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Detection and Diagnosis of Tumor Regions in Thyroid Images using CANFIS Classifier

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Abstract

Thyroid tumor is an uncommon type of cancer. This cancer can be cured if it is detected promptly and treated correctly. This paper presents a tool for the detection and diagnosis of thyroid malignant areas using Co-active Adaptive Neuro-Fuzzy Inference System (CANFIS) classifier. The proposed methodology considers the image enhancement stage, feature extraction along with classification stage. Gaussian filter is applied to enhance the thyroid image in terms of smoothen the edge regions and features are extracted from the enhanced thyroid image. These extracted features are classified using the proposed algorithm to classify the thyroid image into either benign or malignant nodule. The tumor region of interest is segmented by morphological segmentation. The performance of the planned thyroid tumor detection system is analyzed using performance parameters.

Keywords: Thyroid images; Tumor regions; Diagnosis; Segmentation; Co-active Adaptive Neuro-Fuzzy Inference System classifier

Introduction

Thyroid nodules are found in subjects without any symptomatology. The predominance of thyroid nodules is benevolent and not cancerous. Thyroid lump be a set of indication in which the thyroid gland cells grow to be irregular, wildly and form a tumor. Finding cancer in a thyroid nodule is further probably in a person younger than thirty years or older than sixty years. Several types of thyroid cancer are known, such as papillary thyroid carcinoma, follicular thyroid carcinoma, anaplastic thyroid carcinoma, or thyroid lymphoma. The warning sign of the thyroid cancer is expansion of thyroid nodule in thyroid gland. Most people with thyroid nodules have no symptoms. Benign nodules are usually small (less than that one centimeter) and need periodical follow-up. A thyroid tumor is recognizable at its initial stage using ultrasound (US) imaging technique [1]. In addition to volume, location and number of nodules, distinctness of borders, additional nodule filling like calcium deposits or the amount of blood flow, US can evaluates blood surge to the thyroid and its nodules [2].

A method to detect the irregular thyroid nodule from the normal thyroid nodule using Co-active Adaptive Neuro-Fuzzy Inference System (CANFIS) classifier is proposed in this paper. Furthermore, the morphological operations are applied to segment the tumor region on irregular thyroid nodule.

Literature Survey

Tsuda et al. [3] analyzed thyroid cancer in the people of Fukushima (Japan) aged from 18 to 25. The authors screened the thyroid cancer using the ultra sound images. The authors achieved 95% confidence level while screening the thyroid cancer in thyroid ultrasound images. Nugroho et al. [2] used active contour bilateral filtering technique to detect the thyroid nodule in ultrasound images. The irregular boundary of the nodule in the thyroid was detected and segmented accurately using this bilateral filtering approach.The authors detected and removed the speckle noises in the thyroid image before the process of segmentation. Gomathy et al. [4] used Principle Component Analysis method for detecting the thyroid gland in ultra sound images. Region of Interest (ROI) and Morphological operations were used to segment the thyroid area accurately. Du et al. [5] developed a method for detecting the thyroid nodule in ulra sound images. The speckle noises were detected and removed using anisotropic diffusion filter. Local phase symmetry features were extracted from the thyroid images for accurate nodule segmentation.

Gireesha et al. [6] used watershed segmentation algorithm to segment the abnormality in ultrasound thyroid images. SVM classifier was used to classify the malignant and benign thyroid nodules from ultrasound images. The authors achieved an average accuracy of 92.5%, sensitivity of 99.66% and specificity of 80% for thyroid abnormal nodule segmentation. Vaz [7] used multilayer perceptron neural network classifier to classify the abnormal thyroid nodule from the benign nodule. The authors achieved 93.12% of sensitivity for abnormal region segmentation. Gopinath et al. [8] used SVM classifier to detect the thyroid cancer in ultrasound images. The statistical texture features were extracted from test thyroid image and classified with trained features of thyroid images. The authors achieved 96.7% average accuracy and 95% sensitivity for cancer region segmentation in thyroid images. Singh et al. [9] classified thyroid nodules into either benign or malignant nodule using Support Vector Machine (SVM) classifier. Grey level co-occurrence matrix (GLCM) features were extracted from test thyroid ultra sound image and classified with the features trained by SVM classifier. The authors achieved 84.62% segmentation accuracy. Onkendi et al. [10] proposed a method for detecting the thyroid cancer in Primary Hyperparathyroidism. The authors achieved 52% sensitivity, 88% specificity, 47% positive predictive value and 90% negative predictive value by applying their screening methodology over 470 patients.

Maroulis et al. [11] proposed Variable Background Active Contour algorithm for the detection of abnormal nodules in thyroid images. The variable background model improved the sensitivity level of the nodule detection while compared with conventional Active contour model. The authors achieved 91% average accuracy for nodule detection in ultrasound images. Kobayashi et al. [12] applied fuzzy edge detection algorithm in ultra sound thyroid images to detect and segment the abnormal cancer cells. The authors constructed improved generalized fuzzy rules for the cancer cell boundary segmentation.

The conventional methodologies were based on pixel level processing approaches for the detection and segmentation of thyroid cancer in ultra sound images. The main limitations of the conventional methods were its high detection time and low tumor region segmentation accuracy. The limitations in the conventional methods are overcome by CANFIS classifier proposed in this paper.

Material and Method

The ultrasound thyroid images used in this article are obtained from Wilmington Endocrinology dataset (http://www.cancerimagingarchive.net/). A publicly existing open access dataset examined 155 consecutive patients with biochemically proven primary hyperparathyroidism and single parathyroid adenoma recognized by ultrasound imaging method.

This paper proposes an automatic detection and diagnosis system for tumors in thyroid images. The planned systems implemented both tumor region detection and tumor region diagnosis. The tumor region detection stage consists of preprocessing, feature extraction and classifications. The tumor region diagnosis stage consists of morphological analysis of tumor pixels, which can be further classified as kind, sensible and severe. The proposed thyroid tumor detection system is shown in Figure 1.

Preprocessing

Image enhancement in the form of image smoothening which is accomplished in this paper is done by applying the Gaussian filter [13] on thyroid image.

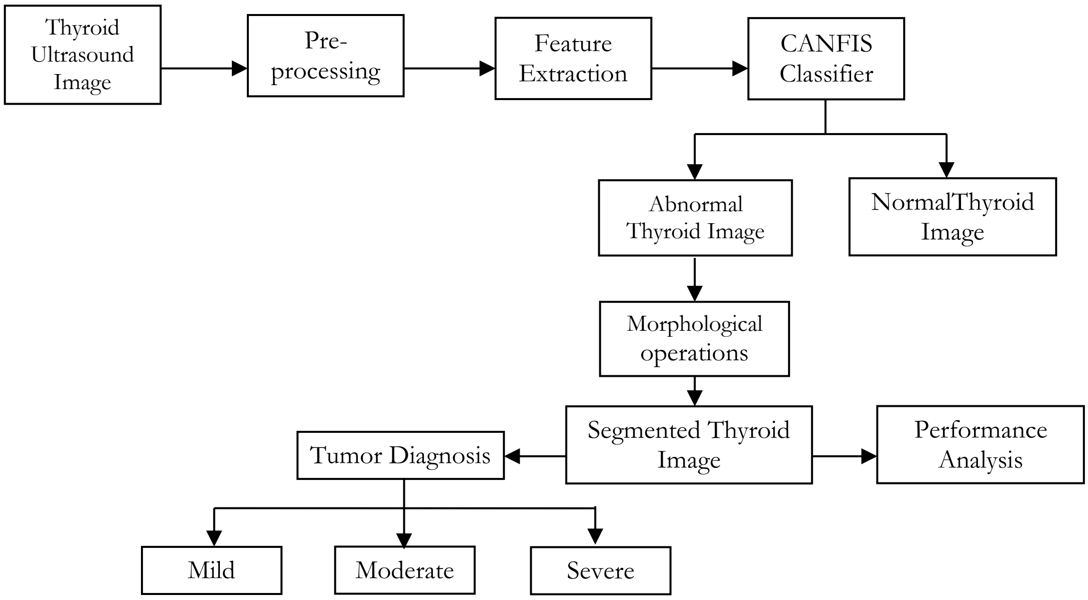

Figure 1. Proposed thyroid tumor detection and diagnosis system

The 2D Gaussian kernel is attained by taking product on two one-dimensional Gaussian kernels, which is further applied on the thyroid image in order to get the smooth regions. Figure 2(a) shows the thyroid image.

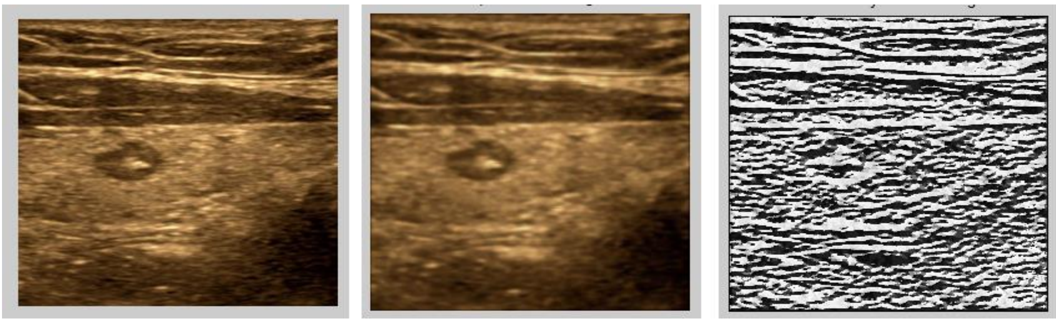

Figure 2 (a). Thyroid image; **(b)** Preprocessed image; **(c)** Local binary pattern feature extracted image

Feature Extraction

In this paper, the features such as LBP (Local Binary Pattern) and Grey Level Co-occurrence Matrix (GLCM) features are extracted from the preprocessed thyroid image and it take part in a vital role in differentiating the malignant from benign abnormal thyroid nodules.

Local Binary Pattern

The most important for texture analysis is to describe the spatial behavior of intensity values in any given neighborhood. Local binary pattern (LBP) is one of the widely used approaches for image analysis. The LBP is an operator that describes the surroundings of a pixel by generating a bit code from the binary derivatives of a pixel. The operator is usually applied to a grey-scale images and derivatives of the intensities. An LBP code for a neighborhood was produced by multiplying the threshold values with weights given to the corresponding pixels, and summing up the result. The procedure is repeated in anticipation of no more pixels in preprocessed image with the LBP feature extraction (Figure 2(b) (c)).

Grey Level Co-occurrence Matrix

Grey Level Co-occurrence Matrix can be constructed using one of the following orientations: 0°, 45°, 90°, and 135°. In this paper, orientation 45° is chosen for constructing the GLCM matrix [14]. The total number of pixel intensity is computed at the orientation of 45° in all the values of image pixels. From the GLCM matrix, the following texture features are determined to differentiate the normal thyroid image and abnormal thyroid image. The extracted GLCM features set are entropy, homogeneity, contrast, energy, correlation coefficient, variance, maximum probability, and inverse different moment. Table 1 shows the GLCM feature values for normal thyroid image, which do not have any lesions, and abnormal thyroid image with lesions (Table 1). The GLCM features for normal and abnormal values derived from simulation results.

Table 1.GLCM features for normal and abnormal thyroid images

GLCM features	Computation Expression	Lesion free thyroid image	Abnormal thyroid image
Entropy	$\sum_{i}^{M}\sum_{j}^{N} P[i,j]logP[i,j]$	1.0899	1.0965
Homogeneity	$\sum_{i=1}^{M}\sum_{j=1}^{N} \frac{P[i,j]}{1+\lvert i-j\rvert}$	4.196	3.5404
Contrast	$\sum_{i}^{M}\sum_{j}^{N} (i-j)^2 P[i,j]$	9.1688	1.0387
Energy	$\sum_{i}^{M}\sum_{j}^{N} P^2[i,j]$	2.1287	1.8824
Correlation coefficient	$\sum_{i=1}^{M}\sum_{j=1}^{N} \frac{(i-\mu)(j-\mu)P[i,j]}{\sigma^2}$	1.0990	-1.2732
Variance	$\frac{1}{2}\sum_{i=1}^{M}\sum_{j=1}^{N} ((i-\mu)^2 P[i,j]+(j-\mu)^2 P[i,j])$	6.7221	6.2724
Maximum probability	$\max_{\mathrm{i,j}}^{M,N} \mathrm{P[i,j]}$	5.2200	4.2239
Inverse differencemoment	$\sum_{i=1}^{M}\sum_{j=1}^{N} \frac{P[i,j]}{\lvert i-j\rvert^k}\ ,\quad i\neq j$	8.9534	8.8174

Classification

Conventional classification methods such as SVM and Neural Networks (NN) classified thyroid images with low classification rate. In order to improve the classification rate, CANFIS classifier is used in this work [15]. This classifier is used to classify the source test thyroid image into either normal or abnormal. The features from the source thyroid image are given as input to X node in CANFIS architecture [16]. The trained patterns (constitute both normal and abnormal case) are fed to Y node in CANFIS architecture. This architecture produces either 0 or 1 based on the trained patterns. The binary value 0 indicates normal category and binary value 1 indicates abnormal category.

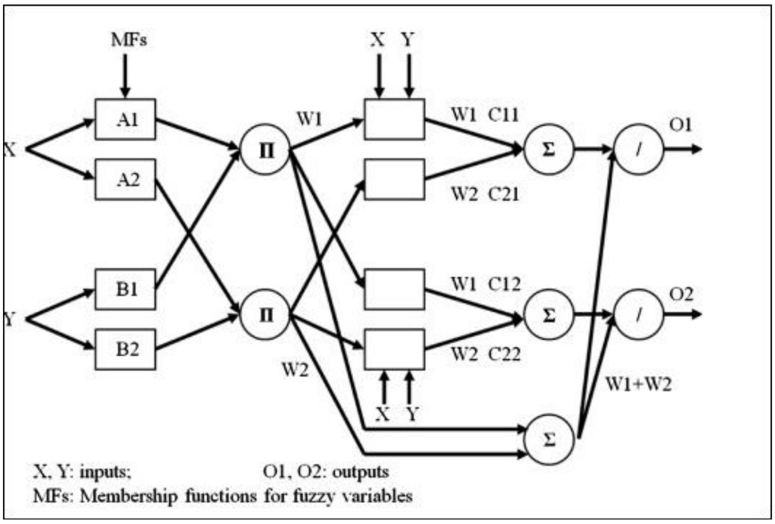

Figure 3. Architecture of CANFIS classifier

Figure 3 shows the architecture of CANFIS classifier. The inputs of this classifier are represented by X and Y which are the extracted features from the pre processed thyroid image. The output is either trained pattern or classified pattern based on mode of this classifier. The operations for eachlayer of the CANFIS classifier is explained in the following equations as:

Layer 1 is represented by,

$G_{1,i} = \vartheta_{A_i}(x)$ for i=1,2,….

$G_{1,i} = \vartheta_{B_i}(y)$ for i=3,4,….

whereas, $\vartheta_{A_i}(x)$ and $\vartheta_{B_i}(y)$ represents the extracted input features from preprocessed thyroid image x and y are the inputs and f is the required output.

Layer 2 is represented by,

$$\vartheta_A(x) = \frac{1}{1 + \left|\frac{x-c_i}{a_i}\right|^{2b_i}}$$

$G_{2,i} = w_i = \vartheta_{A_i}(x)\,.\,\vartheta_{B_i}(y)$, i=1,2,…..where a_i, b_i and c_i are the parameters for the membership function.

Layer 3 is represented by,

$$G_{3,i} = w_i = \frac{w_i}{w_1 + w_2}$$

where, w_1 and w_2 are the weights of the nodes in CANFIS architecture.

Layer 4 is represented by,

$$G_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i)$$

where p_i, q_i, and r_i are design parameters (consequent parameter since they deal with the then-part of the fuzzy rule)

Layer 5 is represented by,

$$G_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

Using CANFIS classifier, the feature extracted image is classified as normal (benign) or abnormal (malignant).

155 ultrasound thyroid images were obtained from an open access dataset in the group of 60 benign and 95 malignant thyroid ultrasound images. The training set is formed by random 30 images

from both benign and malignant categories. Then, remaining 95 images (benign: 30 and malignant: 65) are grouped in testing set for classification.

Segmentation

The tumor region in the classified abnormal thyroid image is further segmented using morphological operations. Dialation and erosion are used as morphological functions. The classified thyroid image is dilated and then eroded [17]. The eroded thyroid image is now absolutely subtracted from the dilated thyroid image, which segments the abnormal regions in the classified abnormal thyroid image.

Evaluation

The performance analysis of this proposed thyroid cancer detection and diagnosis system is analyzed via Specificity, Sensitivity, PPV, NPV, and Accuracy. These performance evaluation parameters are based on evaluating metrics as True Positive (total number of fittingly detected tumor pixels as tumor pixels in resultant thyroid image), True Negative (total number of fittingly detected non-tumor pixels as non-tumor pixels in resultant thyroid image), False Positive (total number of erroneously detected tumor pixels as non-tumor pixels in resultant thyroid image), and False Negative (total number of erroneously detected non-tumor pixels as tumor pixels in resultant thyroid image).

Results and Discussion

Experimental results used in this paper are categorized into detection of tumor region and diagnosis of tumor region.

Detection of Tumor Region

The proposed system for thyroid cancer classification correctly classifies 30 benign images as normal and 64 malignant images as abnormal images. The proposed system reaches 100% average classification accuracy for benign category and 98.4% average classification accuracy for malignant case. The values of evaluating metrics for abnormal thyroid image are shown in Table 2.

Table 2. Performance analysis of thyroid tumor segmentation

Parameters	Value
Sensitivity (%)	99.20
Specificity (%)	99.24
Positive predictive value (%)	77.30
Negative predictive value (%)	99.07
Accuracy (%)	99.08
Detection Time (ms)	0.35

Diagnosis of Tumor Region

The segmented thyroid tumor region is diagnosed using their morphological analysis. In this article, morphological parameters as Tumor Area, Width, Height and Perimeter are calculated. The tumor is diagnosed into mild, moderate and severe based on the determined morphological values. Table 3 shows the extracted values of the morphological parameters.

The conventional methodologies were based pixel level processing approaches for the detection and segmentation of thyroid cancer in ultra sound images. The main limitations of the conventional methods were its high detection time and low tumor region segmentation accuracy. The limitations in the conventional methods are overcome by proposed CANFIS classifier which produces high segmentation accuracy of 99.08%.

Table 3. Morphological analysis of segmented thyroid tumor region

Morphological parameters	Value
Area (μm²)	1514.0 ± 20.1
Width (μm)	59.298484 2.31
Height (μm)	32.953572 ± 1.96
Perimeter (μm)	168.877000 ± 2.85

In this paper, 65 malignant thyroid ultrasound images are tested. The images are categorized as 10 images as mild case, 10 images as moderate case and 45 images as severe case. The proposed thyroid tumor detection and diagnosis system correctly diagnose 10 mild images as mild case, 10 moderate images as moderate case, and 44 severe images as severe case. Hence, the proposed system reaches 100% classification accuracy for mild and moderate case and 98.4% of classification accuracy for severe case.

Conclusion

The methodology proposed in this paper detects and segments the tumor region in thyroid images in an effective manner using classification approach. The morphological features are clearly stated and analyzed to improve the tumor classification and segmentation accuracy. Further, the segmented tumor is also diagnosed into mild, moderate, and severe. The proposed method for tumor region segmentation achieves 99.20% sensitivity, 99.24% specificity, positive predictive value of 77.30%, 99.07% negative predictive value, accuracy of 99.08% with the elapsed time 0.357 milliseconds. The future scope of this research is to detect and segment the abnormalities in parathyroid glands.

List of abbreviations

CANFIS - Co-active Adaptive Neuro-Fuzzy Inference System
ANFIS - Adaptive Neuro-Fuzzy Inference System
GLCM - Gray-Level Co-occurrence Matrix
LBP - Local Binary Pattern
PPv - Positive Predictive Value
NPv - Negative Predictive Value

Conflict of Interest

The authors declare that they have no conflict of interest

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