# DEVELOPMENT OF IMAGE ANALYSIS SYSTEM FOR THE EVALUATION OF THYROID NODULE MALIGNANCY RISK IN ULTRASOUND THYROID IMAGES

[1]**M.Shamilee Devi**

[1]PG scholar, Department of Bio-Medical Instrumentation Engineering, Avinashilingam University, Coimbatore

[1]ragav.sham@gmail.com

**Abstract:** Ultrasound imaging is a vital tool for diagnosis of thyroid nodule, as it provides the internal structure of the body to detect diseases or abnormalities in tissues in non-invasive manner. Unfortunately, the presence of speckle noise in these images affects edges and fine details which limit the contrast resolution and make diagnosis more difficult. So speckle noise reduction has been done as a preprocessing method using Wavelet filter. Furthermore, thyroid nodule malignancy risk assessment is done and classified as normal, benign or malignant using Probabilistic Neural Network (PNN) classifier which helps the radiologists and medical specialists during their medical decision process. If the thyroid nodule is found to be benign or malignant, then segmentation is done using Fuzzy C- Means (FCM) clustering technique. The performance of the classifier is evaluated using statistical parameters such as sensitivity, specificity and accuracy.

**Index Terms:** Speckle noise reduction, Statistical parameters, Thyroid nodule, Ultrasound imaging.

## 1. INTRODUCTION

Nowadays, contemporary ultrasound systems have gained the medical community's confidence among other imaging modalities such as CT, MRI because ultrasound imaging pro- vides many advantages such as being less costly, portability of the device, and safety of the imaging technique to the patient, and the less amount of time required for imaging. Ultrasound systems have accomplished an excellent tradeoff between image quality, low cost, portability and luck of any form of radiation. Ultrasonography is employed by many medical specialties such as Obstetrics and Gynecology, Pathology, Cardiology and Endocrinology. In the later, ultrasonic scanning of the thyroid gland constitutes an important procedure in assessing the thyroid malignancy risk factor. High resolution ultrasonography can detect several characteristics that can be employed as criteria in the differentiation between malignant and benign nodules. Such criteria include margin, shape, echo structure, echogenicity and the presence of calcifications. Accurate estimation of thyroid malignancy risk factor by ultrasound may be regarded as a crucial factor in the reduction of unnecessary surgical interventions. The ultra- sound imaging method is used in medical practices, along with other imaging procedures such as X- Ray, CT, etc., for producing images of live tissue and for the purpose of clinical diagnosis.

Despite the profound advantages of ultrasonography, ultrasound images carry a granular pattern, so called speckle, which constitutes a major image quality degradation factor. Speckle pattern is created when an ultrasonic wave with uniform intensity is incident either on a rough surface or on tissue particles that are spaced at less than the axial resolving distance of the US system. In that case, the reflection beam profile will not have a uniform intensity. Instead it will be composed of many regions with strong and weak intensities.

This complex intensity profile arises because sound is reflected in many different directions from the rough surface or from the small scatterers, thus leading ultrasound waves that have travelled different scan lines to interfere constructively and de- structively towards the ultrasonic transducer. The intensity fluctuations within a uniform anatomic area, caused by the above phenomenon, constitute speckle. The resulting degraded by speckle US image does not correspond to the actual tissue micro- structure. In fact, speckle noise deteriorates image quality, fine details and edge definition. Speckle also tends to mask the presence of low-contrast lesions, therefore reducing the physician's ability for accurate interpretation. Moreover, it constitutes a limit- ing factor in the performance of quantitative procedures such as segmentation and pattern recognition algorithms. Hence, speckle suppression is considered as a pre-processing step towards an efficient segmentation as well as an efficient tool for improving ultrasound image quality and possibly the diagnostic potential of medical ultrasound imaging.

Evaluation of malignancy risk in thyroid nodules represents a typical example of the way ultrasonography is accomplished to gain the confidence of medical community throughout the past years. Features, such as the nodule’s echo-structure and echogenicity (solid or colloid, hyper-hypo or is echogenic), its shape differentiation (round, egg shape, wide or tall), its boundary irregularity degree (from normal to highly irregular borderline), its calcifications pattern (massive, snow-storm etc), are employed towards an improved prognosis. The advent of high resolution ultrasound technology as a preoperative diagnostic tool has made possible the acquisition of detailed information and characteristics of the thyroid gland structure. The increasingly amount of information provided by high resolution ultrasound systems constitutes the clinical decision procedure rather difficult, therefore to increase reliability and reduce the number of operations such as biopsy and fine needle aspiration, Computer-Aided Diagnosis (CAD) is necessary for detection of malignancy risk in thyroid nodules.

## 2. PROPOSED METHOD

Here the input ultrasound thyroid nodule image is subjected to speckle noise reduction using wavelet filter. The texture features are extracted from filtered image and are given to Probabilistic Neural Network Classifier for training. After training, the thyroid nodule gets classified as normal, benign and malignant. If the thyroid image is found to be benign or malignant, segmentation of nodule area is done using Fuzzy C-Means clustering technique. The performance of the classifier is evaluated using parameters such as sensitivity, specificity and accuracy

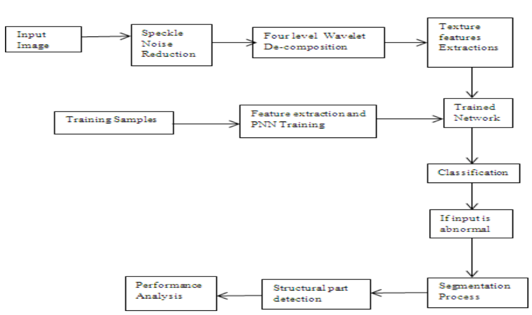


**Figure 1: Block diagram for classification of Ultrasound thyroid nodule image.**

## 3. SPECKLE NOISE REDUCTION

The main objective of image-de-noising techniques is to remove noises while retaining the important signal features as much as possible. One of its main shortcomings is the poor quality of im- ages, which are affected by speckle noise. The existence of speckle is unattractive since it disgraces image quality and affects the tasks of individual interpretation and diagnosis Speckle noise is a high-frequency component of the image and appears in wave- let coefficients. The availability of an accurate and reliable model for speckle noise formation is a prerequisite for development of a valuable de-speckling algorithm .A different type of noise in the coherent imaging of objects is called speckle noise.

### 3.1Wavelet Filter

Wavelets are basically mathematical functions which break up the data into different frequency components, and then each component is studied with a resolution matched to its scale. Wavelets have some advantages over traditional Fourier methods in analyzing physical situations where the signal contains discontinuities and sharp spikes. Wavelets are the better technique to handle the different type of noises which is present in an image. There are different wavelet families which shown different results when they are applied in image processing field. Recently wave- lets analysis is widely applied in the image de-noising due to its multi-resolution and locality property. An input signal frequency representation can be obtained using wavelet transform. The processing is carried out without implementing a very complex transform. It consists of eliminating certain frequencies in order to eliminate any existing noise. Since it is known that when an image is decomposed, the HH, LH, and HL images contain most of the image’s high frequencies and noise, where one can eliminate the noise by eliminating those images.

The following steps perform the wavelet decomposition of the US medical image: In the first stage of the decomposition, spilt the US image into 4 sub bands, namely the HH, HL, LH (high pass) and LL (Low pass) sub bands. The HH sub band gives the diagonal information of the US image; the HL sub band gives the horizontal features while the LH sub band represents the vertical structures of the US image The LL sub band is the low- resolution residual consisting of low frequency components and this sub band is further divided at the higher levels of decomposition. All the wavelet filters use wavelet thresholding operation for de-noising.

**4. DISCRETE WAVELET DECOMPOSITION**

Daubechies wavelet filter of order two is used and found to yield good results in classification and segmentation of thyroid nodule. By applying 2D DWT, two level wavelet decomposition of Region of Interest (ROI) is performed which results in four sub bands. In 2D wavelet decomposition the image is represented by one approximation and three detail images, representing the low and high frequency contents image respectively. The approximation can be further to produce one approximation and three detail images at the next level of decomposition, wavelet decomposition process. LL1, LL2 represent the wavelet approximations at 1st and 2nd level respectively, and are low frequency part of the images. LH1, HL1, HH1, LH2, HL2, HH2 represent the details of horizontal, vertical and diagonal directions at 1st and 2nd level respectively, and are high frequency part of the images.

**5. FEATURE EXTRACTION**

Gray-Level Co-occurrence Matrix (GLCM) is the statistical method of examining the textures that considers the spatial relationship of the pixels. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix. The gray comatrix function in MATLAB GLCM by calculating how often a pixel with the intensity (gray-level) value i occurs in a specific spatial relationship to a pixel with the value j. By default, the spatial relationship is defined as the pixel of interest and the pixel to its immediate right (horizontally adjacent), but you can specify other spatial relation- ships between the two pixels. Each element (i, j) in the resultant GLCM is simply the sum of the number of times that the pixel with value I occurred in the specified spatial relationship to a pixel with value j in the input image. A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels, G, in the image. The matrix element $P(i, j \mid \Delta x, \Delta y)$ P(i, j | Δx,Δy) is the relative frequency separated by a pixel distance (Δx,Δy) . Matrix element also represented as P (i, j | d, θ) which contains the second order probability values for changes between gray level i and j at distance d at a particular angle θ. Various features are extracted from GLCM, G is the number of gray lev- els used and μ is the mean value of P. Px (i) is the ith entry obtained by summing the rows of *P (i, j):*

$$p_x\ i \ = \sum_{j=0}^{G-1} P(i,j) \quad (1)$$

And

$$p_y\ j \ = \sum_{j=0}^{G-1} P(i,j) \quad (2)$$

**6. THYROID NODULE CLASSIFICATION USING PNN**

Probabilistic Neural Network is a type of Radial Basis Function (RBF) network, which is suitable for pattern classification. The fundamental architecture having three layers, an input layer, a pattern layer, and an output layer. The pattern layer constitutes a neural implementation of a Bayes classifier, where the class de pendent Probability Density Functions (PDF) are approximated using a Parzen estimator. Parzen estimator determines the PDF by rectly. Using the Parzen estimator, the classification gets closer to the true underlying class density functions as the number of training sampies increases. The pattern layer consists of a processing element corresponding to each input vector in the training set. Each output class should consist of equal number of processing elements otherwise a few classes may be inclined falsely leading to poor classification results. Each processing element in the pat- tern layer is trained once. An element is trained to return a high output value when an input vector matches the training vector. In order to obtain more generalization a smoothing factor is included while training the network. The pattern layer classifies the input vectors based on competition, where only the highest match to an input vector wins and generates an output. Hence only one classification category is generated for any given input vector. If there is no relation between input patterns and the patterns pro- grammed into the pattern layer, then no output is generated. Compared to the feed forward back propagation network, training of the Probabilistic

Neural Network is much simpler. Since the probabilistic networks classify on the basis of Bayesian theory, it is essential to classify the input vectors into one of the two classes in a Bayesian optimal manner. This theory provides a cost function to comprise the fact that it may be worse to misclassify a vector that is actually a member of class A than it is to misclassify a vector that belongs to class B. The Bayes rule classifies an input vector belonging to class A as,

$$P_A C_A f_A(x) > P_B C_B f_B(x)$$

Where

$P_A$ - Priori probability of occurrence of patterns in class A

$C_A$ - Cost associated with classifying vectors

$f_A(x)$ - Probability Density Function of class A

The PDF estimated using the Bayesian theory should be positive and integratable over all x and the result must be 1. The probabilistic neural net uses the following equation to estimate the probability density function given by,

$$f_A\ x\ = \frac{1}{(2\pi)^{n/2}\sigma^n}\frac{1}{m_n}\sum_{i=1}^{m_A} exp\left[-2\frac{x - X_A \ \wedge_r\ x - X_{Ai}}{\sigma^2}\right] \quad (3)$$

$X_{Ai}$ -ith training pattern from class A

n - Dimension of the input vectors

σ - Smoothing parameter (corresponds to standard deviations of Guassian distribution)

The function $f_A(x)$ acts as an estimator as long as the parent density is smooth and continuous. $f_A(x)$ approaches the parent density function as the number of data points used for the estimation increases. The function $f_A(x)$ is a sum of Guassian distributions.

## 7. THYROID NODULE SEGMENTATION USING FCM TECHNIQUE

The Fuzzy c means was used to create fuzzy partition. FCM algorithm c1assifies the image by grouping similar data points in the feature space into clusters. This c1ustering is achieved by iteratively minimizing a cost function that is dependent on the distance of the pixels to the cluster centers in the feature domain. The Objective function is given in Equation (4),

$$J = \sum_{j-1}^{N}\sum_{i=1}^{c} u_{ij}^{m}\,||x_i - v_i||\wedge_2 \quad (4)$$

Where Uij represents membership of pixel Xj in the ith cluster. The parameter m controls the fuzziness of the resulting partition, and m=2. Xj is the ith of d-dimensional measured data. Vi is center of the cluster. j represents total number of pixels.

One of the important characteristics of an image is that neighboring pixels are highly correlated, i.e. the pixels in the immediate neighborhood possess nearly the same feature data. Therefore, the spatial relationship of neighboring pixels is an important characteristic that can be great aid in image segmentation. In FCM technique, a noisy pixel is wrongly classified be- cause of its abnormal feature data.

Spatial Fuzzy C Means method incorporates spatial in- formation, and the membership weighting of each cluster is altered after the cluster distribution in the neighborhood is considered. The first pass is the same as that in standard FCM to calcu- late the membership function in the spectral domain. In the se- cond pass, the membership information of each pixel is mapped to the spatial domain and the spatial function is computed from that. The FCM iteration proceeds with the new membership that is incorporated with the spatial function. The iteration is stopped when the maximum difference between cluster centers or mem- bership functions at two successive iterations is less than a threshold value 0.02. To develop the spatial information, a spatial function is defined in Equation (5),

$$h_{ij} = \sum_{k\epsilon NB}(x_j)u_{ik} \quad (5)$$

Where NB (Xj) represents a square window centered on pixel Xj in spatial domain. hij stands for the probability that pixel Xj belongs to ith cluster. A 3*3 window was used throughout this work. The spatial function is included into membership function as given in Equation (6),

$$u_{ij} = \frac{u_{ij}^{P}h_{ij}^{q}}{\sum_{k=1}^{c} u_{kj}^{P}h_{kj}^{q}} \quad (6)$$

Where p and q are parameters to control the relative importance of both functions. This scheme greatly reduces the effect of noise and biases the algorithm toward homogeneous cluster ing. In Spatial fuzzy c means the initial membership matrix for initialized clusters generated randomly. The initial membership matrix does not depend on sampies of data sets. If the quantities (like the cluster number, initial center and membership matrix) are not selected correctly for a noisy data, this algorithm will stop in local minimum. Therefore this algorithm becomes limit. Modified Spatial Fuzzy C Means segments normal tissues such as WM, GM, and CSF by considering spatial information because neighboring pixels are highly correlated and also construct initial membership matrix using initial cluster center by incorporating spatial neighborhood information to improve strength of clustering. To make initial cluster center, the square window centered on pixel Xj used in spatial domain to obtain dissimilarities of sampies in square window. To find dissimilarity, Euclidean distance measure is used between the center pixel in window and neighborhood of this pixel. The initial cluster center is defined in Equation,

Where H (xj ) represents a square window centered on pixel Xj in the spatial domain. Then max, min and mean of dissimilarities obtained for Vi. The 3 * 3 window is used throughout this work. So this method finds a reasonable way to get the initial cluster center to initialized membership matrix. This method improves the strength of clusters.

$$V_i = dissimilarities \;\; H \;\; x_i \qquad (7)$$

## 8. EVALUATION METRICS

Evaluation of classification results is an important process in the classification procedure. The performance measures play an important role in evaluating the quality of classification techniques for diagnosis purpose. Different approaches may be employed, ranging from a qualitative evaluation based on expert knowledge to a quantitative accuracy assessment based on sampling strategies. The quality of an image is examined by objective evaluation as well as subjective evaluation. In reality, no classification algorithm can satisfy all these requirements nor be applicable to all studies, due to different environmental settings and datasets used. These criteria include classification accuracy, computation al resources, stability of the algorithm, and robustness to noise in the training data. Classification accuracy assessment is, however, the most common approach for an evaluation of classification performance. There are various metrics used for evaluating classification methods in general or for specific application. The metrics used to evaluate the classification performance are sensitivity, specificity and accuracy. Sensitivity and specificity are statistical measures of the performance of a binary classification test also known in statistics as classification function. For subjective evaluation, the image has to be observed by a human expert which is complicated and does not give the exact quality.

### 8.1 Sensitivity

It is also called as true positive rate which measures the probabil- ity of abnormal class and is classified as abnormal. Sensitivity deals with only positive cases. The formula is given by,

$$Sensitivity = TP/(TP + FN)) \times 100\% \qquad (8)$$

### 8.2 Specificity

It is also called as the true negative rate. It measures the probabil- ity of normal class which is identified as normal. Specificity deals with only negative cases. The formula is given by,

$$Specificity = TN/(TN + FP)) \times 100\% \qquad (9)$$

### 8.3 Accuracy

It measures the quality of the classification. It takes into account true and false positives and negatives. Accuracy is generally re- garded with balanced measure.

$$Accuracy = TP + TN/(TP + TN + FP + FN)) \times 100\% \qquad (10)$$

Where, True Negative (TN) is the number of normal im- ages classified as normal images. False Negative (FN) is the number of abnormal images classified as normal. True Positive (TP) is the number of abnormal images classified as abnormal. False Positive (FP) is the number of normal images classified as abnormal. The performance of the system is examined by demon- strating correct and incorrect patterns. The higher value of both sensitivity and specificity shows better performance of the sys- tem.

## 9. RESULTS AND DISCUSSIONS

The MATLAB is a high-level technical computing language and an interactive environment for algorithm development, using the MATLAB product, technical computing problems can be solved faster, than with traditional programming languages. The result for classification is displayed in Graphical User Interface (GUI).

3 different types of ultrasound thyroid images are taken and pre-processed using wavelet filter in MATLAB environment. The images are classified as normal, benign and malignant using PNN network and the results are displayed in GUI. If the thyroid image is found to be abnormal, segmentation is done using FCM clustering technique.

### 9.1 Qualitative Analysis

In Fig.2 the test image was subjected to speckle noise reduction using wavelet filter and the resulting preprocessed image is given to PNN classifier where it classified the image as normal.

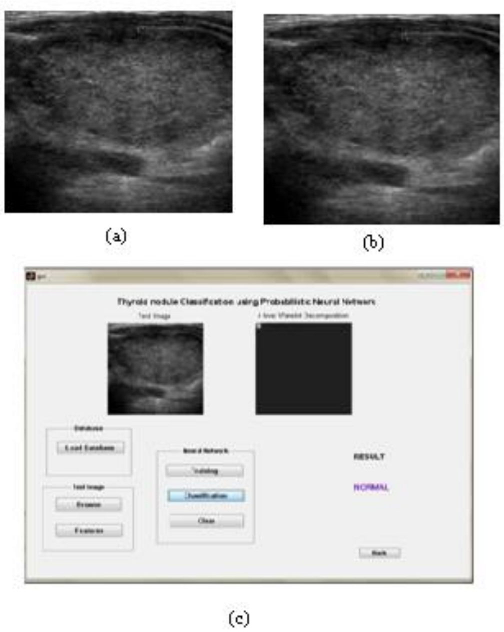


**Figure 2: (a) Test Image 1 (b) Test image filtered by Wavelet filter (c) Classification by PNN Classifier**

In Fig.3 the test image 2 was subjected to speckle noise reduction using wavelet filter and the resulting pre-processed image was given to PNN classifier where it classified the image as benign. Since the image was found to be benign, segmentation of thyroid nodule was done using FCM clustering technique

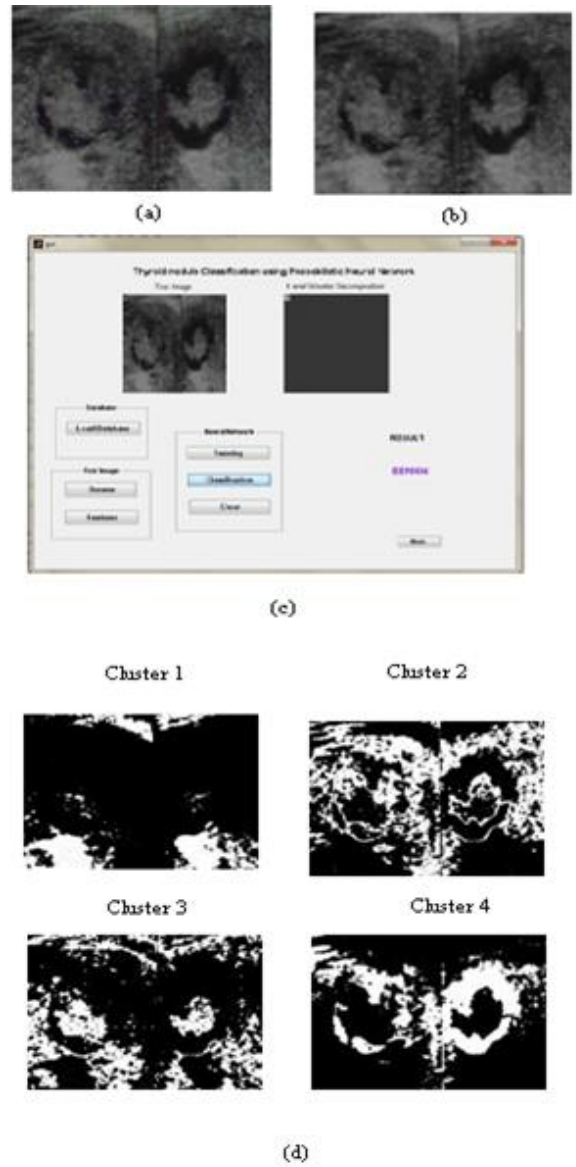


**Figure 3: (a) Test Image 2 (b) Test image filtered by Wavelet filter (c) Classification by PNN Classifier (d) Segmentation by FCM technique**

In Fig.4 the test image 3 was subjected to speckle noise reduction using wavelet filter and the resulting pre-processed image was given to PNN classifier where it classified the image as malignant. Since the image was found to be malignant, segmentation of thyroid nodule was done using FCM clustering technique.

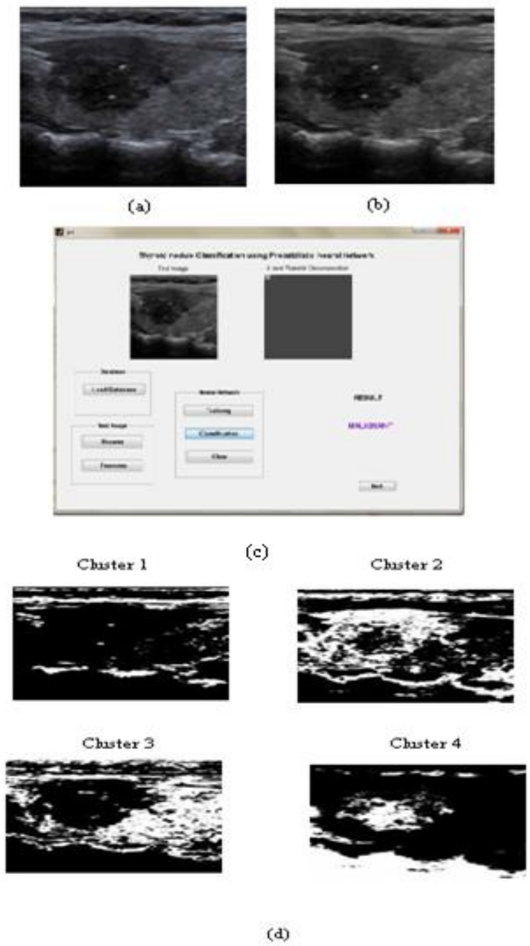


**Figure 4: (a) Test Image 3 (b) Test image filtered by Wavelet filter (c) Classification by PNN Classifier (d) Segmentation by FCM technique**

### 9.2 Quantitative Analysis

For this work, 11 thyroid images which consist of 3 normal thyroid images 4 benign thyroid nodule images and 4 malignant thyroid nodule images were used .The performance of the PNN classifier was evaluated using quality evaluation metrics such as sensitivity, specificity and accuracy. Table 1 show the performance analysis of the classifier where the overall accuracy of the classifier is found to be 90.9%

| TP | TN | FP | FN | Sensitivity | Specificity | Accuracy |
|---|---|---|---|---|---|---|
| 6 | 4 | 1 | 0 | 100% | 80% | 90.9 |

## 10. CONCLUSION

In this work, speckle noise reduction is done as a pre- processing step using wavelet filter. The resulting pre-processed image is subjected to malignancy risk assessment using PNN and the image is classified as normal, benign or malignant. The sensitivity, specificity and accuracy of the classifier were found to be 100%, 80% and 90.9% respectively. If the image is abnormal, then segmentation is done using Fuzzy C-Means clustering technique. The proposed system can further be extended to classify the type of thyroid disease such as papillary and/or mixed papillary and Follicular and/or Hurthle cell thyroid cancer provided that the texture feature vectors are revaluated and the neural net- works are retrained.

## REFERENCES

[1] Changhan Yoona, Gi-Duck Kim, Yangmo Yoo ,Tai-Kyong Song and Jin Ho Chang, ―Frequency Equal Compounding for Effective Speckle Reduction In Medical Ultrasound Im- age‖,Biomedical Signal Processing and Control 8,pp-876– 887,2013.

[2] Y. Guo, Y.Wango and T. Hou ―Speckle Filtering Of Ultra Sound Images Using Modified Non Local Based Algorithm‖, Biomedical Signal and Control 6,pp-129-138.

[3] Pier rick Coupe, Pierre Hellier, Charles Kervrann, and Christian Barillot,―A Non-Local Means Based Speckle Filtering For Ultrasound Images‖, IEEE Transactions on Image Processing, Vol. 18, No. 10,2009.

[4] Hamed Shamsi and Hadi Seyedarabi, ― A Modified Fuzzy C- Means Clustering with Spatial Information for Image Seg- mentation", International Journal of Computer Theory and Engineering, Vol. 4, No.5

[5] Nasrul Humaimi , and Akmal Hayati Rusli , ―Segmentation And Area Measurement For Thyroid Ultrasound Image‖, In- ternational Journal of Scientific and Engineering Research, Volume 2, Issue 12, 2011.

[6] Jianbo Shi and Jitendra Malik ,―Normalized Cuts and Image Segmentation‖, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 22, No. 8,2000.

[7] Mohammad Talebi, ‖Medical Ultrasound Image Segmentation Using Genetic Active Contour‖, Journal of Biomedical Science and Engineering, vol.4,pp-105-109,2011.

[8] Shrikant D.Kale and Krushil M.Punwatkar ,―Texture Analysis of Thyroid Ultrasound Images for Diagnosis of Benign and Malignant Nodule using Scaled Conjugate Gradient BPN network‖, International Journal of Computational Engineering & Management, Vol. 16 Issue 6 2013.

[9] Nikita Singh and Alka Jindal , ―Ultra sonogram Images for Thyroid Segmentation and Texture Classification in Diagnosis of Malignant (Cancerous) or Benign (Non-Cancerous) Nodules‖, International Journal of Engineering and Innovative Technology, Volume 1, Issue 5,2012.

[10] Stavros Tsantis , ―Morphological and Wavelet features to- wards Sonographic thyroid nodules evaluation‖, Computerized Medical Imaging and Graphics ,33 ,pp-91–99,2009