0.2235	6.30E+04	0.6676	0.4711	0.9173	0.2219
N4	0.2118	6.37E+04	0.8046	0.3965	0.7126	0.1572
N5	0.2118	5.06E+04	0.8233	0.3814	0.6728	0.1455

The mammography images utilized for categorization of breast masses were acquired from the Digital Database for Screening Mammography.

The experiment was carried out utilizing various mammography pictures. An experiment was carried out on a large number of mammography samples, some of which were malignant masses and others were benign masses, in order to classify the masses. The statistical measures such as mean, area, standard deviation, variance and entropy of three mammogram samples are shown in table 2.

The Figure 13 displays grey threshold level for normal masses, malignant masses, and benign masses. Grey threshold level is a statistical feature that is used to describe the grey intensity of input image. If the range of the grey level is from 0.19 to 0.25, then categorized as malignant mass, if <=0.19, then the mass is classified as benign mass and if > 0.25, then classified as normal mass. Figure 14 displays variance for normal masses, malignant masses and benign masses. The statistical feature variance is used where the variations in pixel belong to the similar particular class. If the variance of mass is <=0.21, then classified as malignant mass, if >=0.25, then classified as normal mass and if >0.21 to <0.25, then classified as benign mass. Variance is thought to be the best measure in classification if variation in pixels is too large.

Figure 15 shows entropy for normal masses, malignant masses, and benign masses. Entropy is used to describe the surface of the input image. If the range of the entropy of the image is from 0.83 to 0.90, then classified as malignant mass, if the entropy of the mass is >=0.90, then classified as benign mass, if the entropy of the mass is <=0.79, then classified as normal mass.

In Figure 16 displays the standard deviation for malignant, normal and benign masses is shown. Standard deviation is employed to define the deviance of gray weighted values of pixels of mass. If the standard deviation of mass >=0.5, then mass is categorized as malignant mass. If <=0.45, then categorized as normal mass, If the standard deviation from >0.4662 to <0.45, then the mass is classified as benign mass. As shown in Figure 17 the range of mean for malignant masses is from 0.49 to 0.6463, for benign masses is <=0.48 and for normal masses is >0.66. Mean is the best feature to discriminate between malignant, normal and benign masses. Figure 18 displays area for normal masses, malignant masses, and benign masses. The area is employed to describe the total pixels size of the input image. If the image area is from 226.93 to 291.59, then categorized as malignant mass, if the area is <=210.72, then classified as benign mass, if the area of the mass is >311.13, then categorized as normal mass.

By using statistical parameters such as standard deviation, classification rate is good so it can help experts during diagnosis stage. From the figures, it is predicted that statistical features related to gray weighted function such as area, mean, standard deviation, variance, grey threshold level and entropy are used very much effective for classification of masses as shown in table 3.

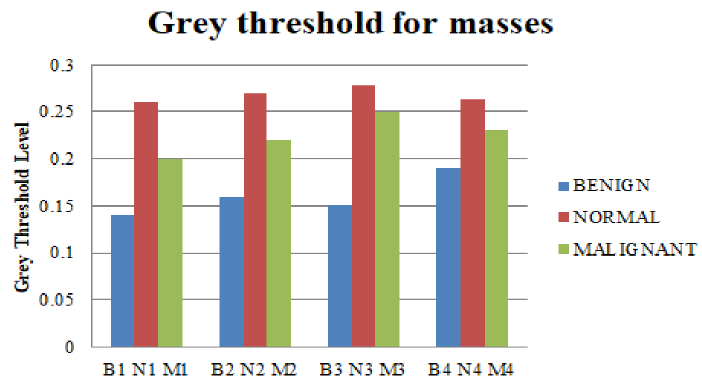


Figure:13 Grey Threshold Level for benign, Normal and Malignant Masses

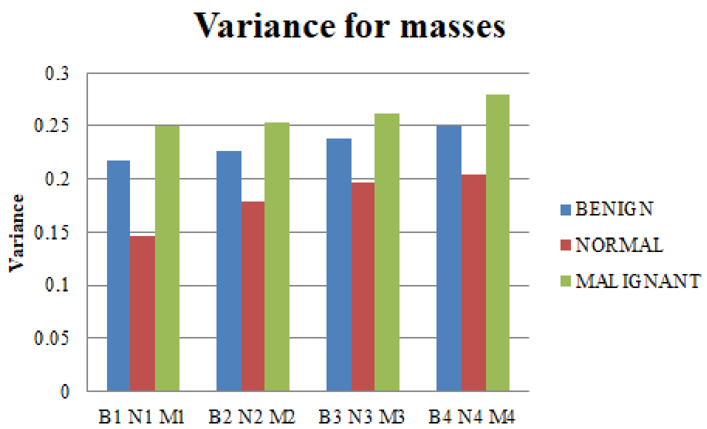


Figure: 14 Variance for benign, Normal and Malignant Masses

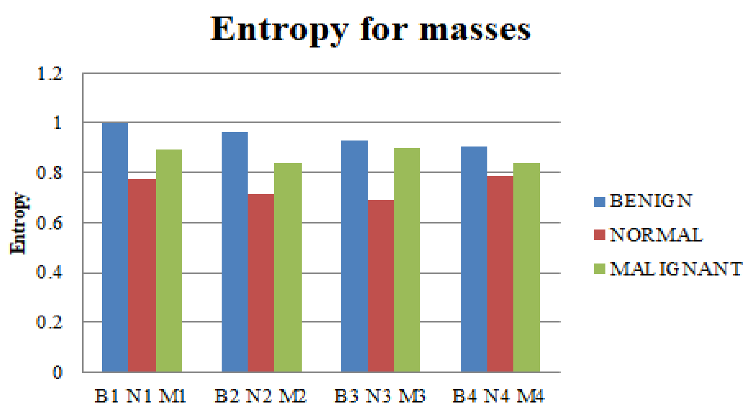


Figure: 15 Entropy for benign, Normal and Malignant Masses

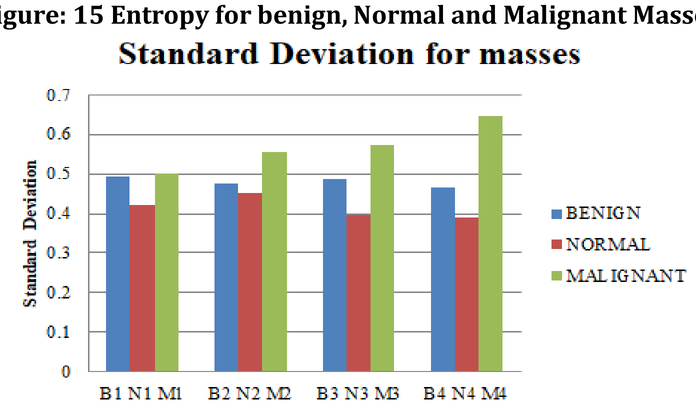


Figure: 16 Standard Deviation for benign, Normal and Malignant Masses

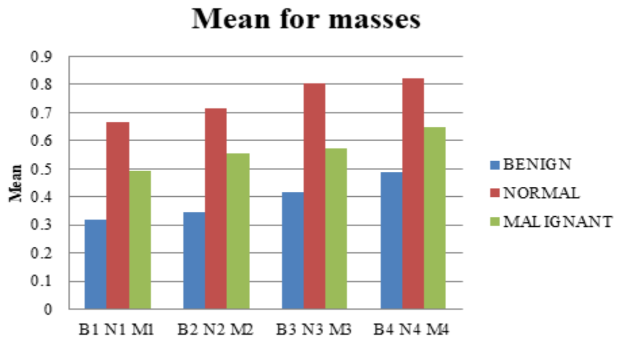


Figure: 17 Mean for benign, Normal and Malignant Masses

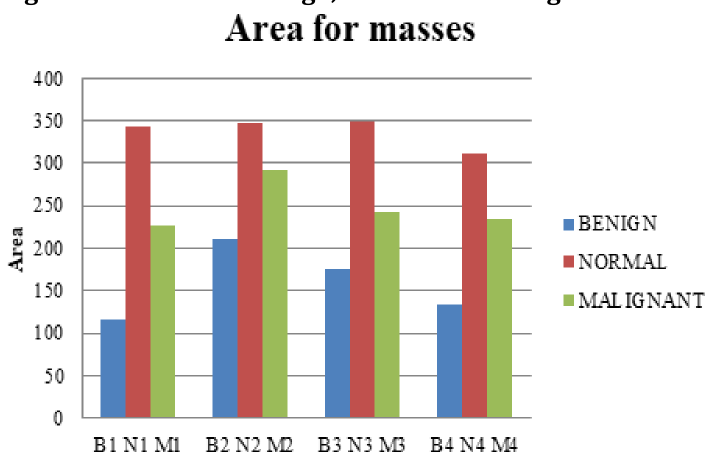


Figure: 18 Area for benign, Normal and Malignant Masses

Table: 3 Statistical Analysis of Breast Masses

Statistical Feature	Malignant Tumor	Benign Tumor	Normal Tumor
Mean	If mean>=0.49 to <=0.6463	If mean<=0.48	If mean>0.66
Standard Deviation	If standard deviation>=0.5000	If standard deviation>=0.4662 to <=0.4932	If standard deviation<=0.4511
Variance	If variance<0.21	If variance>=0.21 to <0.25	If variance>=0.25
Entropy	If entropy>=0.83 to <0.90	If entropy>=0.90	If entropy<=0.79
Area	If area>=226.93 to <=291.59	If area<=210.72	If area>=311.13
Grey Threshold Level	If grey level>0.19 to <=0.25	If grey level <=0.19	If grey level>0.25

Graphical User Interface:
In Figure 19, depicts 6 input parameters for breast cancer for left and right breast, which deploys to recognize" breast cancer or carcinoma" including mean, area, variance, entropy, standard deviation and grey threshold level. Graphical User Interface is connected with .fis files and helps the user interface easily while providing inputs to achieve the results as per the rules. Figure 20 depicts the cancer evaluation result of fuzzy system separately i.e. for a left and right breast.

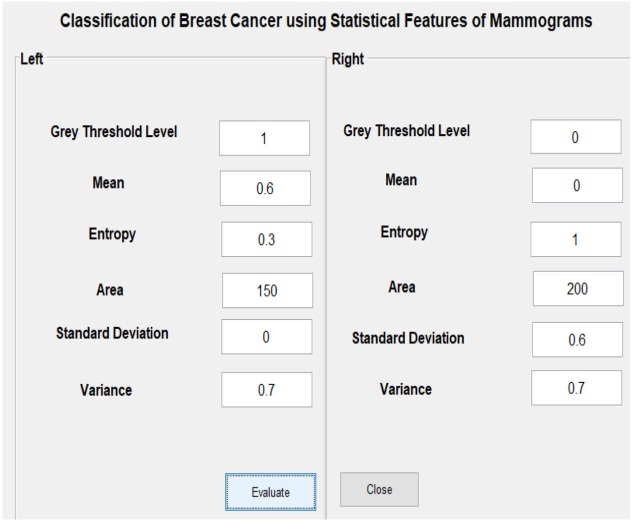


Figure: 19 Graphical User Interface

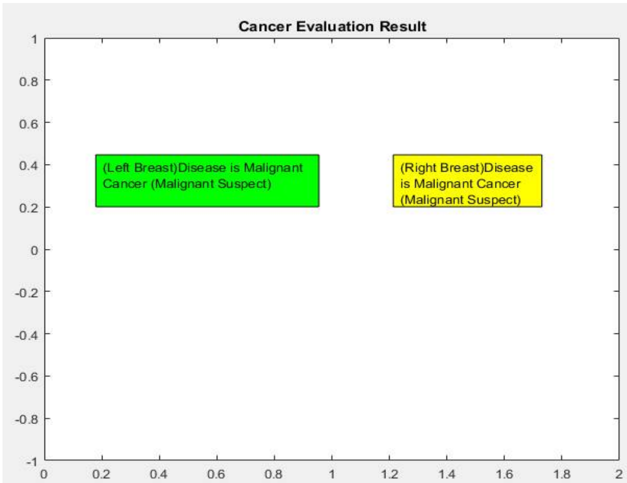


Figure: 20 Cancer Evaluation Result

There are six parameters that are used to detect Carcinoma or Breast cancer are mean, area, variance, entropy, standard deviation and grey threshold level. In graphical user interface (GUI), these six parameters are used on both sides i.e. left and right breast and then the results can be evaluated based on fuzzy rules and dataset. A case study was done on 150 participants to differentiate between normal and cancerous breast using six parameters (mean, area, grey threshold level, standard deviation, entropy and variance). This study was done using Fuzzy rules that allows expert knowledge to include statistical parameters of mammogram and then based on the results gives a precise decision. The outcome of dataset of 141participants was similar with the outcome of other experts. This result can be evaluated as

$$x = y/z \times 100 \quad (1)$$

x = Accuracy

y = No. of correct decisions

z = Total No. of images

A sample of 75 cancerous and 75 non-cancerous mammograms were taken. After extracting the features from mammograms such as area, mean, entropy, standard deviation, variance and grey threshold level, the achieved accuracy was 94%.

Sensitivity is stated as the proportion of True Positives to the sum of True Positives and False Negatives [22].

True Positives= Cancer image is classified as cancer

False Negatives = Cancer image is classified as non-cancer. Equation (2) is used to measure the sensitivity of the system.

$$Sensitivity = \frac{\text{True Positive}}{\text{True Positive+False Negative}} = \frac{71}{71+4} = 0.946 = 94.6\% \quad (2)$$

Specificity is stated as the proportion of True Negative to the sum of True Negative and False Positives [22].
True Negative = Non-cancer image is classified as non-cancer
False Positives= Non-cancer image is classified as cancer. Equation (3) is used to measure the specificity of the system.

$$Specificity = \frac{\text{True Negative (TN)}}{\text{True Negative (TN)+False Positive (FP)}} = \frac{70}{70+5} = 0.933 = 93.3\% \quad (3)$$

CONCLUSION

Breast Cancer is reported as the second utmost deadly cancer in the world, during the last few years public awareness has been increasing. Today millions of women are suffering from breast cancer. Early diagnose of Breast cancer can be treated effectively. For a long survival cancer has to be detected during early stage with accurate treatment. Fuzzy expert system plays an important role to detect breast cancer at an early stage. Breast cancer in early stage shows no symptoms and it is very difficult to detect. Therefore the main reason behind the diagnosis of mass lesions is to get accurate and early detection and thus it decreases the rate of death. So a hybrid fuzzy system is developed in which statistical input parameters are used which are required to diagnose the breast cancer. The fuzzy logic and expert system used as a classifier to differentiate the types of breast cancer. It gives the fast and accurate result as compared to clinical methods. The proposed method achieve best classification rate after check the validity of system the accuracy, sensitivity and specificity are obtained for statistical parameters 94%, 94% and 93%. In future, system can be modified by considering the cell images. By using other algorithms we can try to obtain faster speed and better system performance than others.

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