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Classification of Ultrasoud Thyroid Nodule Using Feed Forward Neural Network

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Abstract: Presently, one of the main issues to create challenges in medicine sciences by developing technology is the disease diagnosis with high accuracy. An automatic system is developed that classifies the thyroid nodule images using machine learning algorithms. Ultrasound imaging is the best way to prediction of which type of thyroid is there. Ultrasound thyroid Nodules images were distinguishing in two groups Benign (non-cancerous) and Malignant (cancerous). Artificial Neural Networks (ANNs) are considered as the best solutions to achieve this goal and involve in widespread researches to diagnose the diseases. In this paper, we consider a Feed Forward Multi-layer Perception (MLP) ANN using back propagation learning algorithm to classify Thyroid disease.

Key words: Ultrasound thyroid Nodules · Gray Level Co-occurrence Matrix method · Artificial Neural Network · Feed Forward Neural Network · Multi-layer Perception Neural Network

INTRODUCTION

Medical imaging is one of the important areas in image processing, as manual diagnosis is more laborious and time consuming comparative to computerized methods. With technology advancements, lots of techniques had originated to detect the many diseases associated with human body [1]. Various Imaging technologies are there like MRI (Magnetic Resonance Imaging), X-rays, Computed Tomography, Optical Coherence Tomography and Ultrasound (US) [2-7]. Thyroid nodules contain two main types i.e. benign and malignant, except these hypothyroidism and hyperthyroidism are also the categories of thyroid disorders.

A ultrasound thyroid nodule examination provides an objective and precise method for detection of a change in the size of the nodule, used to evaluate the Ultrasound features, calcifications, vascularity, size, shape, echogenicity (hypo echoic or hyper echoic), orientation, Texture, mean, variance and composition (cystic, solid, or mixed), as well as presence or absence of coarse and irregular margins [8-11].

Using neural network the thyroid is classified to be benign or malignant. A Feed Forward neural network is a type of artificial neural network where connections between the units do not form a rotation. This is different from Feed Back neural networks or recurrent neural networks. In this network, the information moves in a single direction, from the input nodes, through the hidden nodes (if any) and forward to the output nodes. There are no rotations or loops in the network. Feed forward ANNs which trained by back propagation learning algorithm which pertains under-supervision learning and turn into trained like a human being [1]. In this paper, we used the dataset of UCI machine learning by using Feed Forward MLP ANN to classify Thyroid disease. Due to learning capability, better performance in classification problems as efficient and decision making based on diagnoses features (like human intelligence); Feed Forward MLP ANNs are the best system to do this task proper performance to ANN simulation.

METHODS AND MATERIALS

Thyroid nodules are irregular lumps growing within the thyroid gland which may represent various different conditions including cancer. In last few years, various works are done for the diagnosis of thyroid diseases using various image processing algorithms. These algorithms mainly use Ultrasound images. The image undergoes the contrast enhancement to

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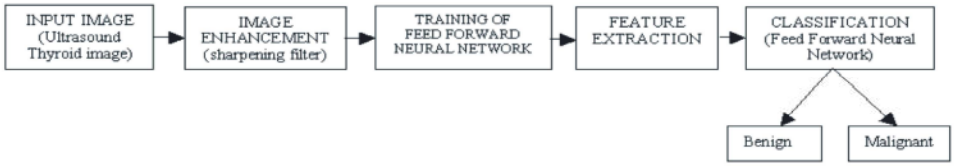

Fig. 1: Classification of Ultrasound thyroid nodule

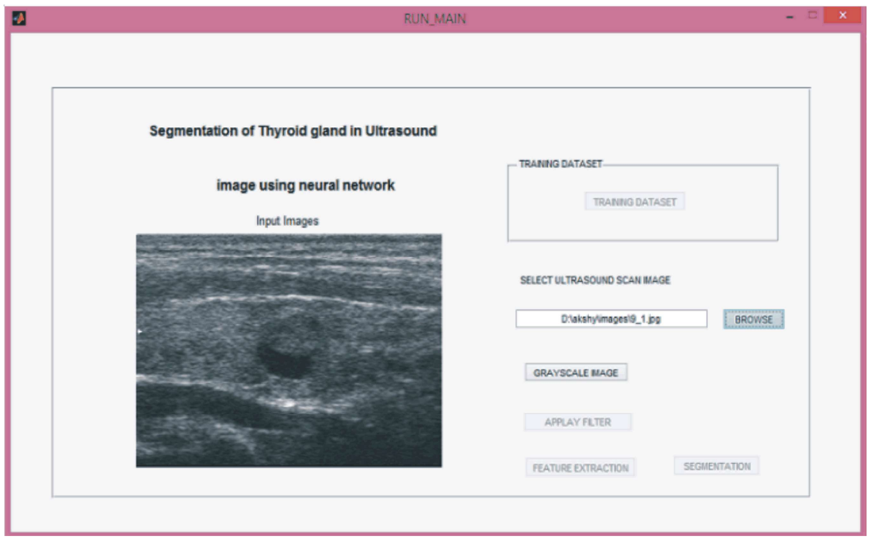

Fig. 2: Ultrasound thyroid nodule input image.

suppress speckle. The enhanced image is used for further processing of segmentation the thyroid region by local region-based active contour. To classify the segmented region using feed forward neural network with the help of extracted features from the segmented output. Figure 1 explains the block diagram of the proposed method for thyroid nodule classification.

Input Image: Most structures of neck, including the thyroid and parathyroid glands, lymph nodes and salivary glands, are well-visualized by lofty frequency ultrasound with excellent anatomic detail. Ultrasound is the preferred imaging modality for thyroid lumps and ultrasonography is serious in the evaluation, preoperative planning and postoperative surveillance of patients with thyroid malignancy. Many other benign and malignant conditions in the head and neck can be evaluated and managed with help of diagnostic ultrasound and ultrasound guided procedures. In the proposed work 497 ultrasound thyroid images have been used. Figure 2 shows the ultrasound thyroid nodule input image.

Preprocessing: The aim of pre-processing stage is an upgradement of the image data that suppresses undesired distortions or enhances some image features related for further processing and analysis task [3]. Such pre-processing operations are also called filtration. In last few years, various types of filters like median filter, wavelet filter and an-isotropic diffusion filter are used to remove or suppress the speckle noise [4, 5]. In this paper, Sharpening filter is used to suppress speckle noise.

In principle, image sharpening consists of adding to the original image a signal that is proportional to a high-pass filtered version of the original image. It is often referred to an unsharp masking on a one-dimensional signal. The given image is first filtered by a high-pass filter that extracts the high-frequency components and then a scaled description of the high-pass filter output is added to the original image, thus producing a sharpened image of the original. Note that the identical regions of the signal, i.e., where the signal is constant, remain unchanged. The sharpening operation can be represented

by $$f(s) = f+\lambda f_s \quad (1)$$

Where Enhanced image f(s) is the addition of Original image (f) and scaled version of the high pass filter (λf_s). It enhances the line structure or details in

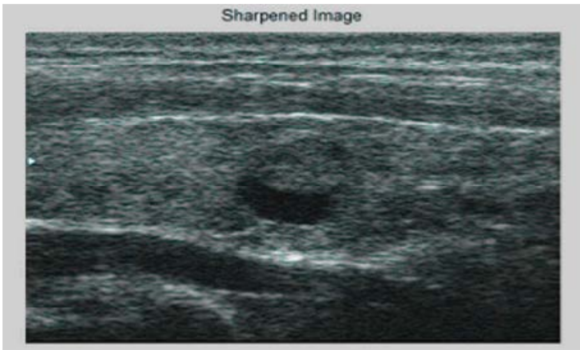

Fig. 3: Sharpened image

the image. Figure 3 shows the enhanced, speckle removed ultrasound thyroid nodule image using sharpening filter.

Feature Extraction: It is a type of representing the interesting part of an image as a compact feature vector. Feature Extraction technique is mainly used to extract features from original image which contains redundant data but not much information. The goal of using feature extraction methods is to transform the input data into a reduced depiction set of features so as to extract related data. If features extracted are carefully selected then it is clear that feature set will extract related information from input data in order to perform desired task using reduced feature set instead of full size input. At first features are extracted from the thyroid region manually selected by the physician and also from non-thyroid region. The growth of malignant tumors tends to distort the surrounding tissue texture, while benign nodules tend to have soft surfaces with more uniform texture around them. Different shapes and margins have different probabilities of malignancy. Thus, texture features have the potential to capture characteristics that are diagnostically important but are not easily visually extracted. There are 78 textural features like Autocorrelation, Correlation, Mean, Standard Deviation, Variance, Sum Average, Entropy, Skewness, Contrast, Difference Entropy, Difference Variance, Maximum probability, Sum Entropy, Sum Variance, Contrast, Energy, Entropy, Sum of Squares, Dissimilarity, Homogeneity, Cluster Shade and Cluster Prominence etc., are extracted from ROIs, which were outlined by radiologist and recognized by biopsy (Figure 4). Among them 10 features of preprocessed ultrasound thyroid nodule image are extracted from the Gray Level Co-occurrence Matrix (GLCM) method [4-9]. Extracted features are then used in feed forward neural network to train the network.

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autoc: [9.747835274908231e+00 1.003031590475651e+01]
contr: [8.664717902145535e-01 3.248834003663212e-01]
corrm: [6.903519376751190e-01 8.850654412207495e-01]
corrp: [6.903519376751123e-01 8.850654412207518e-01]
cprom: [6.432713959401632e+01 9.014408416649349e+01]
cshad: [3.981415675967527e+00 6.353486404871553e+00]
dissi: [6.328092481174552e-01 3.135349987726355e-01]
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homom: [7.186565147116857e-01 8.448832385160490e-01]
homop: [7.067316520080405e-01 8.443086328873112e-01]
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sosvh: [1.016467144272134e+01 1.010861895652032e+01]
savgh: [5.927186211072009e+00 5.926027681791575e+00]
svarh: [1.893163866696640e+01 1.970630617858534e+01]
senth: [2.158170138163715e+00 2.134199198782750e+00]
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indnc: [9.321850721101485e-01 9.652816764525818e-01]
idmnc: [9.871090832573142e-01 9.950276619536308e-01]
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Fig. 4: Extracted Features using GLCM method

Classification: Medical image Classification can play an vital role in diagnostic and teaching purposes in medicine. For these reasons different imaging modalities are used. There are many classifications created for medical images using both grey-scale and color medical images. The best way is to find the texture of the images and have the analysis. Texture classification is an image processing method by which different regions of an image are identified based on texture properties. The next way is by using neural network classification techniques. Multi-layer Perceptron Artificial Neural Network (MLP-ANN) is used in a broad range of uses including function approximation, feature extraction, optimization, compression and classification. It is appropriate for medical imaging uses because of the following reasons:

- For an MLP-ANN with a hidden layer, the output is a nonlinear function of a linear mixture of the neuron outputs in the hidden layer which themselves are nonlinear functions of linear combinations of the input variables. This allows the network to construct parametric nonlinear functions of the participation features. The parameters of the network are estimated by optimizing an objective function (usually the mean square error between the desired and actual outputs) by a back-propagation algorithm.

- Due to the connection between the input features, the intrinsic dimensionality of the input feature space is usually smaller than the number of input features. When the number of neurons in the hidden layer is smaller than that of the input layer, it means that the hidden layer characterizes a lower dimensional feature space, which can have the same number of dimensions as that of the essential feature space.
- Depending upon the desired output, some of the features may be irrelevant. An MLP-ANN automatically ignores them by conveying zero (or very small weights) to them. In a sense, it does the job of feature selection.

In our proposed work, we used a Feed Forward Multi-layer Perceptron Artificial Neural Network, trained with back propagation, for extracting pattern [1-10]. Three different layers in the network are input, hidden and output layer. The connections in the feed forward multi layer perceptron neural network are unidirectional, which means signals or information being practiced can pass through the network in a one direction, starting from the input layer(s), entering through the hidden layers to the output layer. Depending on the number of inputs and extracted features, input and hidden layer contains sufficient number of neurons. Network acknowledges the input in vector form:

$$Yi = [x_{i,1}, x_{i,2},..., x_{i,m}] \quad (2)$$

where $x_{i,m}$ is the m^{th} feature of the i^{th} pixel.

Classification of ultrasound thyroid nodule images using feed forward neural network done by neural network pattern recognition tool in MATLAB [4]. Using this tool, firstly, the ultrasound thyroid nodule images are trained with textural features which were summarized by radiologist and predicted by biopsy with the help of reference images. Then 497 ultrasound thyroid nodule images are tested with respect to the trained image. Overall performance the feed forward neural network classifier is evaluated by confusion matrix. A confusion matrix is a table that is frequently used to describe the performance of a classification model or "classifier" on a group of test data for which the true values are known.

Confusion matrix in neural network pattern recognition tool: It shows the various types of error occurred for the final network. The slanting cells show the number of classes that were correctly classified and the off slanting cells shows the misclassified groups. The blue cell in the bottom right proves the total percent of correctly classified cases (in green) and the total percent of misclassified groups (in red). The results show very good recognition.

Table 1: Equations of Parameters

Parameters	Equations
Accuracy	(TP +TN)/[(TP+FN)+(FP+TN)]
Specificity	TN /(TN+FP)
Sensitivity	TP /(TP+FN)
Positive Predictive Value (PPV)	TP /(TP+FP)
Negative Predictive Value (NPV)	TN /(TN+FN)

The proper procedure of segmentation method the thyroid nodule image are segmented with Quantitative measurement of classification accuracy is calculated in term of True positive (TP), False positive (FP), True negative (TN), False negative (FN) with respect to the ground truth. Table 1 gives the equations of performance parameters.

RESULTS

The ultrasound image database used in the proposed method includes 497 images. Figure 2, 3 and 4 shows the speckled thyroid US images, pre-processed images and extracted features details. Figure 5 and 6 shows the neural network training [Snapshot: Created during the training Neural network using nntraintool] and confusion matrix obtained from classification output.

Table 2 shows the classification results obtained from confusion matrix with Feed Forward Neural Network classifier. It can be noticed that the maximum accuracy, sensitivity and specificity obtained with ANN approach is 68.00%, 69.5% and 59.5% respectively.

Table 2: Results of Feed Forward Neural Network Classifiers

PARAMETERS	Feed Forward Neural Network Classifier
True Positive(TP)	294
True Negative(TN)	44
False Positive(FP)	30
False Negative(FN)	129
Positive Predictive Value (PPV)	90.7 %
Negative Predictive Value (NPV)	25.4 %
Sensitivity	69.5 %
Specificity	59.5%
Accuracy	68.00 %

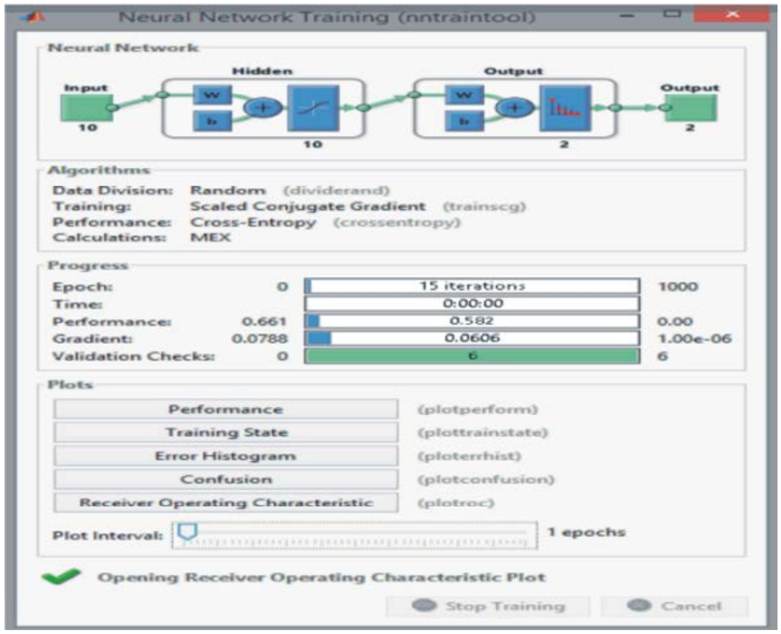

Fig. 5: Neural Network Training

Fig. 6: Result of confusion matrix

DISCUSSION

This proposed method utilizes 10 features to efficiently distinguish between benign and malignant thyroid nodules. The 10 features from the extracted nodule within the ultrasound images were applied as classification criteria. The Artificial neural network utilized all the features to classify the thyroid nodule. Our experimental results suggest that using textural features based on nodule for classifying benign and malignant nodules is effective and reliable. Thus, this system is useful for differential diagnosis of thyroid nodules based on ultrasound images and could lead to a decreased need for thyroid biopsies. Medical costs and adverse reaction will be reduced as well.

CONCLUSION

Thyroid is a disease which is common and found enormously in females; hence the diagnosing should be at the easiness. Compared with MRI and CT, Ultrasound is the finest diagnostic tool for imaging diseases.

Rather than physical diagnosing, approach to classifications remains convenient and time consuming. It reads the pixels and takes the features as criteria for segmentation and classification. Firstly, it reads the ultrasound image, then to eliminate the noise using sharpening filter. Then the features are extracted using GLCM method. Extracted features of Ultrasound thyroid nodule are classified by feed forward neural network. The classification part is functioned by neural network toolbox.

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