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# USING DEEP LEARNING TECHNIQUES TO CLASSIFY THYROID ULTRASOUND IMAGES

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***Abstract:*** This article provides an overview of the existing literature on the processing of medical images related to thyroid cancer finding. The primary objective of this study is to serve as an introduction for those new to this field and as an indication for those seeking precise literature surveys in this area. In today's context, thyroid cancer is a frequently encountered concern due to the potential for malignancies and hyperactivity. Timely diagnosis is crucial in mitigating the increased malignancy of thyroid nodules. To address this, computer-aided detection methods and various image processing techniques are employed to effectively and efficiently classify thyroid nodules. Given the continuous growth of expert observations and the inherent uncertainties in medical knowledge, diagnostic imaging is essential to the medical industry. One often used technique for the precise and unambiguous identification and categorization of anomalies related to the thyroid gland is thyroid ultrasonography imaging. Computerized systems are invaluable tools for extracting features and classifying thyroid nodules, aiming to reduce misdiagnoses and enhance diagnostic accuracy. The main objective of this work is to review existing methods and techniques for automatically classifying nodules in thyroid ultrasound images. Performance indicators for thyroid ultrasound imaging nodule diagnosis are also included, highlighting the primary variations in the approaches taken.

***Index Terms***: ***Thyroid Nodules, Deep Learning, Ultrasonography. Classification***

## I. INTRODUCTION

Thyroid hormones are secreted by the thyroid gland, which is located in the neck area. Through circulation, these hormones control the body's metabolism. It also releases hormones that control a number of body processes. Cells that reproduce abnormally and have the potential to spread to other parts of the body are the cause of thyroid cancer. It comes from the thyroid gland's tissues. Thyroid cancer typically first manifests as a nodule in the thyroid region of the neck. Notably, although these nodules are present in 65% of adults with thyroid cancer, they typically affect less than 10% of those with the disease.

When it comes to helping radiologists and other medical personnel accurately identify malignant spots and facilitate appropriate diagnosis, computer-aided diagnosis (CAD) technologies are indispensable. To avoid making false diagnoses, a number of studies in the field of thyroid medical imaging have been carried out. It's crucial to remember that more women than men are affected by thyroid cancer.

Over the last three decades, thyroid cancer has shown a continuous increase, making it the fifth most common cancer among women in recent years. With the growing number of thyroid disease patients, there is a significant increase in both imaging and clinical data volume. Manual examination of patient data can be time-consuming, labor-intensive, and subject to variation. To address these challenges, computer-aided diagnostic systems have been developed to support clinical professionals in effectively and efficiently diagnosing, treating, and managing thyroid diseases.

A meticulous examination is necessary to assess the structural and functional status of the thyroid gland, as even subtle structural changes can be misleading. It might be difficult for doctors to diagnose thyroid diseases when there are little variations from normal levels because it can be difficult to tell if a structural thyroid problem is developing. Accurate assessment of the gland is crucial to avoid misdiagnosis, a significant issue in the healthcare industry.

Proper diagnosis of the various types of thyroid diseases is of paramount importance, especially since some of these types have a higher likelihood of progressing to cancer. Thyroid cancer has the potential to spread to neighbouring tissues through the lymphatic system or the circulation.

Thyroid cancer can be categorised based on its histological characteristics:

- **Papillary Thyroid Cancer**: Typically observed in youthful females and often associated with ancestral adenomatous polyposis.
- **Follicular Thyroid Cancer**: Common in individuals with Cowden syndrome.
- **Medullary Thyroid Cancer**: Arises from parafollicular cells.
- **Anaplastic Thyroid Cancer**: Known for its resistance to treatment and the potential to cause pressure symptoms.

### 1.1. Basic Diagnostic Approaches

1.1.1 **General Body Assessment:**

Evaluating the overall physical condition of the patient. A comprehensive general body evaluation is an essential first stage in the medical process since it allows medical practitioners to collect vital data for diagnosis, therapy planning, and overall patient monitoring.

1.1.2 **Thyroid Function Assessment through Temperature Testing:**

Monitoring temperature fluctuations over a period of 4 to 5 days to gauge thyroid function.

### 1.2. Medical Diagnostic Techniques

1.2.1 **Blood-Based Thyroid Function Assessment** - This method involves a blood test but can be uncomfortable.

1.2.2 **Precision Biopsy Guided by Ultrasound** - A highly accurate technique where a needle is guided into the affected area with the assistance of ultrasound.

1.2.3 **Immunofluorescence Detection** - This method relies on visualizing samples using ultraviolet rays or fluorescence.

1.2.4 **Radioimmunoassay-Based Testing** - Utilizing a blood sample for analysis.

### 1.3. Diagnosis by Imaging Methods

1.3.1 Clinical Photographs

Digitized images of a patient's body, known as clinical pictures, serve to record wounds, sores, and various skin conditions. Automated analysis of these images enables the ongoing assessment of treatment effectiveness. In dermatological and aesthetic practices, clinical photos are commonly employed to observe alterations in skin or structural features before and after interventions. The diagnosis of melanoma, a type of skin cancer, often involves the examination of clinical images.

1.3.2 X-ray Imaging

The most widely used technique for identifying fractures and a dislocation of the bone is X-ray imaging, which yields a two-dimensional image. Associated data and diagnoses for 100,000 chest X-ray pictures have been made publicly available by the National Institutes of Health (NIH) to aid in the development of imaging analysis tools. In parallel, a dataset including more than 350,000 chest X-rays is available for download from the Massachusetts Institute of Technology (MIT). This dataset allows the detection of 14 prevalent illnesses, including pneumonia and punctured lung, and is a great resource for advancing machine learning prototypes.

1.3.3 Computed Tomography (CT)

Utilizing 360-degree X-rays, the computed tomography (CT) imaging technique generates intricate cross-sectional representations of the body's internal organs, bones, soft tissues, and blood vessels. Most images are captured in the oblique plane, perpendicular to the body's longitudinal axis. These images can be segmented into various planes and subsequently fused to construct three-dimensional images. CT has effectively addressed challenges in biomedical imaging and is now a standard tool for detecting tumors and determining their size, playing a crucial role in cancer diagnosis.

1.3.4 Ultrasound Imaging (US)

As enhanced ultrasonic technology continues to emerge and the US-based digital health system becomes more established, US, a flexible green imaging modality, is becoming more and more popular throughout the world as a primary imaging method in many clinical domains. High-frequency linear transducers (7.5-15.0 MHz) are used in the US, which may penetrate to a depth of up to 5 cm and generate high-definition images. Several important advantages of US over additional medicinal scanning modalities like X-ray, magnetic resonance imaging (MRI) and CT have been established throughout the decades, including non-ionizing radiation, mobility, approachability, and price effectiveness. Many guidelines, including the American Thyroid Association, the American Association of Clinical Endocrinologists and the European Thyroid Association, now recommend US as the first-line imaging modality for detecting thyroid disorders. As a result, various Thyroid Imaging Reporting and Data Systems based on US images have been built in recent years.

1.3.5 Magnetic Resonance Imaging (MRI)

In MRI imaging technique a high magnetic fields use to create pictures of physiological progressions, organs, and tissues within the body. Non-bony bodily parts, also known as soft tissues, are imaged using MRI. CT scans and MRI are fundamentally different in that MRI uses ionising radiation. In comparison to x-rays and CT scans, MRI scans provide better resolution for knee and shoulder problems. The Open Access Series of Imaging Studies (OASIS) programme has compiled neuroimaging datasets with approximately 2000 MRI sessions for biomedical scanning investigators.

1.3.6 Optical Coherence Tomography (OCT)

OCT technology utilizes low-coherence light to capture micrometer-scale, two- and three-dimensional images of biological tissues. This technique is commonly employed in identifying eye issues as it provides a cross-sectional image of the retina, allowing practitioners to distinctly observe each layer. The comprehensive assessment of thickness and mapping of layers that contribute to the conclusion are now achievable through OCT.

1.3.7 Microscopic Images

Microscopic medical images are used to evaluate the tiny structure of the tissue. After a biopsy to obtain tissue for analysis, staining agents are used to reveal cellular characteristics in selected tissue sections. To increase the graphics' colour, visibility, and contrast, counter stains are applied. This type of imaging is commonly used to diagnose malignancy. On a steady basis, the nucleus plus allocation of cells in the tissue, as well as their form and size, are all tested.

1.3.8 Scintigraphy

Scintigraphy, often known as a thyroid scan, is performed in nuclear medicine. Scintigraphy is used to determine the active (functioning) portion of the thyroid gland. The patient is given a radioiodine drug, and then gamma cameras are used to capture photographs of the thyroid and reveal the part of the thyroid that uptakes iodine, i.e. the active or functional component of the thyroid. Scintigraphy imaging is a type of 2-D imaging that is used to examine the thyroid's function.

1.3.9 Fluoroscopy

Used to view a patient's interior anatomy and functionality. It generates moving images in real time using continuous x-rays.

1.3.10 Radioiodine Scan

Before a test, radioactive substance radioiodine is administered by injection, liquid, or tablet to emit gamma rays. Such energy is detected by scanners.

1.3.11 Positron Emission Tomography (PET scan)

Gamma rays are detected by PET from a tracer and shown on a monitor.

## II. Literature Survey

Chaun et al. [1] conducted research in which they categorized thyroid nodules as enlarged follicles. They presented a Support Vector Machine (SVM) based thyroid classification technique. Features such as bigger follicles, follicular cells with follicles, papillary cells with follicles, follicular cells with fibrosis, and papillary cells with fibrosis were extracted using biopsies and regions of interest (ROIs) identified by radiologists. SVM feature selection was utilised to produce a more discriminative feature set for different types of thyroid nodules. SVM models trained with data from the corresponding categories were effectively used to identify six distinct types of thyroid nodules.

Roberto et al. [2] investigated three procedures for utilising 3-D contrast-enhanced ultrasonography to reconstruct intra-nodular vasculature. They used thresholding and three-dimensional representation, preprocessing and morphological opening. In order to improve diagnosis, contrast-enhanced ultrasound imaging (CEUI) was developed. Based on increased intranodular vasculature, microbubbles are injected into lesions to help distinguish between benign and malignant nodules.

Konstantin et al. [3] presented a categorization system for medical applications to validate Fine Needle Aspiration (FNA) tests. They applied the BoxCells algorithm on FNA data and used the Artificial Immune System (AIS) to diagnose thyroid cancer. An AIS-based classifier was used to perform the classification after feature selection reduced the dimensionality of the input.

Rajendra et al. [4] offered a Computer-Aided Diagnosis (CAD) method for 3D contrast-enhanced ultrasound image categorization that automatically distinguishes between benign and malignant thyroid lesions. They used texture-based techniques and the Discrete Wavelet Transform (DWT) to extract characteristics from the thyroid pictures. Using ten-fold cross-validation, these feature vectors were utilised to train and evaluate three distinct classifiers: Probabilistic Neural Network (PNN), Decision Tree (DeTr), and K-Nearest Neighbour (K-NN).

Gopinath et al. [5] suggested using Fine Needle Aspiration Cytology (FNAC) to diagnose thyroid cancer patterns using a computer-aided diagnostic system. Using the Gabor Filter bank at different wavelengths and angles, texture features were extracted and samples were assessed based on region-based morphology. They performed better than the K-NN classifier by using a Support Vector Machine (SVM) classifier to determine whether the malignancy was benign or malignant.

Maria et al. [6] used envelope-based and high-frequency quantitative spectral measurements in a rodent model to differentiate between thyroid cancer and normal/benign thyroids. They combined a two-dimensional feature space with nonlinear classification to differentiate between different types of cancer

Jianruri et al. [7] suggested a system that evaluated elastograms and thyroid B-mode ultrasound pictures as a bag. To improve the identification and categorization of thyroid cancer, a computer-aided diagnosis approach was employed. They constructed B-mode vector images and elastogram feature vectors, applied statistical texture features, and employed traditional supervised methods for classification, including the Multiple Instance Method (MIL) for thyroid nodule classification.

Hanung et al. [8] suggested a study focusing on extracting thyroid nodules from ultrasound images. They determined ROIs from ultrasound images and performed preprocessing using median filtering and morphological methods to alter object structure. Histogram equalization was used to standardize image intensity, and feature extraction was carried out using Gray Level Co-Occurrence Matrix (GLCM) and Gray Level Run Length Matrix (GLRLM). Classification was done using a Multilayer Perceptron to categorize images into cystic and solid categories.

Handgun et al. [9] developed classifier models to differentiate between benign and malignant thyroid nodules using machine learning approaches. Nodules and ultrasound images were scored using a five-tier system of sonographic grading. After the Bayes classifier was utilised and the output was directed using a Bayesian network, an SVM classifier was built using learning strategies from optimisation theory. ROC curve analysis was used to evaluate performance and the Radial Basis Function-Neural Network (RBF-NN) technique was used for clustering.

Liu et al. [10] suggested a Convolutional Neural Network (CNN) based feature extraction technique for ultrasound pictures. To create semantic deep features, they trained CNN on natural datasets and then applied its learnings to ultrasound pictures. To build a hybrid feature space, these deep features were merged with more traditional features like the local binary pattern and the Histogram of Oriented Gradient. The VGG-F model was utilised for both feature extraction and comprehensive classification; it was trained on IMAGENET.

Yezhu et al. [11] used transfer learning, image augmentation, and preprocessing on ultrasound images to solve the thyroid nodule classification problem. They focused on extracting regions of interest (ROIs) and utilized two different methods: traditional augmentation by using original images and convolutional augmentation with a three-layer convolutional network. For classification, they employed a pre-trained residual network (ResNet) for transfer learning and conducted experiments using different datasets.

Xueyan et al. [12] employed machine learning classifiers and deep learning feature extraction to forecast the benignity of thyroid nodules. They employed computer vision techniques, such as local binary patterns and histogram of directed gradients, to capture appearance and form attributes, and they used convolutional autoencoders to extract features from ultrasound pictures. Radiologists supplied data for the Thyroid Imaging Reporting and Data Systems (TIRADS). These characteristics were employed in the training of classifiers, and to lower the false negative rate, a Support Vector Classifier was used.

Zulfanahri et al. [13] suggested a method for dividing thyroid nodules into round, oval, and irregular categories using shape feature analysis. Their method included segmentation utilising active contour and morphological operations, feature extraction using Zernike and invariant moments, and preprocessing with adaptive median and SRB filtering. Correlation-Based Feature Selection (CFS) was used for feature selection, and an SVM classifier was used to classify the outcomes.

Muhammad et al. [14] offered a diagnosis approach for thyroid nodules in ultrasound pictures that is computer-aided. They performed sample augmentation and preprocessed the photos to get rid of annotations. Based on optimising an already-existing deep Convolutional Neural Network (CNN), namely GoogleNet, the photos were categorised.

Jianning et al. [15] presented a method for improving ultrasound (US) image quality. They used a structural element with a diamond shape to apply morphological opening and spatial linear filtering. The filtered image split the image, and the opened image was converted to grayscale. The image was then segmented using thresholding, and a hill climbing algorithm was used to extract features. To perform the final classification, Support Vector Machines (SVM) was used.

Amir et al. [16] utilized online learning methods, normalized features, and feature selection to improve thyroid nodule classification. They employed decision tree-based classifiers, including a simple decision tree and a cost-aware version, along with a weighted majority system for classification.

Farihah et al. [17] employed the British Thyroid Association (BTA) recommendations for US-guided Fine Needle Aspiration Cytology (FNAC) and pathology diagnosis as a reference standard to assess the reliability of an ultrasound classification system for predicting thyroid cancer. They used a conservative method to calculate sensitivity and compared ultrasonography categorization with pathology results

Dandan et al. [18] a system of classification for diffuse thyroid diseases based on ultrasonography scans was proposed. Distinguishing between Hashimoto's illness and Graves disease, the two most common types of diffuse thyroid disease, was the main goal. With a focus on fibre texture variations, new texture features based on the Wavelet Multi-Sub Bands Co-Occurrence Matrix (WMCM) were introduced, and the Grey Level Run Length Matrix (GLRLM) and Grey Level Co-occurrence Matrix (GLCM) were added to broaden the feature space. The Minimal Redundancy Maximum Relevance (MRMR) technique was used for feature selection, and K-NN and SVM classifiers were used to achieve a two-level classification.

Zhang et al. [19] introduced a unique method for categorising thyroid tissue from multi-modality MRI images that uses multichannel features association and fusion learning (FAFL). This technique involved creating multi-channel CNN tensors using a two-layer convolutional neural network, fusing them using a multi-features association layer, and connecting the multichannel CNN tensors for classification. Using a CNN and a deep learning modal support vector network, FAFL generated three modalities for categorization.

Jianxion et al. [20] suggested a semi-supervised technique to identify thyroid nodules in ultrasound pictures using data that is only partially labelled. Pathology reports were employed as "bag labels" and the ultrasound images were handled as a "bag." They created bag instances, preprocessed them, used proposal extraction techniques, and used VGG-16 to categorise areas of interest (ROIs). CNN-based classification with an EM method was applied to the training data that had weak labels, and non-maximum suppression strategies were utilised to merge and renew ROI nodules. The photos were classified as benign or malignant using the trained model.

Frannita et al. [21] utilizing internal content criteria, the classification of thyroid carcinoma in ultrasound (US) images was carried out, categorizing them into three groups based on nodular characteristics. The identification of thyroid carcinoma often relies on the nodular feature, and the diagnostic speed can be influenced by the radiologist's experience. To mitigate the dependence on radiologists, an automated approach was implemented in this study, which involved the analysis of 97 thyroid US images. The proposed procedure begins with pre-processing to enhance detection capability, followed by the application of morphological operations and active contour techniques to accurately identify nodules. The segmented region is then extracted using histogram, Grey Level Co-occurrence Matrix (GLCM), Grey Level Run Length Matrix (GLRLM), and lacunarity. Subsequently, a Multilayer Perceptron (MLP) is employed for data classification based on the extracted values, resulting in an achieved accuracy of 98.97%, kindness of 98.92%, specificity of 99.47%, positive predictive value (PPV) of 99.05%, and negative predictive value (NPV) of 99.50%.

Xu et al. [22] presented a machine learning-based automatic segmentation solution for breast US images. The automatic segmentation results are visually consistent with humanly segmented ground truth, indicating that the proposed technique can differentiate various tissues from breast US pictures in the same way that clinicians can. The suggested method splits US breast images into four major tissues using three orthogonal image planes: skin, fibro glandular tissue, mass, and fatty tissue. CNN specifies the tissue lesson for central pixel inside the picture block. Truthfulness, Precision, Recall, and F1measure, all quantitative criteria for evaluating segmentation results, all exceeded 80%, indicating that the suggested technique is capable of distinguishing practical tissues inside breast US pictures. An additional measure, the Jaccard Similarity Index (JSI), has a rate of 85.1%.

## III. Categorization

We employed a set of predefined criteria, utilizing various classification techniques to categorize regions into distinct groups such as benign or malignant, lesions, and non-lesions. The Thyroid Imaging Reporting and Data System (TIRADS) is instrumental in providing a standardized classification and supporting reporting data system for thyroid-related medical management. This system offers a structured approach to evaluate and communicate findings from ultrasound-based thyroid imaging, facilitating consistency and accuracy in the assessment of thyroid conditions.

**A. Categories:**

**Table 1: Thyroid Imaging Reporting & Data System (Ti-RADS)**

| S.No. | TI-RADS Score | Remarks |
|---|---|---|
| 1 | TI-RADS 1 | Regular thyroid gland |
| 2 | TI-RADS 2 | Benign Circumstances (no chance of cancer) |
| 3 | TI-RADS 3 | Probably Benign nodules (<5% Malignancy) |
| 4 | TI-RADS 4 | Suspicious nodules (5-80% Malignancy) |
| 5 | TI-RADS 4a | Undetermined (5-10% Malignancy) |
| 6 | TI-RADS 4b | Suspicious (10-80% Malignancy) |
| 7 | TI-RADS 5 | Probably Malignant nodules (>80% Malignancy) |
| 8 | TI-RADS 6 | Cancer identified via Biopsy |

**Table 2 : Comparison Using Various Classification Methods**

| Publication year/ Refe rence | Methodology | Data Collected | Accu racy |
|---|---|---|---|
| 2008 [1] | a. co- occurrence matrix wavelet features<br>b. Law texture energy measures | Data set from the ultrasonography system LOQ10 700, approved by General Electric Healthcare, Cambridge, UK.. | 99.8 % |
| 2008 [2] | a. Morphological aperture<br>b. Thresholding and 3D construction. | Pictures taken with the My Lab 70 US gadget and approved by Toronto's "Umber to I" Hospital. | 98% |
| 2009 [3] | a. Box cells population cloning box cells<br>b. Inflation and Deflation of Box cells. | Data collected from department of pathology of medical school of Athens. | 98% |
| 2012 [4] | a. Discrete wavelet transform<br>b. Neural network<br>c. Decision tree | Data collected from "Umber to I" hospital of Toronto. | 93% |
| 2013 [5] | a. Morphological Transform<br>b. Gabo r filter | FNAC image have been used from on-line image atlas papanicolaou society of cytology approve d by atlas committee. | 95% |
| 2014 [6] | a. Effective acoustic concentration<br>b. Effective scattering diameter | Data collected using single element transducer using an Olympus parametric 5900 receiver, strategic test corporation Woborn. | 87% |
| 2014 [7] | a. Mode feature vector | Data base collected from department of ultrasound second Affiliated Hospital of Harbin medical | 96.8% |
| 2016 [8] | a. Gray level co occurrence matrix<br>b. Gray level run length matrix | Image was obtained from Sardji to hospital Yogyakarta database. | 89.74% |
| 2016 [9] | a. classifier model construction | Dataset collected from Institute of Nuclear medicine. | 88.66% |
| 2017 [11] | a. Residual net transfer learning. | Open access provided by Universidad National; Decolombia, Institute Diagnostic medico. | 93.75% |
| 2017 [12] | a. Auto encoders<br>b. Local Binary patterns | Cases collected at East river medical imaging using general Liquid and 69 ultrasound Machines. | 94% |

| | | | |
|---|---|---|---|
| 2017 [13] | a. Active Contour<br>b. Zernike and invariant<br>c. Correlation based feature | US images taken from Department of Radiology Sardji to hospital, Yogyakarta | 91.52% |
| 2017 [14] | a. Online Ensemble<br>b. Offline Ensemble | Data is a publicly available thyroid ultrasound images and from local database. | 96% |
| 2017 [15] | a. Sample Augmentation<br>b. Google Net | Data collected from local database | 92% |
| 2017 [16] | a. Spatial linear filtering<br>b. Thresholding | Dataset collected from Center of machine learning and intelligent systems, university of California | 99.8% |
| 2018 [17] | a. U classification method suggested by BTA. | US images collected from university kebangsaan Malaysia medical center. | 98% |
| 2018 [18] | a. Wavelet Multi–sub-bands Co-occurrence Matrix<br>b. Gray level co-occurrence matrix. | Data collected from department of us of second affiliated hospital of Harbin medical university. | 87.83% |
| 2018 [19] | a. Data augmentation<br>b. Multi–feature association | Data collected using 63AC55 C scanner Philips healthcare. | 80.91% |
| 2018 [20] | a. ROI detection with VGG-16<br>b. ROI merging. | Data collected from the Peking union medical hospital and publicly available database. | 80.91% |
| 2018 [21] | CNN (Histogram, Morphological etc. for pre-processing). | A total of 97 thyroid US pictures were used in this study. | 98.97 % |
| 2021 [22 ] | U-Net | Open source standard dataset DDTI. | 98.95 % |
| 2019 [23 ] | CNN | US breast images from local database. | 85.1% |

## IV. Conclusions

Different techniques were applied by different researchers to process the Thyroid Ultrasound images, but the structures were very difficult to visible due to noise, unclearness, blurred and uncertainty in Thyroid Ultrasound images. To detect the abnormal structure of thyroid, perceptive ways must be found out to analysis and describe the correctness in US image. So the above mentioned techniques and methods are useful to find out the structural behavior of Thyroid US image. Therefore this research would also helpful for characterization of nodules, it is a valuable tool for follow up the diagnosing the nodules in thyroid images and lead to false diagnosis related thyroid diseases. Many physicians are confessed about the nature of various echoes due to low resolution of US. so more efficient classifiers used to improve the accuracy of performance of thyroid nodules as benign/malignant. Studies regarding different feature extraction techniques and classification techniques could be carried out clearly, hardly and correctly. The deep learning and machine learning approaches are much more widely used for the classification of thyroid nodules. This work basically provides a summary about the existing automatic tools available to develop disease diagnosis part easier and also well efficient. Different execution evaluation metrics are studied and future developments and trends are also investigated. Such techniques will help the diagnosis process by automatically detect the nodules in thyroid images and reduce the false diagnosis. The feasible feature extraction and classification methods for detecting thyroid nodules can be determined and applied to ultrasound images using various methods and techniques for application in an integrated real-time system for thyroid gland in future.

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