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SURVEY ARTICLE

Thyroid Classification as Normal and Abnormal using SCG based Feed Forward Back Propagation Neural Network Algorithm

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Abstract-Thyroid is a small butterfly shaped gland located in the front of the neck just below the Adams apple. Thyroid is one of the endocrine gland, which control metabolism by producing hormones. The abnormalities of the thyroid gland is detected and classified by using ultrasound imaging. In our proposed technique, initially the input images are preprocessed using adaptive median filter in order to suppress the presence of noise. After that the normal and abnormal thyroid images are classified using SCG based Feed Forward Back propagation Neural Network (FFBNN) which utilizes the statistical features extracted from the preprocessed image to reduce invasive operations such as biopsy and Fine Needle Aspiration (FNA). Normal and abnormal thyroid ultrasound image classification is compared with LMA based FFBNN algorithm.

Key terms:-Medical imaging; Thyroid; SCG based Feed Forward Back propagation Neural Network (FFBNN); Adaptive Median Filter (AMF); Classification.

1. INTRODUCTION

Now a days Medical image analysis has played more and more important role in many clinical procedures and in detecting different types of human diseases[3][4]. Most of the people have thyroid diseases [4]. Its incidence rate is increasing year by year [10]. Thyroid cancer [8][9] is the second most common cause of death in many countries. US images are often adopted due to their cost-effectiveness and portability in smaller hospitals. The thyroid is well suited to ultrasound [5[6] study because of its superficial location, size and echogenicity [7]. Different advanced techniques[10][11][14] in image classification like Artificial Neural Networks (ANN), Support Vector Machines (SVM), Fuzzy measures, Genetic Algorithms (GA), Fuzzy support Vector Machines (FSVM) and Genetic Algorithms with Neural Networks are being developed for image classification. One of the most popular and important types of NN architecture is Feed Forward Neural Networks. The thyroid ultrasound images fetched from the database are preprocessed using AMF to remove the noise. Then six statistical features are extracted from the preprocessed image and fed to SCG based FFBNN [1][2]to classify whether the given image is normal or abnormal.

Figure1. Sample of Thyroid Images

The rest of this paper is organized as follows. In Section 2 describes about preprocessing, section 3 describes about feature Extraction, section 4 describes about proposed classification, and section 5 describes about experimental results. Finally, the conclusion as well as future directions are summarized in Section 6.

II. PREPROCESSING USING AMF

The input thyroid ultra sound image may contain speckle noise which leads to obtain incorrect result. In order to obtain good accuracy, the noise must be removed from the input image. In our proposed work, we are using adaptive median filter to remove speckle noise. The adaptive median filter works based on the local statistics features which detects the impulse by calculating the difference between the standard deviation of the pixels within the filter window and the concerned current pixel.

Let the database (D) consists of many normal and abnormal thyroid ultrasound images and let $x_{i,j}$ be one of the images taken from the database. The lower and upper bounds of x are $st_{\min}$, $st_{\max}$ correspondingly.

$$st_{\min} \le x_{i,j} \le st_{\max} \ \forall (i, j) \in a \ , \ a \equiv \{1,2,\ldots m\} \times \{1,2,\ldots n\}$$

Lower bound: $st_{\min} = \mu 1(i, j) - um \times \sigma 1(i, j)$

Upper bound: $st_{\max} = \mu 1(i, j) + um \times \sigma 1(i, j)$

Functioning of Adaptive median filtering is detailed below,

1. Initialize the window size w = 3.
2. Compute maximum $\left(st_{i,j}^{\min, w}\right)$, minimum $\left(st_{i,j}^{\max, w}\right)$ and median $\left(st_{i,j}^{med, w}\right)$ of the pixel values in $st_{i,j}^{w}$.

3. If $st_{i,j}^{\min,w} < st_{i,j}^{med,w} < st_{i,j}^{\max,w}$, then go to step 5. Otherwise increment the window size w by 2.
4. If $w \le w_{\max}$ go to 2. Otherwise replace $y_{i,j}$ by $st_{i,j}^{med,w_{\max}}$.
5. If $st_{i,j}^{\min,w} < y_{i,j} < st_{i,j}^{\max,w}$, then $y_{i,j}$ is not a noise candidate otherwise replace $y_{i,j}$ by $st_{i,j}^{med,w}$.
6. The noisy pixels only replaced by the median $st_{i,j}^{med,w}$, while remaining are unaltered. Thus the speckle noise is removed from the given input thyroid ultrasound image and the preprocessed thyroid ultrasound image is represented as x'. This preprocessed thyroid ultrasound image (x') is then given to feature extraction process.

III. STATISTICAL FEATURE EXTRACTION

The preprocessed image x' obtained in the above process is subjected to 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). 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''.

Mean $\mu = \frac{1}{KxL}\sum_{i=0}^{K}\sum_{j=0}^{L} x''(i,j)$

K – Number of rows in the image
L – Number of columns in the image
x''(i, j) – pixel value at point at location (i,j)

Variance $V = \frac{1}{KxL}\sum_{i=0}^{K}\sum_{j=0}^{L} x''(i,j) - \mu(i,j)$

Contrast $C = \sum_{i=0}^{K}\sum_{j=0}^{L} |i-j|^{2}\, x''(i,j)$

Correlation $Cr = \sum_{i=0}^{K}\sum_{j=0}^{L} \frac{(i-\mu_i)(j-\mu_j)x''(i,j)}{\sigma_i \sigma_j}$

Histogram $HI = \sum_{k=HI-10}^{HI+10} h(k)$

Homogeneity $HO = \sum_{i,j} \frac{x''(i,j)}{1+|i-j|}$

$$\text{Energy } E = \sum_{i,j} x''(i,j)$$

$$\text{BDIP } B = \frac{M^2 - \sum_{i,j} x''(i,j)}{\max_{i,j \in B} x''(i,j)}$$

For calculating BDIP, the image is divided into block M x M. For each block BDIP is calculated. These extracted features are given as the input to FFBNN in order to classify the normal and abnormal thyroid ultrasound image, which is detailed in the next section

IV. CLASSIFICATION OF THYROID IMAGES USING FFBNN

In order to classify the normal and abnormal thyroid ultrasound images, SCG based 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 block diagram of proposed work is shown below.

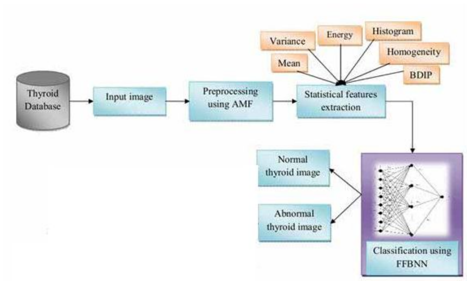

Figure2. Architecture of the proposed Thyroid classification

The neural network consists of 8 input units, h hidden units and only one output unit. The structure of the FFBNN is given as below:

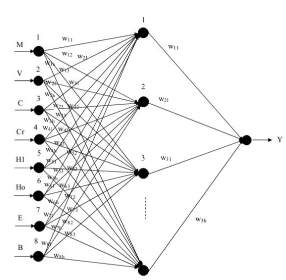

Figure3. Architecture of the FFBNN

We make use of Scaled Conjugate gradient algorithm[12] based Neural Network. SCG belongs to conjugate gradient techniques shows superior convergence than the other techniques. SCG avoids the time consuming line search per iteration by step size scaling process. SCG indicates the quadratic approximation is to the error E in a neighborhood of point w is given as $E_{qw}(y) = E(w) + E'(w)^T y + \frac{1}{2} y^T E''(w)$

To decide the minimum to $E_{qw}(y)$ the critical points for $E_{qw}(y)$ should be established. The critical points are the solution to the linear system defined by Moller is given as

$$E_{qw}(y) = E''(w)y + E'(w) = 0$$

The working mechanism of SCG is given below.

1. Choose initial weight vector w_k and scalars $\sigma > 0, \lambda_k > 0, \overline{\lambda_k} > 0$ and set $p_k, r_k = -E'(w_k)$ success = 1.

2. If success = 1, then compute second order information $\sigma_k = \sigma / |p_k|$

$$s_k = \frac{E'(w_k + \sigma_k p_k) - E'(w_k)}{\sigma_k}$$

$$\delta_k = p_k^T s_k$$

Scale: $s_k = s_k + (\lambda_k - \overline{\lambda_k}) p_k$

$$\delta_k = \delta_k + (\lambda_k - \overline{\lambda_k}) |p_k|^2$$

3. If $\delta_k \leq 0$, then make the Hessian matrix positive definite:

$$s_k = s_k + (\lambda_k - 2\frac{\delta_k}{|p_k|^2}) p_k$$

$$\overline{\lambda_k} = 2\frac{\delta_k}{|p_k|^2}$$

$$\delta_k = -\delta_k + \lambda_k p_k|^2,\ \lambda_k = \overline{\lambda_k}$$

4. Compute step size: $\alpha_k = \frac{\mu_k}{\delta_k}$, $\mu_k = p^T{}_k r_k$

5. Compute the contrast parameter; $\Delta k = \frac{2\delta_k [E(w_k) - E(w_k + \alpha_k p_k)]}{\mu^2{}_k}$

6. If $\Delta k \geq 0$, then a successful reduction in error can be made:

$$w_k + 1 = w_k + \alpha_k p_k$$

$$r_{k+1} = -E'(w_{k+1}),\ \overline{\lambda_k} = 0, \text{success} = 1.$$

7. If $k = \text{mod} N = 0$ then restart the algorithm as $p_{k+1} = r_{k+1}$ else create new conjugate direction

$$\beta k = \frac{|r_{k+1}|^2 - r_{k+1} r_k}{\mu_k}$$

$$p_{k+1} = r_{k+1} + \beta_k p_k$$

8. If $\Delta_k \geq 0.75$, then reduce the scale parameter $\lambda_k = \frac{\lambda_k}{2}$, else reduction in error is not possible $\overline{\lambda_k} = \lambda_k$, success = 0.

9. If $\Delta_k \geq 0.25$, then reduce the scale parameter $\lambda_k = 4\lambda_k$.

10. If the steepest descent direction $r_k \neq 0$ then set k=k+1and go to 2 else terminate and
return the result.

N - Number of iterations, p_k - Search direction, α_k -Step size, $E(w_k)$ - global error function, $E'(w_k)$ - gradient, r_k - steepest descent direction, λ_k - Lagrange multiplier

V. RESULTS AND DISCUSSION

The experimental results to classify thyroid US medical images using FFBNN with SCG training algorithm was shown below. Specificity, Sensitivity and Accuracy are statistical measures of the performance of a classification test. In our proposed method, among 20 abnormal images 18 abnormal images are correctly classified and among 5 normal images 4 normal images are correctly classified as normal. In existing method, 16 abnormal images and 3 normal image are correctly classified

TABLE 1: TRAINING AND TESTING DATA SETS

Stage	**No of data sets used for training**	**No of data used for testing**	**Training algorithm used**	**% of correct classification**
Normal	5	5	LM	60
			SCG	80
Abnormal	12	20	LM	75
			SCG	90

The statistical measures of our proposed SCG based FFBNN technique [12] and Levenberg Marquardt Algorithm (LMA) [13] based FFBNN technique for the abnormality of the thyroid ultrasound image classification is given in Table 2

TABLE 2

PERFORMANCE OF OUR PROPOSED SCG BASED FFBNN TECHNIQUE AND LMA BASED FFBNN TECHNIQUE.

Measures	**Proposed SCG based FFBNN**	**LMA based FFBNN**
Accuracy	94.7	75
Sensitivity	90	88.33
Specificity	66.66	37.5

In table2, accuracy, sensitivity and specificity measures are given. The accuracy of the proposed technique is 94.7%. LMA based FFBNN has 75% of accuracy. Accuracy of the proposed technique is significantly higher when compared to the LMA based FFBNN. It is about 19% higher than the LMA based FFBNN. It represents the proposed technique classifies the thyroid nodule accurately than the other technique. While considering the sensitivity measure, the proposed technique has 90% and LMA based FFBNN has 88.33% of sensitivity. LMA based FFBNN has 37.5% specificity whereas SCG based FFBNN has 66.66% of specificity. It is about 29% higher than the LMA based FFBNN. It indicates that the proposed technique has higher performance.

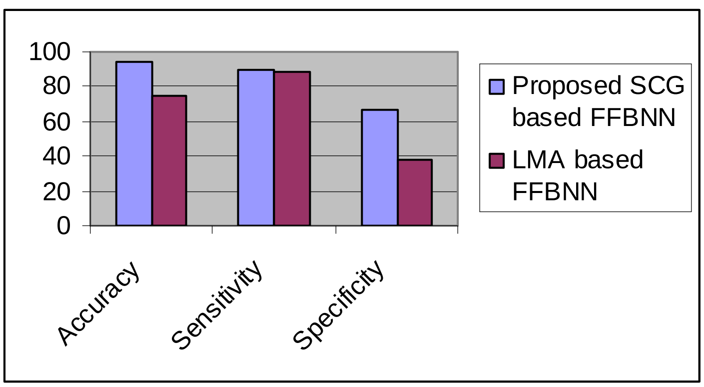

Figure4. Proposed SCG based FFBNN technique and LMA based FFBNN technique's performance in terms of Accuracy, Sensitivity and Specificity

VI. CONCLUSION AND FUTURE WORK

In this project, SCG based FFBNN learning algorithm is used to classify the thyroid images as normal and abnormal. SCG converges in a short time with high correct classification percentage. Similarly the sensitivity and specificity measure of the proposed SCG based FFBNN technique is also remarkably higher than the LMA based FFBNN. It indicates that our proposed SCG based FFBNN technique attained better performance when compared to the LMA based FFBNN. As a future work, we consider using more samples to train the classifier and will also classify the Abnormal Thyroid US medical images as Malignant and Benign nodules.

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