International Journal of Applied Engineering Research
ISSN 0973-4562 Volume 10, Number 9 (2015) pp. 21565-21581

http://www.ripublication.com

Tissue Classification And Boundary Based Segmentation In Thyroid Ultrasound Images

[1]Sheeja Agustin A and [2]S Suresh Babu

[1] Research Scholar, Department of Computer Science,
Noorul Islam Centre for Higher Education, Kumaracoil, Tamil Nadu
[2]Principal T K M College of Engineering Kollam, Kerala .
E-mail: [1]sheejabinudas.mce@gmail.com

Abstract

Computer-assisted image processing techniques are designed and developed to help doctors improve their diagnosis. In this paper, an US thyroid image diagnostic and segmentation system is presented. The thyroid ultrasound images fetched from the database are preprocessed using AMF to remove the noise. Then eight statistical features are extracted from the preprocessed image and fed to FFBNN to classify whether the given image is normal or abnormal. In case an abnormal image is detected, it will be subjected to boundary based segmentation using edge following approach. Followed by, features are mined from the segmented image and given as the input to Adaptive Neuro Fuzzy Inference System (ANFIS) for tissue classification. The ANFIS system classifies the tissues such as malignant and benign. The parameters of ANFIS are optimized by Adaptive Artificial Bee Colony Algorithm (AABC) algorithm to achieve efficient classification. This can help inexperienced physicians to avoid chances of misdiagnosis and to reduce invasive operations such as biopsy and Fine Needle Aspiration (FNA).

Key words: Adaptive Neuro Fuzzy Inference System (ANFIS), Feed Forward Back propagation Neural Network (FFBNN), Boundary Based Segmentation, Adaptive Median Filter (AMF), Adaptive Artificial Bee Colony Algorithm (AABC).

INTRODUCTION

A widely accepted imaging modality for the diagnosis of thyroid disorder is ultrasound scan. Ultrasound (US) is a popular diagnostic technique which is inexpensive, non invasive, fast and does not require ionizing radiations. A critical issue that arises during the diagnosis of thyroid is the lack of proper interpretation of thyroid data. Among all other imaging modalities, ultrasound imaging is non invasive, inexpensive and does not require ionizing radiations. The techniques to process medical images are continuously being developed from time to time. Computerized analysis leads to an improved medical image interpretation, providing a reliable second opinion in detecting disease severity, and leading to more accurate diagnosis.

Several US Computer Aided Diagnosis (CAD) systems have been proposed for the evaluation of the thyroid gland. Eystratios G. et al. [1] have implemented a computer-aided diagnosis (CAD) system prototype called Thyroid Nodule Detector. It was used for the detection of nodular tissue in ultrasound (US) thyroid images and videos acquired during thyroid US examinations. It involves a fuzzy logic-based approach to obtain an uncertainty-aware representation of thyroid ultrasound patterns. Preeti Aggarwal et al. [2] proposed an automatic segmentation method and two tools for segmentation [10] of thyroid US images. Their method was applicable on both lungs CT as well as on thyroid US. Chuan-Yu Chang et al. [3] have presented a model for automatic segmentation of thyroid and volume estimation using progressive learning vector quantization neural network (PLVQNN). The PLVQNN contains several learning vector quantization neural networks, each responsible for segmenting one slice of a thyroid CT image. The method was found to segment the thyroid gland effectively, besides it was capable of estimating the volume of the segmented thyroid.

Dimitris E. Maroulis had presented a computer-aided approach for delineation of thyroid. They developed an algorithm which was based on a novel active contour model [4]. The method provided noise robustness and was able to delineate multiple nodules. Chuan-Yu Chang et al. [5] have proposed the radial basis function neural network to classify blocks of the thyroid gland. After classifying the thyroid gland, its volume has been estimated. The experimental results show that the proposed method can be used to segment the thyroid gland region and to estimate thyroid volume directly from US images. Krit Somkantha et al. [8] proposed an edge following technique for boundary detection of noisy images.

Here an edge following approach with the aid of ANFIS-AABC is proposed for Thyroid Tumor Classification and Segmentation. The thyroid ultrasound images fetched from the database are preprocessed using AMF to remove the noise. Then eight statistical features are extracted from the preprocessed image and fed to FFBNN to classify whether the given image is normal or abnormal [6]. After that, the resultant image is subjected to boundary based segmentation. Then features are extracted and given to ANFIS to classify the tissues such as malignant and benign. The parameters of ANFIS are optimized by AABC algorithm to attain efficient classification.

THYROID TUMOR CLASSIFICATION AND SEGMENTATION TECHNIQUE MAKE THE USE OF ANFIS

In our proposed methodology, the images are fetched from the thyroid database and preprocessed using AMF in order to remove the speckle noise. Then eight statistical features are extracted from the preprocessed images and given to the FFBNN to classify whether the given image is normal or abnormal. The image obtained in the classification process is subjected to segmentation. Then LGXP and Grey Level Co-Occurrence matrix features are extracted from the segmented image and given to ANFIS. ANFIS is used to classify the tissues such as benign and malignant. The parameters of ANFIS are optimized by AABC algorithm to attain efficient classification. The proposed technique is evaluated by giving more number of images to the ANFIS. The performance of the proposed technique is compared with other conventional techniques. Architecture of the proposed technique is given in Figure1.

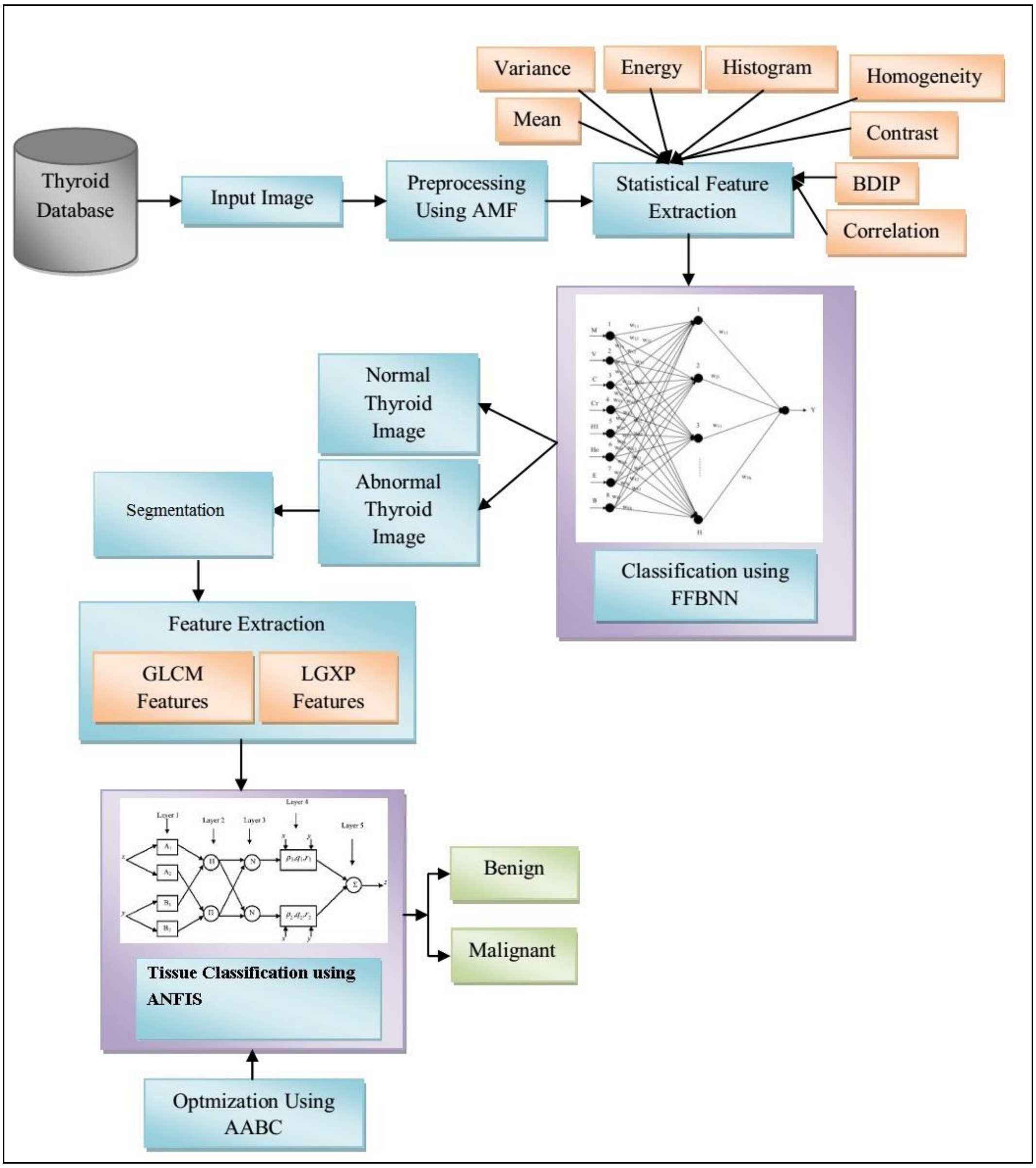


Figure1: Architecture of the proposed Thyroid Tumor classification and Segmentation

Preprocessing using AMF

The input thyroid ultra sound image may contain speckle noise which leads to an incorrect result. In order to obtain good accuracy, the noise must be removed from the input image. In our proposed work, we have used adaptive median filter to remove speckle noise. This preprocessed thyroid ultrasound image x' is then given to the feature extraction process.

Statistical Feature Extraction

The preprocessed image x' obtained in the above process is subjected to the feature extraction process. In order to extract the features, the contrast of the image x' has to be enhanced, which is done by performing adaptive histogram equalization (AHE). AHE is used to enhance the contrast of the image x' by modifying the pixel based on its surrounding pixels. AHE is routine, locally adaptive and habitually produces superior images. Let us consider a moving window w (w= M x M and I be the intensity of pixel (i, j).

This modification is done for all the pixels in the entire image and finally the enhanced image x'' is attained. After that, features such as mean, variance, contrast, correlation, histogram, energy, homogeneity and Block Difference of Inverse Possibilities (BDIP) are extracted from the enhanced image x''.

Classification of Thyroid Images Using FFBNN

In order to classify the normal and abnormal thyroid ultrasound images, Feed Forward Back Propagation Neural Network (FFBNN) is trained using the mean, variance, contrast, correlation, histogram, homogeneity, energy and BDIP features extracted from each and every image in the database. The extracted features are given as the input to neural network for training and classification purpose. The structure of the FFBNN and algorithm used was given in[6].

Segmentation using edge following approach

Image segmentation is a process of assembling parts of an image into separate units that are comparable with respect to one or more features. By segmentation process the abnormal or ROI can be separated from other tissue. Boundary extraction algorithm includes Average edge vector field model, Edge following Technique and finally the selection of initial position. The proposed method provides much more efficient computation time than region growing algorithm and other contour models. The preprocessing stage involves the generation of texture image and the edge map. Edge map is edges of objects in an image derived from Law's texture and Canny edge detection. It gives important information of the boundary of objects in the image that is exploited in a decision for edge following.

Law's Texture

The texture feature images of Law's texture [8] are computed by convolving an input image with each of the masks. Given a column vector $L=(1,4,6,4,1)^T$, the 2D mask l(i,j) used for texture discrimination is $L \times L^{T.}$ The output image is obtained by convolving the input image with the texture mask.

Canny Edge Detection

The canny approach to edge detection is optimal for step edges corrupted by white Gaussian noise. This edge detector is assumed to be the output of a filter that reduces the noise and locates the edges. The first step of canny edge detection is to convolve the output image obtained from the Law's Texture with a Gaussian filter. The second step is to calculate the magnitude and direction of the gradient. The third step is non maximal suppression to identify edges. The broad ridges in the magnitude must be thinned so that only the magnitude at the points of the greatest local change remains. The last step is the thresholding algorithm to detect and link edges.

Boundary Based Segmentation

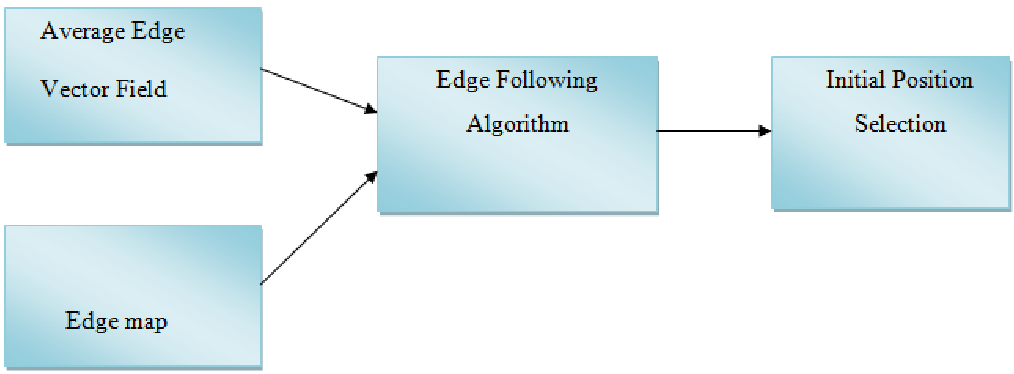


Figure2: Figure showing the stages in Boundary extraction algorithm

Average edge vector field model

Given an image f(x, y), the edge vector field is calculated according to the following equations:

$$\vec{e}(i,j) = \frac{1}{k}\left(M_x(i,j)\,\vec{i} + M_y(i,j)\,\vec{j}\right)$$

$$\vec{e}(i,j) \approx \frac{1}{k}\left(\frac{\partial f(x,y)}{\partial y}\,\vec{i} - \frac{\partial f(x,y)}{\partial x}\,\vec{j}\right)$$

$$k = \max \sqrt{M_x(i,j)^2 + My(i,j)^2}$$

Each component is the convolution between the image and the corresponding difference mask,

$$M_x(i,j) = -G_y \times f(x,y) \approx \frac{\partial f(x,y)}{\partial y}$$

$$My(i,j) = -Gx \times f(x,y) \approx \frac{\partial f(x,y)}{\partial x}$$

where Gx and Gy are the difference masks of the Gaussian weighted image moment vector operator in the x and y directions, respectively,

$$G_x(x,y) = 1/\sqrt{2}\,\Pi\sigma\left(\frac{x}{\sqrt{x^2+y^2}}\right)\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right)$$

$$G_x(x,y) = 1/\sqrt{2}\,\Pi\sigma\left(\frac{y}{\sqrt{x^2+y^2}}\right)\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right)$$

The capability of the previous edge vector field is extended by applying a local averaging operation where the value of each vector is replaced by the average of all the values in the

Local neighborhood,

$$M(i,j) = \frac{1}{M_r}\sum_{(i,j)\in N} \sqrt{M_x(i,j)^2 + \sqrt{My}(i,j)^2}$$

$$D(i,j) = \frac{1}{M_r}\sum_{(i,j)\in N} \tan^{-1}\left(\frac{M_y(i,j)}{M_x(i,j)}\right)$$

where M_r is the total number of pixels in the neighborhood N.

Edge Following Technique

The edge following technique is performed to find the boundary of an object. The edge following technique using information from the average edge vector field and edge map. It gives more information for searching the boundary of objects and increases the probability of searching the correct boundary. At the position (i, j) of an image, the successive positions of the edges are then calculated by a 3 × 3 matrix

$$L_{ij} \;\; r,c \;\; = \alpha M_{ij} \;\; r,c \;\; + \beta D_{ij} \;\; r,c \;\; + \varepsilon E_{ij} \;\; r,c$$

$$0 \leq r \leq 2, 0 \leq c \leq 2$$

where α, β, and ε are the weight parameters that control the edge to flow around an object. The larger value of an element in L_{ij} indicates the stronger edge in the corresponding direction. The 3 × 3 matrices M_{ij}, D_{ij} and E_{ij} are calculated as follows:

$$r,c \;\; = \frac{M \;\; i+r-1, j+c-1}{\max_{ij} M \;\; i,j}$$

$$D_{ij} \;\; r,c \;\; = \frac{D \;\; i,j \;\; - D \;\; i+r-1, j+c-1}{\Pi}$$

$$E_{ij} \;\; r,c \;\; = E \;\; i+r-1, j+c-1 \;\; ,$$

$$0 \leq r \leq 2, 0 \leq c \leq 2$$

where M(i, j) and D(i, j) are the proposed average magnitude and direction of edge vector fields. E(i, j) is the edge map from Law's texture and Canny edge detection. It should be noted that the value of each element in the matrices M_{ij} , D_{ij}, and E_{ij} are ranged between 0 and 1.

Let Ck, k = 1, 2. . . 8 are the constraint masks of edge following to the next direction in object boundary. The constraint mask is selected by considering the direction of the vector model at a position (i, j). The mask which has a similarity in direction of vector is selected to suit the chosen constraint of edge following. The value of each element in each mask dictates the corresponding direction. At the position (i, j), the next direction of the edge following technique is selected as the direction that gives the maximum value of the element-wise multiplication results between L_{ij} and C_k. The next direction can be calculated by

$$D_{ij,opt} = \arg_k \max \sum_{r=o}^{2} \sum_{c=0}^{2} L_{ij} \;\; r,c \;\; C_k \;\; r,c$$

Where k =1, 2. . . 8 denote the eight directions and the edge following is started from the initial position to end position.

Initial Position

This section present a technique for determining a good initial position of edge following that can be used for the boundary detection. Finding the initial position of the classical contour models is still difficult and time consuming. In this proposed technique, the initial position of edge following is determined by the following steps. The first step is to calculate the average magnitude [M (i, j)]. The position with high magnitude should be a good candidate of strong edges on the image. The second step is to calculate the density of edge length for each pixel from an edge map. An edge map [E (i, j)], as a binary image, is obtained by Law's texture and Canny edge detection. The idea of using density is to obtain measurement of the edge length. The density of edge length [L (i, j)] in each pixel can be calculated from

$$L(i, j) = \frac{C(i, j)}{\max_{i,j} C(i, j)}$$

Where C (i, j) is the number of connected pixels at each position of pixel. The third step is to calculate the initial position map P (i, j) from summation of average magnitude and density of edge length,

$$p(i, j) = \frac{1}{2}\ M(i, j) + L(i, j)$$

The last step is the thresholding of the initial position map. We have to threshold the map in order to detect the initial position of edge following. If P (i, j) > T_{max}, then P (i, j) is the initial position of edge following. After determining the suitable initial position, the proposed technique will follow edges along the object boundary until the closed loop contour is achieved.

Tissue classification with the help of ANFIS

In order to classify the tissues such as benign and malignant, some features are mined from the segmented image and fed to ANFIS for tissue classification. ANFIS architecture comprises five layers of nodes. Out of five layers, the first and the fourth layers possess adaptive nodes whereas the second, third and fifth layers possess fixed nodes. The structure of ANFIS having five layered feed-forward neural network is shown in figure 3. In both ANN and FL, the inputs are given to the input layer and the output is obtained from the output layer.

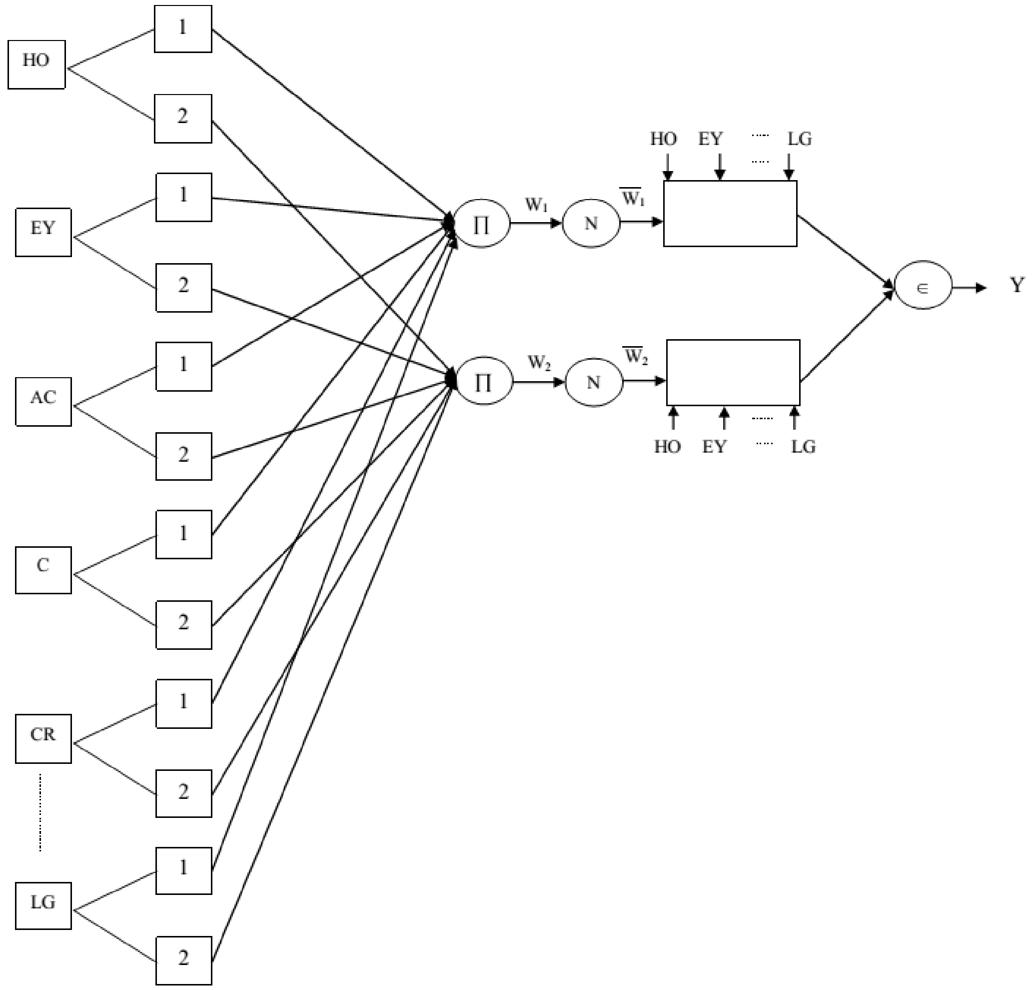


Figure 3: Architecture of ANFIS

Optimization of ANFIS using AABC

To attain efficient tissue classification, parameters of the ANFIS are optimized using the well known optimization algorithm viz. Adaptive Artificial Bee Colony (AABC) algorithm. The architecture of AABC algorithm is shown in Figure 4.

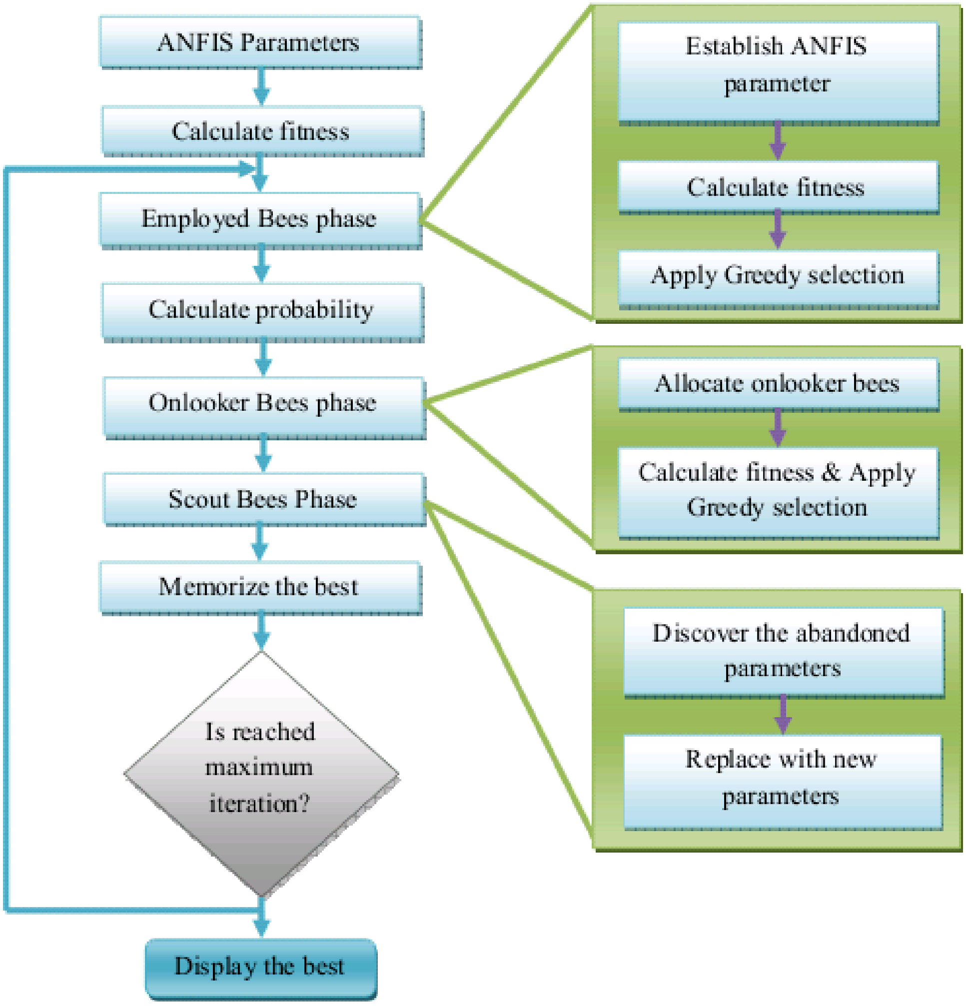


Figure 4: Architecture of AABC algorithm

Initial Phase

Initially the population of the food sources $x_i\,(i = 1,2,\ldots N)$ are generated at random. N is the population size. To assess the best food source, the fitness value of the generated food sources is computed using Equation

$$\textit{Fitness function} \quad F(i) = \min(MSE(j))$$

$MSE(j)$ is the mean square error of j^{th} parameter.

Employed Bee Phase

In the employed bee phase, new population parameters are generated using the equation,

$$V_{i,j} = x_{i,j} + \phi_{ij}\left(x_{i,j} - x_{k,j}\right)$$

Where, k and j are a random selected index, ϕ is a randomly produced number in the range [-1, 1] and $V_{i,j}$ is the new value of the j^{th} position. Then the fitness value is computed for every new generated population parameter of food sources. From the computed fitness value of the population, best population parameter is selected . After selecting the best population parameter, probability of the selected parameter is computed using Equation,

$$P_j = \frac{F_j}{\sum_{j=1}^{d} F_j}$$

Where, P_j is the probability of the j^{th} parameter.

Onlooker Bee Phase

After computing the probability of the selected parameter, number of onlooker bees is estimated. Following, generate new solutions ($V_{i,j}$) for the onlooker bees from the solutions ($x_{i,j}$) based on the probability value (P_j). Then the fitness function is calculated for the new solutions. Subsequently, apply the greedy selection process in order to select the best parameter. From the fourth iteration, the fitness value of the onlooker bees is calculated as given below.

$$V_{(i,j)+1} = \kappa V_{(i,j)} + \frac{1}{2}\kappa V_{(i,j)-1} + \frac{1}{6}\kappa V_{(i,j)-2} + \frac{1}{24}\kappa V_{(i,j)-3} + \phi_{ij}\left(x_{i,j} - x_{k,j}\right)$$

Where κ - constant value

Scout Bee Phase

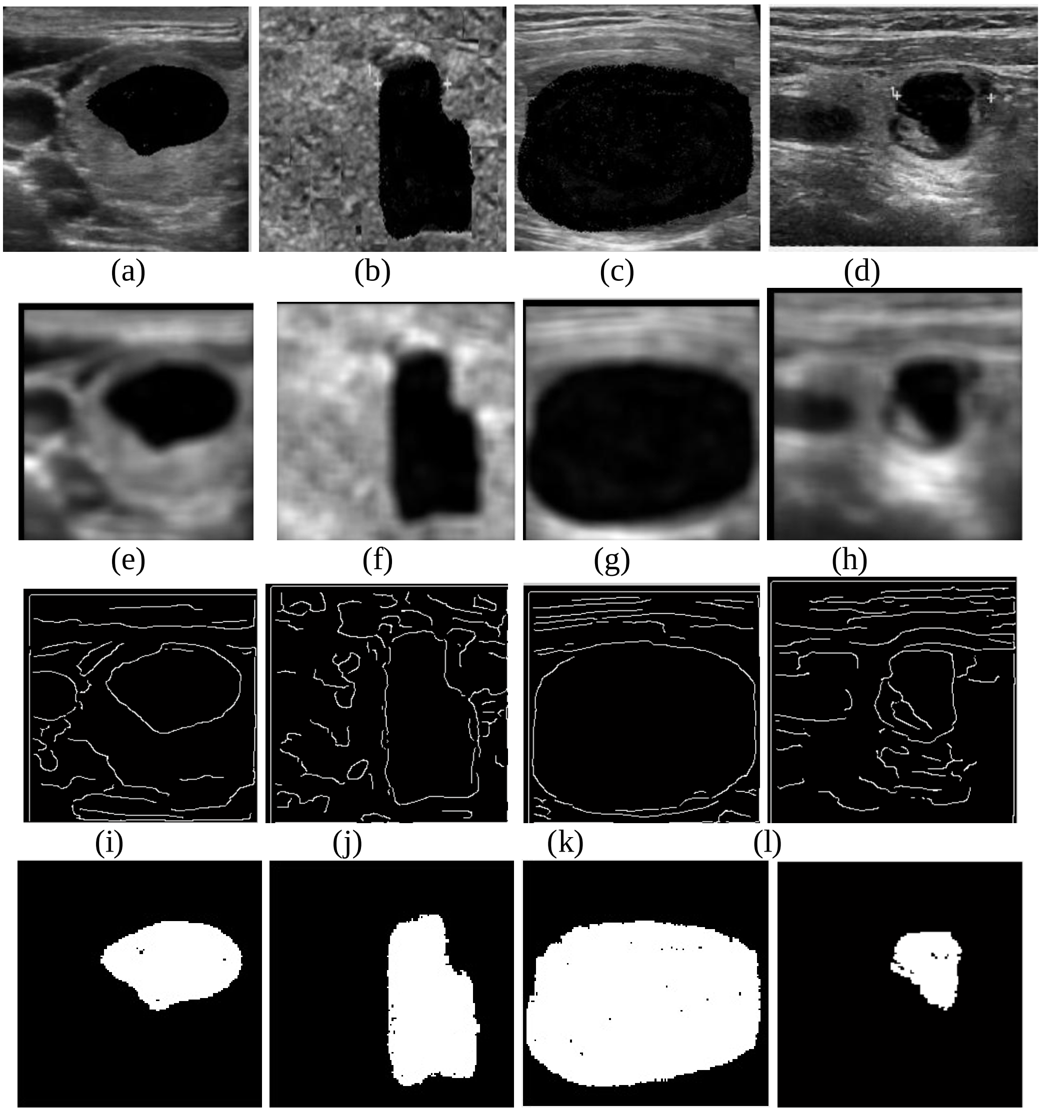
Here, the abandoned parameters for the scout bees are determined. If any abandoned parameter is there, then it is replaced with the new parameter exposed by scouts using $V_{(i,j)+1}$ and the fitness value is evaluated. Then the best parameter achieved so far is memorized. Then the iteration is incremented and the process is continued until the stopping criterion is reached.

RESULT AND DISCUSSION

The proposed thyroid tissue classification system with FFBNN and ANFIS is implemented in the working platform of MATLAB (version 7.12) with machine configuration as follows

Processor: Intel core i7
OS: Windows 7
CPU speed: 3.20 GHz
RAM: 4GB

3.1. Segmentation Result



(a) (b) (c) (d)
(e) (f) (g) (h)
(i) (j) (k) (l)
(m) (n) (o) (p)

Figure5: (a)-(d) input original images, (e)-(h) corresponding texture images, (i)-(l) corresponding edge map, (m)-(p) Segmented output.

Figure 5 shows the segmentation result using edge following approach. The computation time is very less compared to Modified Region Growing (MRG).The proposed method takes 8-10 seconds for segmentation, which is 30 seconds in the previous method MRG. But the limitation of this method is that the region should be closed.

3.2 Performance Analysis

The performance of our proposed thyroid tissue classification system is analyzed by using the statistical measures which are given in [9].

The statistical measures of our proposed SCG based FFBNN and Levenberg Marquardt Algorithm (LMA) based FFBNN techniques for the abnormality of the thyroid ultrasound image classification are given in Table 1.

Table 1: Performance of our proposed SCG based FFBNN technique and LMA based FFBNN technique.

Measures	Proposed SCG based FFBNN	LMA based FFBNN
Accuracy	93.9	75.7
Sensitivity	100	66
Specificity	92.5	77.7
FPR	7	22
PPV	75	40
NPV	100	91
MCC	83.3	37.3

In table1, accuracy, sensitivity and specificity measures are given. The accuracy of the proposed technique is 93.9%. LMA based FFBNN has 75.7% of accuracy. Accuracy of the proposed technique is significantly higher when compared to that of the LMA based FFBNN. It is about 18.2% higher than the LMA based FFBNN.

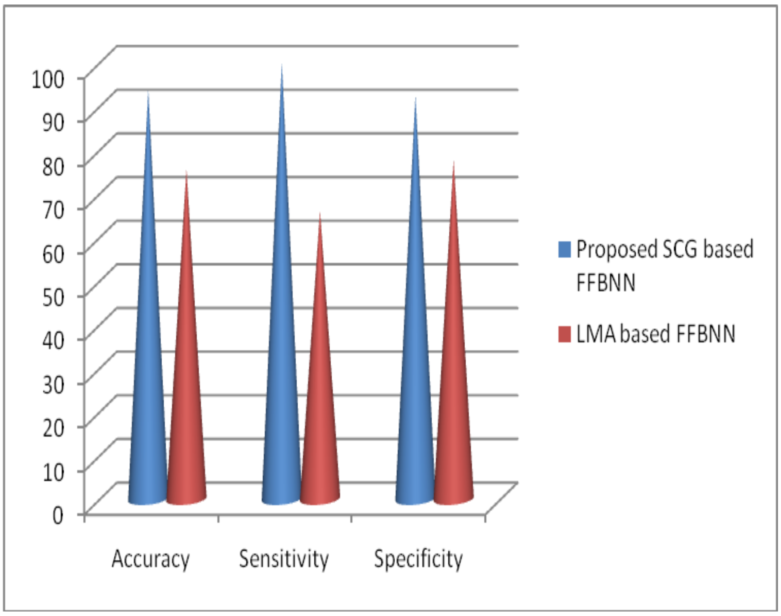


Figure 6: Proposed SCG based FFBNN technique and LMA based FFBNN technique's performance in terms of Accuracy, Sensitivity and Specificity

In figure 6, the accuracy, sensitivity and specificity of the proposed technique are compared with those of the other techniques. By seeing the graph, the accuracy of the proposed technique is extensively higher than the LMA based FFBNN. Similarly the sensitivity and specificity measures of the proposed SCG based FFBNN technique are also remarkably higher than the LMA based FFBNN. It indicates that the performance and the exactitude of the proposed technique are higher.

The statistical measures of our proposed ANFIS-AABC and other techniques such as ANFIS-ABC, ANFIS and FFBNN techniques for the tissue classification are given in Table 2.

Table 2: Performance of proposed ANFIS-AABC based system and other techniques such as ANFIS-ABC, ANFIS and FFBNN

Measures	**Proposed ANFIS-AABC**	**ANFIS-ABC**	**ANFIS**	**FFBNN**
Sensitivity	90	100	60	50
Specificity	100	72.7	90.9	90
Accuracy	95.2	85.7	76.1	71.4
FPR	0	27.2	9	9
PPV	100	76.9	85	83.3
NPV	91.6	100	71	66.6
MCC	90.8	74.7	53.9	45.2

In Table 2, accuracy, sensitivity and specificity measures are given. The accuracy of the proposed technique is 95.2%. ANFIS-ABC, ANFIS and FFBNN have 85.7%, 76.1% and 71.4% of accuracy respectively.

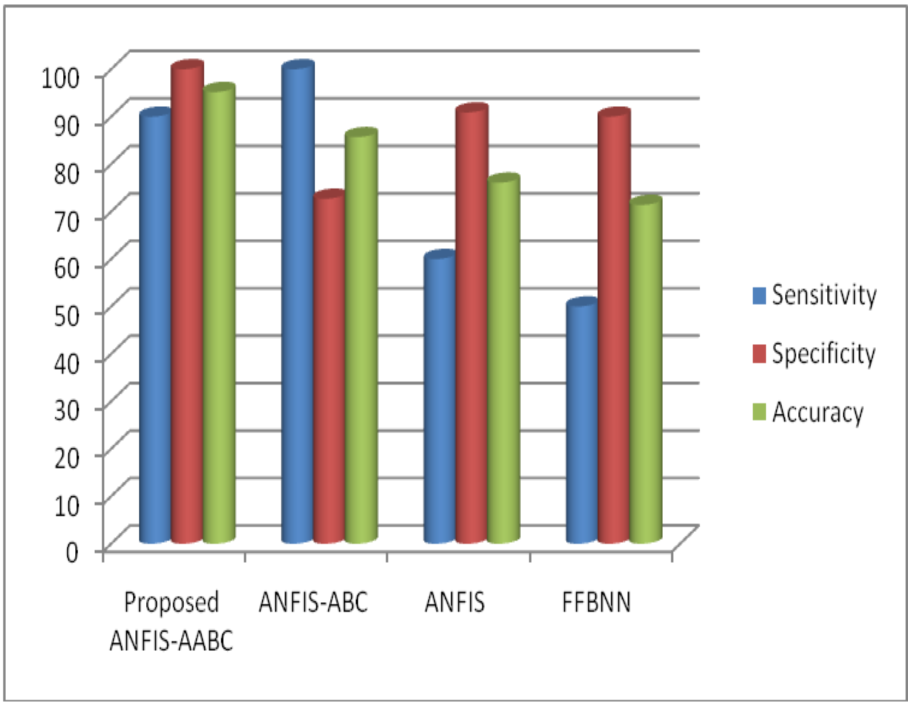


Figure 7: Proposed ANFIS-AABC based system and other techniques such as ANFIS-ABC, ANFIS and FFBNN's performance in terms of Accuracy, Sensitivity and Specificity

In figure 7, the accuracy, sensitivity and specificity of the proposed technique are compared with those of the other techniques. By seeing the graph, the accuracy of the proposed technique is notably higher than the ANFIS, ANFIS-ABC and FFBNN.

Table 3. Comparison of accuracy for the proposed method and recently other work.

Classifier	**Accuracy**
Proposed ANFIS-AABC	95.2%
SVM[12]	92.5%
PNN[13]	90.9%
ANN[12]	87.5%
SVM[11]	84.62%
KNN[11]	46.15%
Bayesian[11]	38.46%

In Table 3, accuracy of the proposed method with existing classifiers is given. The accuracy of the proposed technique is 95.2%. When comparing the proposed technique with the above mentioned techniques, accuracy of the proposed technique is 2.7-56.74% higher than the previous classifiers. Graphical representation of this comparison is shown in figure 8.

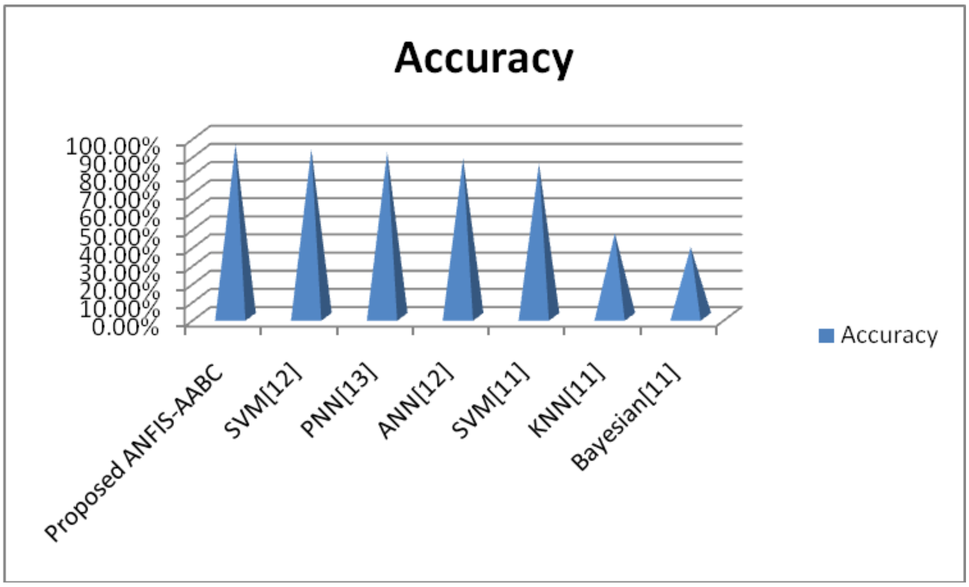


Figure 8. Accuracy for the proposed method and recently other work

5 CONCLUSIONS

The input images fetched from the thyroid database are preprocessed using AMF to remove the noise. After that the normal and abnormal thyroid images are classified using SCG based FFBNN which utilizes the eight statistical features extracted from the preprocessed image. Then the resultant image obtained in the classification process is subjected to segmentation process with the help of Edge following approach which consider intensity and orientation thresholds. Then features are calculated from the segmented image and fed as the input to ANFIS-AABC for tissue classification. The parameters of ANFIS are optimized by AABC algorithm to attain efficient classification. The proposed technique is evaluated by giving more number of images to the well trained ANFIS. The experimental result shows much more efficient computation time and 95.2% of accuracy.

REFERENCES

[1] Eystratios G.et al. “TND: A Thyroid Nodule Detection System for Analysis of Ultrasound Images and Videos” in Journal of Medical Systems, Springer 1271–81,2010

[2] Preeti Aggarwal et al. “Role of Segmentation in Medical Imaging: A Comparative Study” International Journal of Computer Applications (0975 – 8887) vol 29– No.1, September 2011

[3] Chuan-Yu Chang and Yong-Cheng Hong, Pau-Choo Chung and Chin-Hsiao Tseng, “A Neural Network for Thyroid Segmentation and Volume Estimation in CT Images”,Journal of IEEE Computational Intelligence Magazine, Vol.6, No.4, pp.43-55, 2011.

[4] Dimitris E. Maroulis, Michalis A. Savelonas, Dimitris K. Iakovidis, Stavros A. Karkanis and Nikos Dimitropoulos, “Variable Background Active Contour Model for Computer-Aided Delineation of Nodules in Thyroid Ultrasound Images", IEEE Transactions On Information Technology In Biomedicine, Vol.11, No.5,pp.537-543, 2007.

[5] Chuan Yu Chang,YueFong Lei, Chin Hsiao Tseng and Shyang Rong Shih, " Thyroid Segmentation and Volume Estimation in Ultrasound Images", IEEE Transactions on Biomedical Engineering, Vol. 57, No. 6, pp. 1348-1356, 2010.

[6] Sheeja Agustin A and S. Suresh Babu, “Thyroid Classification as Normal and Abnormal using SCG based Feed forward Backpropagation Neural network algorithm”, International journal of Computer science and mobile computing,Vol.3,Issue.2,pp.134-141,2013.

[7] Sheeja Agustin A and S. Suresh Babu,” An Improved Thyroid Tumor Segmentation and Classification Approach using ANFIS-AABC”, International journal of Applied Engineering Research,Vol.9,Issue.22,pp. 13387-13408,2014

[8] Krit Somkantha and Nippon Theera umpon,”Boundary Detection in Medial Images Using Edge Following Algorithm based on intensity gradient and texture gradient features”,IEEE Transactions on biomedical engineering,vol.58,no.3,March 2011.

[9] https://en.wikipedia.org/wiki/Sensitivity_and_specificity.

[10] R. C. Gonzalez and R. E. Woods, Digital Image Processing, 2nd ed. Englewood Cliffs, NJ: Prentice-Hall International Edition, 2002.

[11] Nikita Singh and Alka Jindal, "Ultra sonogram Images for Thyroid Segmentation and Texture Classification in Diagnosis of Malignant (Cancerous) or Benign (Non-Cancerous)", International Journal of Engineering and Innovative Technology (IJEIT) ,Vol. 1, No. 5, pp. 222-227, 2012.

[12] Gireesha H M,Nanda S, “Thyroid nodule segmentation and classification in ultrasound images”, International journal of engineering research and technology,vol.3,Issue.5,pp.2252-2256,May 2014

[13] M.Shamilee Devi ,”Development of Image Analysis System for the Evaluation of Thyroid Nodule