Retraction

Retraction: Classification of abnormalities in breast ultrasound images using ANN, FIS and ANFIS classifier: A comparison (J. Phys.: Conf. Ser. 1916 012015)

Published 23 February 2022

This article (and all articles in the proceedings volume relating to the same conference) has been retracted by IOP Publishing following an extensive investigation in line with the COPE guidelines. This investigation has uncovered evidence of systematic manipulation of the publication process and considerable citation manipulation.

IOP Publishing respectfully requests that readers consider all work within this volume potentially unreliable, as the volume has not been through a credible peer review process.

IOP Publishing regrets that our usual quality checks did not identify these issues before publication, and have since put additional measures in place to try to prevent these issues from reoccurring. IOP Publishing wishes to credit anonymous whistleblowers and the Problematic Paper Screener [1] for bringing some of the above issues to our attention, prompting us to investigate further.

[1] Cabanac G, Labbé C and Magazinov A 2021 arXiv:2107.06751v1
Retraction published: 23 February 2022
Classification of abnormalities in breast ultrasound images using ANN, FIS and ANFIS classifier: A comparison

J Glory Precious 1, Shirley Selvan 2 and R Avudaiammal 2
1 ECE, SRM Institute of Science and Technology,
2 St. Joseph’s College of Engineering
gloryprecious88@gmail.com, shirleycharlethenry@gmail.com, dravudaiamce@gmail.com

Abstract. When diagnosed early, cancer can be cured. The leading cause of death for women is breast cancer, the most common form of cancer in women. However, there are several ways to think about breast cancer, the US is widely used as it is not aggressive and painless. The appearance of dots on ultrasound images reduces image clarity, affecting image quality. Dots are drawn to accurately define distorted images. This is accompanied by the separation of the wound using a level setting method, after which the features of the lesions are removed. Only the most distinct traits are considered. Using the division of ANN, FIS and ANFIS, with an accuracy of 92.3 percent, 88 percent and 96 percent, the inconsistencies in the 41 images of Breast Ultrasound are identified and classified.

Keywords: Breast cancer, Ultrasound, SRAD filter, ANN, FIS, ANFIS

1. Introduction

It is vital to detect breast cancer at a prior stage [1]. There are two kinds of breast cancer: benign that is non-destructive and dangerous that is malignant. To acquire pictures of inward organs, some imaging strategies use ionizing radiation and intense magnetic fields. Ultrasound imaging produces pictures of organs and delicate tissue structures utilizing high recurrence sound waves. Each time an US pulse hits a structure, a small fraction of sound is reflected back to transducer, which is converted into a voltage signal, amplified to get an image. US imaging is a comfortable and safe screening technique for breast masses. However, due to speckles, poor contrast and blurred edges, the accuracy of ultrasound images is impaired. Ultrasonography is now a prime alternative to mammography and has been a great tool in the identification of breast tumors [2]. Speckle makes it difficult to obtain detailed data from the image. Of the filters used to delete speckle, SRAD filter smoothes the homogeneous area, retaining the edges and improving the edges.

Medical images are segmented using [3], K-means clustering and adaptive thresholding. A supervised machine learning based method for diagnosing and predicting breast anomalies has been designed by [4-8]. The anomalies are identified without manual intervention once the area is segmented. Using a normalized cut method, they broke the ROI into clusters and extracted eight characteristics. Using affinity
propagation clustering with an accuracy of 93.18 percent, they categorized the anomalies into benign and malignant groups. Categorized breast anomalies into three groups, namely benign, malignant and cyst. Developed an automated medical image recognition device. A two-layer feed forward neural network categorized the brain anomalies into four distinct groups based on the GLCM texture mechanism with a classification accuracy of 97.5 percent.

2. Methodology

2.1 Image Acquisition

There are a total of 41 images used in this research work, of which 26 are benign and 15 are malignant. There are 41 images retrieved from the database. The images are preprocessed using the SRAD filter after which texture and shape features are extracted from the segmented area.

2.2 Filtering of Breast Ultrasound Images

The ultrasound image is filtered using SRAD filter to remove speckle. The filtered pixel is given as in equation (1)

\[ I_{i,j}^{n+1} = I_{i,j}^n + \frac{\Delta t}{4} d_{i,j}^n \] (1)

Where \( I_{i,j}^{n+1} \) = updated pixel, \( I_{i,j}^n \) = noisy pixel, and \( d_{i,j}^n \) = diffusion function. The diffusion function \( d_{i,j}^n \) is given by equation (2),

\[ d_{i,j}^n = I_{i+1,j}^n + I_{i-1,j}^n + I_{i,j+1}^n + I_{i,j-1}^n - 4I_{i,j}^n \] (2)

Where \( I \) is the matrix’s row number, \( j \) is the matrix’s column number. For example, figure 1 shows an image matrix, where a pixel is considered to be a noisy pixel with an intensity value of 4. The pixel uses the SRAD update feature to replace it with another noise-free pixel value.

\[ = 4 + \frac{\Delta t}{4}(2+1+2+3-4(4)) \]

Figure 1. Image showing a noisy pixel
\[4 - \Delta t\]
\[4 - 0.08(2) (\Delta t = 0.08)\]
\[= 3.84\]

The image matrix is shown in Figure 2, after replacing the noisy pixel with a corrected pixel.

|   | 2   | 3   | 1   | 2   |
|---|-----|-----|-----|-----|
| 1 | 2   | 3   | 1   |     |
| 2 | 1   | 3.84| 2   |     |
| 1 | 1   | 2   | 3   |     |

**Figure 2.** Image showing a corrected pixel

41 images used in our work are filtered prior to segmentation using the SRAD filter.

**Results of Filtering**

Figures 3(a) and 3(b) display images of a benign mass before and after filtering by SRAD filter. As the results of filtering are subjective, image quality is assessed by finding the PSNR [9].

**Figure 3 a.** Input US image of benign mass

**Figure 3 b.** SRAD filtered image

Table 1 presents mean PSNR value of the images prior to and after filtering.

| Type       | Mean PSNR before filtering (dB) | Mean PSNR after filtering (dB) |
|------------|---------------------------------|-------------------------------|
| Benign     | 34.659                          | 37.173                        |
| Malignant  | 32.951                          | 35.676                        |
The mean PSNR value of the benign mass is 34.659 dB before filtering and 37.173 dB after filtering. The mean PSNR value of the malignant mass is 32.951 dB before SRAD filtering and 35.676 dB after SRAD filtering. In the filtered image, the speckle is reduced and this improves the data.

2.3 Segmenting US images

Most of the medical images are segmented using Level set [10]. The gray level images are converted into binary using Otsu thresholding. Figure 4 depicts the work flow of Level Set Segmentation.

Results of segmenting

Figures 5(a) and 5(b) are the results of thresholding and segmenting an image of a benign mass. The centroid of the benign mass obtained is shown as a blue asterix.
Similarly, Figures 6(a) and 6(b) are the results of thresholding and segmenting an image of a malignant lesion.

![Figure 6 a) Image after thresholding](image)

![Figure 6 b) Segmented image of a malignant lesion with centroid](image)

### Performance Analysis of Segmentation

Of the 41 BUS images used, 32 are well-categorized. As a result 78.05% accuracy was found. The performance analysis of the classification is given in Table 2.

| Total No of images | No of lesions correctly segmented | No of lesions incorrectly segmented | Accuracy |
|--------------------|----------------------------------|------------------------------------|----------|
| 41                 | 32                               | 9                                  | 78.05 %  |

### 2.4 Feature Extraction

Unusual segregation into parallel and destructive, highlighted features are taken from the isolated area. To distinguish between cancer and non-cancerous, the texture and composition of the elements are used. Outstanding posture is obtained from the border of the disease until the form is separated. Twelve facial features and 4 facial features are calculated from the area with the wound stages [11].

The texture factors are calculated from the Gray Level Run Length Matrix. LRE relies on long-distance running event and image composition is high. Benign looks the same and has longer messages, so the LRE is benign. Obviously bad weight is not the same, so LRE is low. SRE is part of the short distribution, and with good construction, it is very large. SRE is low in malignant and high in benign. RLN is part of the closest image of the run term. Whenever the length of the run is indistinguishable around the image and is elevated, if the running length is different, it is smaller. GLN is a low-level comparison measure [12]. If the intensity of the gray level is the same as in the image and is higher at a different gray level, it is less. LGRE estimates price distribution at low gray levels. For images with low gray values, LGRE should be very large. HGRE indicates the distribution of high levels of black matter. For images with elevated black properties, HGRE needs to be high. The basic estimates of GRLM's significance found in 26 of the 15 hazardous stocks are given in Table 3.
Table 3. Mean value of GRLM features

| GRLM Features | Mean value for Benign masses | Mean value for Malignant masses |
|---------------|-----------------------------|-------------------------------|
| LRE           | 0.130                       | 0.450                         |
| SRE           | 0.742                       | 0.866                         |
| RLN           | 0.489                       | 0.651                         |
| GLN           | 0.506                       | 0.625                         |
| HGRE          | 0.109                       | 0.622                         |
| LGRE          | 0.171                       | 0.342                         |

As found in Table 3, LRE, RLN and HGRE estimates are significant between benign and malignant.

Texture features energy, entropy, difference, differentiation, homogeneity and standard deviation are extracted from GLCM [13]. The orderliness of an image is defined as energy. It measures uniformity in the distribution of severity. The energy value is high when pixels are similar. The randomness of the distribution of intensity in an image is known as entropy. It’s value is high since all the components of the grid of co-event are comparable. Based on disparity between the two component vectors, surface attributes are utilized. The Moment of Inverse Difference is a proportion of the surface of the picture and is called homogeneity. The homogeneity of the GLCM Contrast is contrarily corresponding. It is resolved in similar field of view by the distinction in the tone and brilliance of the item and different articles. A boundary firmly connected with the mean is the standard deviation. The mean estimation of GLCM highlights removed from benign and malignant masses is introduced in Table 4.

Table 4. Mean value of GLCM features

| GLCM Features | Mean value for Benign masses | Mean value for Malignant masses |
|---------------|-----------------------------|-------------------------------|
| Energy        | 0.098                       | 0.228                         |
| Entropy       | 4.27E+00                    | 5.528                         |
| Dissimilarity | 0.153                       | 0.269                         |
| Homogeneity   | 0.439                       | 0.529                         |
| Contrast      | 0.104                       | 0.382                         |
| Standard Deviation | 0.158                  | 0.238                         |
Entropy and contrast for benign and malignant are highly distinct from the six GLCM highlights extricated. These are consequently viewed as significant attributes. It is picked to separate shape attributes from the majority for proficient grouping.

Shape Features

It is possible that the main characteristics of a clear discharge are the shape of the wound. In the measurement of the shape markers, the outer edge of the tumor is used. The location, perimeter, width of the measurement and the mean value of gray is determined from the tumor. The information provided by these structural attributes is used for cluster segregation [14]. The total number of pixels in the lesion is known as the region. In conjunction with harmful tissue, malignant tumors have a wider range. Border is the size of pixels around a local line. This indicates the length of the wound cycle. The size of a large axis to a small axis is a measure of the size of the wound. Mean Gray Value is for men in an unusual region with intensity pixels. The sum of the solids values divided by the number of pixels equal to MGV. The estimated amount of structural elements based on the hazardous and hazardous lists is given in Table 5.

Table 5. Mean value of Shape features

| Shape Features | Mean value for Benign masses | Mean value for Malignant masses |
|----------------|-----------------------------|-------------------------------|
| Area           | 0.303                       | 0.548                         |
| Perimeter      | 0.560                       | 0.615                         |
| Aspect ratio   | 0.236                       | 0.697                         |
| Mean Gray Value| 0.374                       | 0.224                         |

As found in Table 5, mean estimation of shape highlights, for example, area, perimeter, width to height ratio and mean gray value of malignant is greater than mean value of benign. Region and perspective proportion are to be huge among benign and malignant. The segmented lesion determines surface and shape qualities from it. However, there is certainly not a considerable distinction among benign and malignant in any of the highlights. Both benign and malignant masses have overlapping feature values in US imaging, so statistical analysis is performed to evaluate the critical highlights utilizing SPSS.

2.5 Statistical Analysis

Altogether, 16 qualities have been gotten and not every one of them are adequate to separate among benign and malignant tumors. Utilizing statistical analysis, significant qualities are accordingly inferred.
Surface properties are resolved from the lesion, including GRLM, GLCM and shape qualities. Utilizing measurable examination, significant highlights that separate among benign and malignant are extricated from these 16 highlights. Software version 16.0 of SPSS is utilized for applying measurable examination. With the utilization of SPSS Methods, all highlights have been tried for factual significance. If the P-value is under 0.05 for a component, that is considered as a genuinely huge feature [15] and perceived. For assessing the capacity esteem in SPSS Program, the Paired T test was utilized. Of these 16 highlights, 6 are viewed as significant highlights that can adequately separate among benign and malignant. Relevant features are presented in Table 6.

| Features | Mean value for Benign masses | Mean value for Malignant masses |
|----------|-----------------------------|-------------------------------|
| LRE      | 0.130                       | 0.450                         |
| RLN      | 0.488                       | 0.651                         |
| HGRE     | 0.109                       | 0.622                         |
| Contrast | 0.104                       | 0.382                         |
| Area     | 0.303                       | 0.548                         |
| Aspect Ratio | 0.236                 | 0.697                         |

2.6 Neural Network

Artificial neural networks are commonly used in ultrasound images to classify breast masses. The accuracy and efficiency of the classification is good for ANN [16]. As input to the network, the six extracted main characteristics of benign and malignant are used. ANN is trained with 8 benign samples and 7 malignant samples. ANN is evaluated on the basis of 18 benign and 8 malignant samples. The target is [-1, 1] for benign and [-1, -1] for malignant, respectively. With 31 input neurons, 2 hidden layers and 2 outputs for the classification, a single layer feed forward neural network is constructed. The data set used for training and evaluating the neural network for benign masses is provided in Table 7.

Table 7. Training data and testing data for benign masses

| Input | LRE | RLN | HGRE | Contrast | Area | W to H |
|-------|-----|-----|------|----------|------|--------|
| 1     | 0.067| 0.546| 0.026| 0.643    | 0.187| 0.285  |
| 2     | 0.042| 0.870| 0.051| 0.648    | 0.421| 0.160  |
| 3     | 0.012| 0.547| 0.045| 0.021    | 0.353| 0.275  |
| 4     | 0.030| 0.012| 0.068| 0.017    | 0.243| 0.178  |
Once the neural network is trained with these significant features, it is now ready to be tested with new data. Table 8 shows the data set used for training and testing the neural network for malignant lesion.

|   |     |     |     |     |     |     |
|---|-----|-----|-----|-----|-----|-----|
| 5 | 0.050 | 0.803 | 0.047 | 0.063 | 0.355 | 0.195 |
| 6 | 0.130 | 0.273 | 0.082 | 0.017 | 0.806 | 0.227 |
| 7 | 0.243 | 0.131 | 0.042 | 0.148 | 0.030 | 0.147 |
| 8 | 0.052 | 0.640 | 0.669 | 0.005 | 0.426 | 0.155 |
| 9 | 0.157 | 0.237 | 0.009 | 0.330 | 0.317 | 0.176 |
| 10 | 0.047 | 0.593 | 0.074 | 0.011 | 0.440 | 0.176 |
| 11 | 0.068 | 0.579 | 0.033 | 0.013 | 0.236 | 0.178 |
| 12 | 0.267 | 0.396 | 1 | 0 | 0.256 | 0.167 |
| 13 | 0.143 | 0.311 | 0.040 | 0.063 | 0.254 | 0.223 |
| 14 | 0.186 | 0.373 | 0.023 | 0.256 | 0.172 | 0.226 |
| 15 | 0.233 | 0.160 | 0.016 | 0.046 | 0.160 | 1 |
| 16 | 1 | 0.068 | 0.044 | 0.047 | 0.083 | 0.160 |
| 17 | 0.053 | 0.808 | 0.034 | 0.017 | 0.060 | 0.202 |
| 18 | 0.038 | 0.903 | 0.069 | 0.042 | 0.384 | 0.170 |
| 19 | 0.068 | 0.465 | 0.058 | 0.038 | 0.435 | 0.398 |
| 20 | 0.045 | 0.796 | 0.047 | 0.010 | 0.037 | 0.259 |
| 21 | 0.059 | 0.770 | 0.048 | 0.034 | 1 | 0.150 |
| 22 | 0.101 | 0.445 | 0.057 | 0.109 | 0.028 | 0.308 |
| 23 | 0.054 | 0.639 | 0.033 | 0.009 | 0.221 | 0.131 |
| 24 | 0.035 | 0.1 | 0.097 | 0.017 | 0.437 | 0.151 |
| 25 | 0.137 | 0.203 | 0.017 | 0.172 | 0.330 | 0.249 |
| 26 | 0 | 0 | 0 | 0 | 0.1938 | 0.1793 |

Once the neural network is trained with these significant features, it is now ready to be tested with new data. Table 8 shows the data set used for training and testing the neural network for malignant lesion.
Table 8. Malignant lesion training data and testing data for neural network

| Input | LRE  | RLN  | HGRE | Contrast | Area  | WtoH |
|-------|------|------|------|----------|-------|------|
| 1     | 0.327| 0.673| 0.688| 0.353    | 0.438 | 0.753|
| 2     | 0.300| 0.813| 0.477| 0.284    | 0.579 | 0.641|
| 3     | 0.530| 0.473| 0.370| 0.736    | 0.255 | 1    |
| 4     | 0.296| 0.974| 1    | 0.073    | 1     | 0.763|
| 5     | 0.296| 0.793| 0.461| 0.259    | 0.896 | 0.773|
| 6     | 0.543| 0.430| 0.728| 0.464    | 0.850 | 0.823|
| 7     | 0.336| 0.624| 0.661| 0.215    | 0.146 | 0.633|
| 8     | 0.268| 0.905| 0.718| 0.584    | 0.562 | 0.384|
| 9     | 0.335| 0.592| 0.365| 0.097    | 0.710 | 0.666|
| 10    | 0.238| 1    | 0.839| 0.283    | 0.922 | 0.650|
| 11    | 0.258| 0.883| 0.865| 0.130    | 0.632 | 0.554|
| 12    | 0.867| 0.375| 0.410| 1        | 0.184 | 0.734|
| 13    | 0.892| 0.273| 0.619| 0.229    | 0.184 | 0.664|
| 14    | 0.266| 0.266| 0.614| 0.227    | 0.180 | 0.642|
| 15    | 0.261| 0.830| 0.430| 0.792    | 0.462 | 0.556|

Table 9. Confusion matrix

|           | TP (7) | FP (1) | TN (17) | EN (1) |
|-----------|--------|--------|---------|--------|

From the Confusion matrix in Table 9, it is found that ANN provides a sensitivity of 87.5%, specificity of 94% and accuracy of 92.3% respectively. In the following section, we proceed to classify the abnormalities using a FIS classifier.

2.7 Fuzzy Inference System

A rule-based framework that uses fuzzy logic is Fuzzy inference. It can manage both the values of numerical data and linguistic information. The two forms of methods in FIS are Mamdani and Sugeno.
The fuzzy method widely used is the Mamdani style FIS. It consists of three key components, such as the module for fuzzification, the fuzzy law and the defuzzification module. The goal of fuzzification is to map the inputs to values from 0 to 1, using a set of input membership functions. The inputs to train the FIS are the main features such as LRE, RLN, HGRE, contrast, area and width to height ratio. FIS is trained with 8 benign and 7 malignant samples, respectively.

LRE, HGRE and width to height ratio input variables have 2 membership degrees, namely low and high, and RLN, Contrast and area input variables have 3 membership function degrees, such as low, medium and high. The fuzzy inference engine used in our work is shown in figure 7. FIS classifier training data is shown in Table 10.

![Fuzzy Inference Engine](image)

**Table 10. Training Data for FIS Classifier**

| Significant Features | Low     | Medium | High     |
|----------------------|---------|--------|----------|
| LRE                  | [0.04 0.2] | -      | [0.2 0.5] |
| RLN                  | [0.01 0.4] | [0.4 0.8] | [0.8 0.9] |
| HGRE                 | [0.02 0.08] | -      | [0.4 1]   |
| Contrast             | [0.005 0.07] | [0.07 0.1] | [0.1 0.7] |
| Area                 | [0.03 0.1] | [0.1 0.8] | [0.8 1]   |
| W to H               | [0.1 0.3] | -      | [0.6 1]   |

Fuzzy rules are a collection of linguistic statements used to classifying an input [17]. In our work, we have taken two rules as

**Rules**

---

Retracted
1. If (LRE is low) and (HGRE is low) and (w to h is low) and (RLN is medium) and (Contrast is low) and (Area is medium) then (output is benign) (1)

2. If (LRE is high) and (HGRE is high) and (w to h is high) and (RLN is low) and (Contrast is low) and (Area is low) then (output is malignant) (1)

The target for the benign and malignant should be given in the range of 0 to 1. Target for benign and malignant masses in the FIS classifier is presented in Table 11. The target is specified as [0 0.25 0.49] for benign and [0.5 0.75 1] for malignant.

| Type   | Target          |
|--------|-----------------|
| Benign | [0 0.25 0.49]   |
| Malignant | [0.5 0.75 1] |

The FIS is tested using 18 samples of benign and 8 samples of malignant. The defuzzification module translates the output back to a crisp value. FIS provides a sensitivity of 100%, specificity of 83% and accuracy of 88%.

2.8 Adaptive Neuro Fuzzy Inference System (ANFIS)

The combination of the ANFIS neural network and fuzzy logic is based on the fuzzy inference method of Takagi-Sugeno. In order to deliver improved prediction capabilities, ANFIS combines both the learning capabilities of a neural network and the reasoning capabilities of fuzzy logic. The ANFIS block consists of six main layers: the input layer, the membership feature layer, the law layer, the layer of normalisation, the layer of defuzzification and the output layer. The inputs to train the ANFIS are essential characteristics such as LRE, RLN, HGRE, contrast, area and width to height ratio. The input membership function is Gaussian and the output membership function is constant. Two membership functions are used for each inputs.

The Adaptive Neuro Fuzzy Inference System (ANFIS) classifier exhibits high levels of accuracy, reliability and low computational time. Hence, ANFIS can generate excellent classification results. The target is specified as -1 for benign and 1 for malignant. The ANFIS structure created for our classification is presented in figure 8.

Figure 8. ANFIS Structure with features LRE, RLN, HGRE, Contrast, Area & W/H ratio as inputs
Grid Partitioning

Using grid partitioning, an ANFIS network was developed. There were 64 rules, 6 inputs, 1 output, and 2 Gaussian membership functions per input on the resulting network. In FIS, GENFIS1 uses grid partitioning and produces rules by listing all possible membership function combinations of all inputs. As the number of input variables increases, the number of fuzzy rules increases exponentially. If 'm' is the number of membership functions and 'n' is the number of inputs, then mn is the total number of generated fuzzy rules. The partitioning of the grid is only sufficient for a small number of inputs.

Output

ANFIS classifier provides a sensitivity of 100%, specificity of 94%, and an accuracy of 96%. The output of the ANFIS classifier is given in figure 9.

![Figure 9. ANFIS Output](image)

Performance Analysis of Classifiers

ANN has a sensitivity of 87.5%, 94% specificity and 92.3% precision. FIS, which offers 100 percent sensitivity, 83 percent precision and 88 percent accuracy, is used to boost sensitivity. The ANFIS classifier, which offers 100% sensitivity, 94% specificity and 96% accuracy, is used to boost the specificity. In Table 12, the output analysis is provided.

| Classifier                      | Sensitivity | Specificity | Accuracy |
|---------------------------------|-------------|-------------|----------|
| Artificial Neural Network       | 87.5%       | 94%         | 92.3%    |
| Fuzzy Inference System          | 100%        | 83%         | 88%      |
| Adaptive Neuro Fuzzy Inference  | 100%        | 94%         | 96%      |
3. CONCLUSION AND FUTURE WORK

The purpose of this proposed project is to obtain a large number of unusual people from 41 US photographs. BUS images of malignant and malignant lesions are filtered using SRAD filters to reduce repetitive noise. The abnormal area is subdivided using a standard setting. Many texture features from GRLM, GLCM and structural elements are extracted from a separate wound. Since U.S. factors are between the good and the bad, a statistical analysis is being done. The six characteristics are found to be very different between good and bad. In order to identify the lesions in US images as benign or malignant, three classifiers are used. The accuracies produced by ANN, FIS and ANFIS are 92.3%, 88% and 96% respectively. The best classification algorithm with the highest precision for breast cancer detection and classification is ANFIS. The specificity is less. Therefore, in our next work, the classification of abnormal masses using a deep learning neural network is planned.

References

[1] Anupa maria sabu, D.Narain Ponraj, Dr.Poongodi, (2012). Textural Features Based Cancer Detection: A survey, Journal of Emerging Trends in Computing and Information Sciences, ISSN 2079 8407 vol.3, No.9 Sep
[2] Shirley selvan, Shenbaga Devi et al. (2014.) Automatic Seed Point Selection in Ultrasound Echography Images of Breast using Texture Features, Biocybernatics and Biomedical Engineering.
[3] Shirley Selvan, M. Kavitha, S. Shenbaga Devi, S.Suresh et al. (2010) Feature Extraction for Characterization of Breast Lesions in Ultrasound Echography and Elastography, Journal of Computer Science.
[4] Apoorva Jain, Richa Sharma, (2016). Classification of Breast Masses using Shape and Texture Features, IRA CST - International Journal of Computer Science and Information Technology & Security (IJCSITS), ISSN: 2249-9555 Vol6, No.2
[5] Aysun Okar Atabey, Erkin Arıbal, Rabia Ergelen, Handan Kaya, (2014). Value of Strain Elastography Ultrasound in Differentiation of Breast Masses and Histopathologic Correlation, Breast Health.
[6] Shirley Selvan, M. Kavitha, S.Shenbaga Devi, S. Suresh, (2012) Fuzzy-Based Classification of Breast Lesions Using Ultrasound Echography and Elastography, National library of medicine, Volume 28, Nmber 3.
[7] Ibrahim Sadek, Mohamed Elawady, Viktor Stefanovski, (2016) Automated Breast Lesion Segmentation in Ultrasound Images, Research Gate.
[8] Ines Njeh, Olfa Ben Sassi, Khalil Chfourou, Ahmed Ben Hamida, (2011) Speckle Noise Reduction In Breast Ultrasound Images: Smit (Srad Median Unsharp) Approach, International Multi-Conference on Systems, Signals & Devices.
[9] Minavathi, Murali, S M.S. Dinesh,(2012)Classification of Mass in Breast Ultrasound Images using Image Processing Techniques, International Journal of Computer Applications, (0975 – 8887) Volume 42- No.10.
[10] Muzni Sahar, Hamung Adi Nugroho et al. (2016). Automated Detection of Breast Cancer Lesions Using Adaptive Thresholding and Morphological Operation, International Conference on Information Technology Systems and Innovation (ICITSI) Bandung – Bali.
[11] Nitish Zulpe, Vrushsen Pawar, (2012) GLCM Textural Features for Brain Tumor Classification, ICSIS International Journal of Computer Science, Issues, Vol. 9, Issue 3, No 3.
[12] Shijin Kumar P.S, Dharun V.S,(2017). Extraction of Texture Features using GLCM and Shape Features using Connected Regions, International Journal of Engineering and Technology (IJET), Vol 8 No 6.
[13] D. Devikanniga, A. Ramu, and A. Haldorai, Efficient Diagnosis of Liver Disease using Support Vector Machine Optimized with Crows Search Algorithm, EAI Endorsed Transactions on Energy Web, p. 164177, Jul. 2018. doi:10.4108/eai.13-7-2018.164177

[14] H. Anandakumar and K. Umamaheswari, Supervised machine learning techniques in cognitive radio networks during cooperative spectrum handovers, Cluster Computing, vol. 20, no. 2, pp. 1505–1515, Mar. 2017.

[15] Yanni Su, Yuanyuan Wang, Jing Jiao and Yi Guo, (2011) Automatic Detection and Classification of Breast Tumors in Ultrasonic Images Using Texture and Morphological Features, The Open Medical Informatics Journal, (Suppl 1-M3)26-3

[16] Yongdong Chen, Lijuan Ling, Qinghua Huang, (2016) Classification of Breast Tumors in Ultrasound Using Biclustering Mining and Neural Network, International Conference on Image and Signal Processing, BioMedical Engineering and Informatics

[17] M. Sussman, P. Smereka and S.J. Osher, (1994) A Level Set Approach for Computing Solutions to Incompressible Two-Phase Flow, J. Comput. Phys., 94, pp. 146 – 159.