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Classification of Thyroid Nodules in Ultrasound Images Based On Texture Analysis

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Abstract: **Thyroid is a butterfly-shaped gland in the front of the neck. It is found below the voice box. Thyroid nodule is one of the indicative of thyroid cancer. Nodule can be due to the growth of thyroid cells or a cyst in the thyroid gland. It is very important to differentiate between the thyroid nodule as benign or malignant. This paper presents characterization and classification of thyroid nodule using Ultrasonography. It includes extraction of set of features by using Gray Level Co-occurrence Matrix GLCM, Wavelet Transform and Local Ternary Pattern (LTP). These features are reduced to set of selected features by using PCA algorithm. The selected features are given to SVM classifier for the classification of thyroid nodule as benign or malignant. The performance of classifiers is evaluated with the accuracy, sensitivity and specificity.**

Keywords: **Gray level Co-occurrence Matrix (GLCM), Wavelet Transform, Local Ternary Pattern (LTP), Principal Component Analysis (PCA) and Support Vector Machine (SVM) Classifier..**

I. INTRODUCTION

Now a day, Thyroid nodules are a very common clinical problem. An increasing number of thyroid nodules are now diagnosed due to the ever increasing use of imaging. In medical field, Fine Needle Aspiration (FNA) is the standard procedure of choice for distinguishing benign and malignant thyroid nodules. Sometimes for accurate result, requires repeated biopsy. However, FNA is relatively invasive, costly and uncomfortable for patients.
Ultrasound is an important modality for assessment of thyroid lesions and it is also frequently used to guide biopsy.

In this paper, classification of thyroid nodule as benign or malignant will be carried out by using ultrasonography.

II. LITERATURE REVIEW

Priti Shivaji Dhaygude and S. M. Handore[1] extracted GLCM features for thyroid nodule detection. They have used level set segmentation method to obtain good results from medical images having the boundary of the regions of interest. Then they extracted GLCM features. These features were given to Artificial Neural Network for classification of thyroid nodule as benign or malignant. Their work provides efficient platform for researches and scientist.

Ms. Nikita Singh and Mrs Alka Jindal[2] proposed a classification method for thyroid using the Bayesian, KNN and SVM segmentation of thyroid nodules. In this study, texture feature method like GLCM was used for classifying texture of images and these features were used to train the classifiers such as SVM, KNN and Bayesian. From the experimental results, it is concluded that SVM gives the better classification accuracy than KNN and Bayesian.

Shrikant D.Kale and Krushil M.Punwatkar[3] used GLCM as texture characterization technique. The 10 GLCM feature are selected for feature extraction and GLCM matrix is calculated for four different orientation and different pixel distance from 1 to 15. The extracted features are classified using SVM classifier with linear kernel for diagnosis of thyroid nodule malignancy risk. This method minimize the misdiagnosis rate of pathological diseases.

Robert M.Haralick, K. Shanmugam and It'shak [4] proposed GLCM technique to extract textural features like contrast, correlation, homogeneity and energy for wide variety of image classification applications.

Ramaraj.M and S.Raghavan[5] showed the prominent applications of the wavelet and multi resolution transform for cancer diagnosis system.

Vikas and Amanpreet Kaur[6] had used (Local Ternary Pattern) LTP Techniques to compute upper and lower binary codes of regions for low resolution images. This method provides efficient and accurate results.
The literature reveals that ultrasonography is the powerful modality for thyroid cancer detection effectively and accurately. Thus, in this work ultrasonography is preferred for better diagnosis of thyroid cancer.

III. METHODOLOGY

This work presents a method to detect the thyroid cancer based on GLCM, Wavelet transform and LTP features. Fig.1 shows the steps involved in the classification and detection of thyroid nodules.

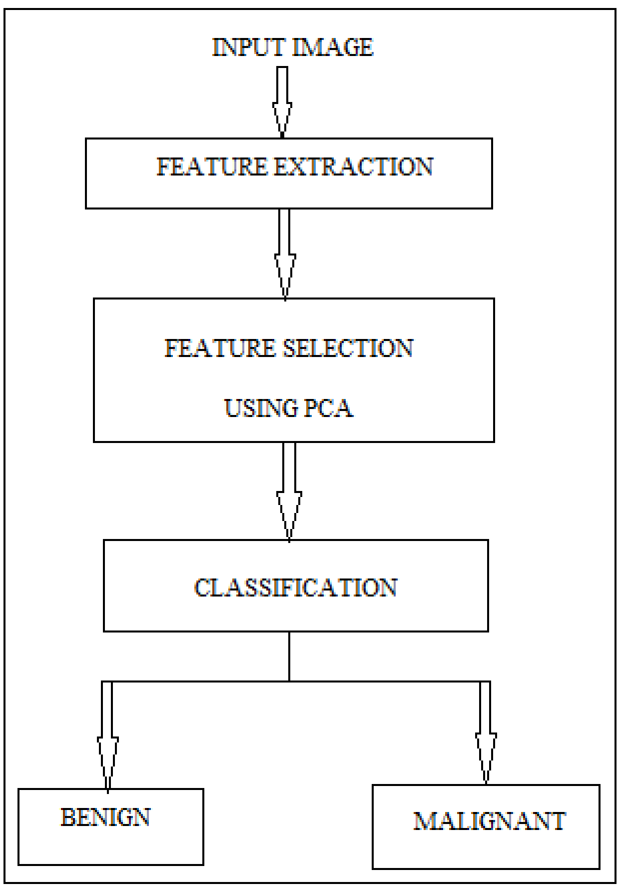

Fig. 1 : Block diagram of the method

The work is carried out in the following stages.
1. Data Collection: Collection of ultrasonogram of thyroid.

2. Feature extraction: Extraction of global and local features from ultrasonogram to characterize the nodule.

3. Feature Selection: Extracted features are selected using Principal Component Analysis algorithm.

4. Classification: Classification of the nodule as benign or malignant.

1. Data Collection.

A dataset of ultrasound images are of size 128X128 which are DICOM in nature. These images are obtained from Philips HD11XE, 3-12MHz frequency, and are provided by JSS Hospital, Mysuru. These images are labelled by the expert radiologist.

2. Feature extraction

A. Gray Level Co-occurrence Matrix (GLCM)
GLCM Provides valuable information about the relative position of the neighboring pixels in an image[4]. Given a gray scale image I, of size NXN, the co-occurrence matrix P can be defined as

$$P(i,j) = \sum_{x=1}^{N}\sum_{y=1}^{N}\begin{cases}1 & ; I(x,y) = i \text{ and } I(x+\Delta x, y+\Delta y) = j \\ 0 & ; \text{otherwise}\end{cases} \quad (1)$$

Here, the offset (Δx, Δy), is specifying the distance between the pixel-of-interest and its neighbor. Co-occurrence matrix using a set of offsets can be chosen(i.e., [0 Δ] for 0 degree: P horizontal, [-Δ, Δ] for 45 degree: P right diagonal, [-Δ 0] for 90 degree: P vertical, and [-Δ −Δ] for 135degree: P left diagonal)

Using GLCM, parameters like Contrast, Correlation, Energy and Homogeneity are computed for an ultrasound image of the size 128X128.

The mathematical equations for textural features are given below.

Contrast	$\sum_i \sum_j \lvert i-j \rvert^2 P(i,j)$	(2)
Correlation	$\sum_i \sum_j \frac{(i-\mu x).(j-\mu y)P(i,j)}{\sigma x.\sigma y}$	(3)
Energy	$\sum_i \sum_j \lvert P(i,j) \rvert^2$	(4)
Homogeneity	$\sum_i \sum_j \frac{P(i,j)}{1+\lvert i-j \rvert}$	(5)

Notation	Meaning	
μx	$\sum_i \sum_j i\,.\,P(i,j)$	
μy	$\sum_i \sum_j j\,.\,P(i,j)$	(6)
σ_x^2	$\sum_i \sum_j (i-\mu_x)^2\,.\,P(i,j)$	
σ_y^2	$\sum_i \sum_j (j-\mu_y)^2\,.\,P(i,j)$	

B. Wavelet Transform

A wavelet transform is a multiscale transform which is suitable for edge detection. It is used to decompose an image into a low-frequency component (LL) and a set of higher-frequency components (horizontal direction HL, vertical direction LH and diagonal direction HH) details at varying scales of resolution. This feature extraction method was computationally efficient because the feature vectors are analyzed by multiscale representation. Here, Daubechies2 wavelet is used for 2-level decomposition to compute the energies of horizontal, vertical and diagonal components. Totally, 8 features are extracted using Wavelet Transform.

C. Local Ternary Pattern (LTP)

Local Binary Pattern (LBP) operator was proposed by T.Ojala, M.Pietikainen and D. Harwood[7] for rotation invariant texture classification. The LBP extraction algorithm contains two main steps, that is, the thresholding step and the encoding step. They encoded the neighbour pixel values into 2-valued codes(0,1) by considering centre pixel value as threshold. The binary numbers obtained from the thresholding step are encoded and converted into a decimal number to characterize a structural pattern. Since the centre pixel value gets changed after encoding, LBP is more sensitive to noise.

To overcome noise sensitivity, Xiaoyang Tan and Bill Triggs[8] presented a new texture operator which is more robust to noise. They encoded the neighbour pixel values into 3-valued codes (-1,0,1) instead of 2-valued codes(0,1) by adding user threshold. This operator is known as Local Ternary Pattern (LTP). Fig. 2 shows an example of LTP operator. The mathematical expression of the LTP can be described as follows:

$$\mathrm{LTP}_{P,R} = \sum_{p=0}^{P-1} 2^p s\left(i_p - i_c\right), \qquad s(x) = \begin{cases} 1, & x \geq t, \\ 0, & -t < x < t, \\ -1, & x < -t, \end{cases} \tag{7}$$

where ic and ip ($p = 0, \ldots, P - 1$) denote the gray value of the center pixel and gray value of the neighbor pixel on a circle of radius R, respectively, P is the number of the neighbors and t denotes the user threshold. After thresholding step, the upper pattern and lower pattern are constructed and coded as shown in Fig. 2

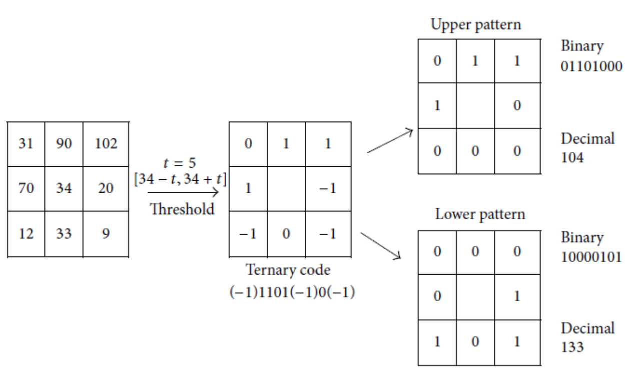

Fig. 2 : LTP Operator.

The LTP operator is the concatenation of the code of the upper pattern and lower pattern. Then the 30 features are extracted by using LTP operator.

3. Feature selection

Principal Component Analysis (PCA) is a variable reduction procedure. It is used to standardize the data in an image. PCA rotates the original data to new coordinates, making data as flat as possible. The extracted features are of 42 in number. In order to reduce the number of features with prominent values, PCA is used. PCA reduces 42 features into few prominent features in this work. This helps in the selection of significant features for classification purpose.

4. Classification

Support Vector Machines (SVM) are supervised learning models with associated learning algorithms that analyze the data used for classification. SVM constructs a hyperplane which can be used for image classification. It achieves significantly higher search accuracy than other methods. In this work, the selected features are given to the SVM classifier for the classification of thyroid nodule as benign or malignant.

4.1 Performance evaluation

Evaluation of the proposed thyroid nodule classification method is carried out by calculating the performance in terms of true positive (TP-number of benign nodules correctly detected in the US images); false positive (FP-number of benign nodules detected as malignant in the US images); true negative (TN-number of malignant nodules correctly detected in the US images) and false negative (FN-number of malignant nodules detected as benign nodules by the system). By using these matrices sensitivity, specificity and accuracy can be obtained.

$$\text{SENSITIVITY} = \frac{TP}{TP+FN} \tag{8}$$

$$\text{SPECIFICITY} = \frac{TN}{FP+TN} \tag{9}$$

$$\text{ACCURACY} = \frac{TP+TN}{TP+TN+FP+FN} \tag{10}$$

IV. RESULTS

Selection of ROI in benign and malignant ultrasound thyroid images is done by expert radiologist.
The range of GLCM and wavelet transform feature values extracted from benign and malignant images are tabulated in Table-1 and Table-2 respectively.

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

GLCM FEATURES	BENIGN	MALIGNANT
CONTRAST	0.0320- 0.1654	0.0659-0.2041
CORRELATION	0.8754- 0.9847	0.8334-0.9689
ENERGY	0.1756- 0.5894	0.1552-0.4062
HOMOGENEITY	0.9173- 0.9840	0.8981-0.9671

Table-2: Range of values obtained for different features using Wavelet transform for benign and malignant thyroid images.

WAVELET BASED FEATURES	BENIGN	MALIGNANT
Entropy	-2.3599e+09 to -1.8076e+08	-1.8308e+09 to -3.2790e+08
Ea	97.5977-99.5522	97.6737-99.4148
Eh1	0.0386-0.4822	0.0497-0.6040
Eh2	0.3493-1.6395	0.4659-1.6098
Ev1	0.0035-0.0205	0.0036-0.0617
Ev2	0.0280-0.1426	0.0345-0.2840
Ed1	0.0008-0.0052	0.0007-0.0108
Ed2	0.0135-0.1123	0.0185-0.2176

A ratio of 60:40 is considered for training and testing. Among 12 benign images, 9 images are used for training and 3 images are used for testing. Similarly, among 14 malignant images 10 images are used for training and 4 images are used for testing.

The performance of SVM classifier is tabulated in Table-3.

Table-3: The performance of the SVM classifier.

CLASSIFIER/PARAMETERS	SVM CLASSIFIER
TP	2
FP	1
TN	4
FN	0

Out of 3 benign images, 2 are classified as benign and 1 as malignant. And all the 4 malignant images are classified as malignant by SVM classifier. Therefore from the proposed method, we are able to get 85.71% accuracy.

V. CONCLUSION

This proposed method is efficient and powerful in detecting and classifying the thyroid nodule as benign or malignant in ultrasound images. Feature extraction includes local features (LTP) and global features (GLCM, Wavelet transform). PCA is used to extract the significant features from the feature set. SVM is used for classification. Quantitative analysis is done by calculating the accuracy of the classifier. This method can be considered as the second opinion in improving the diagnostic accuracy.

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