

Classification of Thyroid Nodules in Ultrasound Images using kNN and Decision Tree

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Abstract - Thyroid nodules are abnormal growth which can be solid or cystic lumps within the thyroid glands. Differentiating between benign and malignant thyroid nodules is important for providing appropriate treatment where ultrasound imaging plays an important role. In digital image processing techniques, the characterization of the thyroid tissue offers the texture description using the ultrasound images. This paper presents the characterization and classification of thyroid nodules in ultrasound images. It includes extraction of two sets of features based on GLCM and Gabor filters. The performance of the classifiers was evaluated with the accuracy, sensitivity and specificity.

Key Words: Ultrasound Thyroid Images, Thyroid Nodule, GLCM, Gabor Filter, kNN, Decision Tree

1. INTRODUCTION

Thyroid nodules are commonly found in regions where there is less supply of iodine in unselected adults between the age of 18-65 years are reported [1]. Ultrasound is a one of the widely used medical imaging techniques, providing substantial clues in differential diagnosis having an advantage of non-invasiveness, low cost and short acquisition time [2]. Echogeneity, texture and shape are the useful features of the US images usually correlated with the pathology of the thyroid nodules [3].

Assessment of the calcification patterns in ultrasound thyroid nodules is carried out by Lu et. al [4] based on GLCM and gabor filter, the textural features based on local binary patterns are extracted by Liu et. al [5] to classify benign and malignant thyroid nodules using SVM. Multiple feature extraction process proposed by Chen et. al [6] included statistical moments, geometrical moments and textural moments which are extracted from region of interest [ROI]. Literature also reveals the application of kNN [7-8] & Decision Tree [9-10] for the classification of thyroid nodules.

2. DATASET

Dataset of ultrasound thyroid images includes 28 benign and 15 malignant nodules of different patients which are DICOM in nature. These images are set of B-mode images obtained from Philips HD11XE, 3-12MHz frequency, and are provided by JSS hospital, Mysuru. These images are labeled by the expert radiologist.

3. METHODOLOGY

Characterization and classification of thyroid nodules involve feature extraction and classification. The steps followed for implementation are shown in Fig-1. Gray level co-occurrence matrix (GLCM) and Gabor filter based features are used for texture characterization which helps in differentiating malignant thyroid nodule from benign nodule using k-nearest neighbor (kNN) and decision tree (DT) classifiers. Performance of the classifiers is evaluated using accuracy, sensitivity & specificity.

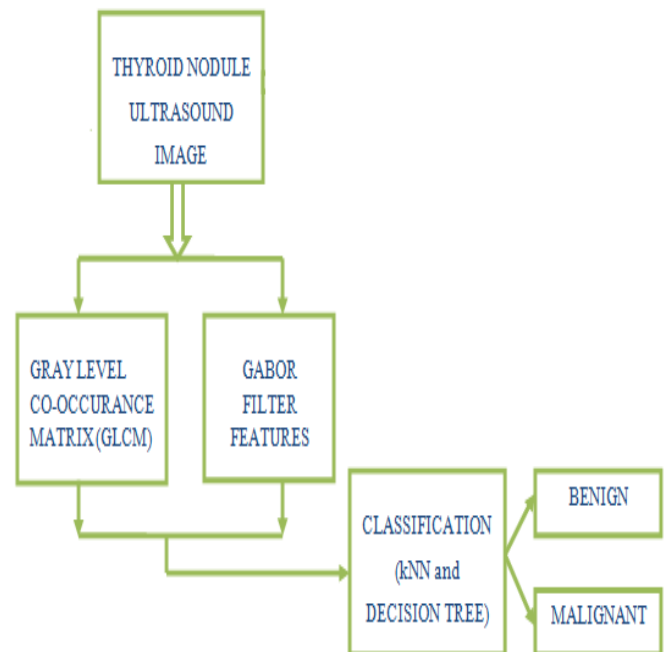


Fig -1: Flow diagram for thyroid nodule characterization and classification

3.1 Feature Extraction

Feature extraction is a method of capturing visual content of an image to ease the classification process. In this paper two different sets of features are extracted using GLCM

and Gabor filters. These features are computed with the help of statistical approach.

3.1.1 Gray level Cooccurrence Matrix (GLCM)

Gray Level Cooccurrence Matrix is a matrix where the number of rows and columns is equal to the number of quantized gray levels. The second order statistical probability values for changes between gray level i and j at a particular displacement distance (d) and (θ) [11]. The texture-content information is specified by the relative frequency C(i,j), represents the number of occurrence of gray levels i and j within, at a certain (d,θ) pair. The measure of probability is given by

$$Pro = \{p(i, j) | (d, \theta)\} \tag{1}$$

Where p(i,j) is defined as

$$p(i,j) = \frac{C(i,j)}{\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} C(i,j)} \tag{2}$$

The sum in the denominator represents the total number of gray level pairs within the window and C(i,j) represents the number of occurrences of gray levels i and j within the window.

Eight different features [3] are used to quantitatively evaluate the textural characteristics of the thyroid nodules.

3.1.1.1 Autocorrelation

Autocorrelation is a measure of the linear dependency of gray levels on those of neighboring pixels or specified points which indicates local gray-level dependency on the texture image.

$$Correlation = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \frac{(i - \mu_x)(j - \mu_y)p(i,j)}{\sigma_x \sigma_y} \tag{3}$$

3.1.1.2 Variance

Variance refers to the gray level variability of the pixel pairs and is a measurement of heterogeneity.

$$Variance = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i - \mu_x)^2 p(i,j) + \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (j - \mu_y)^2 p(i,j) \tag{4}$$

3.1.1.3 Cluster Prominence

It is a measure of asymmetry.

$$Pr = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i + j - \mu_x - \mu_y)^4 p(i,j) \tag{5}$$

3.1.1.4 Cluster Shade

Cluster shade is a measure of the skewness of the matrix.

$$Shade = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i + j - \mu_x - \mu_y)^3 p(i,j) \tag{6}$$

$$Where \ u_x = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} i \cdot p(i,j) \tag{7}$$

$$u_y = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} j \cdot p(i,j) \tag{8}$$

$$\sigma_x = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i - \mu_x)^2 \cdot p(i,j) \tag{9}$$

$$\sigma_y = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (j - \mu_y)^2 \cdot p(i,j) \tag{10}$$

u_x and u_y are the mean and σ_x and σ_y are the standard deviation.

3.1.2 Gabor Filter Features

Gabor filter was first introduced by Dennis Gabor [12-13], a linear filter whose impulse response is defined by a sinusoidal plane wave modulated by a Gaussian function. Due to its optimal localization properties both in spatial and frequency domain, sharper boundaries can be detected.

Gabor function is given by

$$g(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp\left[-\frac{1}{2}\left(\frac{\hat{x}^2}{\sigma_x^2} + \frac{\hat{y}^2}{\sigma_y^2}\right)\right] \exp(2\pi jW\hat{x}) \tag{11}$$

$$\hat{x} = x \cdot \cos\theta + y \cdot \sin\theta \tag{12}$$

$$\hat{y} = -x \cdot \cos\theta + y \cdot \sin\theta \tag{13}$$

Where $\sigma_x \sigma_y$ - scaling parameters of the filter describing the neighborhood of a pixel where weighted summation takes place, W - central frequency of the complex sinusoidal and $\theta \in (0, \pi)$ - orientation of the normal to the parallel strips of the Gabor function.

Set of descriptors are computed from the feature vector which is constructed with the absolute values of the response as components namely mean and energy.

3.2. Classification

Features which are obtained from GLCM and Gabor Filter are applied directly to k-Nearest Neighbor and Decision tree classifiers to categorize the benign and malignant thyroid nodules.

3.2.1 k- Nearest Neighbor (kNN)

Classification in k-Nearest Neighbor takes place by locating the nearest space and labeling the unknown instance with the same class label as that of the known neighbor. Based on the known value of k, label is assigned among the k training samples nearest to that unknown data. Euclidean distance is the one of commonly used distance measures used to find the k-nearest neighbor and is given by

$$Euclidean = \sqrt{\sum_{i=1}^k (x_i - y_i)^2} \quad (14)$$

The minimum distance between the training and test samples gives best classification of the test samples.

3.2.2 Decision Tree (DT)

Decision Tree provides understandable and interpretable information regarding the predictive ability of the classification. Origin of measure and measure structure is the main criteria for splitting the tree. A binary criterion is used in the classification process, where value 0 is assigned when the tree recognizes benign attribute and 1 when the tree recognizes malignant attribute. Tree recursively selects the best attribute to split the data and expands the leaf nodes of the tree until the stopping criterion is met.

3.2.3 Performance Evaluation

Evaluation of the proposed thyroid nodule classification method is carried out by calculating the performance in terms of true positive (TP), false positive (FP), true negative (TN) and false negative (FN) metrics. TP is defined as the number of benign nodules correctly detected in the ultrasound images; FP is defined as the number of benign nodules detected as malignant; TN is defined as the number malignant nodules correctly detected; and FN is defined as the number of malignant nodules detected as benign nodules by the system. By using these metrics we can obtain more meaningful performance measures like sensitivity, specificity and accuracy values as mentioned below.

$$Sensitivity = \frac{TP}{TP+FN} \quad (15)$$

$$Specificity = \frac{TN}{FP+TN} \quad (16)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (17)$$

4. RESULTS

Selection of ROI in benign and malignant ultrasound thyroid images is done by expert radiologist as shown Fig-2. Fig-3 shows the extracted ROI of benign and malignant images and Fig-4 shows the magnitude and real part of the Gabor function applied to the extracted ROI with scale 5 and orientation 8.

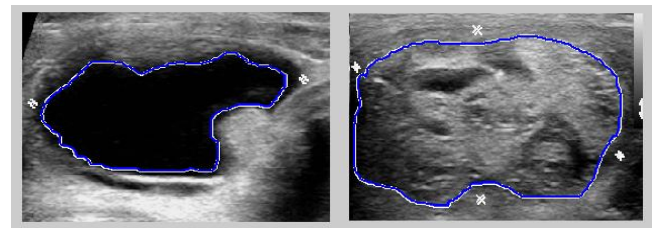


Fig -2: Benign and malignant thyroid US images

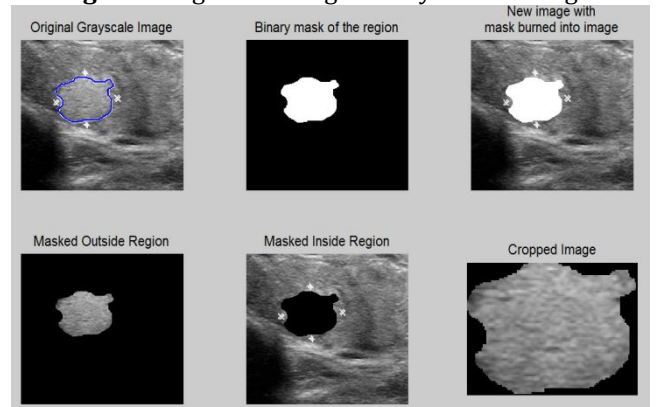


Fig-3: Extracting the required ROI

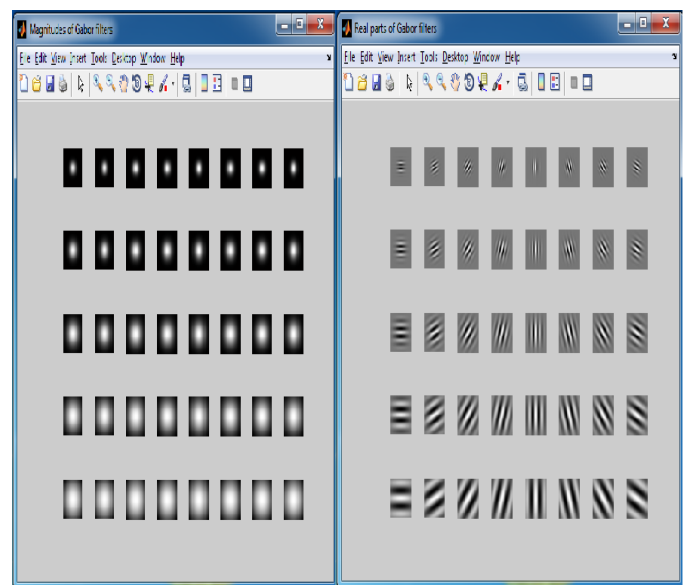


Fig -4: Magnitude and Real part obtained after the application of Gabor filter

The range of GLCM feature values for benign and malignant images is tabulated in Table-1. Table-2 represents the range of features based on Gabor filter.

Table-1: Range of values obtained for different textural features using GLCM for benign and malignant thyroid images

BENIGN THYROID IMAGES

MALIGNANT THYROID IMAGES

Statistical Textural Features	Range	Statistical Textural Features	Range
Autocorrelation	1.0417 - 18.0433	Autocorrelation	3.0228 - 11.8281
Variance	1.0185 - 18.0826	Variance	3.0213 - 11.8043
Cluster Prominence	0.1458 - 302.4462	Cluster Prominence	25.4707 - 323.6245
Cluster Shade	-34.0501 - 7.7284	Cluster Shade	0.1385 - 22.0674

Table-2: Range of values obtained for different textural features using Gabor filter for benign and malignant thyroid images

BENIGN THYROID IMAGES

MALIGNANT THYROID IMAGES

Gabor Filter Features	Range	Gabor Filter Features	Range
Mean	0.1778 - 1.9405	Mean	0.6494 - 1.4330
Energy	4.7930e+003 - 2.2026e+006	Energy	3.7669e+005 - 3.4235e+006

60:40 ratio is taken for training and testing. Among 28 benign images, 17 are used for training and 11 are used for testing. Similarly among 15 malignant images 9 are used for training and 6 are used for testing. The performance of the kNN and Decision Tree classifiers are tabulated in Table-3 and Table-4.

Table-3: Confusion matrix of kNN and Decision Tree classifier

PARAMETER/ CLASSIFIERS	KNN CLASSIFIER	DECISION TREE CLASSIFIER
True Positive(TP)	8	11
True Negative(TN)	6	6
False Positive(FP)	3	0
False Negative(FN)	0	0

Out of 11 benign images, 8 are classified as benign and 3 as malignant and all the 6 malignant images are classified as malignant according to kNN classifier. All the 11 benign

images are classified as benign and all the 6 malignant images are classified as malignant by decision tree.

Table-4: Performance of kNN and decision tree classifier

PARAMETERS/ CLASSIFIERS	KNN CLASSIFIER (%)	DECISION TREE CLASSIFIER (%)
ACCURACY	82.3529	100
SENSITIVITY	100	100
SPECIFICITY	66.6667	100

Decision tree classifier achieves 100% accuracy and kNN 82.35%. The receiver operating curve is an objective means for accessing the performance of an imaging system. The area under the curve denotes the accuracy. The ROCs of kNN and decision tree obtained are shown in Fig-5 and Fig-6.

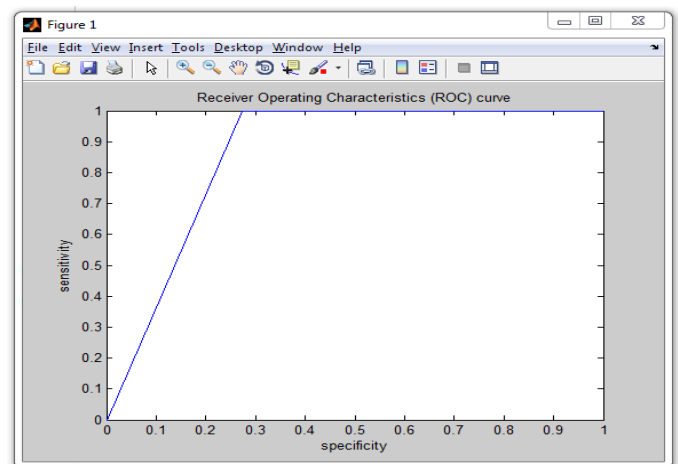


Fig -5: Receiver Operating Curve of kNN

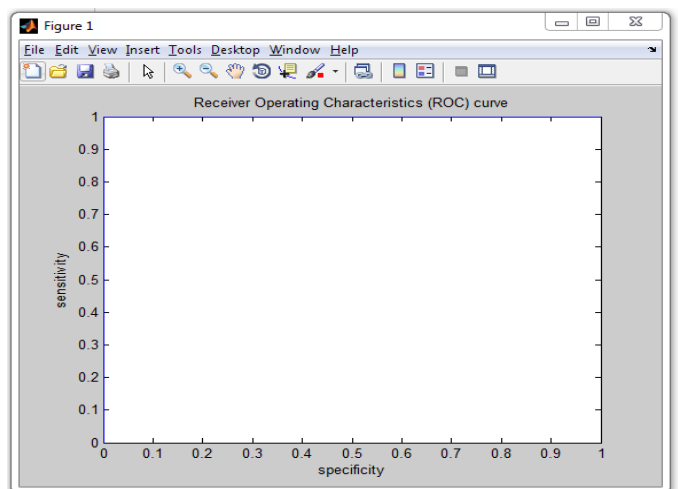


Fig -6: Receiver Operating Curve of decision tree

3. CONCLUSION

This method is efficient in detecting and classifying the thyroid nodules in ultrasound images for the above said dataset. GLCM and Gabor filter based features are used for texture characterization. The obtained features are applied directly to the kNN and decision tree classifier whose quantitative analysis is done by calculating the accuracy, sensitivity and specificity. This method can be considered as the second opinion in improving the diagnostic accuracy.

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BIOGRAPHIES



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