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RESEARCH ARTICLE

Texture Analysis of Ultrasound Medical Images for Diagnosis of Thyroid Nodule Using Support Vector Machine

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*Abstract— **A texture analysis of medical images gives the quantitative information about the tissue characterization & internal structure of organs for possible pathology. The physician deducing the useful information concerning internal body parts for the pathology or lesions. This is the till subjective matter of concern & thus to provide the objectification of disease diagnosis from the medical image, this paper gives the idea for thyroid nodule diagnosis using texture of the ultrasound images. Thyroid gland is located at the base of the neck, just below Adam's apple which produces hormones that control body metabolism. The nodules are found in thyroid may be benign or malignant. In this paper, gray level co-occurrence matrix (GLCM) is used as the texture characterization technique. The 10 GLCM feature are selected for feature extraction & GLCM matrix is calculated for four different orientation & 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. The experimental results show the performance measure of SVM classifier in terms classification accuracy, Positive predicted rate, Negative predicted rate, sensitivity & specificity.***

Keywords— Texture analysis; thyroid nodule; GLCM; SVM

I. INTRODUCTION

A thyroid is small gland located at the base of the neck, just below the Adam's apple. It is butterfly shaped with two cones like lobes on either side. Thyroid gland produces the T3 & T4 hormones, which control the rate of many activities in the body. One of the common disorders of thyroid gland is the occurrence of the thyroid nodule. The thyroid nodule can be solid mass, cysts which either benign (non cancerous) or malignant (cancerous) [1]. A National Cancer Registry program (NCRP) maintains the reliable data of cancer patient on the magnitude & pattern of cancer in India. The projection of thyroid cancer cases in year of 2010 is around 16,215 & by the year of 2020 goes up to 19,113. The cases of malignant thyroid nodule are found to be more in female to that of male. The projection of thyroid cancer in female for year of 2010, 2015 & 2020 is 11,751; 12,808 & 13,955 significant over male i.e. 4,464; 4,798 & 5,158 for the respective years [3]. The other figures of thyroid disease are turn out to be 42 millions in the Indian context from the projection of various studies on thyroid diseases [2].

All radiological modalities like ultrasound, CT, Scintigraphy, SPECT, MR, PET, X-rays etc. play an important role in process of disease diagnosing and have become major evidence to ensure disease. The preferred diagnosis method used for possible lesions are ultrasonography. Because as ultrasound (US) possesses a rare combination of advantages including portability, invasive, real-time data acquisition and affordability [4]. Ultrasonography is a diagnostic imaging tool used to visualize subcutaneous body structures and internal organs. The physicians are deducing useful information concerning the tissue characterization and structure. Thus, Ultrasonography has become an invaluable tool for the accurate diagnosis and follows up of different pathologies in a variety of tissues and organs [5].

The detection of the pathological diseases such as thyroid nodule by physicians is still subjective matter & while making manual diagnosis from images, some relevant information need not to be recognized by human visual system. In the suspicious cases FNA, Cytological test are done to find the malignancy risk in thyroid gland nodule. Thus to provide the objectification for thyroid nodule disease diagnosis the various texture characterization techniques are utilized which draws statistical information from Ultrasonography image. Thus this texture quantitative information is used to classify into benign & malignant thyroid nodule.

II. **RELATED WORK**

There have been various attempts towards the subjective techniques for diagnosis of thyroid gland nodule. Some of the earlier research for thyroid nodule diagnosis is described. In [4], the 13 GLCM texture & geometric features extracted from thyroid images by region based active contour segmentation method & classified using SVM, KNN and Bayesian [4].

In [5], the Contour let Transform (CT) using LP and DFB filters to the 3rd level decomposition are used for detection hypoechoic and isoechoic nodules from normal thyroid nodule. A Gaussian kernel SVM classifier is applied along the SFFS algorithm with or without coefficient thresholding. In [6], the texture features based on the CT using different types of filters banks with a selection scheme SFFS algorithm were classified by k-NN algorithm.

In [7], a novel computational approach using Radon Transform for the thyroid tissue characterization of US image were utilized. Supervised classification experimentation using KNN (k=5), SVM with polynomial kernel was done to differentiate normal and nodular thyroid US images for detection malignancy risk. In [8], the normal and hypoechoic nodule were classified using 2 First-order and 168 co-occurrence features drawn from manual rectangular ROI & PCA for optimal subset using Binary Logistic Regression.

In [9], a novel approach that correlates thyroid malignancy, LBP, FLBP, and FLGH Ultrasound texture features which discriminated by SVM with linear, polynomial and Gaussian kernel with or without fusion of texture using 10 fold cross validation or 1 way ANOVA. In [10], a novel fuzzy feature extraction method (FLBP). The FLBP approach was experimentally evaluated using supervised SVM with linear, polynomial, radial basis, sigmoid kernel for classification of nodular and normal thyroid US images. In [11], the joint texture analysis on US and Cytological images were processed to optimally highlight the cancerous region in same image. The 20 textural features were generated which contain 4 GH, 10 GLCM and 6 RLM from US image. 20 morphological and textural features were extracted from segmented nuclei of Cytological image. An SVM classifier with 2nd degree polynomial kernel & Bayesian with quadratic kernel were used in distinguishing correctly low from high-risk thyroid nodules.

III. **MATERIAL & METHOD**

Medical ultrasound images of thyroid gland are selected for texture analysis in experimental work. These ultrasound images contained some of abnormal images having benign thyroid nodule (non cancerous) and malignant thyroid nodule (cancerous). The total 85 thyroids ultrasound images were used which contains total 48 cancerous and 37 non-cancerous nodules was selected in database. These thyroid images are available in image gallery of Wilmington Endocrinology PA on website. The image size of 546×410, with 24 bit depth size, true color image, format of images are JPEG.

The Matlab R2010a software utilizing image processing toolbox is used for experimental work. The preprocessing steps required for the texture analysis is gray scale conversion of true color image & then image resizing into 256×256. Then GLCM texture feature extraction & classification of texture feature are carried out & described in following section.

A. Texture Analysis Method

The texture features analysis is a useful way of increasing the quantitative information obtains from medical images. It is an ongoing field of research, with applications ranging from the segmentation of specific anatomical structures and the detection of lesions, to differentiation between pathological and healthy tissue in different organs. Texture analysis uses radiological images obtained in routine diagnostic practice, but involves an ensemble of mathematical computations performed with the data contained within the images [12].

According to the methods employed to evaluate the inter-relationships of the pixels, the forms of texture analyses are categorized as structural, model-based, statistical and transform methods [13].

B. Statistical Methods

These are based on representations of texture using properties governing the distribution and relationships of grey-level values in the image & normally achieve higher discrimination indexes than the structural or transform methods [12].

C. Texture Feature Extraction Methods

Medical images possess a vast amount of texture information relevant to clinical practice. For example, US images of tissues are not capable of providing microscopic information that can be assessed visually. However, histological alterations present in some illnesses may bring about texture changes in the US image that are amenable to quantification through texture analysis. This has been successfully applied to the classification of pathological tissues from the liver, thyroid, breasts, kidneys, prostate, heart, brain and lungs [12].

The most commonly used texture features are Gray Level Histogram, Run-length matrix, Gray Level Co-occurrence matrix, contour let transform, Wavelets transform, Radon Transform, Local Binary Pattern, Fuzzy Local Binary Pattern, Fuzzy local Gray Histogram.

These texture feature found in literature of texture analysis on ultrasound medical images of thyroid gland for detection of thyroid nodule as a benign or malignant tissue from normal one. In this paper, gray level co-occurrence matrix (GLCM) based texture feature extraction approach is fallowed which explain next in detail. The ten texture features extracted from GLCM are described mathematically next section D.

D. Gray Level Co-Occurrence Matrix

Using histograms in calculation will result in measures of texture that carry only information about distribution of intensities, but not about the relative position of pixels with respect to each other in that texture. Using a statistical approach such as co-occurrence matrix will help to provide valuable information about the relative position of the neighboring pixels in an image.

Given an gray scale image I, of size N×N, the co-occurrence matrix P can be defined as

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

Here, the offset (Δx, Δy), is specifying the distance between the pixel-of-interest and its neighbor. Note that the offset (Δx, Δy) parameterization makes the co-occurrence matrix sensitive to rotation. Choosing an offset vector, such that the rotation of the image is not equal to 180 degrees, will result in a different co-occurrence matrix for the same (rotated) image. This can be avoided by forming the co-occurrence matrix using a set of offsets sweeping through 180 degrees at the same distance parameter Δ to achieve a degree of rotational invariance (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).

The GLCM matrix computed from the thyroid gland ultrasound images are of the size 256×256. Then texture features were extracted from GLCM matrix from each of the thyroid gland ultrasound image database & the mathematical equations for the texture features are given as follows:

Autocorrelation $\sum_i \sum_j (i \cdot j) P(i,j)$ (2)

Contrast $\sum_i \sum_j |i - j|^2 P(i,j)$ (3)

Correlation	$\sum_i \sum_j \frac{(i-\mu x).(j-\mu y)P(i,j)}{\sigma x.\sigma y}$	(4)
Cluster Prominence	$\sum_i \sum_j (i + j - \mu x - \mu y)^4 P(i,j)$	(5)
Cluster Shade	$\sum_i \sum_j (i + j - \mu x - \mu y)^3 P(i,j)$	(6)
Dissimilarity	$\sum_i \sum_j \lvert i - j \rvert P(i,j)$	(7)
Energy	$\sum_i \sum_j \lvert P(i,j)\rvert^2$	(8)
Entropy	$-\sum_i \sum_j P(i,j) \log(P(i,j))$	(9)
Homogeneity	$\sum_i \sum_j \frac{P(i,j)}{1+\lvert i-j \rvert}$	(10)
Maximum Probability	$\max_{i,j} P(i,j)$	(11)

Notation & expression used for calculating the GLCM statistics are as shown below.

Notation	Meaning	
μx	$\sum_i \sum_j i \,.\, P(i,j)$	(12)
μy	$\sum_i \sum_j j \,.\, P(i,j)$	(13)
σ_x^2	$\sum_i \sum_j (i - \mu_x)^2 \,.\, P(i,j)$	(14)
σ_y^2	$\sum_i \sum_j (j - \mu_y)^2 \,.\, P(i,j)$	(15)

The above motioned ten features extracted 85 image database are utilized for feature classification. The feature classification is done to identify the malignant thyroid nodule from that of benign thyroid nodule. The classification method used in evaluation is described in next section.

E. Classification Method

In this paper, nodule detection is nothing but a two-class problem as Benign or Malignant Nodule. Let vector $x \epsilon R^n$ denote a pattern to be classified, and let y denote its class label. In addition, let $\{(x_i, y_i), i=1,2, \ldots, l\}$ denote a given set of training examples. The next thing is to construct decision function *f(X)* for correctly classify the given input vector space[15].

1) Linear SVM Classifiers

Let us begin with the simplest case, in which the training patterns are linearly separable. That is, there exists a linear function of the form

$$f(X) = w^T x + b \tag{16}$$

Such that training vectors from the two different classes are separated by the hyperplane $f(x) = w^T x + b = 0$. For a given training set, while there may exist many hyperplanes that separate the two classes, the SVM classifier is based on the hyperplane that maximizes the separating margin between the two classes Mathematically, this hyperplane can be found by minimizing the following cost function:

$$J(w) = \tfrac{1}{2} w^T w = \tfrac{1}{2}\|w\|^2 \tag{17}$$

Subject to the separability constraints

$$y_i(w^T x_i + b) \geq 1 \;\; ; i=1, 2, \ldots, l. \tag{18}$$

This specific problem formulation may not be useful in practice because the training data may not be completely separable by a hyperplane. In this case, slack variables, denoted by ξ_i, can be introduced to relax the separability constraints in (18) as follows:

$$y_i(w^T x_i + b) \geq 1 - \xi_i, \;\; \xi_i \geq 0 \;\; ; i=1,2,\ldots,l. \tag{19}$$

Accordingly, the cost function in (17) can be modified as follows:

$$J(w) = \tfrac{1}{2}\|w\|^2 + C \sum_{i=1}^{l} \xi_i \tag{20}$$

The modified cost function in (20) constitutes the so-called *structural risk*, which balances the *empirical risk* (i.e., the training errors reflected by the second term) with model complexity (the first term). The regularization parameter controls this trade-off. The purpose of using model complexity to constrain the optimization of empirical risk is to avoid *over fitting*, a situation in which the decision boundary too precisely corresponds to the training data, and thereby fails to perform well on data outside the training set.

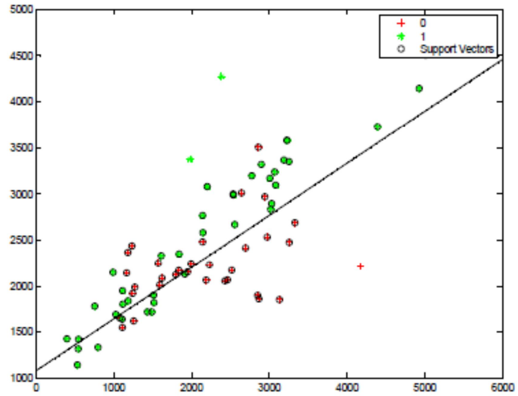

Fig 1. SVM classification of texture feature vectors

IV. RESULT

The SVM classifier is trained with 90% of features vector from the database & 10% of features vector is used in testing. The dataset are prepared using the four directional orientations (0^0, 90^0, 45^0, & 135^0) & for each pixel distance starting from 0, 1… up to 15. This each dataset extracted single orientation & single pixel distance was trained & tested using support vector machine classifier with linear kernel. The following chart shows the performance measure of SVM classifier (linear kernel) for feature vector along four different orientation & pixel distance.

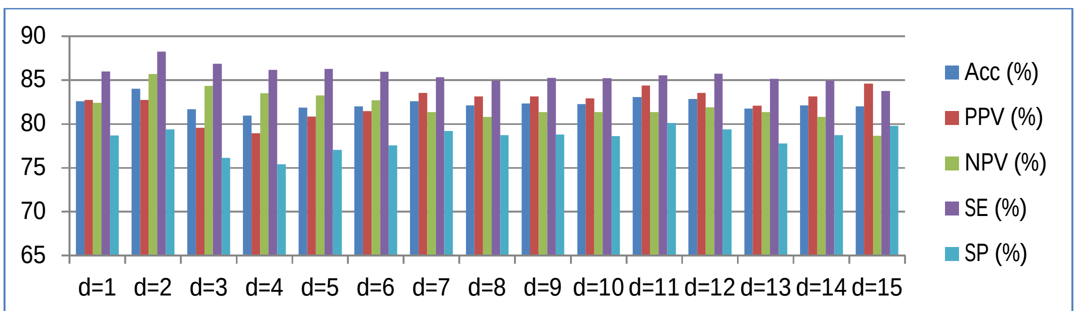

Chart 1: Performance measure for 0^0 orientation

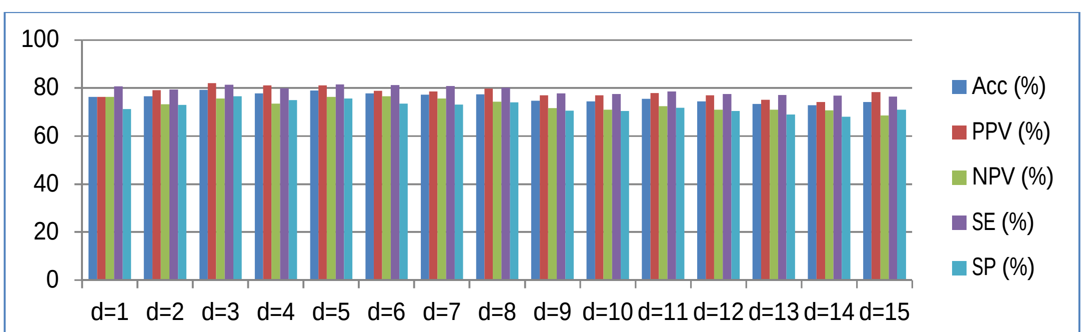

Chart 2: Performance measure for 90^0 orientation

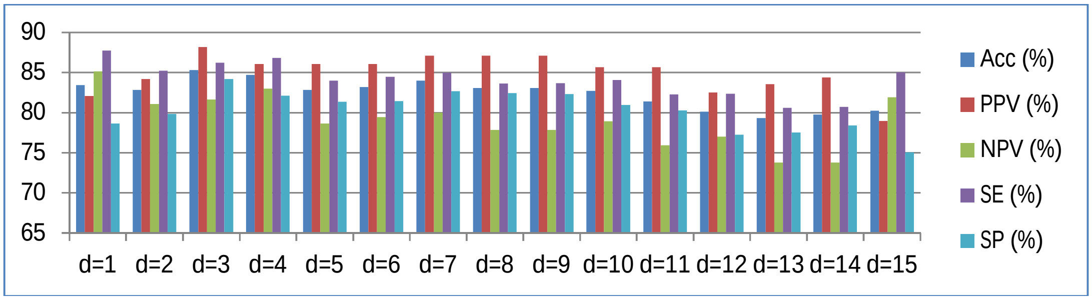

Chart 3: Performance measure for 45^0 orientation

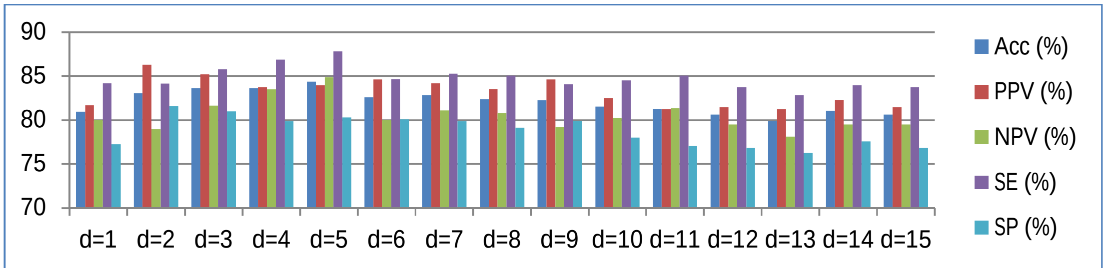

Chart 3: Performance measure for 135^0 orientation

V. **CONCLUSION**

Texture analysis of ultrasound medical images using quantitative information of the tissue characterization is used for the detection of thyroid nodule. The 10 gray level co-occurrence based texture features being extracted from 37 benign and 48 malignant thyroid images are use to classify into risk of malignancy using SVM Classifier with linear kernel. The performance of classifier shows the classification accuracy of 82.28 ± 0.70%, 76.023 ± 2.04, 82.39 ± 1.83, 82.14 ± 1.31. This classifier accuracy is calculated as mean of accuracies mentioned in charts of performance measure of classifier for 0^0, 90^0, 45^0, 135^0 orientations respectively. Thus, it's providing the objective method to physician to diagnosis of thyroid gland ultrasound images for detection of nodules malignancy risk. The classification of benign & malignant nodule will provide the second opinion to the physician about treatment of patient's and thus, the proposed work will help the physician to minimize the misdiagnosis rate of pathological diseases.

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